Intraday Liquidity Spillovers in Commodity Futures Markets

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Master Thesis

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Abstract

In this thesis intraday liquidity relations in the soybean crush complex (meal, oil and beans) are examined by studying idiosyncratic and cross-market spillovers of liquidity. Liquidity is a major determinant of derivative pricing, hedging effectiveness and a key driver of co-movements of prices and price-volatilities among markets. A comprehensive multidimensional liquidity measure is derived from the full limited order book (LOB) of the Chicago Mercantile Exchange (CME) for January 2015 to December 2015. A Vector Heterogenous Autoregressive (VHAR) model is adapted to estimate high-resoluted idiosyncratic and cross-market liquidity spillovers in the short-, medium-, and long-run. Results show that liquidity is mostly determined by its own liquidity returns within 30 seconds. Positive cross-market spillovers predominantly occur within 5 minutes and negative cross-market spillovers occur in lags from 5 minutes until one trading day. There is evidence for a so-called 'flight-to-liquidity' on a daily time window. Each market provides consistent spillovers to all other markets. During the pre-harvest period the nature of spillovers tends to deviate and the 'leading' liquidity role of the soybean market is more pronounced in this period. Furthermore, spillovers differ in nature between regular and extended trading hours, potentially because of different trading strategies.

Keywords: Liquidity spillovers, limit order book, futures markets, commodity markets, multivariate HAR model

JEL classifications: G13, C22, Q14

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1. Introduction

Co-movements in price returns and their volatility significantly impact pricing in commodity futures markets, and influence decisions for portfolio and risk management. Since commodity futures markets serve both as an asset class for investors and as a risk sharing mechanism for hedgers, common factors that influence pricing are strikingly important in commodity futures markets. The existence of co-movements of commodity prices have been a topic of debate over the last decades. Pindyck & Rotemberg (1990) argue that unrelated raw commodities show co-movement beyond economic fundamental causes. More recently, Ai et al. (2006) present evidence against this excessive commodity price co-movement phenomenon. De Nicola et al. (2016) argue that co-movements among major agricultural, energy, and food commodity are widely present and have been booming over the last years. While scholars do not agree on this topic, these co-movements potentially have great impact. As independence of asset-pricing decreases, shocks to one asset could have serious market wide adverse effects. Since the strong relationship between price volatility and liquidity in futures markets is well-embodied in the literature it is interesting to assess liquidity co-movements (Bessembinder and Seguin, 1993; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Szymanowska et al., 2014). Cross-market liquidity co-movements could potentially explain cross-market price and price volatility correlations, as is discussed by Zhang & Ding (2018) who link co-movement of commodity price returns and their volatilities to liquidity co-movements.

A substantial number of studies has focused on co-movements of returns and price volatilities between commodity markets but less studies have assessed liquidity commonalities and spillovers. Chordia et al. (2001) were the first to refer to commonality in liquidity by exploring potential common underlying determinants of microstructure market phenomena. The authors show that liquidity of NYSE stocks correlates with market- and industry wide liquidity, controlling for well-known individual liquidity influencers such as volatility, volume, and price. According to the authors, liquidity commonality indicates that inventory risk and asymmetric information both have an effect on the liquidity of one asset. Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Brockman and Chung (2002) further emphasize the major role of common factors (e.g. liquidity commonality) on the microstructure of markets. Market wide commonalities and potential financial contagion is researched by Rösch and Kaserer (2013), who find significant liquidity commonality in the Xetra electronic market of Deutsche Börse based on a volume-weighted spread measure for liquidity. Not only do the authors find evidence that there is indeed liquidity commonality, they also identify that liquidity commonality increases during market downturns, is large during crisis events, and becomes weaker the further one digs into the Limit Order Book (LOB). The nature of liquidity relations and their magnitudes are especially interesting for agricultural commodity markets, due to potential seasonal production cycle effects and perishability. Furthermore, due to the diverse strategies of traders and their activity, liquidity relations may differ from day to night trading (i.e. Regular Trading Hours (RTH) vs. Extended Trading Hours (ETH)). Mancini et al. (2013) further emphasize liquidity downturns or shocks, as they state that the liquidity on individual foreign exchange rate markets are mostly determined by market wide liquidity shocks. This damages the positive effect of portfolio diversification and implies a relative high risk of liquidity dry-ups in market downturns.

The scarce literature on liquidity relations and spillovers mainly focuses on stock markets and equity derivatives. Other markets are less researched, while their characteristics can give interesting insights. For instance, agricultural commodity futures markets are important to study given their unique financial relevance as an asset class and hedge mechanism. Moreover, due to both physical and financial interrelations among various commodity futures markets interesting liquidity dynamics may occur. Our dataset, the soybean complex, gives the opportunity to examine liquidity spillovers in a relative stable environment given the relative balanced relationship between soybeans and the quantity of meal and oil produced (Simon, 1999; Mitchell, 2010).

The objective of this study is to examine intraday liquidity relations among futures markets in the soybean complex and to explore the reaction span and persistence of these liquidity spillovers over time. In addition, this study examines differences between liquidity spillovers during regular and extended trading hours and discrepancies due to seasonal effects. Understanding liquidity dynamics can clarify systematic liquidity crises, for example the 2010 Flash Crash (Kirilenko et al., 2017). Furthermore, liquidity plays a substantial role in overall derivative pricing (Amihud et al., 2006; Acharya & Pedersen, 2005).

Cespa & Foucault (2014) argue that variations in demand and supply liquidity are potential drivers of liquidity spillovers. A framework of liquidity and its implications is formalized by Gromb & Vayanos (2010) and Brunnermeier & Pedersen (2008). From the liquidity supply side, Kyle & Xiong (2001) state that liquidity suppliers have limited resources and hence adverse shocks possibly enhance liquidity spillovers. Furthermore, Kyle & Xiong (2001) argue that liquidity transmissions and other financial contagion are of great relevance to commodity futures markets as these factors curtail the mitigating effects of portfolio diversification and could substantially reduce hedging effectiveness. Furthermore, agricultural commodity futures markets are prone to seasonality effects caused by the growth cycle of the underlying products and exogenous factors that influence this cycle and overall yield

(Sørensen, 2002). Studying potential differences in liquidity spillovers due to seasonality contributes to understanding commodity futures dynamics.

Intraday liquidity spillovers from the soybean complex are studied in this thesis. From each market a time series of liquidity is created and compared to the series of the other two markets. The data used is high-frequency comprehensive limit-order book (LOB) data obtained from the Chicago Mercantile Exchange. The data is structured such that snapshots of the LOB are obtained for every 7.5 seconds as the average price duration for soybean contracts is around 7.6 seconds (Arzandeh & Frank, 2017). In order to capture multiple dimensions of liquidity, a comprehensive order weighted average liquidity measure is obtained by calculating the costs of a round trip (CRT) trade of a certain dollar value V based on Irvine et al. (2000).

Since the start of this millennium, high-frequency financial data became more widely available. However, tools to retrieve, clean, and analyze the data are limited. In this thesis, different methods to analyze high-frequency financial data are combined to give clear and well-grounded insights to liquidity dynamics in commodity futures markets. To study the actual dynamics of liquidity among different commodity markets, a VHAR model as proposed by Corsi (2009) is adjusted to a multivariate setting in line with Souček and Todorova (2013). The VHAR is generally used to capture the dynamics of second moments of price returns. However, in this thesis, the model is adapted to analyze intraday liquidity spillovers. Instead of using squared price returns (i.e. realized price variance), intraday estimations of liquidity levels are utilized. This is in line with Hasbrouck (2018), where the HVAR technique is used to conduct multiple price discovery analyses on high-frequency US equity market data. The main advantage of the VHAR over other autoregressive models is the lag structure, which is characterized by the separation between short, medium, and long run spillovers effects. From these three lag windows, the average liquidities are calculated and used in the model. This implies estimation of the effects of short, medium and long run liquidity on current liquidity, hence enabling us to capture trading heterogeneity due to information asymmetry (Corsi, 2009).

This study contributes to the literature in several ways. First, to our knowledge it is the first study that analyzes multi-dimensional liquidity in a high-frequency framework with data derived from the full - instead of top of the book - LOB snapshots of futures contracts. Second, whereas most scholars use larger intervals this research examines direct intraday idiosyncratic and cross-market liquidity spillovers of related commodity futures markets. Third, seasonality and trading hours effects on liquidity spillovers are assessed by creating subsamples of certain periods, and subsamples of regular and extended trading hours. Finally, this study demonstrates drivers behind potential liquidity crises.

2. Liquidity and its Measurement

Liquidity encloses the ability to trade on a market, it consists of four dimensions: immediacy, resilience, width, and depth (Harris, 1990). Immediacy is the speed at which a certain amount of assets can be sold or bought. Resilience refers to the time of recovery of the price due to liquidity shocks. Width identifies the spread between the best bid and ask price and accounts for the cost of the transaction. The last dimension is market depth, which refers to the amount of securities tradeable at a certain price and hence to the ability to sustain a certain price level after relatively large market orders come in. As early as 1988, Grossman & Miller pointed out that the bid-ask spread which captures the width solely, a generally accepted single dimension measure for liquidity, is limited due to its negligence of immediacy. A measure which captures immediacy as well is preferred in this research as the immediacy demand is high in futures markets. Market makers supply immediacy when they trade with hedgers and temporarily take up the price risk until final buyers and sellers arrive (Grossman & Miller, 1988).

