The Effect of Algorithmic Trading on Agricultural Commodities Market Quality

By

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Abstract

The growing use of algorithms has significantly changed trading. These changes have been subjected to an ongoing debate in the finance literature. Some studies have found that algorithmic trading (AT) has a positive effect on market quality by increasing the competition, trading volume and liquidity, and lowering trading costs. Algorithmic traders provide liquidity when it is expensive and take it when it is cheap. On the other hand, others argue that AT may increase volatility and adverse selection. The difference in speed between fast and slow traders not only causes adverse selection, but it leads to wider spreads. We study the effect of AT on market quality, trade size and volatility, focusing on five agricultural commodity futures markets listed in the CME Group during the period of December 2015 to March 2016. The commodities include wheat, soybean, corn, lean hogs and live cattle. We control for USDA announcements released during the period of study, the day of the week, and intraday movements of AT. We find that AT improves market quality by narrowing the effective half spread (an estimate of the liquidity cost) in all markets. The effect is stronger in lean hogs and live cattle markets where AT also decreases the adverse selection (the reflection of the existence of different levels of information in the market). Algorithmic traders are more active when transaction costs and information asymmetry are lower. AT also decreases volatility in all markets. Our results show that the USDA announcements are significant only in the soybean market. We also find that the effect of the day of the week on AT is only significant in the corn market. The effect of the opening time of the market on AT is positive in soybean and corn, and negative in live cattle. The closing time is negative in all markets except live cattle where it is not significant. Finally, we perform an impulse response analysis. We find that the initial reaction of QHS and RS to a shock of AT is positive, the reaction of EHS and PI is negative, and the effect is always temporary.

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1. Introduction

For many years, market participants used physical venues to meet and exchange their trading interests and designated market intermediaries managed the floor-based trading. In the last decades, significant changes have been observed as trading became more automated. In the 1970s, with the introduction of the New York Stock Exchange (NYSE)'s designated order turnaround (DOT) financial markets began to computerize. This system directs orders electronically to the NYSE (Abergel et al. 2012). But security trading became electronic when the National Association of Securities Dealers (NASD) launched a computer-assisted market making system for automated quotation (AQ) in the U.S., forming NASDAQ (Black 1971). Following these events came program trading development, index arbitrage automation and computerized matching engines, and more recently, applying a big variety of trading strategies at millisecond scale (Abergel et al. 2012).

Agricultural commodity markets such as wheat, soybean, corn, hogs, and cattle transitioned to the electronic platform relatively more recently. For example, the Chicago Mercantile Exchange (CME) Group, which is the largest U.S. futures exchange and a leading exchange for agricultural products, closed almost all of its pits and trading floors and shifted to trading on the electronic platform in July 2015 (Gousgounis and Onur 2017). Irwin and Sanders (2012) report that the number of contracts trading electronically in corn, soybean and wheat futures markets has grown from 1% in 2000 to 92%, 92% and 96% in 2011, respectively. The growth has been slower for lean hogs and live cattle as it has increased from 0% in 2000 to 62% and 68% in 2011, respectively. Irwin and Sanders (2012) attribute the slower movement of meat markets to their more domestic nature. Even though the transition in agricultural commodity markets started later than it did in financial markets, the speed of growth has been dramatically high.

Technology has been used increasingly in areas like trading, order generation and order routing in the form of automated systems. The use of automated systems in the market is referred to as "automated trading" (Haynes and Roberts 2015). Haynes and Roberts (2019) calculate the percentage of electronic trades completed manually or by automated trading in the CME Group in two different periods, November 12, 2012 to October 31, 2014 and November 1, 2014 to October 31, 2018. In grains and oilseed markets, they show that manual trading decreased from 55.4% to 41.3% and automated trading increased from 39% to 55.2%. In livestock markets, manual trading declined from 56.3% to 40.1% and automated trading rose from 32.4% to 59.5%. The remaining percentages, 3.4% for grains and oilseed markets and 0.4% for livestock markets, belong to the non-electronic trading category. The above statistics clearly indicate the rapid growth of automated trading in these markets.

The term “algorithmic trading” (AT) is a subset of automated trading and it is defined as using computer algorithms to manage trading decisions and orders (Haynes and Roberts 2015). AT has changed the traditional relationship between investors and market access intermediaries. As electronic trading rose, broker activity declined because computers made trading easier and cheaper (Hendershott and Moulton 2007). Also, the “electronification” of the markets and electronic association of market participants came together and led to market access to be decentralized (Gomber et al. 2011). Traders do not stand in the pits trading futures contracts with hands signals anymore. Instead, today these transactions are done electronically by algorithms and large broker-dealers use algorithms to execute orders for their customers.

At present, a variety of algorithms are used. Algorithms can monitor commodity markets and trading venues to determine the time, price and quantity of orders. More recent algorithms read and interpret economic news. They can also be used to decrease the market impact of large orders by breaking them into smaller pieces. They have the capacity to use both limit orders and marketable orders and act as both liquidity demander and supplier (Hendershott, Jones and Menkveld 2011). Algorithmic traders (ATs) apply highly automated strategies to place and update orders in multiple markets at the same time (Kirilenko et al. 2011). For example, arbitrageurs apply algorithms to analyze market data (past prices, current quotes, news, etc.) to find price discrepancies or trading patterns that can be profitable (Abergel et al. 2012).

The growing use of technology has caused trading to have a very fast pace in analyzing data and acting accordingly and it has increased the importance of speed in market participation. High frequency trading (HFT) or low latency trading is a subgroup of algorithmic trading and refers to the activity of updating orders and positions at a very high speed (Boehmer, Fong and Wu 2018; Gomber et al. 2011; Ersan and Ekinci 2016; Haynes and Roberts 2015). HFT is not a trading strategy but applying the most updated technological means in market data analysis to achieve the highest returns of trading strategies (Gomber et al. 2011).

Constantly monitoring the market and its new information, processing and acting is costly for human traders because it needs attention and human’s attention and time is limited.

HFT can reduce the cost of monitoring, updating, and order placement and increase capacity and facilitate gains from trade (Biais et al. 2010). High frequency traders (HFTs) can also increase competition and help to provide liquidity (Carrion 2013). Abergel et al. (2012) argue that this competition might serve to tighten bid-ask spreads and reduce transaction costs and information asymmetry for all market participants. However, HFT is not necessarily beneficial to the market. The ability of HFT to process the information and revise orders very fast may lead to adverse selection. If new information comes to the market, HFTs can update their positions before other traders can cancel or revise their orders (Brogaard, Hendershott and Riordan 2017). Foucault, Roell and Sandas (2003) argue that this risk causes traders to act more conservatively and reduces market liquidity.

The empirical and theoretical finance literature have been engaged in an ongoing debate regarding AT. Some studies have found that AT has a positive effect on market quality by increasing the competition, trading volume and liquidity, and lowering trading costs and the spreads. ATs provide liquidity when it is expensive and take it when it is cheap (Hendershott, Jones and Menkveld 2011; Hendershott and Riordan 2013; Carrion 2013). On the other hand, others argue that AT may increase volatility through the increase in message traffic. The speed advantage of ATs increases adverse selection costs for slow traders and decreases their ability to gain larger returns. Because unlike fast traders, slow traders can only react to long run opportunities created by news. This difference in speed not only causes adverse selection, but it leads to wider spreads (Han, Khapko and Kyle 2014; Brogaard, Hendershott and Riordan 2014; Foucault, Hombert, and Roşu 2016).

In addition to the mixed results found in the financial literature, to our knowledge, no studies have been performed on agricultural commodity markets. Most of the research on AT has been performed for large hybrid markets, such as the NYSE and NASDAQ. In hybrid markets trading occurs through both a trading floor and an electronic system. On the floor, transactions are facilitated by designated market makers (i.e., quote-driven market) whereas in the electronic system buy and sell orders are centralized in a limit order book (LOB) and automatically matched by a computer algorithm (i.e., order-driven market). However, agricultural commodities such as wheat, soybean, corn, hogs and cattle are traded in a pure order-driven system at the CME Group where trading occurs only through a centralized LOB. Park and Ryu (2019) show that in order-driven markets the speed of order submission affects trader behavior. They find that fast traders prefer using limit orders rather than market orders when compared with slow traders. In quote-driven markets slow traders have the option of trading on the floor, which may result in transaction prices that are different from the posted bid or ask. That is, market microstructure dynamics differ between both trading systems and therefore the effect of AT on market quality cannot be extrapolated from one system to the other. Moreover, trading agricultural commodities also differs from other financial instruments because of the differences in market characteristics like tick size, commodity availability, and traded volume. The tick size is the minimum price change between bid and ask prices, therefore directly affecting the size of the bid-ask spread, a commonly used measure of trading costs and a reflection of the level of market quality. Agricultural commodity prices are, by nature, dependent on supply and demand factors and known to be more volatile relative to other markets. Volatility has not only been found to be a determinant of trading costs (Frank and Garcia 2011), but it is also a reflection of new information in the market, which may prompt the use of algorithms to respond quickly to those changes (Hasbrouck 2018). Finally, previous research has shown that less frequently traded stocks may exhibit different transmission of information dynamics (Manganelli 2005; Zhang, Russell and Tsay 2001). The low trading volume of agricultural commodities relative to other markets may therefore be associated with a different response of market quality to algorithmic trading.

The objective of this study is to examine the impact of AT on market quality, focusing on agricultural commodities. Because the dataset from the CME Group doesn't include the information to identify whether an order is generated manually by a human or by a computer algorithm, we use Hendershott, Jones and Menkveld's (2011) commonly used measure of AT The measure is based on the number of changes observed in the LOB as indicative of the level of AT. We examine the relationship between AT and different measures of market quality, including bid-ask spread, effective spread, adverse selection and realized spread. Because AT, measures of market quality, traded volume and volatility are determined jointly, we estimate a Vector autoregression (VAR) model. We control for announcement days, day of the week, and time of the day. We then perform an impulse response analysis to examine the impact of a shock of AT on market quality and the time it takes to the market to recover after a shock.

We find that AT improves market quality by narrowing the effective half spread (an estimate of the liquidity cost) in all markets. The effect is stronger in lean hogs and live cattle markets where AT also decreases the adverse selection (the cost incurred by the liquidity providers caused by the existence of different levels of information in the market, or information asymmetry). The inverse relationship between AT and effective half spread and adverse selection shows that ATs are more active if transaction costs and information asymmetry are lower.

The thesis is organized as follows. First, we review the previous studies related to the effects of AT on different markets. Second, in the methods section, we discuss the proxy used to estimate AT activity in the market and the measures of market quality being used. Next, we introduce the empirical VAR model used to estimate the relation between AT and market quality and the impulse response function. Then we describe our dataset and provide some basic statistics of the data as well as stationarity test results. Finally, in the results section, we explain our findings.

2. Background

The evidence of the effect of AT on market quality is mixed. This section discusses studies supporting each side of the debate. Note that studies might be specific to the sample period, the product being traded, and the identification method used for the algorithmic trading.

In a theoretical study, Foucault, Hombert and Roşu (2016) compare the trading strategy in two cases of fast (when the trader can trade ahead of incoming news) and slow (when she cannot) traders by proposing a dynamic model of trading on news. They argue that the speed advantage of algorithmic traders would increase adverse selection costs and the fast traders are responsible for a larger fraction of trading volume. The reason is that fast traders can react to both short and long run news when slow traders can only react to long run opportunities created by news. Han, Khapko and Kyle (2014) study how relative differences in order cancellation speeds affect spreads. They focus on quote adjustment and show that when new information comes into the market, fast traders can update quotes faster than slow traders and this leads to wider spreads and imposes adverse selection on slow traders. They compare "pre- and post-information-arrival" spreads and argue that if there are no HFTs in the market, order adjustments won't cause adverse selection and slow traders post low bid-ask spreads. Roşu (2015) develops a model in which traders receive private signals about the value of assets and differ in their information receiving and processing speed, not in their trading speed, and there is a positive information processing cost that makes traders ignore information that is relatively old. He finds that although the market is very efficient and liquid, because HFTs increase competition, slow traders lose the majority of the profits by being slow. Also, he supports Foucault, Hombert, and Roşu's (2016) findings of fast traders being responsible for a larger fraction of trading volume.

Although the theoretical studies all point to an increase of adverse selection, the results of empirical studies do not always agree. Hendershott, Jones and Menkveld (2011) use five years of NYSE data from 2001 to 2005. NYSE started “automated quote dissemination” in 2003. They use this update as an instrument for the effect of AT on liquidity and the rate of electronic message traffic as a proxy for AT. They show that as AT increases, effective spread and adverse selection decrease, and realized spread increases, which indicates that AT decreases the costs for liquidity providers. Using the same proxy for AT activity, Viljoen, Westerholm and Zheng (2014) study the share price index (SPI) 200 future contracts traded on the Australian Securities Exchange (ASX) from January to December 2009. They find that AT improves standard measures of liquidity by narrowing the spreads and reducing adverse selection, which is in line with Hendershott, Jones and Menkveld’s (2011) results. Moriyasu, Wee and Yu (2018) study the Tokyo Stock Exchange (TSE), from 2007 to 2012, using the same proxy as the two previous studies, and find that AT lowers quoted and effective spreads. It also decreases both realized spread and adverse selection. They use a two-stage least squares (2SLS) model and the introduction of a new trading platform to facilitate AT activity in January 2010 as an instrumental variable (the new platform reduced latency, the time difference between order placement and execution).

While these three studies found consistent results using the same proxy for AT activity in three different markets, other studies performed on the same market lead to contrasting results. For example, Hasbrouck (2018), studying a sample of the Center for Research in Security Prices (CRSP) daily stock file and the NYSE’s daily trade and quote (TAQ) database from January to April 2011, finds that slower traders lose to faster traders all the time. He shows that faster traders, that are able to monitor the market and react as well as place their orders faster, can gain larger returns than slower traders.

Riordan and Storkenmair (2012) study the impact of an upgrade of trading systems on the Deutsche Boerse (DB) in April 23, 2007 that reduces the system latency from 50 to 10 milliseconds. Using a VAR model for the period of February 22 to June 19, 2007 they show that technological upgrades result in a reduced effective spread (by -1.91 on average) and adverse selection (by -4 on average) but a higher realized spread (by 5.39 on average). Hendershott and Riordan (2013) use one month of AT data in the 30 Deutscher Aktien Index (DAX) stocks traded on the DB in January 2008, which identifies algorithmic orders. They find that algorithmic traders improve market liquidity by providing liquidity when it is scarce (expensive) and consuming it when it is plentiful (when the bid-ask quotes are narrow).

Using a sample of NASDAQ trading data for 2008 and 2009 that directly identifies HFT participation, Carrion (2013) shows that spreads are wider when HFTs provide liquidity and tighter when HFTs take liquidity, meaning HFTs provide liquidity when it is scarce and consume it when it is plentiful. The study cannot prove that HFTs increase adverse selection, and also notes that results cannot be generalized to other markets that are organized differently. Using NASDAQ data from 2008 to 2009, the same dataset as Carrion (2013), Brogaard, Hendershott and Riordan (2014) find that HFTs improve price efficiency by trading in the direction of permanent price changes and in the opposite of transitory pricing errors through liquidity demanding orders. HFT causes narrower spreads and lower trading costs. Hirschey (2013) also use NASDAQ data in 2009, the same dataset as Carrion (2013) and Brogaard, Hendershott and Riordan (2014), and find opposite results. The study finds that HFTs appear to impose some adverse selection costs on non-HFT traders and increase their trading costs. Using a VAR model, the study shows HFT traders are faster in reaction to news and seem to lead non-HFT traders.

Chaboud et al. (2014) study the three major currency pairs: the euro-dollar, dollar-yen, and euro-yen in 2006 and 2007 using electronic broking service (EBS) minute-by-minute trading data. In this dataset the volume and source of trade (human or computer) are identified. Using a VAR model, they find that algorithmic strategies are positively correlated and not as diverse as non-algorithmic ones. By comparing U.S. nonfarm payroll announcements and non-announcement days, they find that AT provides liquidity when it is scarce. They show that in this market ATs have an advantage in finding and reacting to arbitrage opportunities.

Malinova, Park and Riordan (2013) study the impact of a new regulation on the Toronto Stock Exchange (TSX) from March 1, 2012 to April 30, 2012. Starting on April 1, 2012 the new regulation changed the fees from trade-based to message-based (trade, submission, cancellation, modification). Using a dataset that identifies the market participants, this study shows that this new regulation decreases the AT activities resulting in an increase in bid-ask spread, effective spread and adverse selection, and a decrease in realized spread.

The above studies show the ongoing debate regarding the effect of AT on the market and the importance of focusing on each market and scenario separately. Also, none of these studies were performed for agricultural markets. This study contributes to the literature by investigating the effect of AT on market quality on agricultural markets.

3. Methods

As AT has grown over the past few years, a dramatic improvement in market liquidity has been witnessed. However, a causal and positive relationship between AT and liquidity is not clear. As discussed in the previous section, the results for their relationship are mixed. In this section we explain the AT proxy and measures of market quality used in this study, as well as the VAR model and the impulse response function.

3.1. AT proxy

Publicly available data from the CME Group does not identify whether an order was generated by a computer algorithm or an actual trader. We therefore use a proxy for AT following Hendershott, Jones and Menkveld's (2011) procedure (examples of studies that have used this proxy are Viljoen, Westerholm and Zheng 2014 and Moriyasu, Wee and Yu 2018). The AT measure is based on the level of "message traffic" as indicative of the level of algorithmic trading. Any update in the market including an order submission, revision, cancelation or trade is called a "message." Many AT strategies involve frequent updates and the proportion of updates that leads to a trade, as opposed to submission, revision and cancelation, is typically much smaller for ATs than non-ATs (Boehmer, Fong and Wu 2018). So, we expect to see a higher level of "message traffic" as AT activity increases in the market. Because an increase of message traffic can also be reflective of the increased volume of trading, as it appears to be the trend in most markets, the measure is normalized using the observed flow of funds. The AT proxy, as defined in Viljoen, Westerholm and Zhang (2014) is,

$$AT = \frac{-dollar\ volume}{message\ traffic} \tag{1}$$

where *dollar volume* is the sum of the volume (number of contracts) of a trade times the price of the trade for all trades observed over a period of time $\bar{t}$, and *message traffic* is the sum of the number of trades and the number of order submissions, revisions and cancellations calculated using the aggregated depth in the LOB over a period of time $\bar{t}$. We use the level of message traffic as indicative of the level of AT, thus the negative sign in the equation. If *message traffic* in the denominator increases, AT increases.