The most common measures of liquidity in the literature are either order- or trade-based. Trade-based liquidity measures cover trading volume, trading value, the amount of trades, and the turnover ratio. A main drawback of trade-based measures is that a real trade is needed to materialize. Thus, it is an *ex-post* measure which gives a delayed estimate of liquidity. An advantage of calculating *ex-ante* liquidity from LOBs is that there is no need for an actual trade. However, as LOB data are not widely available, guidance on calculating liquidity from order book data is rather limited. Most measures of liquidity can be considered to be proxies instead of being based on the genuine liquidity dimensions. For example, Goyenko et al. (2008) wrote an influential paper concerning liquidity proxies and they did not discuss LOBs. A problem arising with the use of LOBs to obtain a liquidity measure is the opportunity for traders to place *iceberg orders* or *hidden-size orders*, which essentially are orders that are bigger than the actual size they have been placed for. Besides, *dark pool trading*[1] has been on the rise (Gould et al., 2013), which potentially distorts the estimation of liquidity from LOB data.

Table 1 shows several market liquidity measures as discussed in the literature. Scholars that assessed liquidity beyond the width dimension mostly measure the rise (fall) of the market price because of a certain amount of buying (selling) orders coming in, quantified by the price impact function which measures the depth dimension of liquidity (Hasbrouck, 2004; Frank & Garcia, 2011; Weber & Rosenow, 2006). Other scholars focus on the depth dimension as well but base their liquidity measure on quoted depth (Chordia et al., 2001; Coppejans et al., 2001;

[1] Dark pools vary over different exchanges, mostly, dark pools are LOBs in which all orders are hidden or pools where traders can only submit a desired quantity and direction of trade. This order will be executed at the market price

Kirilenko et al., 2017). The change in inventory holdings, LOBs, and total trading volumes are used as proxies for liquidity. Kyle (1985) advocate that depth is the single best estimator for liquidity. Hautsch and Huang (2012) propose an impulse response function that captures both the short run price effects of a limit order (width, depth, and immediacy dimension) and the long run price impact of a limit order (resiliency). Shang et al. (2018) examine the effects of USDA announcements on liquidity costs by assessing the bid-ask spread. Aidov and Daigler (2015) use depth up to five levels in the limit order book to estimate liquidity. Furthermore, Aitken & Comerton-Forde (2003) suggest a liquidity measure that is based on the bid-ask spread, order depth and on the probability of the execution of orders in the LOB. This method implies that if the probabilities of execution of orders relatively far away from the mid-quote price are high, the liquidity is low.

Irvine et al. (2000) design a Cost-of-Round-Trip (CRT) liquidity measure that captures the width, immediacy, and depth dimension of liquidity and above all, does not depend on actual trades and is practicable in an intraday framework. The proposed CRT measure calculates the costs involved by simultaneously buying and selling an exact equal monetary amount V. On both the bid and ask side, an average contract or asset price can be calculated for executing that certain monetary amount V, the difference between the two is referred to as the *liquidity spread*. Irvine et al. (2000) find evidence that this CRT method is

Table 1. Studies proposing liquidity measures

Study	Publication	Market	Exchange	Measures	LOB data	Trade-based	Intraday	Dimensions
Irvine et al. (2000)	Working Paper	Stocks	TMX	Cost of Round-Trip trade	Yes	No	Yes	Immediacy, depth and width
Chordia et al. (2001)	Journal of Financial Economics	Stocks	NYSE	Quoted spread, Effective spread, Depth	No	No	No	Width or Depth
Coppejans et al. (2001)	AFA 2002 Atlanta Meetings	Stock index futures	OMX	Market depth	Yes	No	Yes	Depth
Aitken & Comerton-Forde (2003)	Pacific-Basin Finance Journal	Stocks	Jakarta Stock Exchange	Execution probability	Yes	Yes	No	Immediacy, depth and width
Hasbrouck (2004)	Journal of Financial and Quantitative Analysis	S&P500, Euro, Pound, pork belly contracts	CME	Non-linear price impact function	No	Yes	Yes	Depth
Weber & Rosenow (2006)	Quantitative Finance	Stocks	NASDAQ	Virtual non-linear price impact function	Yes	No	No	Resilience and Depth
Hachmeister (2007)	Springer	Stocks	Xetra	Volume-weighted spread based on a roundtrip order of monetary size V	Yes	No	Yes	Immediacy, depth and width
Frank & Garcia (2011)	American Journal of Agricultural Economics	Live cattle and lean hogs futures	CME	Non-linear price impact function	No	Yes	No	Depth
Hautsch & Huang (2012)	Journal of Economic Dynamics and Control	Stocks	AEX	Impulse Response function	Yes	No	Yes	Immediacy, resiliency, depth and width
Rösch & Kaserer (2013)	Journal of Banking & Finance	Stocks	Xetra	Volume-weighted spread based on a roundtrip order of monetary size V	Yes	No	No	Immediacy, depth and width
Lehecka et al. (2014)	Applied Economic Perspectives and Policy	Corn futures	CME	Market depth	No	Yes	Yes	Depth
Aidov and Daigler (2015)	Journal of Futures Markets	Multiple Futures	CME	Market depth	Yes	No	Yes	Depth
Kirilenko et al. (2017)	The Journal of Finance	E-mini S&P 500 stock index futures	CME	Inventories for different types of traders	Yes	No	Yes	Depth
Shang et al. (2018)	Agricultural Economics	Corn futures	CME	Bid-ask spread	No	No	Yes	Width
Zhang & Ding (2018)	Quantitative Finance	Cattle, Copper, Corn, Oil and Gold futures	CME	Amihud (proxy for price impact)	No	Yes	No	Depth

the best single estimator for liquidity. The liquidity measure has two major advantages. First, it considers *ex-ante* liquidity unlike *ex-post* measures (e.g. other general liquidity measures that make use of volume measures). Second, the CRT approach calculates the liquidity based on the width (actual bid-ask spread) and the depth (adverse price movements as result of orders exceeding bid-ask size). According to Hachmeister (2007), the combination of width and depth implicitly accommodates the immediacy dimension. Rösch & Kaserer (2013) use a CRT based liquidity measure on an electronic order-driven market system Xetra of Deutsche Börse and find commonality among individual stock liquidity and market liquidity by regressing the first on the latter. Furthermore, they find that liquidity commonality substantially increases during times of financial turmoil.

To assess liquidity from LOB data the CRT method is preferred over the price-impact measures, quoted depth or width measures, the probability-of-execution method, and the impulse response function. The price impact function method is particularly useful when data is limited and thus a liquidity *proxy* is utilized (i.e. in pit trading). The probability-of-execution method is comprehensive and convenient; however, it relies on probabilities of orders being executed which demands extensive data or, at least, time intervals in which sufficient trade takes place to set up different *bands* of execution probabilities. In a high frequency framework, determining execution probabilities for every interval requires excessive computing power and are not economically explainable, as the execution of limit orders further away from the mid-quote would have a zero or very low probability. For our analysis, a measure based on total depth or the bid-ask spread is not suitable as it omits crucial dimensions of liquidity which are significant determinants of liquidity (Black et al., 2016). However, as depth is broadly supported as a reliable liquidity measure the total depth is used as liquidity measure to test for robustness for the liquidity spread measure (Kyle, 1985; Berkman, 1992; Ahn et al., 2001; Kirilenko, 2017).

The high-frequency of the data grants a very precise estimation of liquidity, which adds substantial additional value to the explanation of liquidity compared to lower-frequency liquidity proxies (Goyenko et al., 2008). Cao et al. (2009) find that a liquidity measure calculated in a CRT framework has additional value over other liquidity measures. On top of that, Ernst et al. (2009) empirically compare different liquidity measures and find that the CRT liquidity measure is the most accurate of the liquidity measures based on LOB data. The authors also find that liquidity measures based on LOB data outperform non-LOB liquidity measures.

3. Methodology and Data

3.1. Liquidity measure

The CRT based liquidity measure is used to compute market liquidity. The liquidity measure combines multiple liquidity dimensions into one scalar and resembles the liquidity costs of trading on each 7.5 seconds timestamp. In the CRT framework from which the liquidity measure is calculated, a certain dollar amount *V* should be determined to estimate the costs occurring when similarly selling and buying this amount *V* (i.e. the costs occurring when 'making a roundtrip' of the amount of *V*, hence the name Cost-of-Round-Trip (CRT)) with information obtained from the LOB. The liquidity measure is an order-size dependent volume weighted spread based on the roundtrip costs of volume *V*. Based on Rösch & Kaserer (2013) the following equation is specified:

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

$L_t(V)$ represents the liquidity at time *t* for the CRT of *V*, $ask_{i,t}$ and $bid_{j,t}$ denote respectively the ask price at rank $i = (1,..,10)$ and bid prices at rank $j = (1,..,10)$ on moment *t*, in which each rank indicates the distance from the mid-quote price ($P_{mid,t}$). *n* refers to the number of orders which it takes to fulfill a total order with size *V*. $\sum_i ask_{i,t}\, n_{i,t}$ and $\sum_j bid_{j,t}\, n_{j,t}$ respectively denote the sum of the amount of orders on different levels multiplied with the corresponding price for each order subject to the total amount of execution *V*. 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 side. This is normalized by dividing by the total orders that are executed and ultimately divided by the mid-quote price. Finally, the amount is multiplied by 10,000 in order to obtain the liquidity in basis points[2]. Following Gomber et al. (2015) and Hachmeister (2007), the liquidity scalar can be divided in three equations: the normal bid-ask spread, and two equations of the adverse price movement (APM) covering the bid and the ask side. Respectively, the ask and bid APM equation can be expressed as:

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

and

[2] In this research, basis points (bps) are referred as hundredths of one percent

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

where $\bar{P}_{A,t}(V)$ and $\bar{P}_{B,t}(V)$, respectively, resemble the quantity weighted average execution price for volume V on both the ask and the bid side. The difference of 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 the CRT liquidity measure calculation is given in the appendix.

A dollar amount of V equal to the complete order book value is preferred in the sense that it gives the most complete 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 on 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. To assure that sufficient liquidity information from the LOB is obtained and that it resembles the total liquidity costs, four different Vs are implemented. First, the 0.1% percentile V in terms of dollar volume is identified over all 'snapshots' of the LOBs and used as the first V. Each of these snapshots represent an overview of the LOB at the end of 7.5 seconds intervals. Second, two *V's* 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. From the four different values of V the Adverse Price Movements (APMs) on both the bid and ask side are calculated from which the liquidity scalars are obtained. Finally, from the eight-different liquidity scalars the arithmetic mean is obtained which equals the liquidity measure used in the analyses. Note that in case V does not exceed the first rank dollar depth levels at both sides (i.e. the dollar amount of all orders at the first bid and ask), the adverse price movements are zero and the liquidity spread equals the quoted spread. In this 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) is equal to the average price in the total order book.

3.2. Spillovers analysis using a VHAR model

Considering the frequency properties of the data, a Vector Heterogenous Autoregressive model (VHAR) is an adequate method to measure liquidity relations among different futures markets. The VHAR is introduced by Corsi (2009) to model realized price returns in an intraday setting. The VHAR method captures short, medium, and long run lag effects which are based on moving averages retrieved from short, medium, and long run windows. Lags that have an actual effect on the variable of interest can increase exponentially in a high-frequency setting. Therefore, a VHAR is a simple, yet effective tool, to aggregate lags and yield robust dynamic relations. The model includes both a short- and a long-memory component (Corsi, 2009). By this mechanism, the model captures the presence of heterogeneity of trading preferences among traders, which is referred to as the heterogenous market hypothesis (Müller et al., 1997). Bubák et al. (2011) and Souček & Todorova (2013) were the first to implement multivariate VHAR models to study realized volatility spillovers among different markets. However, in contrast to Souček & Todorova (2013) and Bubák et al. (2011), in this study, the moving averages of the liquidity levels are used to obtain spillover effects based on three different lag windows. This grants us insights to the magnitude and persistence of liquidity spillovers. The use of levels is in line with Hasbrouck (2018), who investigates price discovery (quotes) from a dataset with timestamps up to nanoseconds. The author uses restrictions based on a VHAR model to avoid using a large number of lags in a classic VAR model using a very high resoluted dataset. In contrast to this thesis, where the lag structures generally have the same order of magnitude compared to model proposed by Corsi (2009), Hasbrouck (2018) uses lags from 10 microseconds to 1 seconds (a factor difference of 10,000).

For each commodity the three different lagged effects of the liquidity measure of the commodity itself and another commodity are obtained. Hereby controlling for autocorrelation and obtaining the genuine liquidity spillover effects from one market to another market. This set-up allows to study both the lead-lag relationship for a market's own liquidity (idiosyncratic) as well as spillovers from other markets (cross-market). This analysis is done for every possible combination of the commodities analyzed. This gives the following VHAR specification for analyzing the relations of liquidities, $L(V)$ of futures contract *a* and *b*:

$$\begin{aligned} L_{a,t} = \beta_{a,0} + \beta_{a,1} L_{a,t-1|t-lag1} + \beta_{a,2} L_{a,t-1|t-lag2} + \beta_{a,3} L_{a,t-1|t-lag3} + \\ \beta_{b,1} L_{b,t-1|t-lag1} + \beta_{b,2} L_{b,t-1|t-lag2} + \beta_{b,3} L_{b,t-1|t-lag3} + \varepsilon_{a,t} \end{aligned} \tag{4}$$

In equation (4) the liquidity measure ($L_{a,t}$) depends on a constant ($\beta_{a,0}$), three moving averages of the own liquidity (with effects $\beta_{a,1}$, $\beta_{a,2}$, and $\beta_{a,3}$), and t three moving averages of the liquidity of the other market (effects given by $\beta_{b,1}$, $\beta_{b,2}$, and $\beta_{b,3}$). $L_{a,t-1|t-lag1}$ is the average liquidity over a time window from *t-1* until lag 1. To test for significance for the variables a Wald test is implemented, the null hypothesis is tested whether the coefficients of the lagged liquidity variables of futures contract b are jointly equal to zero ($\beta_{b,1} = \beta_{b,2} = \beta_{b,3} = 0$). If the null hypothesis is rejected, the liquidity of futures contract b does have a significant spillover to futures contract a. Additionally, Granger causality tests are performed to study the exact causal relations among the markets. To examine the persistence of the spillovers, the regression is repeated with a reduced lag structure.

To control for possible correlation in liquidities among markets, a two-staged analysis with an orthogonalized model is carried out (Souček & Todorova, 2013). First, to get rid of possible correlation the lags are regressed on each other as in equation (5):

$$L_{a,t-1|t-k} = c_a + \alpha_b L_{b,t-1|t-k} + \omega_{a,t-1|t-k} \quad (5)$$

In this equation the residual ($\omega_{a,t-1|t-k}$) describes the variation that is not explained by the average liquidity of contract *b* ($L_{b,t-1|t-lag1}$). The ultimate orthogonalized version of the model is specified as:

$$L_{a,t} = \beta_{a,0} + \beta_{a,1} L_{a,t-1|t-lag1} + \beta_{a,2} L_{a,t-1|t-lag2} + \beta_{a,3} L_{a,t-1|t-lag3} + \beta_{b,1} \omega_{b,t-1|t-lag1} + \beta_{b,2} \omega_{b,t-1|t-lag2} + \beta_{b,3} \omega_{b,t-1|t-lag3} + \varepsilon_{a,t} \quad (6)$$

3.3. Data

Data consists of futures prices from the soybean commodity complex (i.e. soybean, soybean meal, and soybean oil) traded at the CME Globex electronic trading system. Two trading sessions are distinguished for each day: Regular Trading Hours (RTH) and Extended Trading Hours (ETH). 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[3]. An overview of the smoothened (i.e. moving averages of almost one day) market depth over the dataset for the first ten stairs of both the bid and ask is shown in Figure 1, from this figure it is clear that market depth is significantly lower in the summer period.

The data are snapshots of LOBs with intervals of 7.5 seconds. According to Arzandeh & Frank (2017), average price duration of soybean contracts is around 7.6 seconds. This price duration is used as proxy to determine optimal spacing in order to obtain sufficient information and not include too much noise in the analysis. Arzandeh & Frank (2017) point out that optimal spacing for analyzing price returns and variance of highly-liquid contracts, such as S&P e-mini futures, is approximately one second. This is in line with the practices of Hasbrouck (2004) and Cao et al. (2009), who use intervals of one second to assess highly liquid markets. As the liquidity of agricultural commodity markets is significantly lower, 7.5 second spacing is preferred.