Hendershott, Jones and Menkveld (2011) show that this measure considers two possible scenarios associated with AT in the market. The first scenario accounts for existing algorithmic traders and changes in their strategies, as the measure captures increases or decreases in order submissions and cancelations, as well as the case when they slice and dice large orders into smaller pieces. The second scenario is concerned with the number of algorithmic traders and their fraction of all market participants. As AT is known by lower transaction sizes and more frequent submissions, amendments and cancellations of orders, this AT measure will have a positive correlation with all these AT activities (Hendershott, Jones and Menkveld 2011).

3.2. Market quality

One measure of market quality is the liquidity cost. Its most common gauge is the bid-ask spread (BAS) which measures the wideness between the prevailing asking and buying prices.

There is a simple intuition in estimating the liquidity cost. In the absence of trading costs associated with microstructure effects, transactions would happen at the true underlying commodity price, and therefore the difference between the transaction price and an estimate of the true underlying commodity price would show the trading cost (Bessembinder and Venkataraman 2010). The (half) bid-ask spread is the simplest and most standard measure of market quality, which summarizes the difference between the underlying fundamental value of the commodity and the transaction price, if the transaction is executed at the quoted price. The underlying fundamental value of the commodity is not observed and the most common proxy being used is the quote midpoint. The quoted half spread is defined as,

$$QHS_t = \frac{Ask_t - Bid_t}{2M_t} \tag{2}$$

where M_t is the midpoint between the prevailing ask and bid quotes immediately before the transaction at time t.

Transactions may happen at prices different to the best quotes, in which case the effective half spread (EHS) represents a more accurate measure of the cost incurred by the trader. Transactions occur at prices other than the best quotes when the depth at the best bid or ask is “consumed” and orders are filled at the next LOB level. It can also occur in the presence of hidden orders at quotes not observed in the book (Bessembinder and Venkataraman, 2010). The EHS is defined as,

$$EHS_t = q_t \frac{P_t - M_t}{M_t} \tag{3}$$

where P_t is the price of the t^{th} trade, and q_t is the trade direction indicator (1 for a buyer-initiated trade and -1 for a seller-initiated trade). The EHS is the deviation between the transaction price and the efficient price and therefore represents an estimate of the "execution" cost paid by the liquidity takers or gross revenue of the liquidity providers (Bessembinder and Venkataraman, 2010). ATs can act as both liquidity providers (suppliers) and liquidity takers (demanders). A trader is a liquidity provider if she places limit orders and is a liquidity taker if she places market orders.

The effective spread can be further decomposed into informational (adverse selection) and non-informational (inventory and order processing) components. The informational component is commonly referred to as the adverse selection component, reflecting the presence of buyers and sellers who do not necessarily possess the same level of information. Informed traders disclose their private information through trade. The new information is then incorporated into prices, leading to a permanent change in the underlying fundamental value of the commodity. The permanent price change, or price impact of a trade (PI), or the amount of adverse selection cost incurred by the liquidity providers (or their gross losses to informed liquidity demanders), can therefore be estimated by comparing the efficient price of the *t*th trade with the efficient price of the $(t+n)$th trade as follows,

$$PI_{\mathrm{t}} = q_t \frac{M_{t+n} - M_t}{M_t}. \tag{4}$$

If there are informed traders in the market, prices would rise after a buy or fall after a sell. This adverse price movement causes market makers to gain less than the effective spread. The price impact of trade can be used as a proxy for the degree of information asymmetry across trades (Bessembinder and Venkataraman 2010). In previous studies n is commonly set to five minutes after the trade (for instance, Hendershott, Jones and Menkveld 2011; Boehmer, Fong and Wu 2018; Moriyasu, Wee and Yu 2018; Brogaard, Hendershott and Riordan 2017; Gousgounis and Onur 2017; Riordan and Storkenmair 2012; Viljoen, Westerholm and Zheng 2014). The horizon can be thought of as long enough to incorporate the permanent impact of the trade so that quotes are subsequently stabilized and temporary (i.e., non-informational) effects dissipated. It can also be thought of the length of time in which traders can close their positions (Conrad, Wahal, and Xiang 2015). The literature is not clear about this time frame.

Although the most common time frame is five minutes, some studies tried to examine other time frames. Conrad, Wahal and Xiang (2015) argue that 5 minutes is too long and use 20 seconds. Carrion (2013) calculate the spreads for 1, 5 and 30 minutes. None of these studies report a major difference in their results. In this study we use 2- and 5-minute time frames. That is, we use the most common time frame of five minutes and we also consider the fact that trading in these markets has a very high speed and five minutes might be too long.

The non-informational component, or market making (liquidity providing) net revenue after losing to better informed traders (liquidity takers), often referred to as the temporary price impact of a trade, or the realized spread (RS), captures inventory and order processing costs of liquidity providers. It can be thought of as the residual between the estimated half spread and the price impact of a trade,

$$RS_t = EHS_{\mathrm{t}} - PI_{\mathrm{t}} = q_t \frac{P_t - M_{t+n}}{M_t}. \tag{5}$$

In an ideal market where everyone has the same level of information and speed, no one is able to gain from a trade. So, a decrease in PI and RS, decreases the loss of liquidity providers (gain of liquidity takers) and net revenue of liquidity providers, and improves market quality.

3.3. Empirical model

We estimate the relationship between algorithmic trading and the different measures of market quality described above. In the model we account for the joint determination of AT, liquidity cost, volume and volatility and we control for announcement days, day of the week, and time of the day.

AT and liquidity are jointly determined as algorithms may be triggered by low trading costs, and the level of liquidity depends on technological and other costs incurred by liquidity providers. AT is also determined jointly with traded volume and volatility. Easley and O'Hara (1987) study the traded volume effect on prices and show a close relationship between volume and traders' information, where informed traders would rather trade larger amounts. So, an increase in traded volume can be a reflection of new information and increase AT activities. On the other hand, Viljoen, Westerholm and Zheng (2014), Hendershott, Jones and Menkveld (2011), and Hendershott and Riordan (2011) find a negative effect of AT on volume as ATs break large orders into smaller ones in order to reduce their impact on the market.

The relationship between volatility and HFTs has been shown to be negative by Aït-Sahalia and Saglam (2013), who argue that when volatility increases, HFTs are likely to decrease their activities due to higher risks of informational disadvantage. In contrast, empirical evidence for SPI 200 future contracts trading on the ASX (Viljoen, Westerholm and Zheng 2014) and for several equity markets from around the world (Boehmer, Fong and Wu 2018) show a positive relationship between AT and volatility. Volatility reflects new information and an increase in volatility due to AT is a result of faster price adjustments.

Liquidity cost measures, volume and volatility have been found to be determined jointly in financial and metal (Wang and Yau 2000) as well as in agricultural (Frank and Garcia 2011) future markets. The relationship between liquidity cost measures and volume is negative because higher spreads increase the costs for traders which decreases the trading volume, and trading larger orders decreases the costs for traders which decreases the spreads. The relationship between liquidity cost measures and volatility is positive because an increase in volatility exposes liquidity providers to higher risk of informational disadvantage. Therefore, liquidity providers increase the spread to compensate for possible losses. Volume and volatility affect each other positively as both reflect the presence of new information in the market.

Using Durbin (1954) and Wu-Hausman (Wu 1974; Hausman 1978), we test our variables for endogeneity. We construct a 2SLS model for each equation, using own-lags of variables being tested as instrumental variables. The null hypotheses of these tests is that the variable being tested is exogenous. Our results show that AT, spreads, size and volatility should be treated as endogenous in our model as the p-value in all cases is less than 0.05.

We specify a multivariate VAR model to represent the simultaneity between AT, the liquidity measures, volume and volatility. VAR models for market microstructure have been introduced by Hasbrouck (1991) and become popular (see Wee and Yang 2016; Hendershott, Jones and Menkveld 2011; Hendershott and Riordan 2011; Chaboud et al. 2014; Hirschey 2013; Riordan and Storkenmair 2012). The multivariate VAR model is specified in equations 6-1 to 6-4:

$$AT_{\bar{t}} = \alpha_1 + \sum_{j=1}^{J} \gamma_{1j} AT_{\bar{t}-j} + \sum_{j=1}^{J} \delta_{1j} SP_{\bar{t}-j} + \sum_{j=1}^{J} \upsilon_{1j} SZ_{\bar{t}-j} + \sum_{j=1}^{J} \vartheta_{1j} VL_{\bar{t}-j} + \partial_1 DN_{\bar{t}} + \sum_{w=1}^{W} \rho_{1w} DW_{w,\bar{t}} + \sum_{i=1}^{I} \beta_{1i} DI_{i,\bar{t}} + \varepsilon_{1,\bar{t}} \quad (6\text{-}1)$$

$$SP_{\bar{t}} = \alpha_2 + \sum_{j=1}^{J} \gamma_{2j} AT_{\bar{t}-j} + \sum_{j=1}^{J} \delta_{2j} SP_{\bar{t}-j} + \sum_{j=1}^{J} \upsilon_{2j} SZ_{\bar{t}-j} + \sum_{j=1}^{J} \vartheta_{2j} VL_{\bar{t}-j} + \partial_2 DN_{\bar{t}} + \sum_{w=1}^{W} \rho_{2w} DW_{w,\bar{t}} + \sum_{i=1}^{I} \beta_{2i} DI_{i,\bar{t}} + \varepsilon_{2,\bar{t}} \quad (6\text{-}2)$$

$$SZ_{\bar{t}} = \alpha_3 + \sum_{j=1}^{J} \gamma_{3j} AT_{\bar{t}-j} + \sum_{j=1}^{J} \delta_{3j} SP_{\bar{t}-j} + \sum_{j=1}^{J} \upsilon_{3j} SZ_{\bar{t}-j} + \sum_{j=1}^{J} \vartheta_{3j} VL_{\bar{t}-j} + \partial_3 DN_{\bar{t}} + \sum_{w=1}^{W} \rho_{3w} DW_{w,\bar{t}} + \sum_{i=1}^{I} \beta_{3i} DI_{i,\bar{t}} + \varepsilon_{3,\bar{t}} \quad (6\text{-}3)$$

$$VL_{\bar{t}} = \alpha_4 + \sum_{j=1}^{J} \gamma_{4j} AT_{\bar{t}-j} + \sum_{j=1}^{J} \delta_{4j} SP_{\bar{t}-j} + \sum_{j=1}^{J} \upsilon_{4j} SZ_{\bar{t}-j} + \sum_{j=1}^{J} \vartheta_{4j} VL_{\bar{t}-j} + \partial_4 DN_{\bar{t}} + \sum_{w=1}^{W} \rho_{4w} DW_{w,\bar{t}} + \sum_{i=1}^{I} \beta_{4i} DI_{i,\bar{t}} + \varepsilon_{4,\bar{t}} \quad (6\text{-}4)$$

where $SP_{\bar{t}}$ represents the different measures of market quality (QHS_t, EHS_t, PI_t, and RS_t) averaged over the period $\bar{t}$. As discussed above, we use n=2 and 5 minutes to calculate liquidity cost measures PI_t and RS_t. The variable $SZ_{\bar{t}}$ is the average traded volume over the period $\bar{t}$ (size). $VL_{\bar{t}}$ is the volatility computed as the standard deviation of the quote midpoint over the period $\bar{t}$. This is the standard measure of volatility used in previous studies (Shang, Mallory and Garcia 2018; Hendershott, Jones and Menkveld 2011; Brogaard, Hendershott and Riordan 2017; Foucault, Roell and Sandas 2003; Wang, Garcia and Irwin. 2014). Adjemian and Irwin (2018) study the effect of the USDA announcement on price, volatility and volume in the CME Group data for corn, soybean and wheat electronic futures markets. They use different measures of volatility such as the standard deviation of returns, the coefficient of variation of returns and the hi-low volatility and show that the results of their study do not change across different measures. We use an interval length of $\bar{t}$=5 and 10 minutes to calculate the AT measure, average liquidity measures, size and volatility. The literature is not clear about the length on these intervals. We follow Viljoen, Westerholm and Zheng (2014) who use 10-minute intervals to calculate the AT measure and average liquidity measures. We also use 5 minutes to calculate the AT measure, average liquidity measures, size and volatility as trading in these markets has a very high speed and 10 minutes might be too long. To determine the number of lags (J) for the autoregressive terms, we calculate Akaike's information criterion (AIC) for each spread measure separately. We also tested the residuals of each equation, using the number of lags determined by AIC, using the autocorrelation function (ACF) and no autocorrelation was detected in the residuals of wheat, soybean and live cattle. In corn and lean hogs, only RHS_t shows 2 or 3 lags slightly outside of the 95% confidence zone of the ACF. The dummy variable $DN_{\bar{t}}$ equals 1 on announcement days and 0 otherwise. The dummy variables $DW_{w,\bar{t}}$ are for days of the week where $w=\{2 \ldots 5\}$, DW_2=1 for Tuesdays and 0 otherwise, DW_3=1 for Wednesdays and 0 otherwise, DW_4=1 for Thursdays and 0 otherwise, and DW_5=1 for Fridays and 0 otherwise. The dummy variables $DI_{i,\bar{t}}$ captures the time of the day effect, where $i=\{1, 2, 3\}$, DI_1=1 for the opening time and 0 otherwise, DI_2=1 for the midday and 0 otherwise, and DI_3=1 for the closing of the market and 0 otherwise.

The importance of announcements can be found in many studies like Brogaard, Hendershott and Riordan (2014), Lehecka, Wang and Garcia (2014), Scholtus, Dijk and Frijns (2012), Adjemian and Irwin (2018), Joseph and Garcia (2018) and Shang, Mallory and Garcia (2018). These studies find a positive correlation between HFT and macro news. Scholtus, Dijk and Frijns (2012) argue that this positive correlation leads to adverse selection for slow traders. Lehecka, Wang and Garcia (2014) use the CME Group data for corn futures prices from July 2009 to May 2012 and show the effect of USDA announcements before and after being released due to adjustments in trade decisions. They show that return variance and volume after the report release are larger relative to non-report days at the same time of the day. Adjemian and Irwin (2018) study the CME Group data for corn, soybean and wheat electronic futures markets for the period of July 20, 2009 to July 22, 2014 and find higher volatility and volume immediately after the USDA announcement release. Joseph and Garcia (2018) study CME Group data for the soybean market from June 2010 to May 2014 and find higher volatility and volume after the announcements release. Wang, Garcia and Irwin (2012) study the effect of USDA announcements on the electronically traded corn futures of the CME Group from January 14, 2008 to January 29, 2010 and find significantly higher BAS on the days that the reports are released. Shang, Mallory and Garcia (2018) study CME Group data for corn future markets from January 2008 to October 2011 and find that after the announcement release volume and the informational component of the liquidity cost increases and the inventory component decreases.

The day of the week is included as a control variable due to the "weekend effect." Traders tend to close their positions on Fridays because they do not want to keep open positions during the weekend as the long period of not being able to trade introduces a risk. Studies show this effect leads to higher returns on Fridays and lower returns on Mondays. These studies also show that the difference in returns can be seen in other days of the week too (French 1980; Keim and Stambaugh 1984; Jaffe and Westefield 1985; Basher and Sadorsky 2006). However, many studies fail to find any significance in these two particular days (Compton and Kunkel 2000; Christophe et al. 2009; Viljoen, Westerholm and Zheng 2014). For example, Wang, Garcia and Irwin (2012) study the electronic traded corn futures of the CME Group from January 14, 2008 to January 29, 2010 and find the days of the week insignificant. According to Hendershott and Riordan (2013), returns affect the AT strategies. They study the 30 Deutscher Aktien Index Stocks on the DB in January 2008 and show that ATs are more likely to sell if the recent returns are negative and vice versa. There are studies showing the "weekend effect" in terms of liquidity costs. Frank and Garcia (2011) study live cattle future contracts trading in the CME Group from January 2005 to October 2008 and find that the liquidity costs are lower and trading activity is higher earlier in the week. Wang, Garcia and Irwin (2012) show slightly higher but insignificant BAS on Thursdays and Fridays in the corn market.

Intraday patterns of AT and liquidity measures are well documented in market microstructure studies. For example, Barclay and Hendershott (2003) study NASDAQ data from March to November 2000 and report a U-shape intraday pattern for trade volume and average return volatility. Shang, Mallory and Garcia (2018) examine intraday patterns in corn futures contracts from January 2008 to October 2011 and find that the BAS, volume and volatility are at the highest level at the opening time. Viljoen, Westerholm and Zheng (2014) find a U-shape pattern for trade size, number of trades, number of updates and liquidity measures (spreads) and reverse U-shape pattern for AT in SPI 200 future contracts traded on the ASX.

To study the dynamics of the VAR model, we perform an impulse response analysis. Impulse response functions (IRFs) show the effect of a one standard deviation shock of an endogenous variable on current and future values of other endogenous variables (Hamilton 1994). In IRFs, the order of variables in the VAR model matters because each variable is affected by the shock to variables above and not below them in the list. So, in our case, the first variable is AT because the objective is to study the effect of AT on other variables. The last variables are liquidity measures because we are interested in the effect of shock on these variables. The order for size and volatility is not clear so we construct the function using different orders for these variables.

4. Data

We study the effect of AT on market quality for five major agricultural commodities: wheat, soybean, corn, lean hogs and live cattle. To construct our variables, we need the bids and asks in the LOB, and the corresponding times, the number of updates (trades, order submissions, revisions and cancellations), prices, volumes (number of contracts), and the direction of the trades (buyer or seller initiated). The *market depth* files from the CME Group provide every incremental book update required to reconstruct the top ten LOB levels for grains and the top five levels for meats. We reconstruct the LOB for the period of December 2015 to March 2016 following the procedure described in Arzandeh and Frank (2019). We roll over futures contracts when its aggregate traded volume is lower than that of the second nearest contract for two consecutive days. Our reconstructed LOB incorporates the two-level implied LOB. Our dataset is similar to that used in Arzandeh and Frank (2019) except that we reconstruct the full LOB, without taking snapshots at regular times, to extract M_{t+n}. Also, the last observation for Ask_t, Bid_t, M_t, P_t *and* q_t is 2 and 5 minutes before the market closes as the last 2 and 5 minutes of the trading day are used to compute M_{t+n} for PI_t and RS_t.