[3] Trading hours are in U.S. Central Time

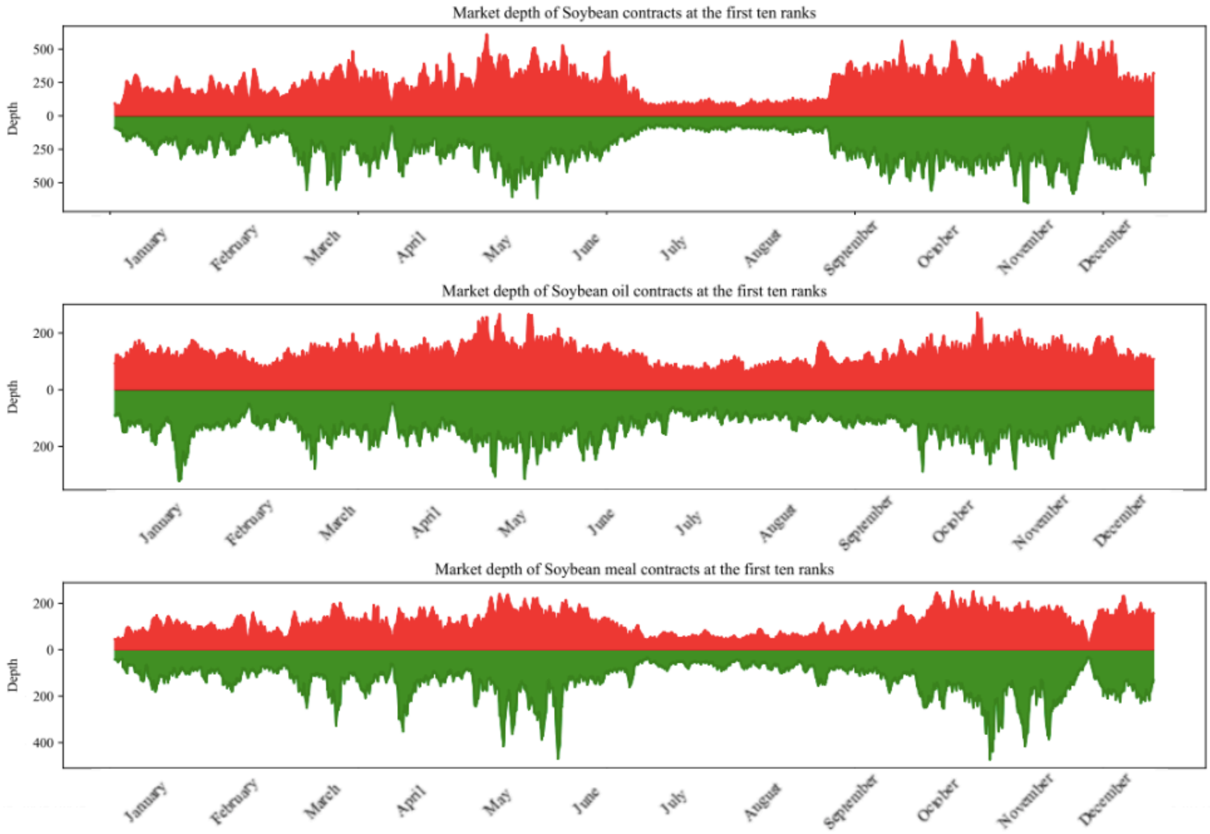

Figure 1. Market depth over the three markets of the first ten ranks on both the bid (green) and ask side (red)

In contrast to the lag structure based on days, weeks, and months that is popular in VHAR-models, in this research two different intraday lag structures are defined. According to Kirilenko (2017), the first four lags of one-minute intervals of inventories of traders show significant positive autocorrelation in the E-mini S&P 500 stock index futures market. This suggest that traders positively react to liquidity approximately in a time span of four minutes. In the corn futures market, Lehecka et al. (2014) find that the incorporation of information takes about ten minutes based on the returns after the announcement of USDA reports. Kauffman (2013) reports that post-announcement volatility in corn futures markets does not last longer than 30 to 60 minutes. Based on these empirical findings, this research examines the liquidity dynamic fundamentals by assessing two different lag structures. At first, a lag structure of 5 minutes, 60 minutes, and 290 minutes is implemented. To cover the short run effect, the first lag window is based on 5 minutes. The second lag window is based on one hour to study the typical maximum reaction span of traders (Kauffman, 2013). The longest lag window is 290 minutes long, which exactly equals one RTH trading session. This window will cover relatively long-memory effects. Secondly, a shorter lag structure is implemented which contains lags of 30 seconds, 5 minutes, and 30 minutes to assess the liquidity spillover persistence in a shorter time frame. To avoid begin- and end-of-day effects, the first and last 15 minutes of each session are deleted. This means that all the liquidity relations that are found and assessed stem from normal trading behavior.

A problem that occurs with large high-frequency data is the potential of a sheer amount of noise in the data as a result of relative stable periods with low trading volumes. The data is therefore filtered, all sessions that contain more than 95% duplicates of observations are removed. The liquidity measure (L) from the three different markets seem to have a skewed right tailed distribution, with a high kurtosis. The distributions of liquidity measure are shown in Figure 2. From this figure it is clear that the soybean market generally has a lower CRT liquidity measure with thinner tails compared to soybean meal and soybean oil market which implies a more consistent and a relative high liquidity compared to the other markets. Note that a high liquidity scalar

Table 2: Summary statistics for soybean, soybean oil, and soybean meal futures markets

	Soybean				
	Price	Orders	LS	LS Returns	Orders Returns
Mean	946.299	518.190	9.142	0.000	0.000
Standard deviation	54.027	385.391	3.454	0.116	0.117
Minimum	844.250	23.000	0.000	-12.274	-2.233
Maximum	1062.000	8081.000	235.554	11.528	2.958
Kurtosis	-1.150	7.946	76.419	664.818	18.117
Skewness	-0.097	2.029	5.252	-0.165	-0.199
Observations	2042962	2042962	2042962	2042962	2042962
	Soybean Oil				
	Price	Orders	LS	LS Returns	Orders Returns
Mean	3056.557	274.337	12.611	0.000	0.000
Standard deviation	217.993	167.753	11.545	0.150	0.116
Minimum	2538.000	24.000	0.000	-12.270	-2.758
Maximum	3528.000	6020.000	453.146	12.105	3.340
Kurtosis	-0.955	17.615	122.843	301.969	24.173
Skewness	-0.375	2.531	9.457	-0.025	-0.114
Observations	2042920	2042920	2042920	2042920	2042920
	Soybean Meal				
	Price	Orders	LS	LS Returns	Orders Returns
Mean	3203.617	261.397	13.637	0.000	0.000
Standard deviation	214.670	183.408	9.163	0.122	0.122
Minimum	2664.000	20.000	0.000	-5.128	-2.312
Maximum	3878.000	4828.000	277.907	3.917	2.394
Kurtosis	-0.166	12.658	32.873	31.832	19.299
Skewness	0.088	2.478	4.926	0.069	-0.172
Observations	2042962	2042962	2042962	2042962	2042962

Orders refer to the total orders on the first ten stairs in the LOB, LS denotes the liquidity spread, LS returns are the logarithmic returns of the liquidity spread, and the orders return refer to the logarithmic returns of the total orders should be interpreted as low liquidity. The number of observations among the markets are not similar, this implies that ultimately the number of observations of the actual model is lower as it only takes periods into account where the snapshots of all markets are non-zero. Practically this means that once a session of a certain market is filtered out (e.g. a trading session that contains more than 95% duplicates of snapshots), this session is deleted for all markets.

Figure 3 displays the logarithmic liquidity spread returns over the entire dataset. During certain periods the volatility of liquidity seems to be relatively high, for instance during the summer months July and August in which generally not much trade takes place. To test the (non-)stationarity of the different variables ADF tests are implemented. From these tests it can be concluded that the series of the liquidity measure are stationary. The results of the Ljung-Box test to check for autocorrelation on the liquidity for all three commodities show significant autocorrelation of the first 40 lags with a 1% confidence level. The autocorrelation and high kurtosis make a VHAR an appropriate tools to analyze liquidity spillovers.

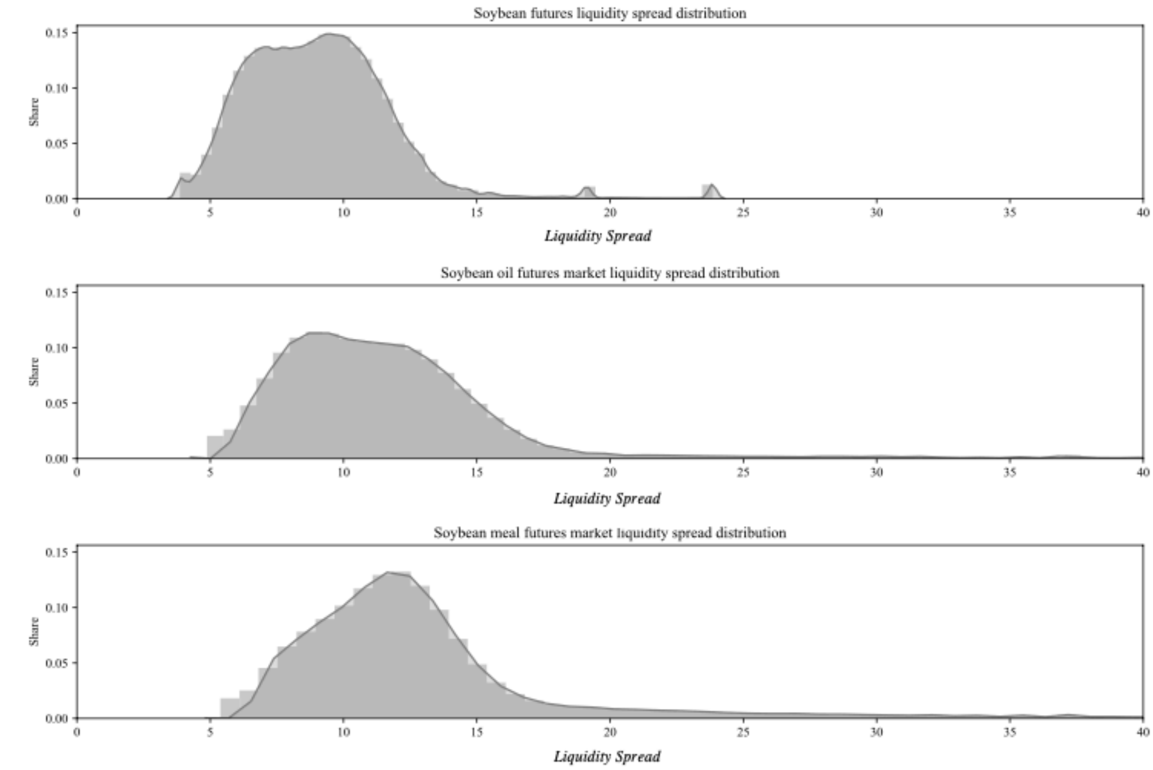

Figure 2. Histograms of CRT liquidity in soybean, soybean oil, and soybean meal futures markets