Wheat, soybean and corn futures contracts trade in the morning (8:30 am to 1:20 pm CT) and in the evening (7:00 pm to 7:45 pm CT). We perform the analysis for the morning session from Monday to Friday because the volume traded in the evening session and on Sunday is low (there is no trading on Saturdays). Lean hogs and live cattle futures contracts trade in one session only (8:30 am to 1:05 pm CT). For the period under study, there is no trading on the two federal holidays of January 18 and February 15. We eliminate the data for the days with extended trading halts which is mostly the case for a few futures contracts with partial pre-holiday (a day prior) and post-holiday (a day after) trading with extended trading breaks. These dates are December 25, January 1 and 18, February 9 and 15, and March 25 for all markets. Also, December 18 and 21 and February 8 for live cattle. The number of observations is 2283 for grains, 2122 for lean hogs, and 2027 for live cattle. The live cattle dataset has the lowest quality among commodities as, in addition to these extra missing dates, the dataset for some dates is incomplete.

4.1. Announcements, day of the week, and intraday seasonality effects

The effect of announcements is captured by using USDA reports released from December 2015 to March 2016. For grains, we use WASDE, Grain Stock (GS), Prospective planting (PP) and Crop Production (CP) reports. WASDE provides forecast and supply/demand for major global crops and U.S. livestock, GS contains stocks of all major crops, PP forecasts the expected acres of major crops to be planted, and CP reports crop production data such as acreage, area harvested and yield in the U.S. For meats, we use Cattle on Feed (CoF), Livestock

Slaughter (LS), Hog and Pigs (HP) and Cold Storage (CS) reports. CoF is the monthly report of the number of cattle and calves on feed, placements, marketing and other disappearances, LS is the monthly report of red meat production and the number of major live cattle slaughtered in commercial use, HP reports inventory by class and weight, and CS reports the end of month meat stocks.

The literature is not clear about the length of the effect of the USDA announcements on the markets. Lehecka, Wang and Garcia (2014) show that the effect on the prices of CME corn futures markets lasts for 10 minutes. Joseph and Garcia (2018) study CME Group data for the soybean market and find the effect on volume and volatility is gone after 20 minutes. Shang, Mallory and Garcia (2018) study CME Group data for corn future markets and show that the effect on liquidity costs lasts for about 30 minutes. These studies also show the effect of the announcement before the release time due to the anticipation. The USDA announcements are released at 12 pm ET for grains and 3 pm ET for meats. We define our interval 30 minutes before and 30 minutes after the announcement release time to capture its effect before and after the release time on the market. For meat announcements, because they are released after the closing time (1:05 pm CT), we consider the last half hour of the releasing day and the first half hour of the next day as our 30-minute intervals.

Karali (2012) studies the effect of the USDA announcements on the covariance of returns in soybean, corn and lean hogs futures markets traded in the CME group in the period of January 1995 to April 2009 in an attempt to find out if the reports related to one market can affect the others. Her results show that the commodity returns in these markets are significantly affected by other markets news. In this study, we use all the announcements released in the period of our study for all commodities, to capture the effect of the news related to each market on itself as well as other markets. We define one dummy variable that takes the value of 1 on the intervals defined above for each day when there is a USDA announcement and zero otherwise. Table 1 specifies the announcements days, as well as the values of the dummy variables used for the day of the week, and the times used to define the intraday periods.

Table 1: Dummy variables used in the VAR model

Name		Description
Announcements (DN)	$DN=1$	Dec 09- WASDE/CP (Grain) Dec 18- CoF (Meat) Dec 22- CS (Meat) Dec 23- LS/HP (Meat) Jan 12- WASDE/GS/CP (Grain) Jan 21- LS (Meat) Jan 22- CS/CoF (Meat) Feb 19- CoF (Meat) Feb 23- CS (Meat) Feb 25- LS (Meat) Mar 09- WASDE/CP (Grain) Mar 18- CoF (Meat) Mar 21- HP (Meat) Mar 22- CS (Meat) Mar 24- LS (Meat) Mar 31- PP (Grain)
Day of the week (DW_w)	w=2	Tuesday
	w=3	Wednesday
	w=4	Thursday
	w=5	Friday
Intraday seasonality (DI_i)	i=1	8:30 to 9:00 (Grain)/ 8:30 to 9:30 (Meat)
	i=2	10:30 to 11:20 (Grain)/ 10:40 to 11:30 (Meat)
	i=3	12:50 to 13:20 (Grain)/ 12:40 to 13:05 (Meat)

4.2. Descriptive statistics

In this section we report some basic statistics of our dataset. Figures 1.1 to 8 show the average price, volume, volatility, AT and spreads for each commodity. The average of a variable in each interval is computed using all the observations in the four-month period for that specific interval.

Figures 1.1 to 1.5 show the average price. At the beginning of the day, the price increases in wheat, soybean and corn, and decreases in lean hogs and live cattle. Toward the end of the day, it increases in all commodities except lean hogs. The price behavior in wheat and soybean seems to be similar. In general, we cannot identify a clear intraday pattern in price movements.

Average volume (figures 2.1 and 2.2) changes slightly for all commodities and increases at the end of the day except soybean and corn. Barclay and Hendershott (2003) report a U-shape intraday pattern for trade volume in NASDAQ and Shang, Mallory and Garcia (2018), studying the CME electronic corn futures, find that volume is at its highest level at the opening time.

Volatility (figures 3.1 and 3.2) shows a U-shape pattern in all commodities. In the meats, the U-shape pattern happens later during the day. The U-shape pattern for volatility is in line with the findings of Shang, Mallory and Garcia (2018). Higher volatility at the beginning and at the end of the day also might be a result of the release of information overnight and attempt to close positions at the end of the day.

AT activity is shown in figure 4.1 for grains and in figure 4.2 for meats. In figure 4.1, the increase in AT activity at the beginning of the day and the decrease at the end of the day are clear, and this result is in line with Viljoen, Westerholm and Zheng (2014) for the SPI 200 future contracts traded on the ASX who find a reverse U-shape pattern for AT. In figure 4.2 the pattern is less clear. The reverse U-shape pattern for lean hogs seems to happen later during the day. AT is higher at the start of the trading day but it decreases in the first half hour. Then it increases again and shapes the reverse U until the end of the day. For live cattle AT is higher at the beginning and at the end of the day but it varies during the day. The reverse U-shape pattern in AT might be a reflection of the U-shape pattern observed for volatility, as an increase in volatility tends to decrease AT activity due to higher risk of informational disadvantage. In other words, HFTs try to protect themselves against the situation that they have informational disadvantage by reducing their activity (Aït-Sahalia and Saglam 2013).

Shang, Mallory and Garcia (2018) for BAS, and Viljoen, Westerholm and Zheng (2014) for QHS, EHS and PI, find a U-shape pattern. In our data a clear pattern for liquidity cost measures cannot be identified. In figure 5, QHS decreases at the end of the day for all commodities, and it also decreases at the beginning of the day for all commodities except soybean. In figure 6, EHS, at the end of the day, increases in all commodities except live cattle. At the beginning of the day, it decreases for all commodities except corn. In figure 7, PI decreases toward the end of the day. At the opening time, it decreases in soybean and live cattle, and increases in the rest of the commodities. In figure 8, RS increases at the end of the day in all commodities except live cattle, and at the beginning of the day, it increases in soybean and live cattle, and decreases in the rest of the commodities. Note that in this study and in Viljoen, Westerholm and Zheng (2014) the data for the last 5 minutes of the trading day have been eliminated in order to calculate PI and RS as explained above.

Figure 1.1: Average price (U.S. Cents per bushel). Wheat

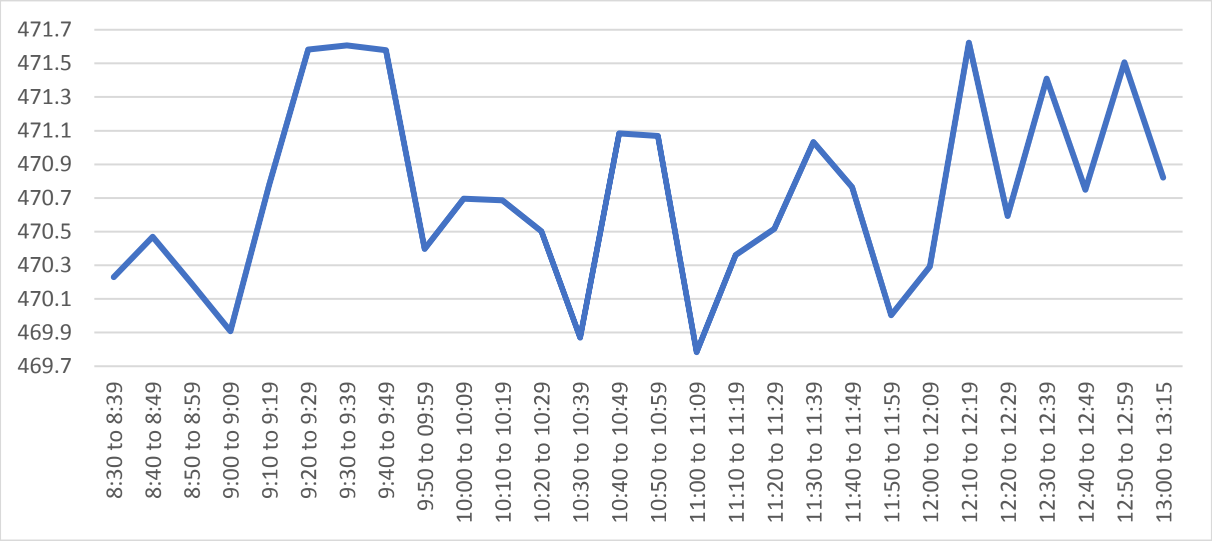


Figure 1.2: Average price (U.S. Cents per bushel). Soybean

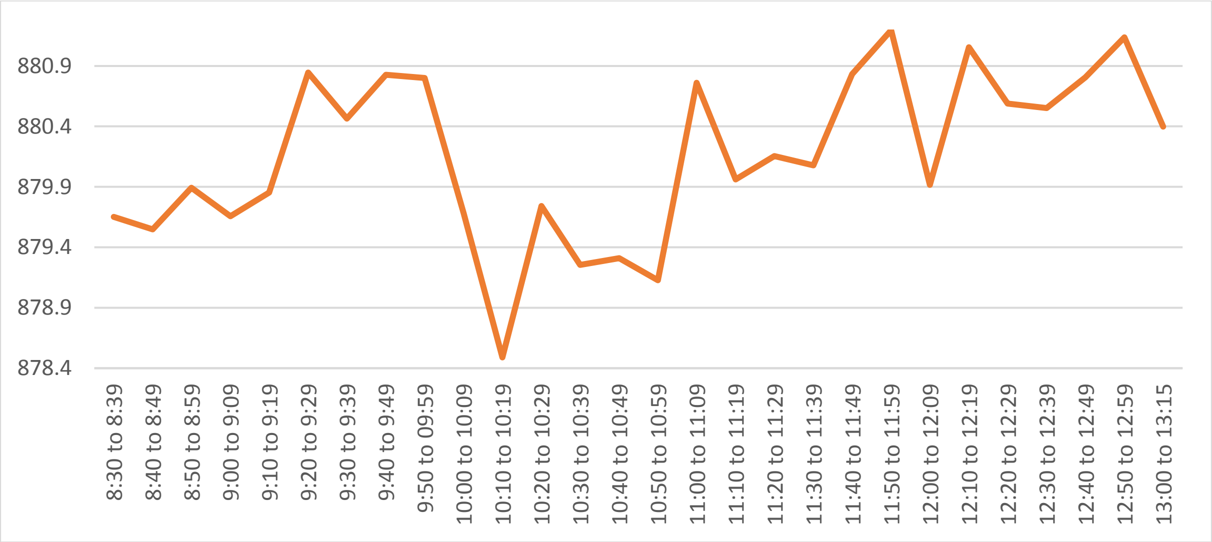


Figure 1.3: Average price (U.S. Cents per bushel). Corn

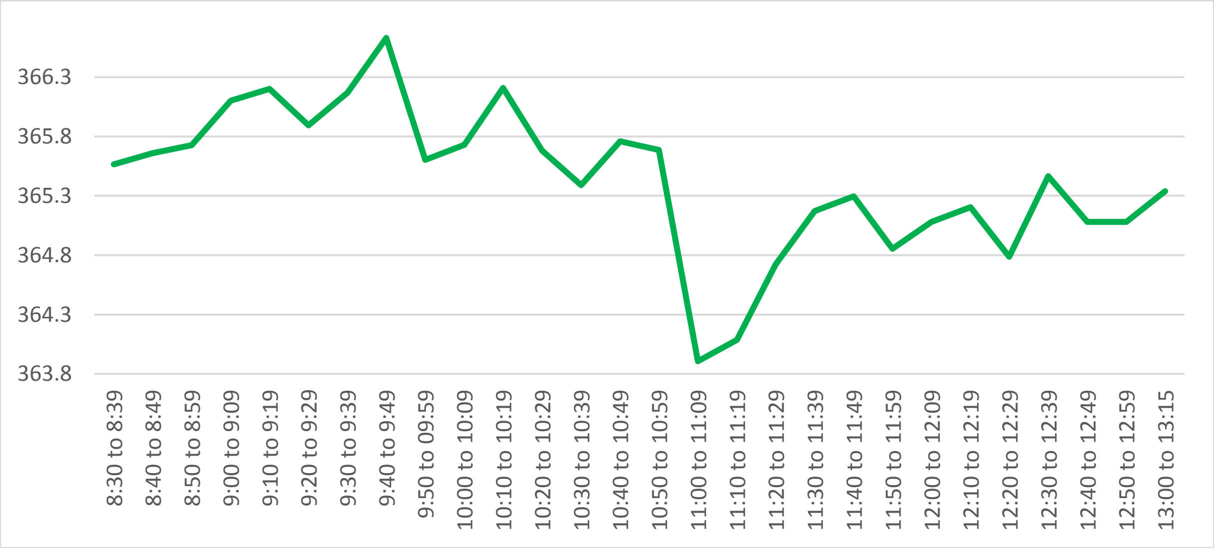


Figure 1.4: Average price (U.S. Cents per pound). Lean hogs

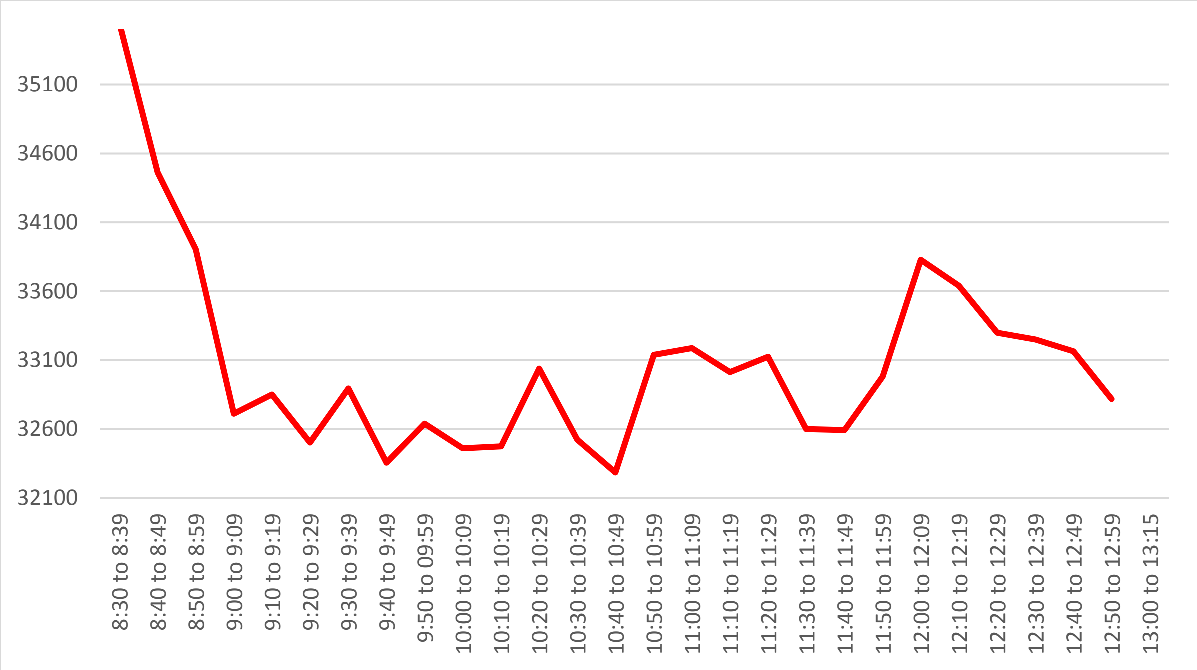


Figure 1.5: Average price (U.S. Cents per pound). Live cattle

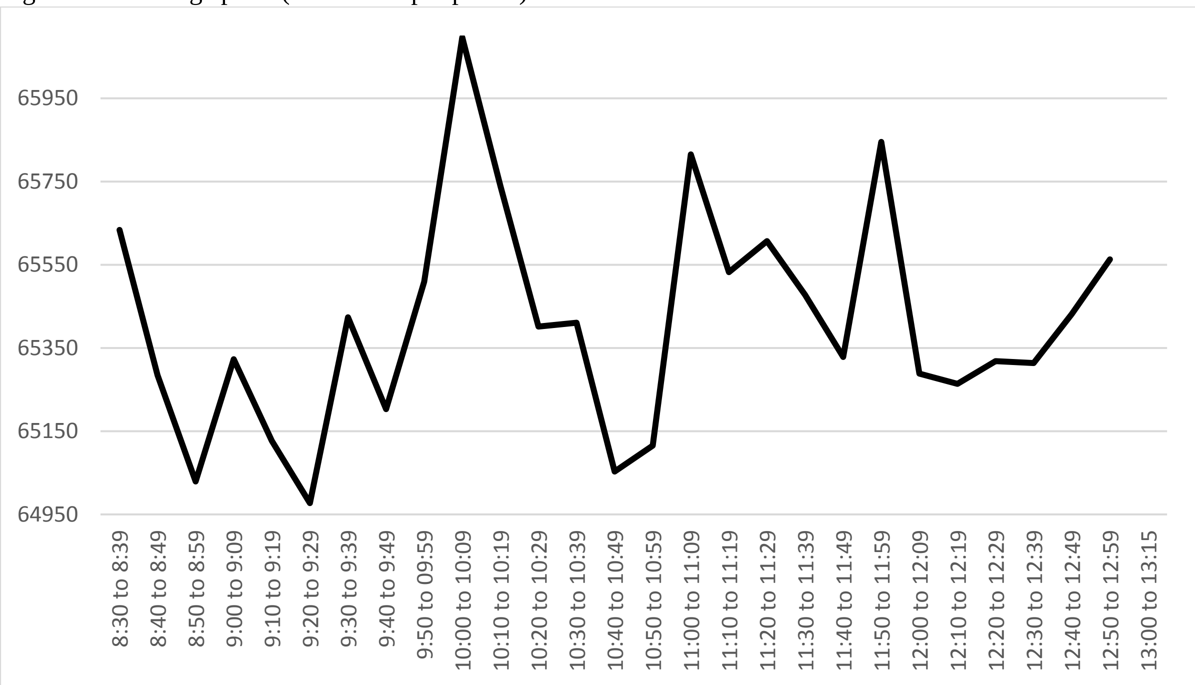


Figure 2.1: Average volume (number of contracts). Grains

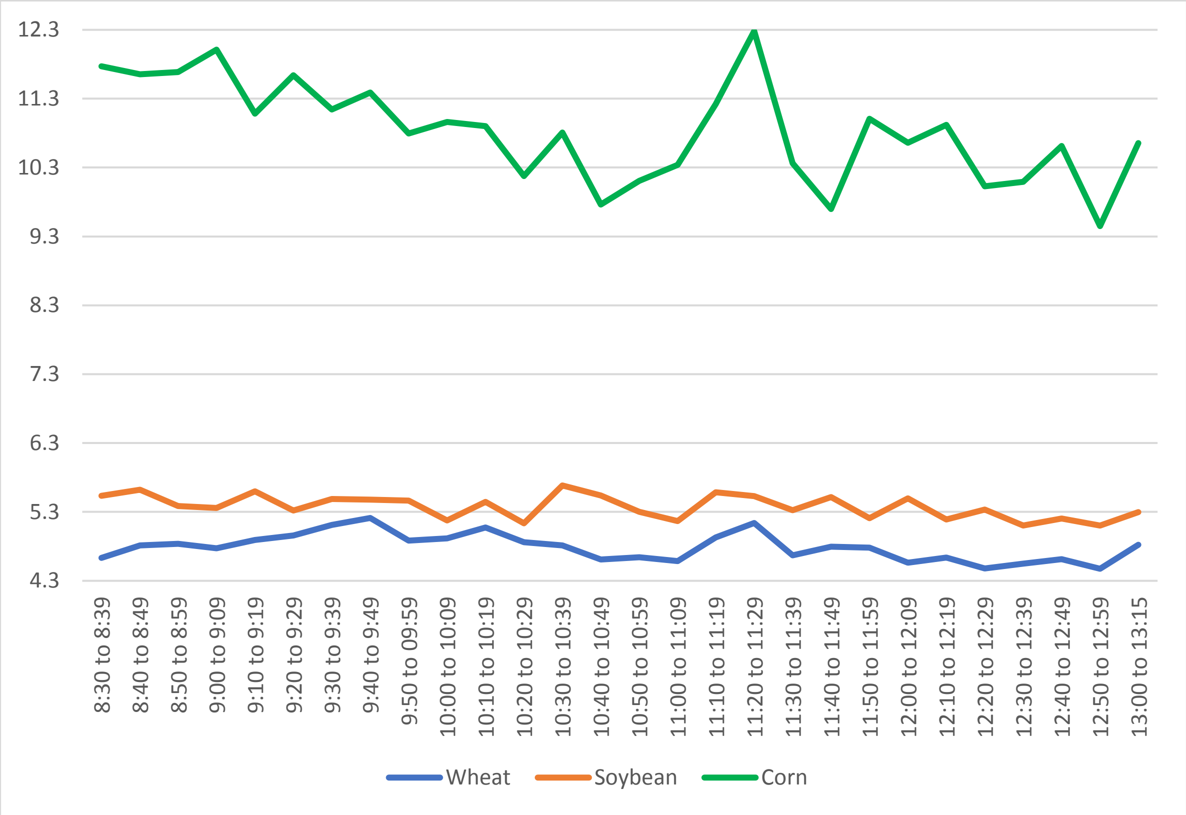


Figure 2.2: Average volume (number of contracts). Meats

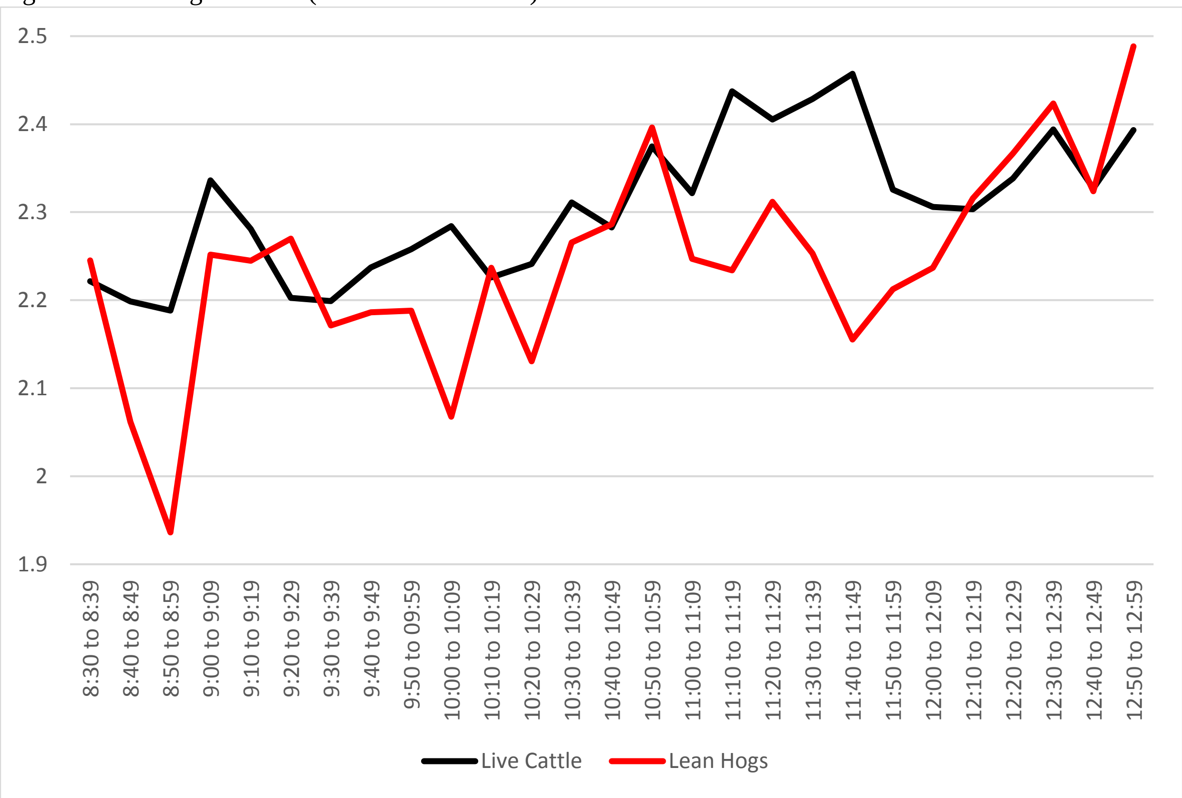


Figure 3.1: Average volatility. Grains

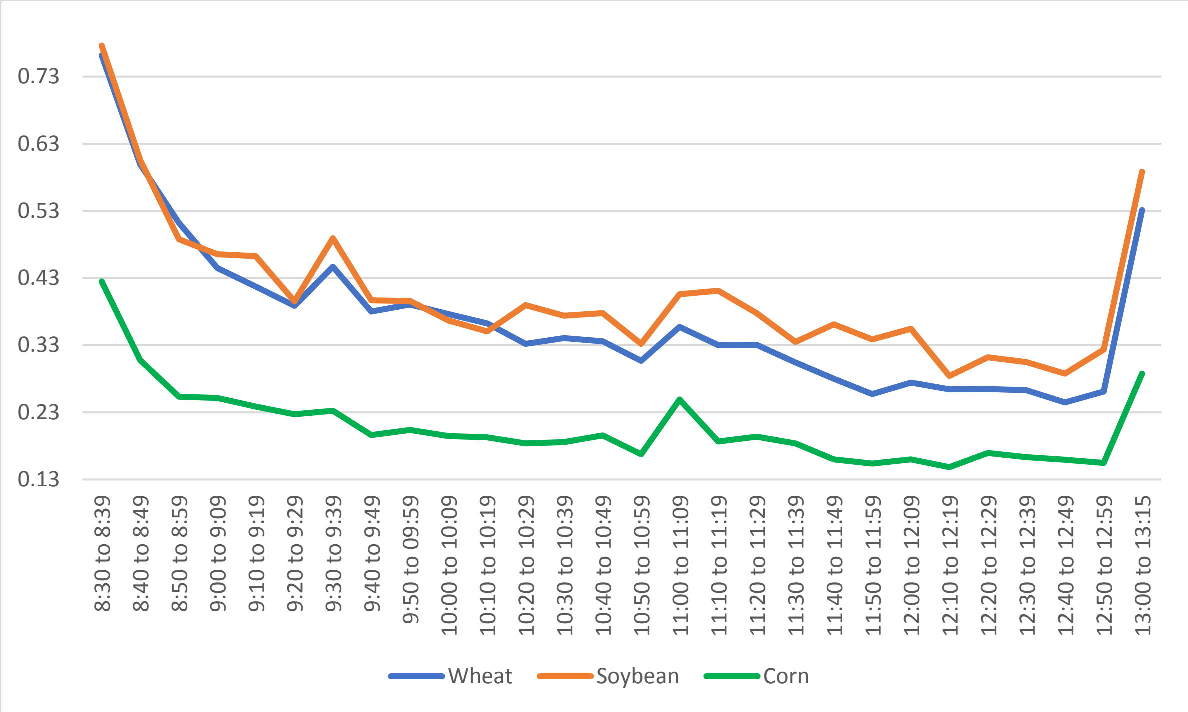


Figure 3.2: Average volatility. Meats

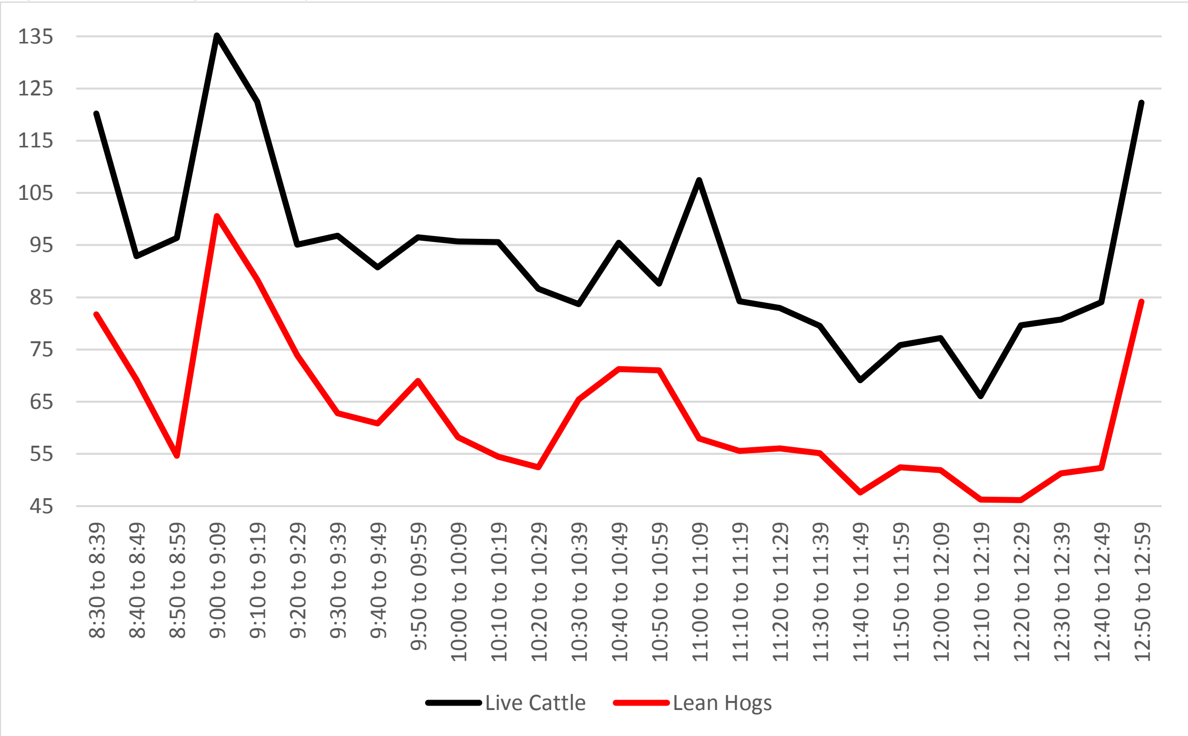


Figure 4.1: Average AT. Grains

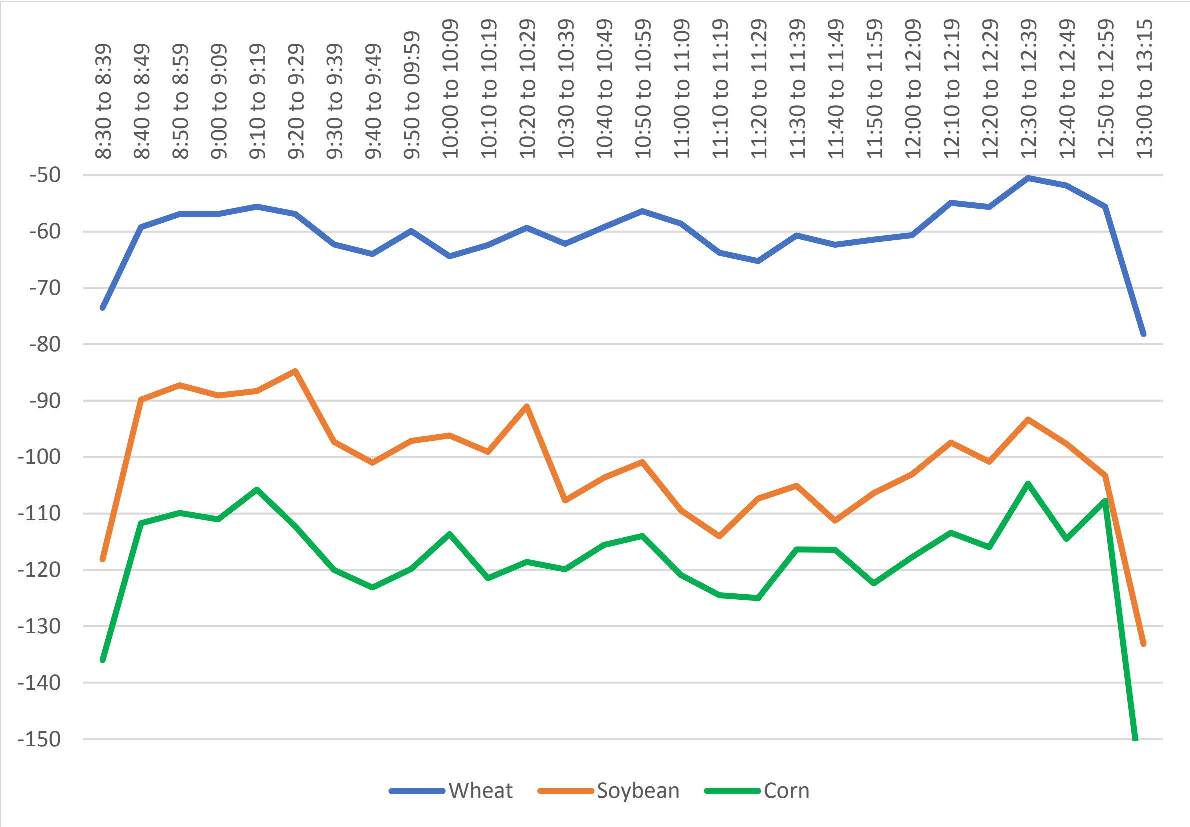


Figure 4.2: Average AT. Meats

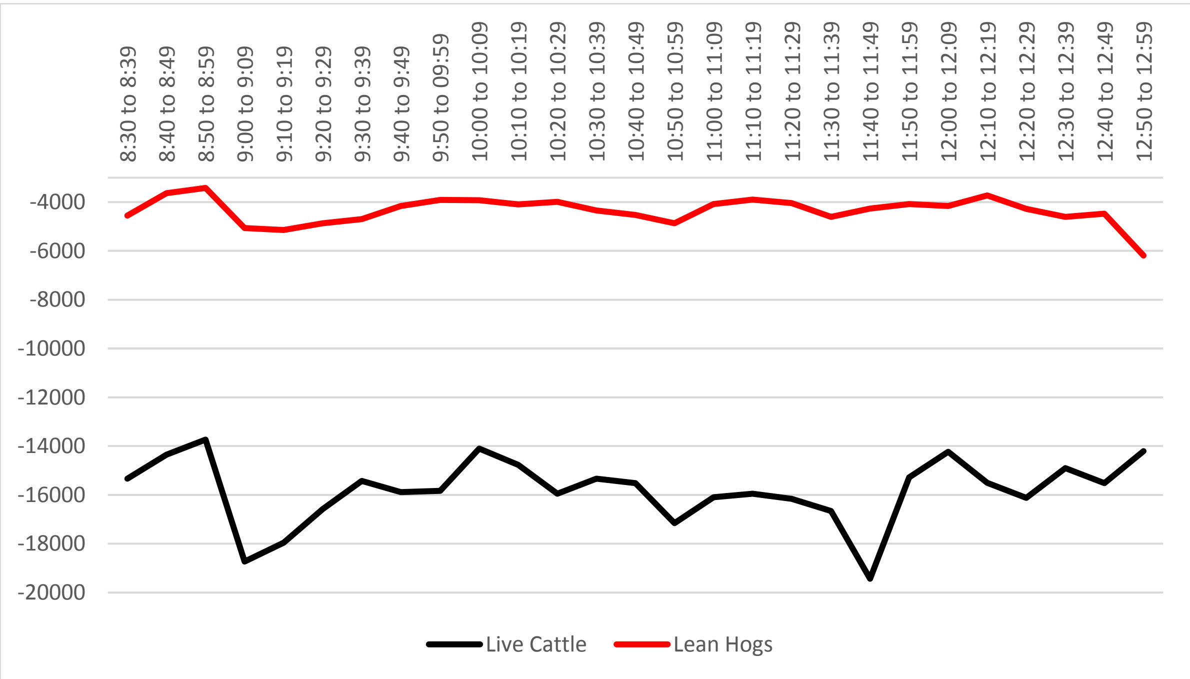


Figure 5: Average QHS

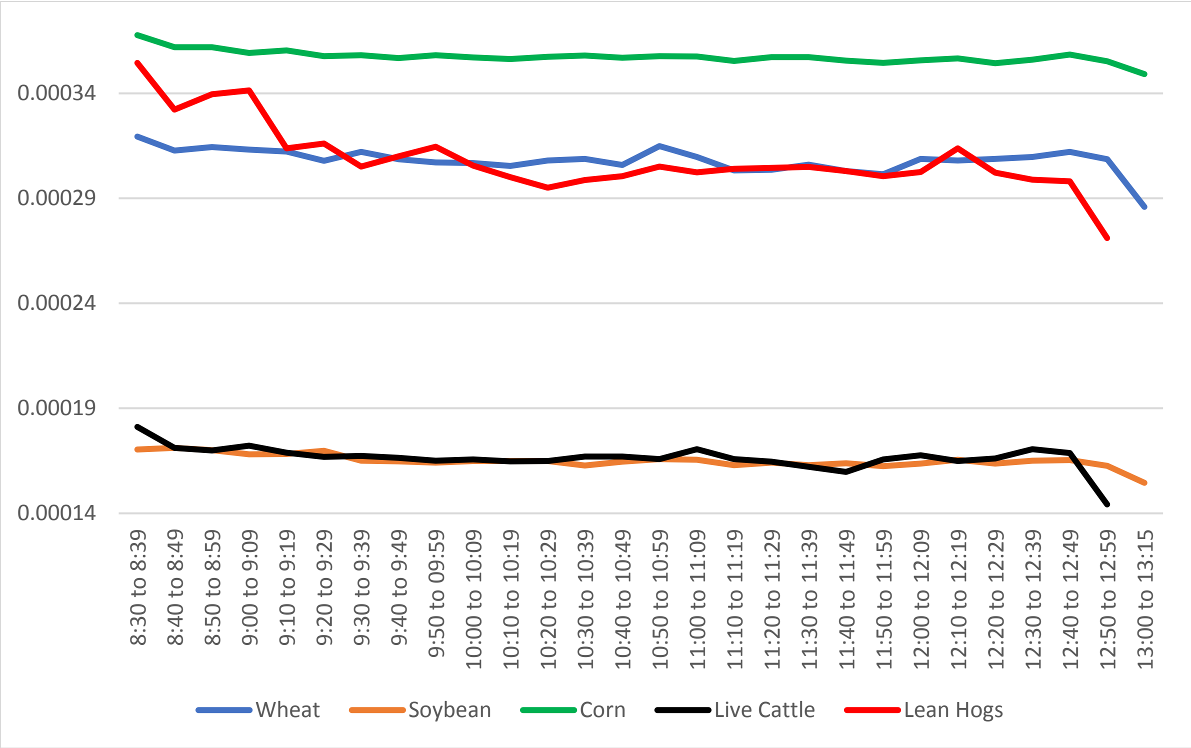


Figure 6: Average EHS

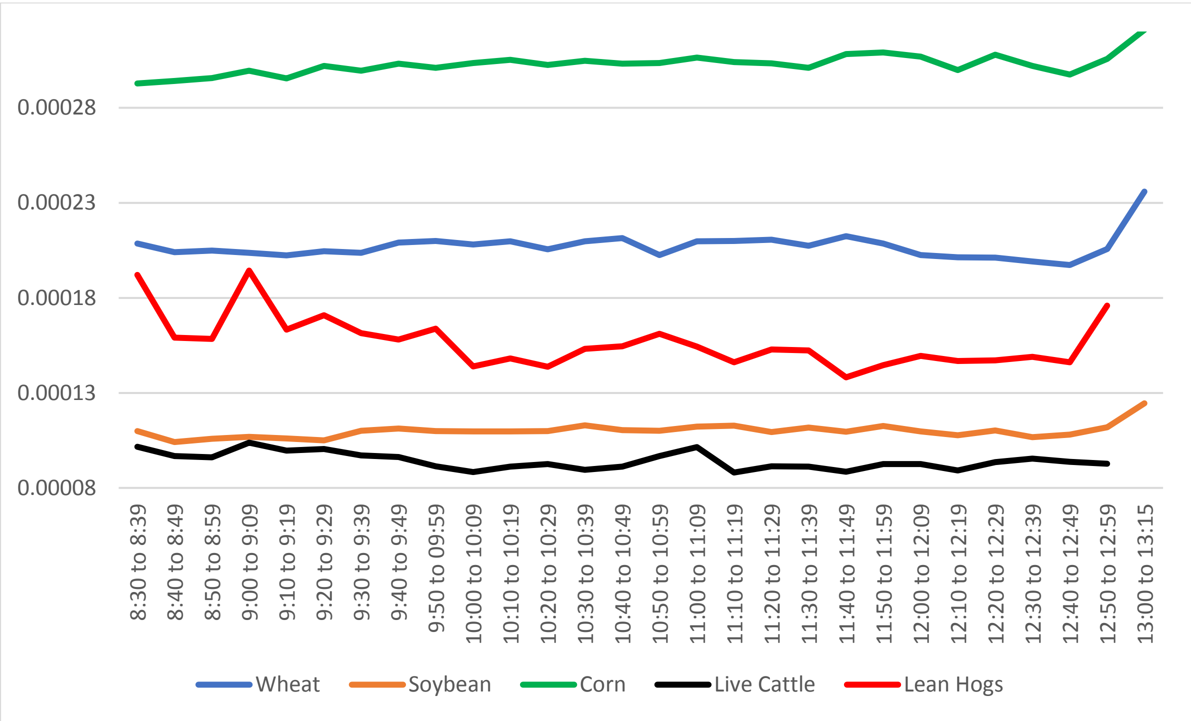


Figure 7: Average PI

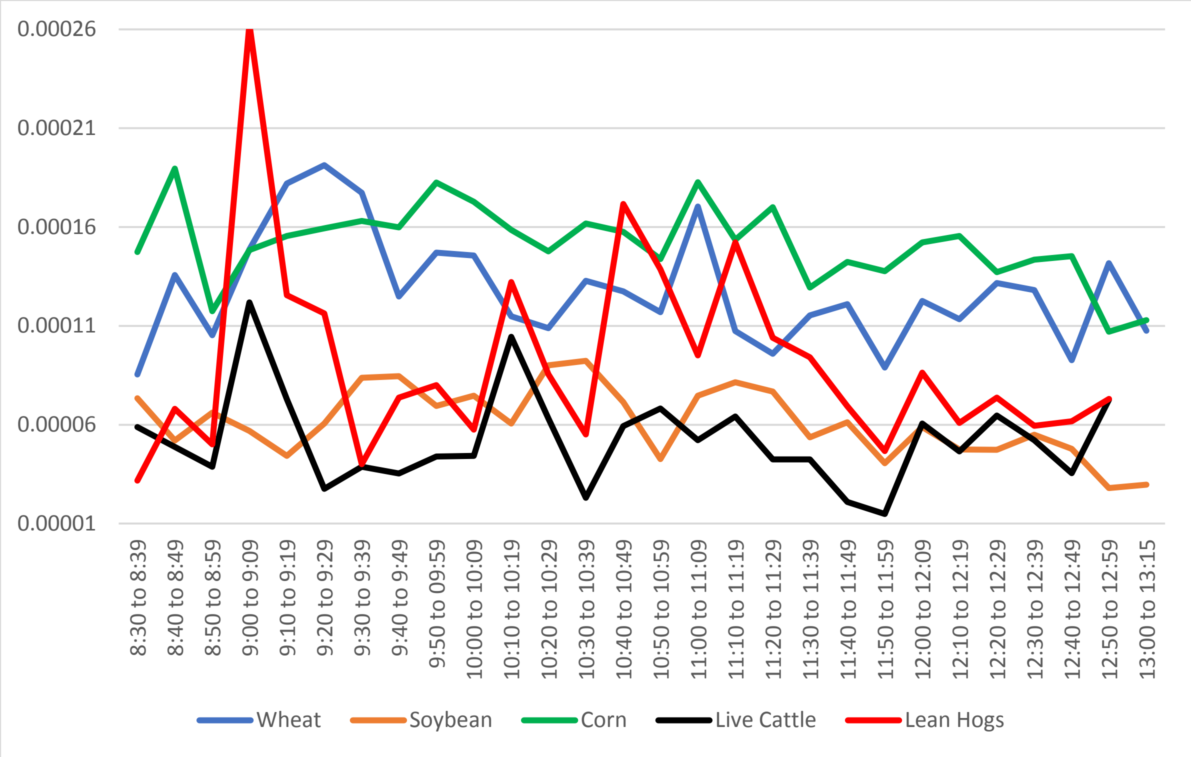
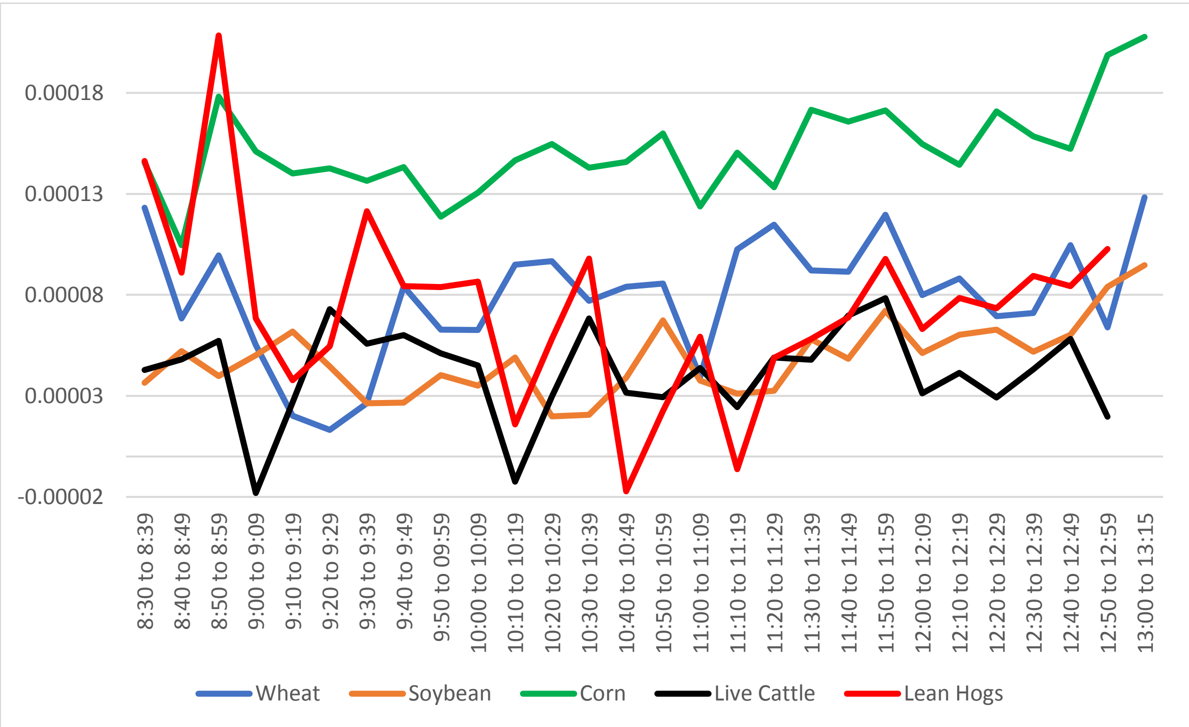


Figure 8: Average RS



4.3. Stationarity

We test the time series used in the VAR model (equations 6-1 to 6-4) for unit root using the Augmented Dickey-Fuller test (Dickey and Fuller 1979). The results of the unit root tests depend on the number of lags included in the test. Studies have shown different ways of determining the maximum and the optimal number of lags in conducting these tests. To determine the maximum number of lags, we use a rule introduced by Schwert (1989). Based on this rule, the maximum number of lags is $L_{\max}$=12(number of observations/100)$^{0.25}$. To determine the optimal number of lags, we use the AIC. To determine if the model in the ADF test needs a constant or a trend, we follow the procedure described in Enders (2004). The results show no unit root in our series.

We also use Kwiatkowski, Philips, Schmidt and Shin's KPSS test for stationarity (Kwiatkowski et al. 1992). The results of the KPSS test defers from ADF results in less than half of cases, showing that the series are non-stationary. Arltova and Fedorova (2016) study different unit root and stationarity tests and offer appropriate tests for different sample sizes. According to their results, KPSS is recommended for small sample sizes of up to 50 observations and ADF is recommended for large samples. Given the strong ADF results of rejecting unit root and following their recommendation, we consider our series to be stationary. In table 2, we report the results of the ADF test.

Table 2: Augmented Dickey-Fuller test for unit roots

	Wheat			Soybean			Corn			Lean hogs			Live cattle		
	τ^*	Lag		τ	Lag		τ	Lag		τ	Lag		τ	Lag	
AT	-6.149	26	B	-5.21	26	B	-5.74	26	B	-6.11	25	C	-6.85	25	B
QHS	-17.45	2	B	-13.71	3	B	-11.71	3	B	-11.42	4	B	-15.25	2	B
EHS	-20.03	2	B	-15.73	3	B	-14.84	3	B	-19.81	2	B	-23.53	1	B
PI	-31.37	1	B	-32.07	1	B	-34.07	1	B	-23.11	3	C	-32.61	1	B
RS	-31.58	1	B	-32.09	1	B	-33.26	1	B	-23.02	3	C	-32.55	1	B
Size	-7.18	26	B	-6.31	25	B	-6.63	26	B	-5.19	25	C	-14.90	4	B
Vol	-5.87	26	B	-16.79	4	B	-13.13	26	B	-6.08	25	C	-6.66	25	B

* test statistic, 5% critical value: -3.41, C: constant, B: both constant and trend

5. Results

In this section, we provide a summary of the results in tables 3 to 7. We use n=2 and 5 minutes to calculate liquidity cost measures PI and RS. Our results do not change significantly between both set of results, so we only discuss the n=5 time frame and 10 minutes for $\bar{t}$. In the tables we only report the significant coefficients.

Table 3 shows the effect of AT on the spreads, size and volatility. The effect of AT on QHS is positive in wheat. In corn, the second lag is positive and the fifth lag is negative. In live cattle, lags 2 and 5 are negative, and lags 4 and 7 are positive. AT has a negative effect on EHS in soybean and corn. In wheat and lean hogs, the first lag is negative and the lags 7 in wheat and 9 in lean hogs are positive. In live cattle, lags 1 and 4 are negative, and lag 3 is positive. The negative effect of AT on QHS and on EHS found is more in line with previous studies performed for non-agricultural commodities such as Hendershott, Jones and Menkveld (2011) for NYSE data, Boehmer, Fong and Wu (2018) for Thompson Reuters Tick History (TRTH) database, Moriyasu, Wee and Yu (2018) for TSE. This effect is due to more competition and lower trading costs. The QHS measures liquidity cost using the best quotes, however transactions not always happen at the best quotes. The EHS reflects such market behavior more accurately in measuring liquidity cost and therefore provides a more realistic estimate of the liquidity cost. We investigate this further by examining the effect of AT on each component of the EHS, i.e., non-informational (RS) and informational (PI).