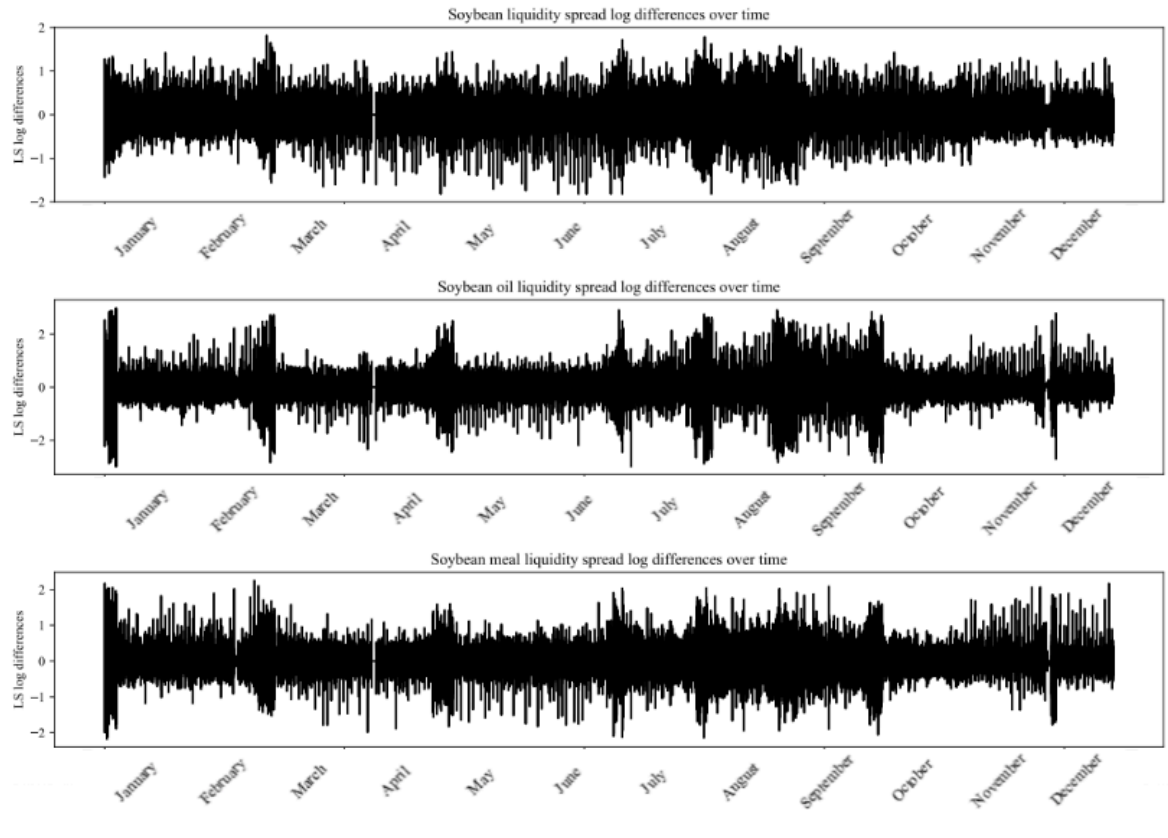

Figure 3. Logarithmic returns of the CRT based liquidity

4. Results

In this section the results of the VHAR analyses are discussed. First, the results of the default model are discussed in combination for the Granger causality tests outcomes. Second, to assess the persistency of liquidity relations the model with a compressed lag structure is discussed. Furthermore, the analysis is replicated for the subsamples of Regular Trading Hours (RTH), Extended Trading Hours (ETH), and pre-harvest period. Finally, the robustness checks are discussed.

4.1 Lag structure I

Table 3 shows the F-statistics and corresponding significance of the Granger causality tests. The table shows the statistics of sets of independent variables on the dependent variables. For example, the highest number in the second column of the left-hand matrix shows a F-statistic of 2028.82 from the Granger test whether the liquidity in the soybean meal market has a causal effect on the liquidity of the soybean market. It turns out that all markets are intertwined with each other considering the liquidity spillovers based on the high significance levels. Especially the statistics of the models implied with the first lag structure are highly significant. By reducing the lag window, the significance of liquidity spillovers declines. However, the liquidity relations are still strongly significant.

Table 3. Granger Causality tests for cross-market liquidity spillovers

	Lag structure (I)				Lag structure (II)		
	Independent				Independent		
Dependent	ZS	ZM	ZL	Dependent	ZS	ZM	ZL
ZS		2028.82***	716.42***	ZS		157.74***	84.82***
ZM	446.30***		948.27***	ZM	121.05***		115.90***
ZL	324.46***	2111.86***		ZL	64.88***	309.36***	

*, **, and *** represent 10%, 5%, and 1% significance.

In Table 4 the regression results of the six bivariate models are shown. The subscripts j in $\beta_{a,j}$ (j=1,2,3) denote the autocorrelation estimates for the moving average based on 5 minutes, 60 minutes, and 290 minutes (or one RTH-session) lags. The $\beta a_{,j}$ parameters in the tables refer to the idiosyncratic liquidity spillovers. The $\beta_{b,j}$ parameters denote the spillovers of the liquidity from the opposite market to the first market in the j-th lag window (the cross-market effects). In the first model (Soybeans – Soy meal), the β_a estimates are the idiosyncratic liquidity effects of soybeans on soybeans whereas the β_b estimates denote the cross-market effect from the liquidity of the meal market to the liquidity in the soybean market. Using Wald tests, it is tested whether all cross-market lags are equal to zero and hence do not significantly affect the endogenous market's liquidity.

Table 3 shows the idiosyncratic and cross-market liquidity relations among the three futures markets. In all markets it can be seen that especially the first moving average lag of the commodity's own liquidity has a significant effect on the current liquidity. In all markets the short run liquidity impact ($\beta_{a,1}$) lies between 0.9000 and 0.9500 and strongly deviates from zero. In the medium run, effects are positive and strongly significant. In the long run window, the idiosyncratic liquidity relations are again strongly positive. The cross-market liquidity relations are similarly significant compared to the idiosyncratic effects. All markets are positively influenced by the short run liquidity in other markets. Especially the short run (5 minutes) cross-market effects from beans to both oil and meal (respectively 0.0305 and 0.0216) are strong in magnitude compared to the short run cross-market spillovers from meal and oil to soybeans (respectively 0.0114 and 0.0051). This implies that the soybean market has a 'leading' role in terms of liquidity. This leading role holds for the medium run effects from soybean to meal and oil as well, although the direction is not similar. Apart from the medium run cross-market effect from beans to oil, all medium and long run cross-market effects are negative. This means that, within 5 minutes liquidity holds a positive cross-market relation whereas this turns negative on a one-hour and one-trading day time span.

Table 4. Regression results of total sample with normal lag structure

	Soybeans – Soy meal		Soybeans – Soy oil		Soy oil- Soy meal	
	Soybeans	Soy meal	Soybeans	Soy oil	Soy oil	Soy meal
β_0	0.0994***	0.0845***	0.1031***	0.0991***	0.1296***	0.1175***
	(0.004)	(0.008)	(0.004)	(0.015)	(0.009)	(0.005)
$\beta_{a,1}$	0.9045***	0.9484***	0.9086***	0.9101***	0.9042***	0.9468***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,2}$	0.0451***	0.0387***	0.0528***	0.0579***	0.0554***	0.0382***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,3}$	0.0371***	0.0024***	0.0257***	0.0113***	0.0147***	0.0042***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{b,1}$	0.0114***	0.0305***	0.0051***	0.0216***	0.0479***	0.0117***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.001)	(0.000)
$\beta_{b,2}$	-0.0018***	-0.0195***	-0.0027***	0.0200***	-0.0241***	-0.0050***
	(0.001)	(0.002)	(0.000)	(0.004)	(0.002)	(0.001)
$\beta_{b,3}$	-0.0078***	-0.0047**	-0.0013***	-0.0242***	-0.0096***	-0.0043***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.001)	(0.001)
Adj. R-squared	0.790	0.886	0.790	0.756	0.756	0.886
Wald-statistic	676.27***	148.76***	238.81***	108.15***	703.95***	316.09***

Wald test based on the following null hypothesis: *($\beta b,i(i=1,2,3) = 0$)*. The standard errors are given in parentheses. *, **, and *** represent 10%, 5%, and 1% significance.