The effect of AT on PI is positive in soybean and negative in corn, lean hogs and live cattle. A negative effect of AT on PI shows that a higher level of AT leads to lower losses for liquidity providers or lower gains for liquidity takers and therefore improves market quality (Hendershott, Jones and Menkveld 2011; Moriyasu, Wee and Yu 2018; Boehmer, Fong and Wu 2018). ATs are fast and have the chance to update their orders with the release of new information before another trader can take advantage of their otherwise stale order. So, gain or loss of trade will decrease for both sides. The positive effect of AT on PI shows that in a market that not all or majority of traders use AT, ATs are able to process the new information faster and adjust their orders faster than other traders and that will increase adverse selection and decrease market quality.

The effect of AT on RS is positive in lean hogs and live cattle which shows that AT increases the benefits for liquidity providers (Boehmer, Fong and Wu 2018), and negative in soybean (in line with Hendershott, Jones and Menkveld 2011; Viljoen, Westerholm and Zheng

2014; Moriyasu, Wee and Yu 2018). The negative sign shows that AT improves market quality by increasing the competition in liquidity provision, and increasing the liquidity takers' speed which decreases the liquidity providers' revenue and RS is narrower as a result. On the other hand, if liquidity takers are not as fast as liquidity providers, liquidity providers' revenue will increase hence the positive sign.

In all markets except live cattle, AT affects size negatively in the first lag. This reflects ATs strategies of breaking large orders into smaller ones in order to reduce their impact on the market (Viljoen, Westerholm and Zheng 2014; Hendershott, Jones and Menkveld 2011; and Hendershott and Riordan 2011). The positive effect of AT on size can be a result of lower trading cost. AT can reduce trading cost and enable traders to trade in larger volumes. The effect of AT on volatility is negative in most lags in all commodities. A negative relationship between AT and volatility shows that when volatility increases, HFTs face higher risks of informational disadvantage so they decrease their activities and it causes volatility to decrease (Aït-Sahalia and Saglam 2013). The positive relationship is because volatility reflects new information in the market and causes ATs to adjust their positions faster and increase volatility.

Table 4 shows the effect of spreads, size and volatility on AT. QHS affects AT positively in wheat, soybean and lean hogs. In corn and live cattle, the first lag is positive. A wider QHS leads to higher costs and can reduce AT activity. But these costs affect liquidity takers as liquidity providers receive the spread. So, a higher QHS can make liquidity provision more attractive (Malinova, Park and Riordan 2013). EHS affects AT negatively in soybean and live cattle. In wheat and corn, the first lag is negative. The effect is positive in lean hogs. The negative effect means that a narrower EHS leads to higher AT activity, or that ATs are more active when trading is cheaper. (Boehmer, Fong and Wu 2018; Hendershott, Jones and Menkveld 2011; Moriyasu, Wee and Yu 2018). The positive effect of EHS on AT is not expected, as higher trading cost discourages ATs to be active in the market. As mentioned before, EHS is a more reliable measure of the liquidity cost.

The effect of PI on AT is negative in wheat, soybean and lean hogs. In live cattle, the first lag is negative. When information asymmetry is high, ATs, as liquidity providers, are more likely to lose to informed liquidity demanders. So, they decrease their activity. But if liquidity takers are not as fast as liquidity providers, they cannot take advantage of their information and liquidity providers have the ability to increase their gain of the trade. RS affects AT positively in wheat, soybean and lean hogs. In corn the second lag and in live cattle the first lag is positive.

As mentioned in previous sections, RS shows liquidity providers net revenue after losing to better informed liquidity takers. So, a higher RS encourages the liquidity providers to be more active in the market.

Trade size affects AT mostly positively. Easley and O'Hara (1987) find that informed traders favour larger trading amounts, and Kyle (1985) argue that larger sizes have greater effect on prices. So, size reflects new information and an increase in size can trigger more AT activity. The negative effect of size on AT in further away lags is somehow unexpected. The effect of volatility on AT is positive in wheat and corn and negative in live cattle. In soybean the first lag is positive. The positive relationship between AT and volatility is due to volatility reflecting the existence of new information in the market that can affect AT activity, and faster price adjustments by ATs can lead to an increase in volatility (Viljoen, Westerholm and Zheng 2014; Boehmer, Fong and Wu 2018).

In table 5, the results show a negative effect of USDA announcements on AT activity in the soybean market only.

The day of the week (table 6) appears to have a significant effect on AT in the corn market only. In this market, Thursday and Friday have a negative effect on AT activity. It has been shown that different days of the week have different levels of returns. Returns affect AT strategies as ATs are more likely to sell if the recent returns are negative and to buy if they are positive (Hendershott and Riordan 2013).

The time of the day effect on AT are shown in table 7. In soybean, all three intraday time periods are significant. In corn opening and closing, and in wheat and lean hogs, the closing is significant. In live cattle, opening and midday are significant. Finding a negative sign for closing in all commodities except live cattle is in line with Viljoen, Westerholm and Zheng (2014) as they found a reverse U-shape pattern for intraday AT activities.

Table 3: The effect of AT on spreads, size and volatility

		Wheat	Soybean	Corn	Lean hogs	Live cattle
QHS		0.00000011***(L1)	-	0.000000028***(L2) -0.000000023***(L5)	-	-0.0000000002**(L2) 0.00000000017*(L4) -0.00000000018** (L5) 0.00000000016*(L7)
EHS		-0.00000014***(L1) 0.000000057*(L7)	-0.000000028***(L1)	-0.000000031*(L1)	-0.0000000013*** (L1) 0.00000000077*(L9)	-0.0000000003***(L1) 0.00000000022**(L3) -0.00000000039*** (L4)
PI		-	0.00000024**(L4)	-0.0000003*(L2)	-0.000000014***(L4)	-0.0000000022***(L4)
RS		-	-0.00000024**(L4)	-	0.000000014***(L4)	0.000000002**(L4)
Size	QHS	-0.0034**(L1)	-0.0018**(L1) 0.0019**(L2) 0.0022**(L8) -0.002**(L9)	-0.0044**(L1) 0.006***(L3) -0.0064***(L7)	-0.000018***(L1) 0.00001*(L9)	-0.0000033*(L10)
	EHS	-0.0052*** (L1)	-0.0021**(L1) 0.0025***(L2) 0.0024**(L8) -0.0024***(L9)	-0.0048**(L1) 0.0058**(L3) -0.0038*(L7)	-0.000019***(L1) 0.000012**(L9)	0.0000036**(L5)
	PI	-0.004***(L1)	-0.0023***(L1) 0.0019**(L2)	-0.0073***(L1) 0.0063***(L3)	-0.000017***(L1)	0.000004**(L5)
	RS	-0.0042*** (L1)	-0.0024***(L1) 0.0019**(L2)	-0.0066***(L1) 0.0072***(L3) -0.0056***(L7)	-0.000017***(L1)	0.000004**(L5)

Vol	QHS	-0.00098*** (L1) 0.00074**(L2) -0.00072** (L7)	-0.0012***(L1) 0.00052**(L2) 0.00055**(L3)	-0.00031***(L1) 0.00032***(L3)	-0.0015***(L1)	-0.0005**(L3) -0.00048**(L4) -0.00058**(L11) -0.00057**(L12)
	EHS	-0.00088** (L1) 0.00096*** (L2) -0.00085** (L7)	-0.00086***(L1) 0.00047*(L2) 0.00047*(L3)	-0.0003***(L1) 0.00036***(L3)	-0.0013***(L1) 0.00088*(L6) -0.00087*(L8)	-0.00041*(L3) -0.00056**(L4)
	PI	-0.0015*** (L1) 0.00066**(L2) 0.00055*(L3)	-0.001***(L1) 0.00043*(L2) 0.00075***(L3)	-0.00036***(L1) 0.00035***(L3)	-0.0015***(L1)	-0.00042*(L3) -0.00054**(L4)
	RS	-0.0015*** (L1) 0.00068**(L2) 0.0006**(L3)	-0.001***(L1) 0.00044*(L2) 0.00075***(L3)	-0.0003***(L1) 0.00038***(L3)	-0.0015***(L1)	-0.00042*(L3) -0.00054**(L4)

Significant at 1%***, 5%**, and 10%* levels, only significant coefficients are reported.

Table 4: The effect of spreads, size and volatility on AT

		Wheat	Soybean	Corn	Lean hogs	Live cattle
QHS		94524.29***(L1) 66365.26**(L5)	159375.1**(L1) 173152.3**(L8)	263364.2***(L1) -148180*(L2) -133660.4*(L3) 201477.2**(L4)	3019124*(L7)	35400000***(L1) -30900000***(L3)
EHS		-49044.5**(L1) 42614.47**(L3)	-199287.1***(L8)	-93046.47***(L1) 72184.69**(L3) -81578.21**(L4) -79463.43**(L7)	2864601*(L7)	-13700000*(L4)
PI		-11279.82***(L1)	-26632.05***(L1)	-	-471789.7***(L1)	-1740175**(L1) 1455953*(L4)
RS		10987.85***(L1)	25702.68***(L1)	6922.12*(L2) -6526.77*(L7)	495706.6***(L1)	1867172**(L1) -1606093**(L4)
Size	QHS	2.39***(L1) -0.97*(L2)	6.59***(L1) -2.44***(L2) -1.57*(L4)	2.83***(L1) -0.9**(L4)	718.59***(L1) 398.46**(L5)	827.21*(L2) -1433.32***(L5) 1035.74**(L10)
	EHS	2.34***(L1)	6.68***(L1) -2.68***(L2) -1.66*(L4)	2.94***(L1) -0.84**(L4)	709.16***(L1) 385.95**(L5)	895.6*(L2) -1204.91**(L5)
	PI	2.69***(L1) -0.97*(L2)	6.53***(L1) -2.91***(L2)	3.09***(L1) -0.73**(L4)	687.52***(L1)	848.39*(L2) -1164.03**(L5)
	RS	2.76***(L1) -0.98*(L2)	6.62***(L1) -2.94***(L2) -1.39*(L4)	3.11***(L1) -0.77**(L4) -0.69*(L5)	692.64***(L1)	849.17*(L1) -1162.34**(L5)
Vol	QHS	-	6.66**(L1) 5.32**(L4) -5.49**(L7)	-	-	-5.15*(L6)
	EHS	-	7.39***(L1) 5.17**(L4) -5.53**(L7)	-	-	-
	PI	4.51**(L1)	11.82***(L1) 5.67**(L4)	14.12**(L1)	-	-
	RS	4.54**(L1)	11.78***(L1) 5.67**(L4)	12.53**(L1)	-	-

Significant at 1%***, 5%**, and 10%* levels, only significant coefficients are reported.

Table 5: The effect of announcements on AT

	Wheat	Soybean	Corn	Lean hogs	Live cattle
QHS	-	-5.511*	-	-	-
EHS	-	-5.481*	-	-	-
PI	-	-	-	-	-
RS	-	-	-	-	-

Significant at 1%***, 5%**, and 10%* levels, only significant coefficients are reported.

Table 6: The effect of days of the week on AT

	Wheat	Soybean	Corn	Lean hogs	Live cattle
QHS	-	-	-6.477***(Thur), -4.499**(Fri)	-	-
EHS	-	-	-6.218***(Thur), -4.928**(Fri)	-	-
PI	-	-	-4.893**(Thur)	-	-
RS	-	-	-5.115**(Thur), -3.922*(Fri)	-	-

Significant at 1%***, 5%**, and 10%* levels, only significant coefficients are reported.

Table 7: The effect of intraday intervals on AT

	Wheat	Soybean	Corn	Lean hogs	Live cattle
QHS	-15.834***(C)	8.692***(O), -7.462***(M), -18.999***(C)	4.783*(O), -21.159***(C)	-1432.38***(C)	-897.903**(O), -681.588*(M)
EHS	-15.561***(C)	8.579***(O), -7.179***(M), -19.588***(C)	4.765 *(O), -21.346***(C)	-1377.458***(C)	-837.549**(O), -895.949**(M)
PI	-15.593***(C)	7.078***(O), -5.931***(M), -20.458***(C)	4.176 *(O), -22.063***(C)	-1397.103***(C)	-849.139**(O), -888.522**(M)
RS	-15.514***(C)	7.141***(O), -5.977***(M), -20.409***(C)	-21.587***(C)	-1398.6***(C)	-855.045**(O), -892.966**(M)

Significant at 1%***, 5%**, and 10%* levels, O opening, M midday, C closing time, only significant coefficients are reported.

The appendix (Tables A.1 to A.4) shows the VAR estimates for AT, each measure of market quality (QHS, EHS, PI and RS), size and volatility. The first part of each table shows the results for AT (equation 6-1) and the second part shows the results for the measures of market quality, size and volatility (equation 6-2 to 6-4).

We estimated impulse response functions using different orders of the variables. The results are similar for different orders, so here we report the set of results of the order that places AT first and spreads last. The results are shown in figures 9.1 to 12.5. Each time period is 10 minutes long.

In all cases the effect of AT on all spread measures is temporary as it approaches zero eventually. The initial reaction of QHS is always positive. The effect lasts longer in wheat and soybean compared to the other markets. In corn and lean hogs, it disappears in 40 and 90 minutes. In live cattle, it disappears in less than 20 minutes. The initial reaction of EHS is always negative and it also disappears in less than 50 minutes in wheat and less than 20 minutes in lean hogs. For soybean and corn, it takes longer and bounces back a few times until it finally disappears in more than one hour. In live cattle, it takes about ten minutes to observe a significant reaction of EHS to a shock of AT, but the effect goes back to the initial level before the shock after one hour.

A shock of AT on PI is not significant in corn and it is negative in the other markets. This effect only lasts for less than 10 minutes in wheat and soybean markets. In the lean hogs market, it bounces one time and it dissipates at around one hour. In live cattle, the effect is only significant between 40 and 50 minutes. The effect of AT on RS is also not significant in corn and it is positive in the other markets. This effect dissipates even faster. In lean hogs and live cattle, the effect has a small bounce before dissipating in less than one hour. Based on these results, a shock of AT decreases EHS and PI in all markets and improves market quality but the effect is gone within one hour.