The results from the Wald test indicate that all markets do influence the other markets in terms of liquidity. As both the short run idiosyncratic and cross-market relations seem to explain a lot the next section provides a lag structure that zooms in further and assesses liquidity spillovers within a total lag structure of 30 minutes.

4.2. Lag structure II

The results for the shorter lag structure are shown in Table 5. The moving average parameters $\beta_{a,j}$ relates to lags of 30 seconds, 5 minutes, and 30 minutes (for $j=(1,2,3)$). Based on the 30 seconds lag, the idiosyncratic impact for all futures contracts is just above 1 and highly significant. Considering the magnitude of the short-run effects in the default lag structure in combination with the magnitude of the short-run idiosyncratic impact in a 30 seconds span, it can be inferred that the short run idiosyncratic liquidity (within 30 seconds) has the strongest effect on the current liquidity. Whereas in the default lag structure the short run effects are captured in a five-minutes window, in this model the medium-run effects are based on a five-minute window.

Table 5. Regression results of total sample with shorter lag structure

	Soybeans – Soy meal		Soybeans – Soy oil		Soy oil- Soy meal	
	Soybeans	Soy meal	Soybeans	Soy oil	Soy oil	Soy meal
β_0	0.0274***	0.0088**	0.0268***	0.0092	0.0237***	0.0184***
	(0.002)	(0.004)	(0.002)	(0.007)	(0.004)	(0.002)
$\beta_{a,1}$	1.0056***	1.0031***	1.0056***	1.0071***	1.0068***	1.0032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\beta_{a,2}$	-0.0450***	-0.0353***	-0.0445***	-0.0446***	-0.0451***	-0.0357***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,3}$	0.0353***	0.0303***	0.0355***	0.0328***	0.0323***	0.0303***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{b,1}$	0.0002	0.0075***	0.0007***	0.0014	0.0057***	0.0005*
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
$\beta_{b,2}$	0.0021***	-0.0002	0.0001	0.0059***	0.0041***	0.0023***
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
$\beta_{b,3}$	-0.0015***	-0.0055***	-0.0004***	-0.002	-0.006***	-0.0019***
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Adj. R-squared	0.941	0.963	0.941	0.935	0.935	0.963
Wald-statistic	52.57***	40.35***	28.27***	21.63***	103.12***	38.63***

Wald test based on the following null hypothesis: ($\beta b,i(i=1,2,3) = 0$). The standard errors are given in parentheses. *, **, and *** represent 10%, 5%, and 1% significance.

The results in Table 5 show that the medium run idiosyncratic liquidity relations are, for all markets, negative. This contrast both to the short run and long run idiosyncratic effects as these are, in all markets, positive. It implies that an increase in the liquidity in a five-minutes lag window leads to a decline in the current liquidity. This contrasts to the outcomes from the models with the larger lag structure, where there are strong positive liquidity relations within a 5-minute span. From this it can be stated that the own market's spillovers are exceptionally short lived. These results are remarkably robust over the three markets and six models. There is evidence that within a 30 seconds and 5 minutes lag span, the cross-market liquidity relations are positive. On the contrary, the cross-market spillovers on a time span of 30 minutes are consistently negative. Together with the outcomes of the model with the normal lag structure, it can be stated that positive cross-market spillover effects mostly occur within 5 minutes and negative spillovers occur in a time frame over 30 minutes. From the model with the shorter lag structure it is clear that the positive idiosyncratic spillovers occur in the very short run and in time spans greater than 30 minutes. There is evidence that positive cross-market spillovers seem to occur within 30 minutes lag spans.

By comparing the two lag structures a few observations can be made. First, the liquidity is mainly caused by the market's own liquidity. Second, this positive idiosyncratic liquidity effect is very short lived, since the major autocorrelation is captured within 30 seconds and the medium idiosyncratic effects are consistently negative. Third, cross-market liquidity relations seem to be consistently positive within 30 minutes and negative on a time span longer than 30 minutes. Finally, liquidity dynamics from beans to oil and meal are more pronounced in terms of economic significance than vice versa.

4.3. Regular and Extended Trading Hours

The Globex trading hours can be divided into two sessions: Regular Trading Hours (RTH) and Extended Trading Hours (ETH). During RTH, the trading volumes are significantly higher compared to ETH. To assess the effect of variation in trade activity on liquidity dynamics, a Chow test is implemented to evaluate a potential difference in the two samples. In all models, the Chow test indicates a structural difference between the two subsamples (see appendix). In Table 6 and Table 7 the regression results of respectively the day and night sessions are shown. The first thing that stands out by comparing the daily subsample to the night sample is that the idiosyncratic effects are not consistently positive anymore. In contrast to the total and ETH samples, the long run idiosyncratic spillovers are generally negative.

What stands out by comparing the two samples is that during ETH, the idiosyncratic relations seem to be consistently positive. This does not hold during RTH trading. Furthermore, in both the RTH and ETH sample, the short run cross-market spillovers are positive. The 'liquidity leading' role of the soybeans futures market that can be distinguished from the default analysis is more pronounced in the subsample of RTH as the magnitudes of the parameters are respectively 0.0407 and 0.0817.

Table 6. Regression results of sample with Regular Trading Hour (RTH) sessions

	Soybeans – Soy meal		Soybeans – Soy oil		Soy oil- Soy meal	
	Soybeans	Soy meal	Soybeans	Soy oil	Soy oil	Soy meal
β_0	0.1263***	0.1129***	0.1270***	0.1148***	0.1435***	0.1350***
	(0.008)	(0.018)	(0.008)	(0.02)	(0.010)	(0.009)
$\beta_{a,1}$	0.9146***	0.9926***	0.9298***	0.9461***	0.9001***	0.9845***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$\beta_{a,2}$	0.0570***	-0.0055***	0.0535***	0.0445***	0.0855***	0.0018
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$\beta_{a,3}$	0.0060**	-0.0029*	-0.0038*	-0.0135***	-0.0166***	-0.0037**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$\beta_{b,1}$	0.0190***	0.0407***	0.0129***	0.0817***	0.0905***	0.0253***
	(0.001)	(0.005)	(0.001)	(0.005)	(0.002)	(0.002)
$\beta_{b,2}$	-0.0133***	-0.0199***	-0.0108***	-0.0619***	-0.0826***	-0.0186***
	(0.001)	(0.006)	(0.001)	(0.007)	(0.002)	(0.002)
$\beta_{b,3}$	-0.0030***	-0.0126**	-0.0004	-0.0045	0.0065***	-0.0013
	(0.001)	(0.005)	(0.001)	(0.005)	(0.002)	(0.002)
Adj. R-squared	0.737	0.879	0.737	0.814	0.815	0.879
Wald-statistic	318.49***	34.69***	133.89***	104.30***	845.69***	85.29***

Wald test based on the following null hypothesis: *($\beta b,i(i=1,2,3) = 0$)*. The standard errors are given in parentheses. *, **, and *** represent 10%, 5%, and 1% significance.

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

	Soybeans – Soy meal		Soybeans – Soy oil		Soy oil- Soy meal	
	Soybeans	Soy meal	Soybeans	Soy oil	Soy oil	Soy meal
β_0	0.1407***	0.0827***	0.1408***	0.1147***	0.1318***	0.1105***
	(0.006)	(0.011)	(0.006)	(0.022)	(0.012)	(0.006)
$\beta_{a,1}$	0.9015***	0.9307***	0.9033***	0.9060***	0.9030***	0.9294***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,2}$	0.0422***	0.0527***	0.0483***	0.0556***	0.0529***	0.0516***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,3}$	0.0392***	0.0078***	0.0325***	0.0186***	0.0184***	0.0096***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{b,1}$	0.0079***	0.0235***	0.0042***	0.0067**	0.0321***	0.0093***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.002)	(0.000)
$\beta_{b,2}$	0.0012*	-0.0174***	-0.0026***	0.0247***	-0.0107***	-0.0032***
	(0.001)	(0.003)	(0.000)	(0.005)	(0.002)	(0.001)
$\beta_{b,3}$	-0.007***	-0.0016	-0.0002	-0.0160***	-0.0064***	-0.0043***
	(0.000)	(0.002)	(0.000)	(0.004)	(0.002)	(0.001)
Adj. R-squared	0.757	0.882	0.757	0.740	0.741	0.882
Wald-statistic	302.38***	71.97***	128.85***	34.56***	269.64***	193.92***

Wald test based on the following null hypothesis: *($\beta b,i(i=1,2,3) = 0$)*. The standard errors are given in parentheses. *, **, and *** represent 10%, 5%, and 1% significance.