Figure 9.1: The effect of AT on QHS- Wheat

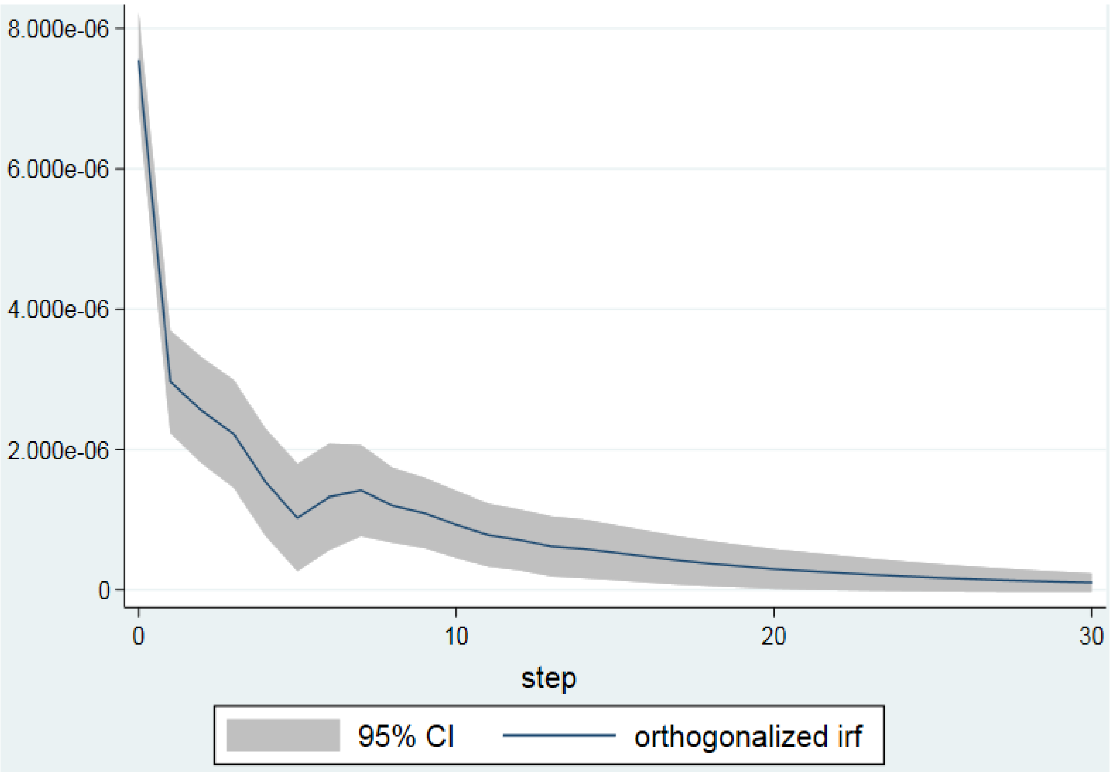


Figure 9.2: The effect of AT on QHS- Soybean

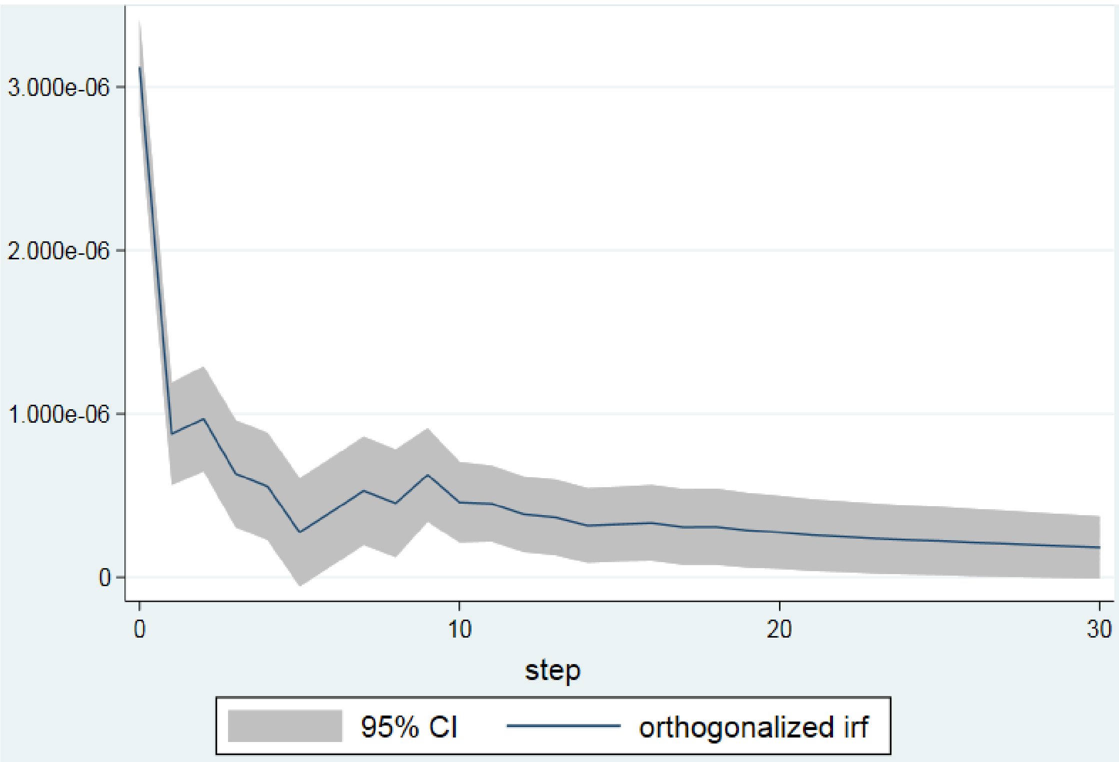


Figure 9.3: The effect of AT on QHS- Corn

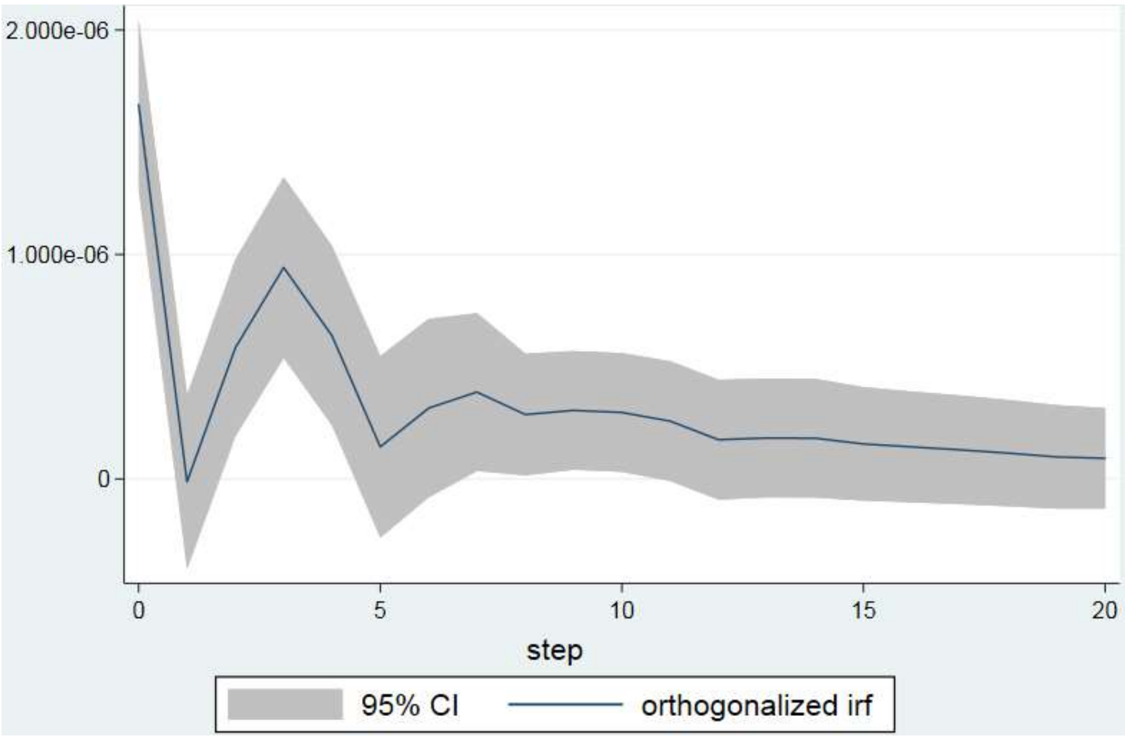


Figure 9.4: The effect of AT on QHS- Lean hogs

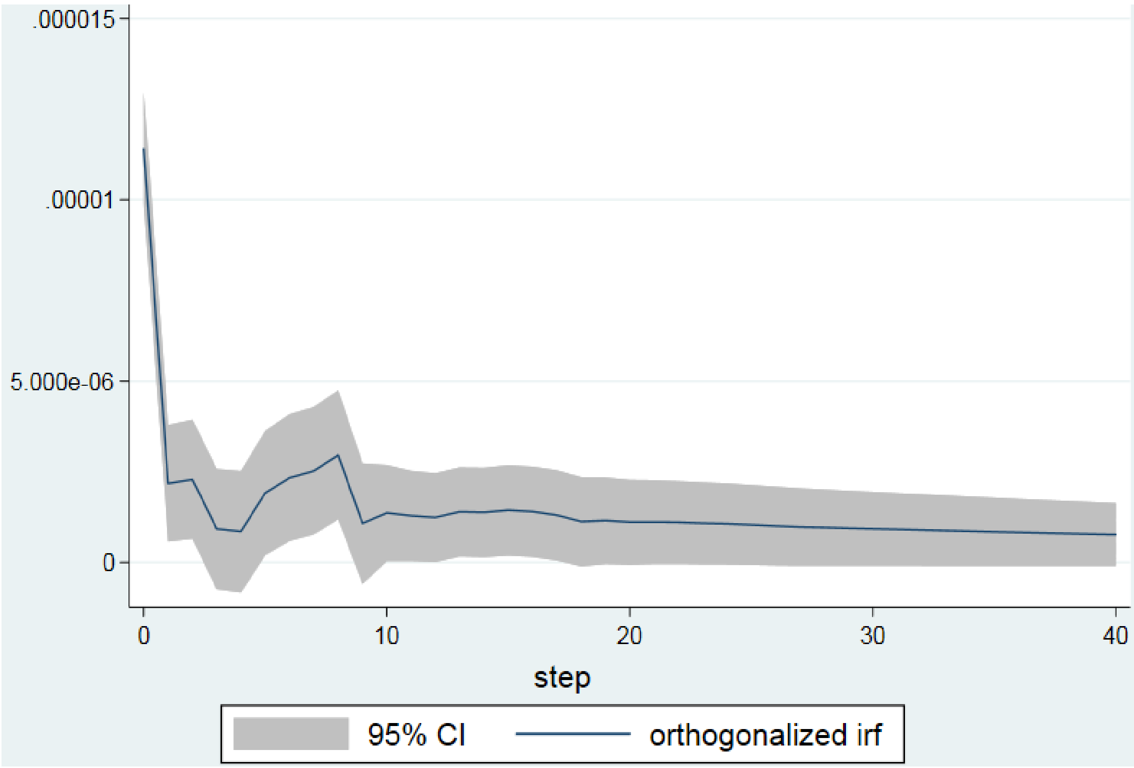


Figure 9.5: The effect of AT on QHS- Live cattle

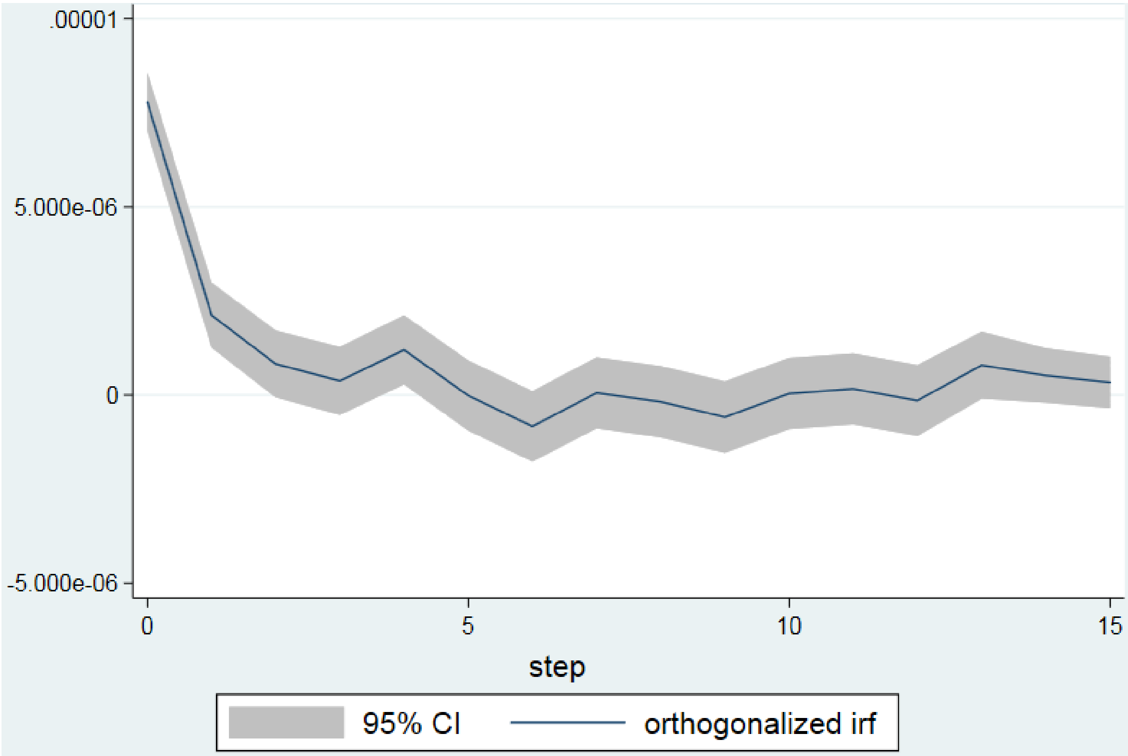


Figure 10.1: The effect of AT on EHS- Wheat

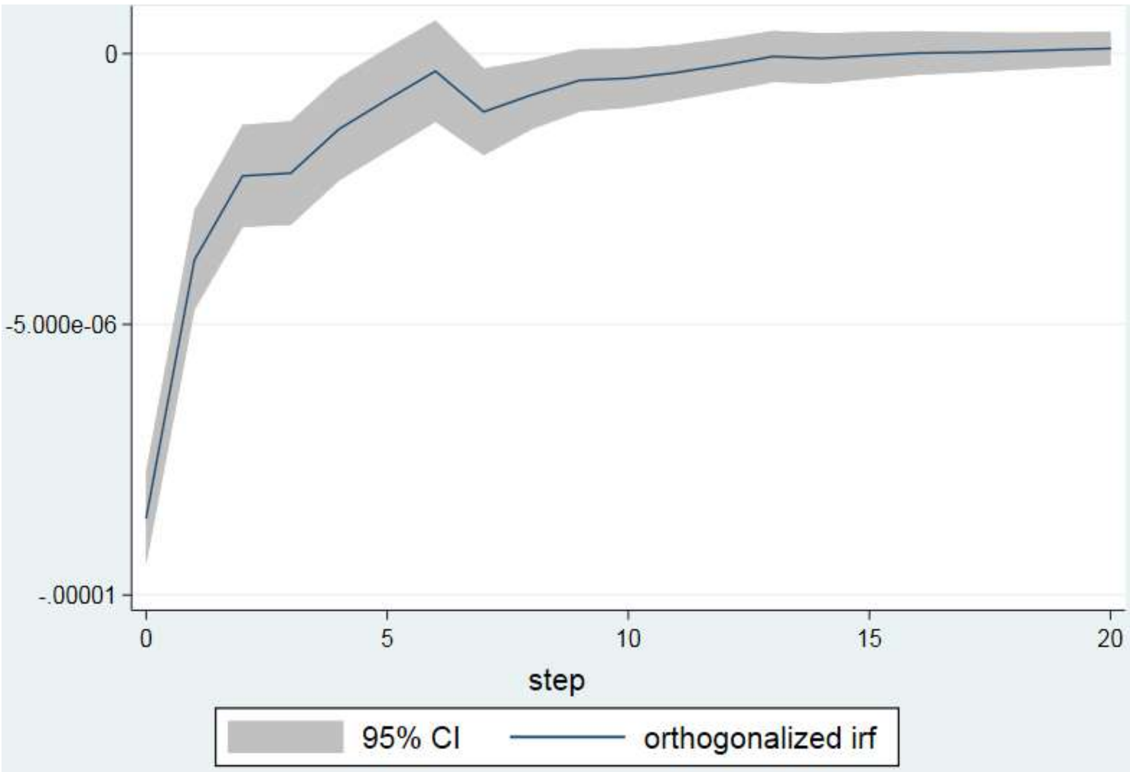


Figure 10.2: The effect of AT on EHS- Soybean

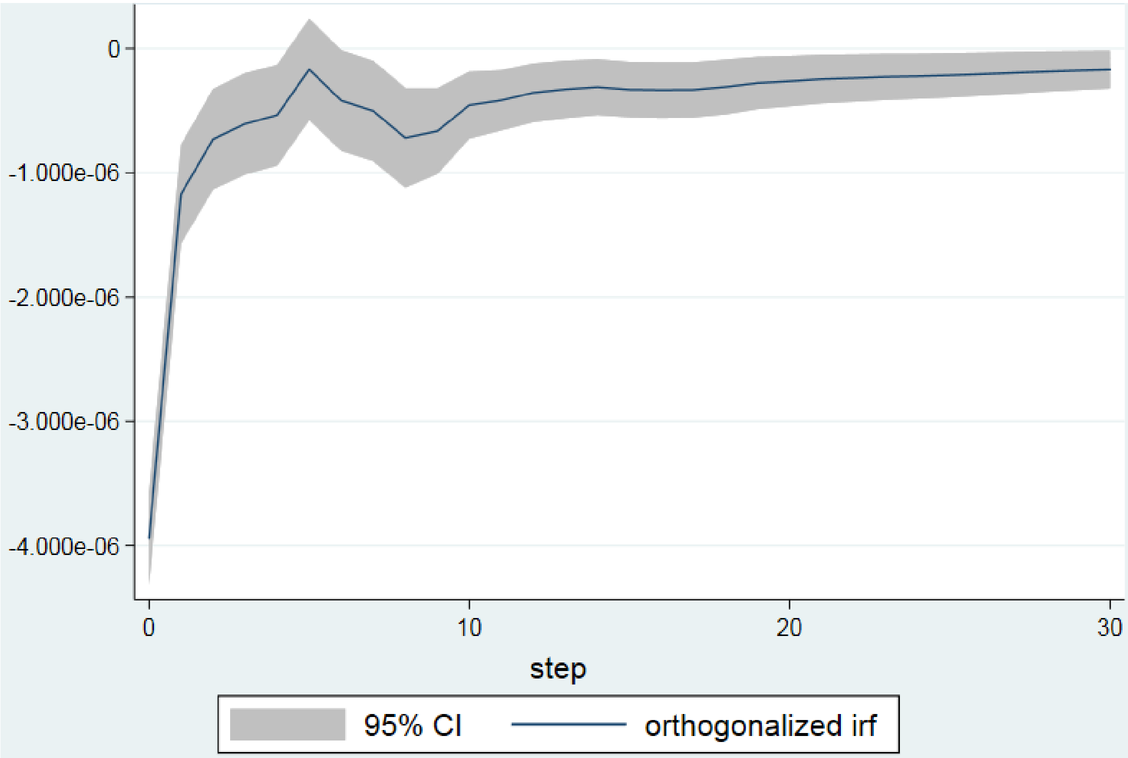


Figure 10.3: The effect of AT on EHS- Corn

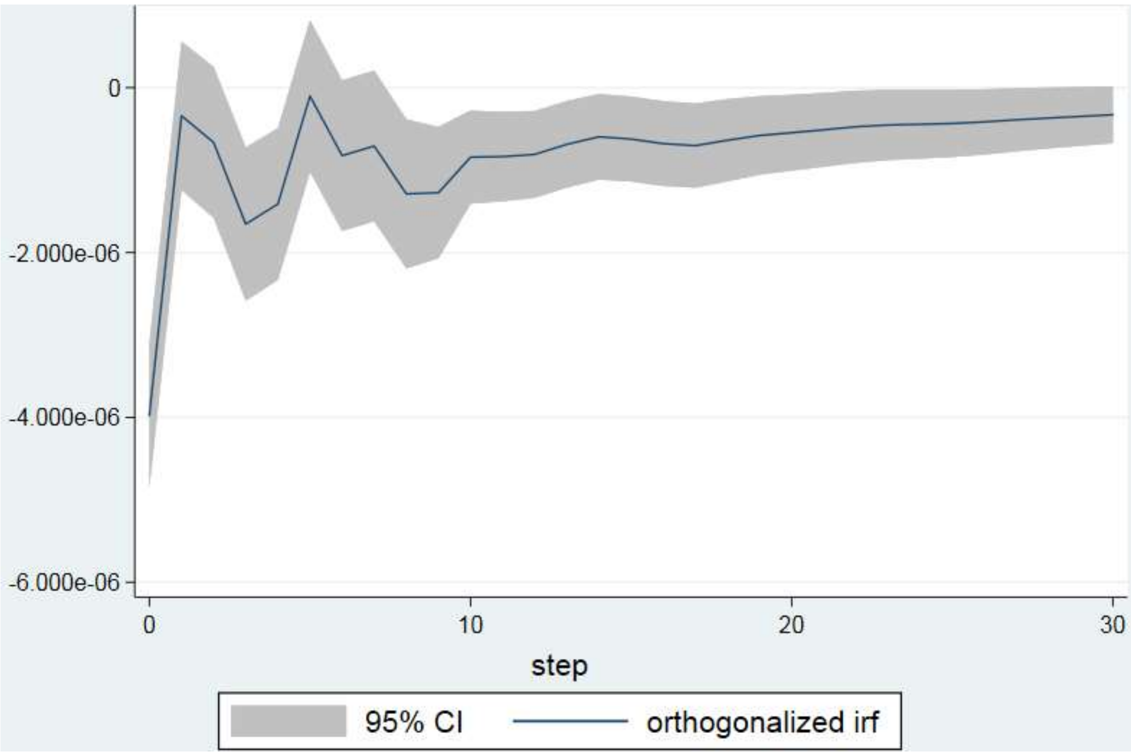


Figure 10.4: The effect of AT on EHS- Lean hogs