4.4. Seasonality

Table 8 displays the result of the analysis of the subsample that contains data for May, June, and July. This period is characterized as relatively illiquid and unstable as yields can be crucially influenced by exogenous factors. In this subsample, the magnitudes of the short run cross-market effects from the smaller futures markets (oil and meal) to the soybean market are smaller compared to the default model. In contrast, the short-run spillover from soybeans to oil is substantially larger, this also holds for the medium run cross-market spillover. This indicates a stronger 'leading' effect of the soybean market in this period. Surprisingly, the long run cross-market effects change from consistently significant negative to almost consistently significant positive. This indicates that traders tend to move into markets that have shown increased activity during that day. Heterogenous and insecure expectations could lead traders to adapt their strategies to others' behavior and hence potentially affect spillovers. Subsequently, during this period which is characterized as relative unstable, herd behavior seemed to be relatively high.

Table 8. Regression results of pre-harvest period sample (May, June, and July)

	Soybeans – Soy meal		Soybeans – Soy oil		Soy oil- Soy meal	
	Soybeans	Soy meal	Soybeans	Soy oil	Soy oil	Soy meal
β0	0.1071***	-0.0483***	0.1417***	-0.2062***	-0.1400***	0.0790***
	(0.011)	(0.017)	(0.011)	(0.042)	(0.024)	(0.011)
βa,1	0.8938***	0.9064***	0.8930***	0.8744***	0.8713***	0.9052***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
βa,2	0.0277***	0.0610***	0.0261***	0.1135***	0.1135***	0.0647***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
βa,3	0.0606***	0.0211***	0.0593***	-0.0116***	-0.0127***	0.0227***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
βb,1	0.0055***	-0.0112***	0.0011**	0.0377***	0.0484***	0.0046***
	(0.001)	(0.003)	(0.000)	(0.006)	(0.004)	(0.001)
βb,2	-0.0046***	0.0138***	-0.0030***	0.0369***	-0.0661***	-0.0072***
	(0.001)	(0.005)	(0.001)	(0.011)	(0.006)	(0.001)
βb,3	0.0029**	0.0206***	0.0060***	-0.0176*	0.0550***	0.0044***
	(0.001)	(0.004)	(0.001)	(0.010)	(0.005)	(0.001)
Adj. R-squared	0.692	0.827	0.693	0.768	0.768	0.827
Wald-statistic	23.71***	36.41***	53.47***	63.03***	151.24***	19.44***

Wald test based on the following null hypothesis: *(βb,i(i=1,2,3) = 0)*. The standard errors are given in parentheses. *, **, and *** represent 10%, 5%, and 1% significance.

4.5. Robustness checks

To check the robustness of the results three alternative approaches are implemented. Results can be found in the appendix. Overall, it can be concluded that the spillover estimates are substantially robust.

First, an orthogonalized model as described in the methodology section is used to control for possible correlation among the liquidity scalars. Controlling for potential correlation effects has minimal effects on the parameter estimates. There are some minor changes in the magnitudes of the idiosyncratic spillovers. In contrast, the cross-market spillovers hardly differentiate between the default and orthogonalized model. These observations further establish the findings that cross-market liquidity relations are present and that it is not the effect of an unobserved external driver.

Second, following Kirilenko et al. (2017) a more general liquidity measure is used: the total depth at the first ten ranks of the order book. Although depth is widely accepted as liquidity measure, it only comprehends a single dimension of liquidity in contrast to the multidimensional CRT liquidity measure. The overall spillover effects with this alternative liquidity measure are less pronounced compared to the base model. However, the Wald statistics show consistent robust cross-market spillover effects. The decrease in explanatory value is not a surprise. Multiple dimensions in the liquidity spread measure potentially have a relatively uniform effect on each other component compared to a one-dimensional depth measure. Most of the parameters have similar values and significance levels. Most striking is the consistency of positive short run cross-market liquidity relations. It seems that the medium run idiosyncratic effects consistently turn negative. This implies that traders tend to increase (decrease) trading activity in a market where in the time span of 30 minutes until 5 minutes before trading decreased (increased). The introduction of depth as liquidity measure further confirms the existence of cross-market liquidity spillovers.

Third, price volatility is an important factor for traders to decide whether a market is interesting to enter as the high volatility potentially leads to high payoffs for immediacy providers. To control for this, the model is extended with variables for realized price variances over the lag windows of 5 minutes, 60 minutes, and one trading day. The realized price variances are based on the sums of the squared price returns over the three windows, as these values are relatively high, they are normalized by dividing them with 100. The corresponding parameters denote the impact of the realized price variances in the three different lag windows on the current liquidity. From the results it is clear that all idiosyncratic and cross-market effects are consistent while taking into account the price variance as control variables. Despite the additional explanatory variables, the actual liquidity spillovers hardly change in coefficient and significance.

5. Conclusions and Discussion

Using a unique data set that contains the full LOB of the futures markets within the soybean crush complex (soybean, soymeal, soy oil) significant intraday idiosyncratic and cross-market liquidity interrelations are identified. Short, medium, and long run lag windows are created that aggregate liquidity in the three markets. Additionally, the lag windows are compressed to study the span of the idiosyncratic and cross-market liquidity relations. To assess potential differences in magnitudes of liquidity spillovers during RTH and ETH, and during pre-harvest and non-pre-harvest months the sample is divided in subsamples and the results are compared. Firstly, this gives strikingly interesting insights in traders' behavior during active trading hours. Secondly, the distinction between the pre-harvest and non-pre-harvest period indicate traders' sensitivity to insecurity of market forecasts and hence potential herd behavior.

Not surprisingly, liquidity faces heavy positive autocorrelation, this holds for the models with the normal and compressed lag structure. By reducing the lag structure, it is clear that the heavy short-run idiosyncratic positive autocorrelation is strongest and persists within a 30 seconds span. Consistent over the markets, the medium-run and long-run idiosyncratic effects are both positive. This implies that a market's liquidity is heavily determined by its own lags. In a market in which liquidity is on the rise, it is expected that within 30 seconds the liquidity intensifies. In the meantime, within time spans of 5 minutes the idiosyncratic liquidity relation is negative. The consistency of the short run idiosyncratic liquidity relations does hold for the cross-market effects as well. However, positive cross-market spillovers occur within 5 minutes. Compared to the idiosyncratic effects, cross-market liquidity spillovers are relatively delayed. This implies that traders tend to base trading decisions in market *a* mainly on very short run (30 seconds) developments in market *a* while shocks in other markets are mainly incorporated in market *a* over a time span of 5 minutes. Overall, it can be concluded that the liquidity in commodity markets in the soybean complex positively influence the liquidity in a span of 30 seconds. The cross-market spillovers seem to be present although more pronounced in a span of 5 minutes.

The default model indicates consistently positive short cross-market spillovers while the medium- and long-run cross-market spillovers tend to be negative. Taken into account the strong and significant positive coefficients of the short-, medium-, and long-run idiosyncratic liquidity effects it seems that, in a long-run daily window, traders tend to prefer to trade in markets with high liquidity. If the liquidity has been relatively high the last day in one market, the current liquidity of that market tends to be high as well while the last day's liquidity of one market has consistently negative effects on the liquidity of other markets. In other words, in the long-run traders tend to be active in markets were liquidity has been relatively high at the expense of other markets which is called a ’flight-to-liquidity’. This effect holds for all markets.

This research finds evidence for deviating liquidity relations between Regular Trading Hours (RTH) compared to Extended Trading Hours (ETH). Idiosyncratic relations tend to be less pronounced and deviating during RTH compared to the ETH and total sample which could mean that intra-market herd behavior is stronger during ETH. Increased algorithmic trading during ETH which potentially implies a greater presence of similar trading strategies could explain this. It is also clear that during the pre-harvest months liquidity relations deviate. During the period of this subsample exogenous factors influencing the commodity yields have the strongest effect. In general, the ‘leading’ effect of the soybean market in terms of liquidity is relatively stronger. As the soybean growth is crucial for all three markets and most sensitive during that period, it is not a surprise that this market’s liquidity has strong spillovers to the other (smaller) markets.

The results of this research are robust for a different liquidity measure, potential correlation between liquidity estimations among markets, and the effect of the realized price variance in the different lag structures on liquidity. However, certain drawbacks occur while using LOB data and a VHAR approach. First, LOB data does not always reflect all committed liquidity. As mentioned before, iceberg orders and dark trading can possibly affect liquidity while this is not taken into account in the CRT liquidity calculation. Second, the decision to use time periods of 7.5 seconds based on the average price duration is only a proxy for ‘liquidity duration’. Third, heterogenous trading behavior may be different from the chosen lag windows. The evidence for very short liquidity spillovers (i.e. faster than 30 seconds) could be an interesting follow-up research. Fourth, the CRT liquidity measure does not comprehend the resiliency dimension of liquidity. However, the CRT method is widely approved in literature. Finally, as the dataset comprehends one year (2015), there might be risks involved concerning external validity as external factors might have influenced traders’ behavior particularly in that year.

Further research may examine the drivers behind particular liquidity transmissions and the seasonal effects. Researching liquidity spillovers in the family of grain contracts (corn, wheat, and soy) would be a very interesting start. This could give insights in the impact of the degree of similarities among commodities and the intensity of cross-market liquidity spillovers. Furthermore, it would be interesting to apply the VHAR method with more granular time intervals to explore liquidity spillovers in a very high resolute environment and hence to reveal the effects of algorithmic trading.

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Appendix

To illustrate the liquidity measure with an example, 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 in terms of market depth has a dollar 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 a LOB as given in Figure A1. As can be seen Figure A1, first the normal bid ask spread is calculated with the quoted bid and ask to capture the market's width ($Ask_1 - Bid_1/mid\text{-}quote$). 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 basis points (bps). Furthermore, the average order price for the execution of an \$15,000 order on both the ask and bid side is calculated. 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 orders up and until the third rank are taken into account for the calculation of the average bid price $\bar{P}_{B,t}(V)$. 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 mid-quote price, reflects the APM. In the example of Figure A1 the adverse price movement of the bid price is $(416.00 - 415.3974 = 0.6026)$ which equals the relative value of ($\frac{0.6026}{416.25} = 14.5\ bps$). By summing the bid-ask spread and the relative APMs of the ask and bid side, the liquidity metric is calculated for each snapshot, which equals a liquidity scalar of 64.0 bps in this example (for this V).

Limit Order book of Corn December Futures January 3 2015

Volume: 15000\$ — Market sell order

Execution of 36.11 contracts with an average price of: 415.3974 \$

APM (Bid1 - average execution price) / MP = 14.5 bps

Volume: 15000\$ — Market buy order

Execution of 35.88 contracts with an average price of: 418.0602 \$

APM (average execution price - Ask1) / MP = 37.5 bps

Rank	BidQty	Bid (\$)	Ask (\$)	AskQty	Rank
1	5	416	416.5	2	1
2	8	415.5	417	15	2
3	25	415.25	417.5	2	3
4	7	415	419	5	4
5	8	414.5	419.25	5	5
6	5	414	419.5	21	6
7	25	412.5	419.75	63	7
8	5	411	420	385	8
9	35	410.25	420.25	1	9
10	23	410	420.5	1	10

Mid-quote: 416,25

$$quoted\ spread = \frac{0.5}{416{,}25} = 12.0\ bps$$

$$L = APM(b) + APM(a) + spread$$

$$64.0 = 14.5 + 37.5 + 12.0$$

Liquidity = 64.0bps

Figure A 1 Example of Cost-of-Rountrip liquidity measure calculation

Table A1. Results of ADF and Ljung-Box tests

	Soybeans		Soybean Oil		Soybean Meal	
	LS	LS returns	LS	LS returns	LS	LS returns
ADF	-72.757	-294.197	-66.045	-294.924	-46.399	-296.038
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ljung-Box	51426000	247230	53187000	217230	59857000	230770
	(0.000)	(0.000)	(0.0000)	(0.000)	(0.000)	(0.000)

The p-values are given in parentheses.

Table A2. Chow tests on subsamples

	RTH vs. ETH	Pre-harvest vs. non-pre-harvest
Soy oil - Soy meal	90.50***	256.68***
Soy oil - Soybeans	104.91***	180.25***
Soy meal - Soybeans	301.56***	169.66***
Soy meal - Soy oil	303.63***	173.02***
Soybeans - Soy oil	148.19***	158.33***
Soybeans - Soy meal	100.83***	68.68***

*, **, and *** represent 10%, 5%, and 1% significance.

Table A3. Regression results of the orthogonalized model

	Soybeans – Soy meal		Soybeans – Soy oil		Soy oil- Soy meal	
	Soybeans	Soy meal	Soybeans	Soy oil	Soy oil	Soy meal
β_0	0.1244***	0.1307***	0.1122***	0.2415***	0.2897***	0.1320***
	(0.004)	(0.005)	(0.004)	(0.008)	(0.008)	(0.005)
$\beta_{a,1}$	0.9205***	0.9541***	0.9146***	0.9125***	0.9267***	0.9544***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,2}$	0.0421***	0.0348***	0.0493***	0.0606***	0.0416***	0.0347***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,3}$	0.0239***	0.0015**	0.0239***	0.0077***	0.0086***	0.0012**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{b,1}$	0.0114***	0.0305***	0.0051***	0.0216***	0.0479***	0.0117***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.001)	(0.000)
$\beta_{b,2}$	-0.0018***	-0.0195***	-0.0027***	0.0200***	-0.0241***	-0.0050***
	(0.001)	(0.002)	(0.000)	(0.004)	(0.002)	(0.001)
$\beta_{b,3}$	-0.0078***	-0.0047**	-0.0013***	-0.0242***	-0.0096***	-0.0043***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.001)	(0.001)
Adj. R-squared	0.790	0.886	0.790	0.756	0.756	0.886
Wald-statistic	676.29***	148.77***	238.79***	108.15***	703.96***	316.09***

Wald test based on the following null hypothesis: *($\beta b,i(i=1,2,3)$ = 0)*. The standard errors are given in parentheses. *, **, and *** represent 10%, 5%, and 1% significance.

Table A3. Regression results of the orthogonalized model

	Soybeans – Soy meal		Soybeans – Soy oil		Soy oil- Soy meal	
	Soybeans	Soy meal	Soybeans	Soy oil	Soy oil	Soy meal
β_0	0.1244***	0.1307***	0.1122***	0.2415***	0.2897***	0.1320***
	(0.004)	(0.005)	(0.004)	(0.008)	(0.008)	(0.005)
$\beta_{a,1}$	0.9205***	0.9541***	0.9146***	0.9125***	0.9267***	0.9544***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,2}$	0.0421***	0.0348***	0.0493***	0.0606***	0.0416***	0.0347***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,3}$	0.0239***	0.0015**	0.0239***	0.0077***	0.0086***	0.0012**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{b,1}$	0.0114***	0.0305***	0.0051***	0.0216***	0.0479***	0.0117***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.001)	(0.000)
$\beta_{b,2}$	-0.0018***	-0.0195***	-0.0027***	0.0200***	-0.0241***	-0.0050***
	(0.001)	(0.002)	(0.000)	(0.004)	(0.002)	(0.001)
$\beta_{b,3}$	-0.0078***	-0.0047**	-0.0013***	-0.0242***	-0.0096***	-0.0043***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.001)	(0.001)
Adj. R-squared	0.790	0.886	0.790	0.756	0.756	0.886
Wald-statistic	676.29***	148.77***	238.79***	108.15***	703.96***	316.09***

Wald test based on the following null hypothesis: *($\beta b,i(i=1,2,3)$ = 0)*. The standard errors are given in parentheses. *, **, and *** represent 10%, 5%, and 1% significance.

Table A5. Regression results with three lags of realized price variances as control variables

	Soybeans – Soy meal		Soybeans – Soy oil		Soy oil- Soy meal	
	Soybeans	Soy meal	Soybeans	Soy oil	Soy oil	Soy meal
β_0	0.1001***	0.0847***	0.1031***	0.1014***	0.1334***	0.1175***
	(0.004)	(0.008)	(0.004)	(0.015)	(0.009)	(0.005)
$\beta_{a,1}$	0.9045***	0.9484***	0.9086***	0.9101***	0.9042***	0.9468***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,2}$	0.0451***	0.0387***	0.0529***	0.0579***	0.0554***	0.0381***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{a,3}$	0.0370***	0.0024***	0.0256***	0.0113***	0.0147***	0.0042***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta_{b,1}$	0.0114***	0.0306***	0.0052***	0.0217***	0.0479***	0.0117***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.001)	(0.000)
$\beta_{b,2}$	-0.0018***	-0.0196***	-0.0027***	0.0198***	-0.0241***	-0.0050***
	(0.001)	(0.002)	(0.000)	(0.004)	(0.002)	(0.001)
$\beta_{b,3}$	-0.0078***	-0.0046**	-0.0013***	-0.0242***	-0.0097***	-0.0043***
	(0.000)	(0.002)	(0.000)	(0.003)	(0.001)	(0.001)
$\gamma_{,1}$	0.4061**	-0.5732***	0.3996**	-0.9016	-0.9711	-0.5720***
	(0.173)	(0.163)	(0.173)	(0.593)	(0.593)	(0.162)
$\gamma_{,2}$	0.0723	-0.0455	0.1100**	-0.1597	-0.1905	-0.0208
	(0.055)	(0.052)	(0.055)	(0.190)	(0.190)	(0.052)
$\gamma_{,3}$	-0.0463*	0.0133	-0.0310	-0.0173	-0.1234	0.01040
	(0.024)	(0.023)	(0.024)	(0.084)	(0.084)	(0.023)
Adj. R-squared	0.790	0.886	0.790	0.756	0.756	0.886
Wald-statistic	675.92***	148.75***	239.03***	106.72***	704.52***	315.51***

Wald test based on the following null hypothesis: $(\beta_{b,i}(i=1,2,3) = 0)$. The standard errors are given in parentheses. *, **, and *** represent 10%, 5%, and 1% significance.