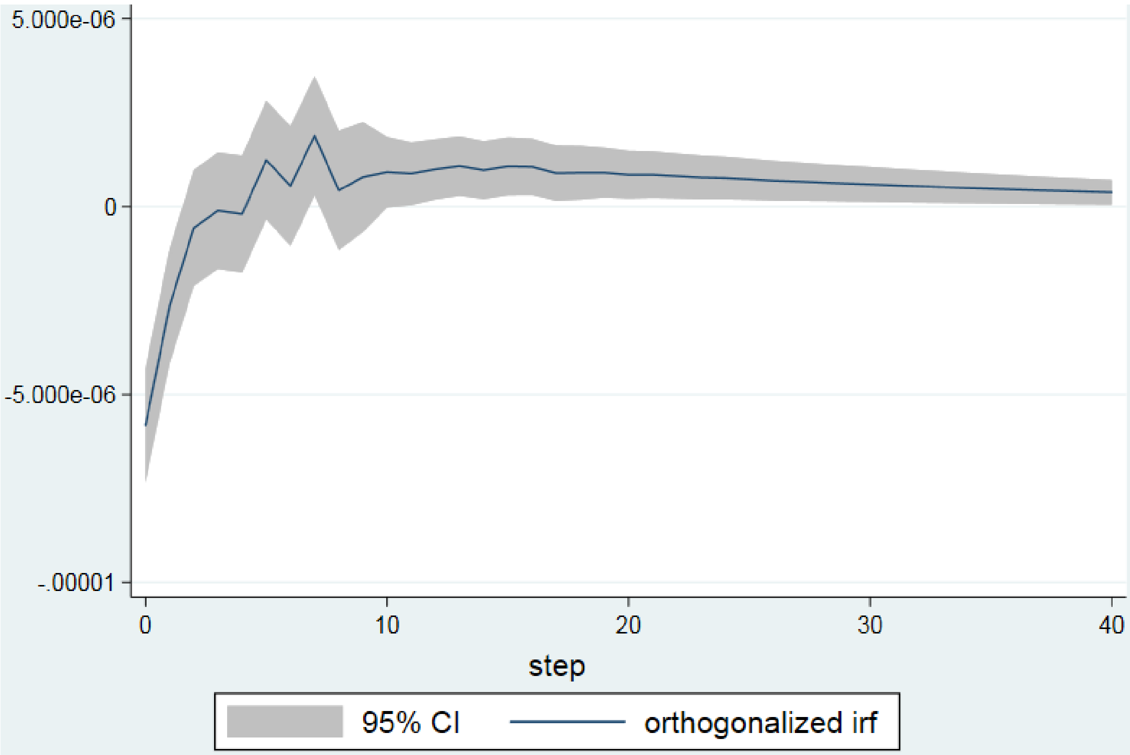


Figure 10.5: The effect of AT on EHS- Live cattle

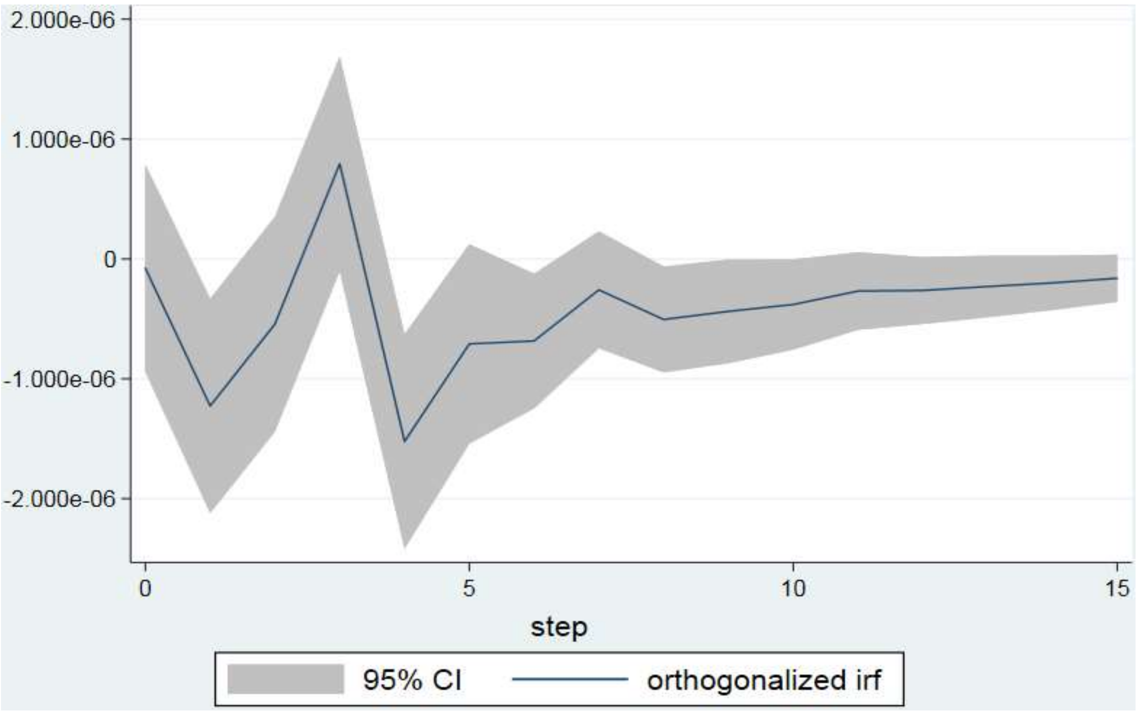


Figure 11.1: The effect of AT on PI- Wheat

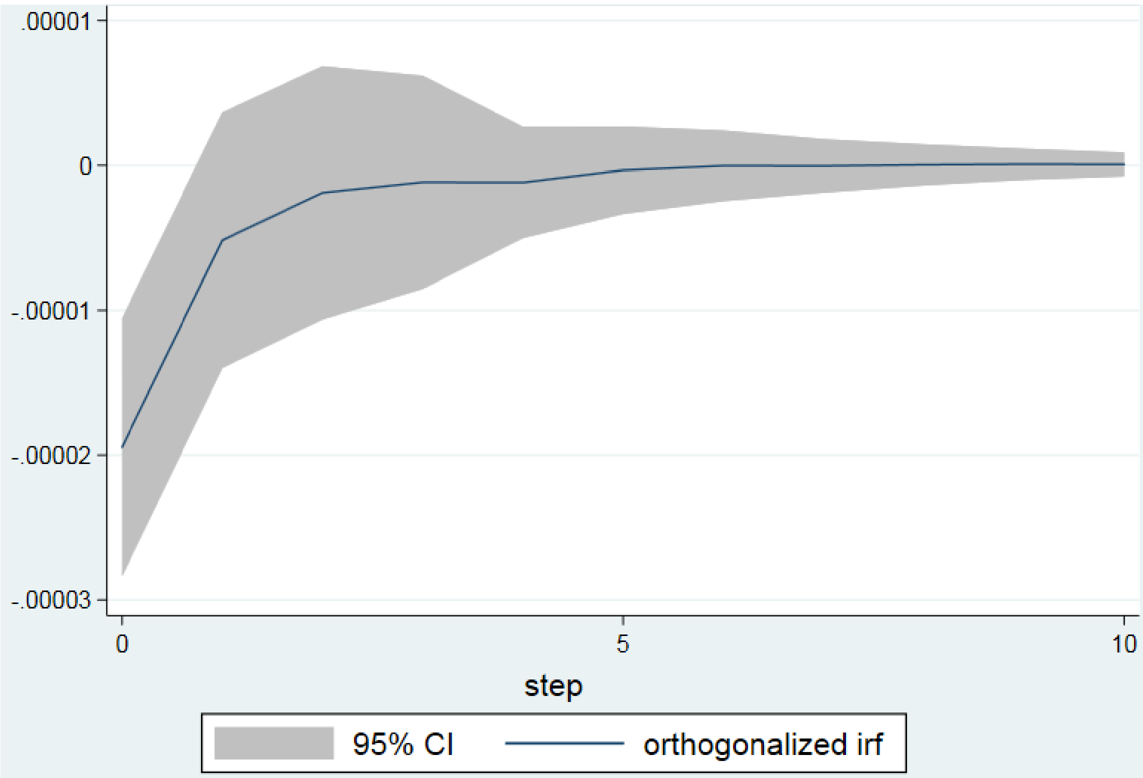


Figure 11.2: The effect of AT on PI- Soybean

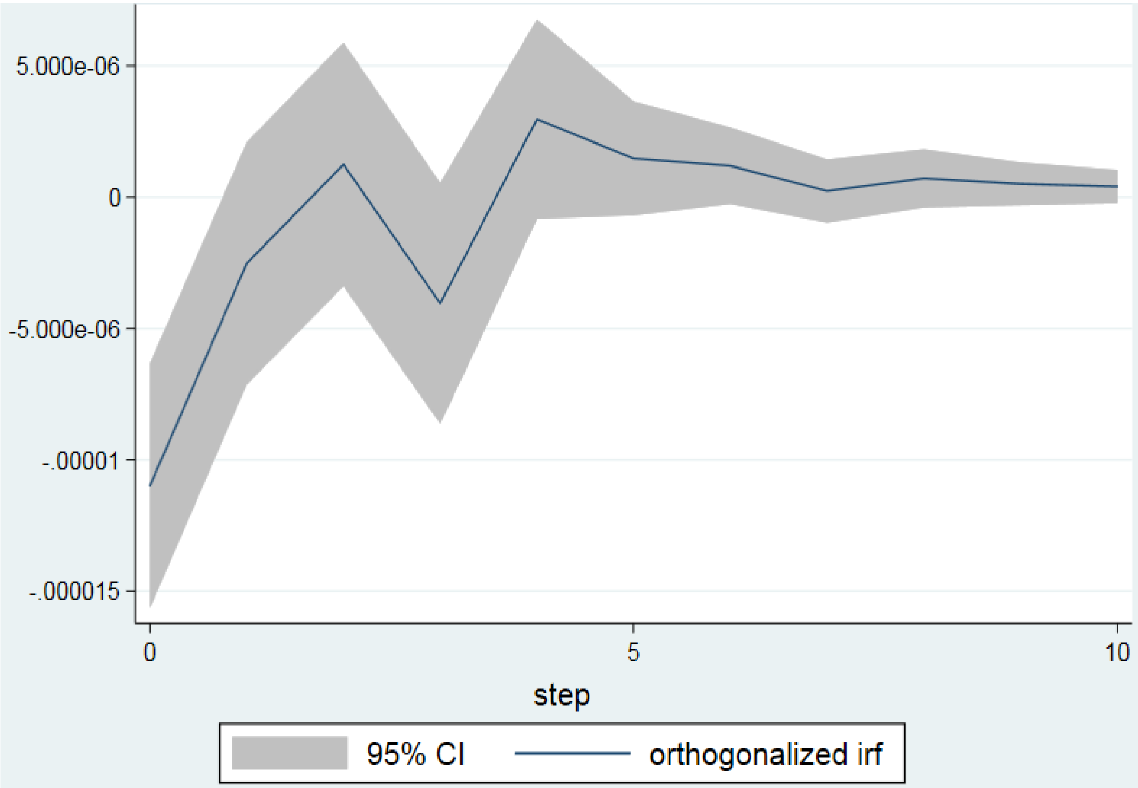


Figure 11.3: The effect of AT on PI- Corn

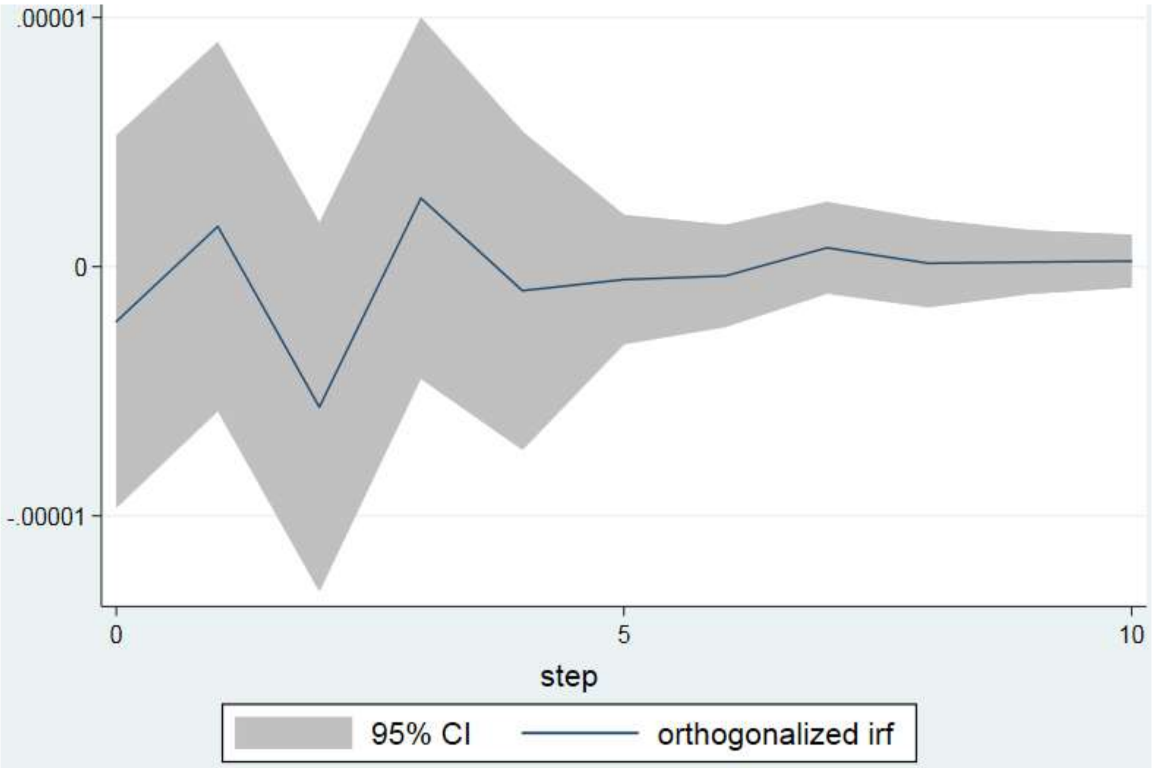


Figure 11.4: The effect of AT on PI- Lean Hogs

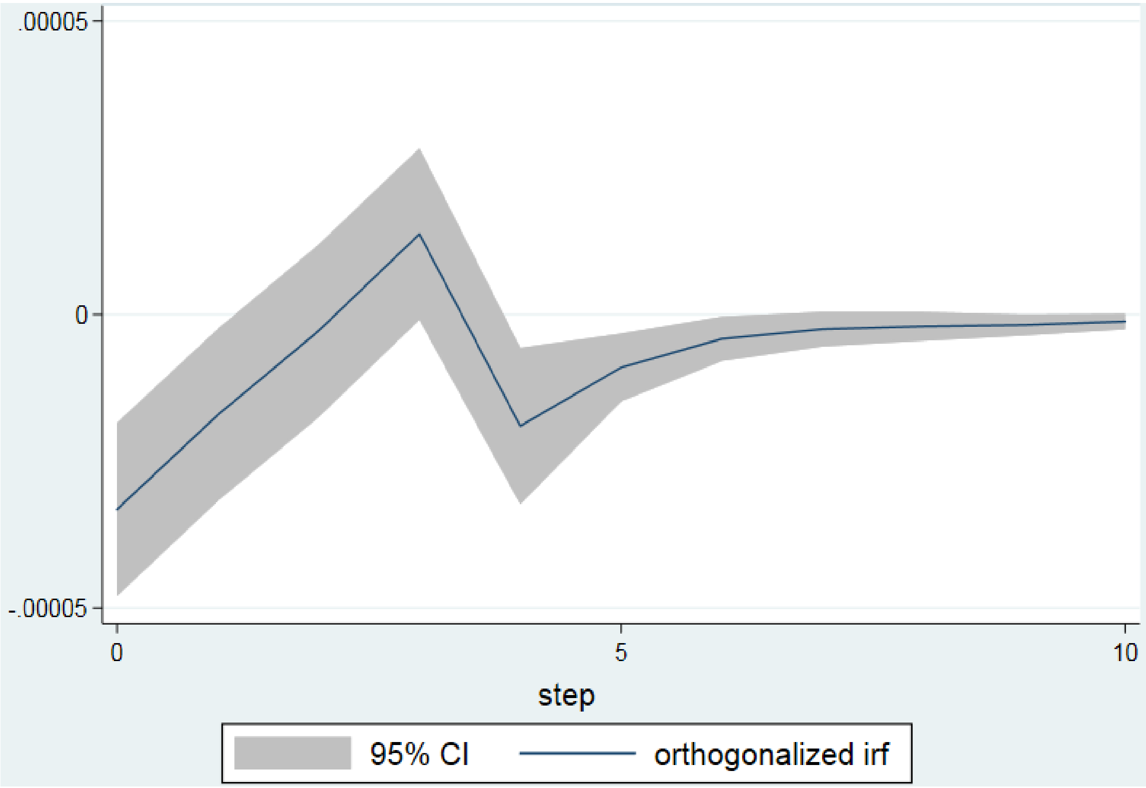


Figure 11.5: The effect of AT on PI- Live cattle

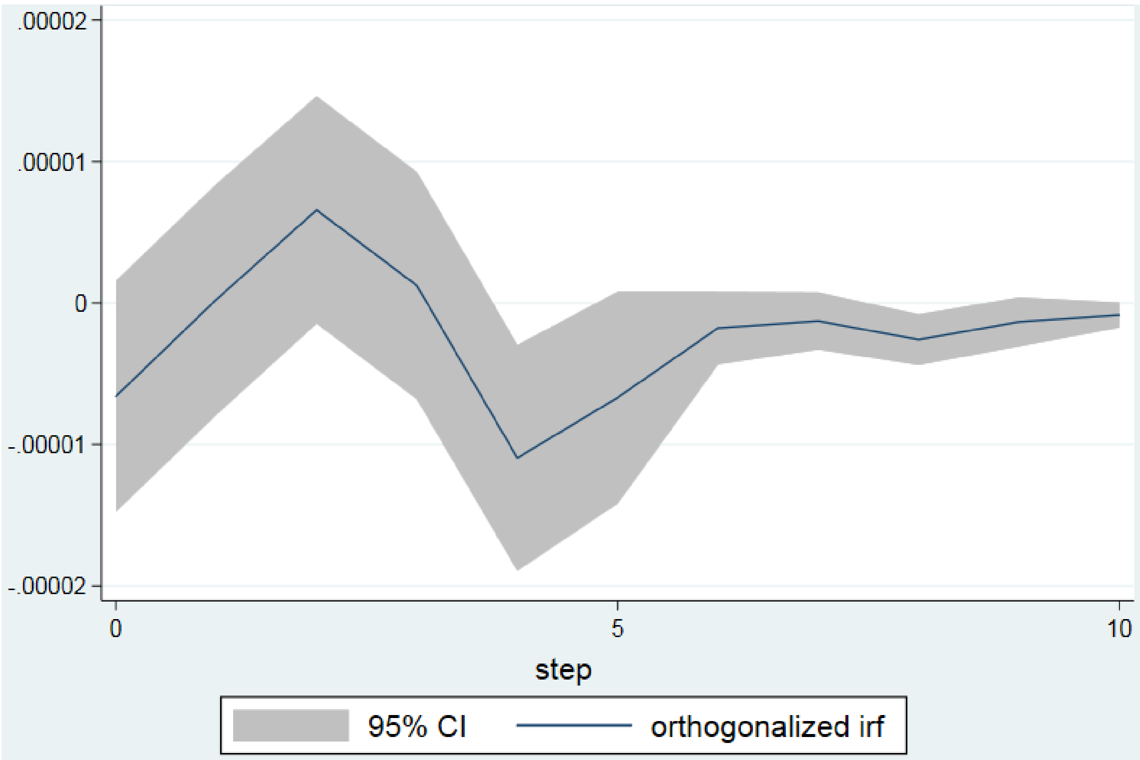


Figure 12.1: The effect of AT on RS- Wheat

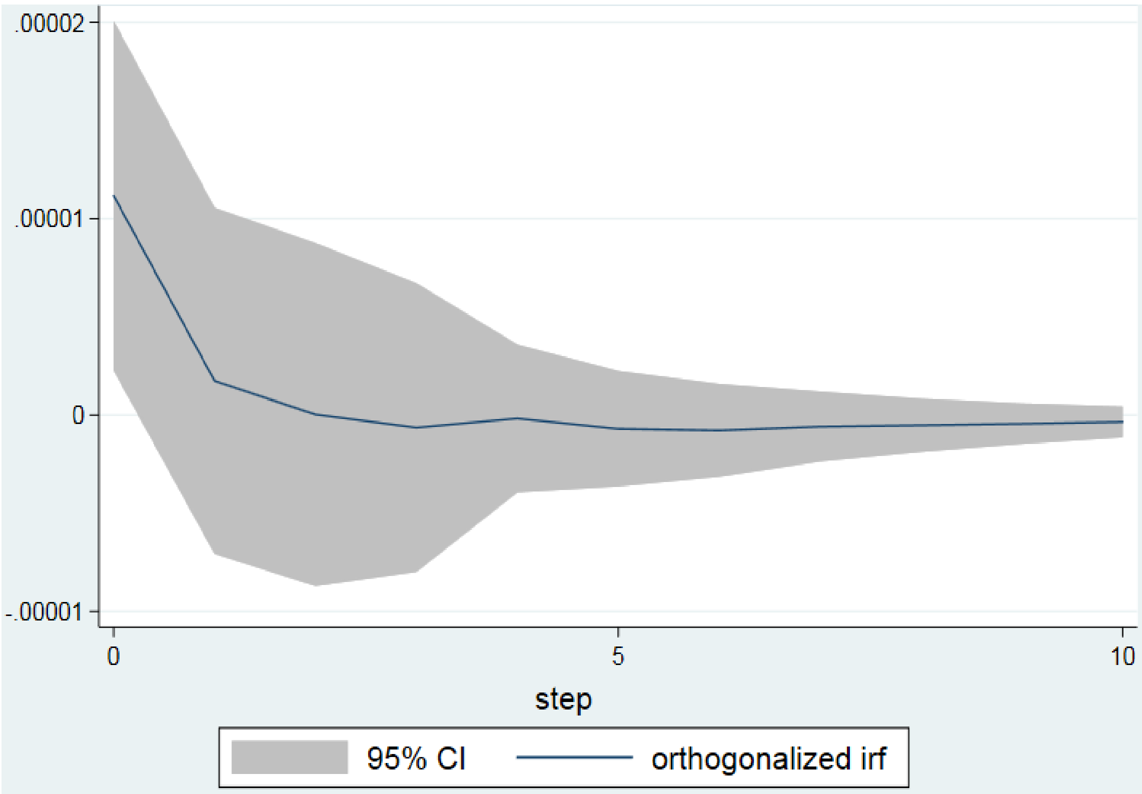


Figure 12.2: The effect of AT on RS- Soybean

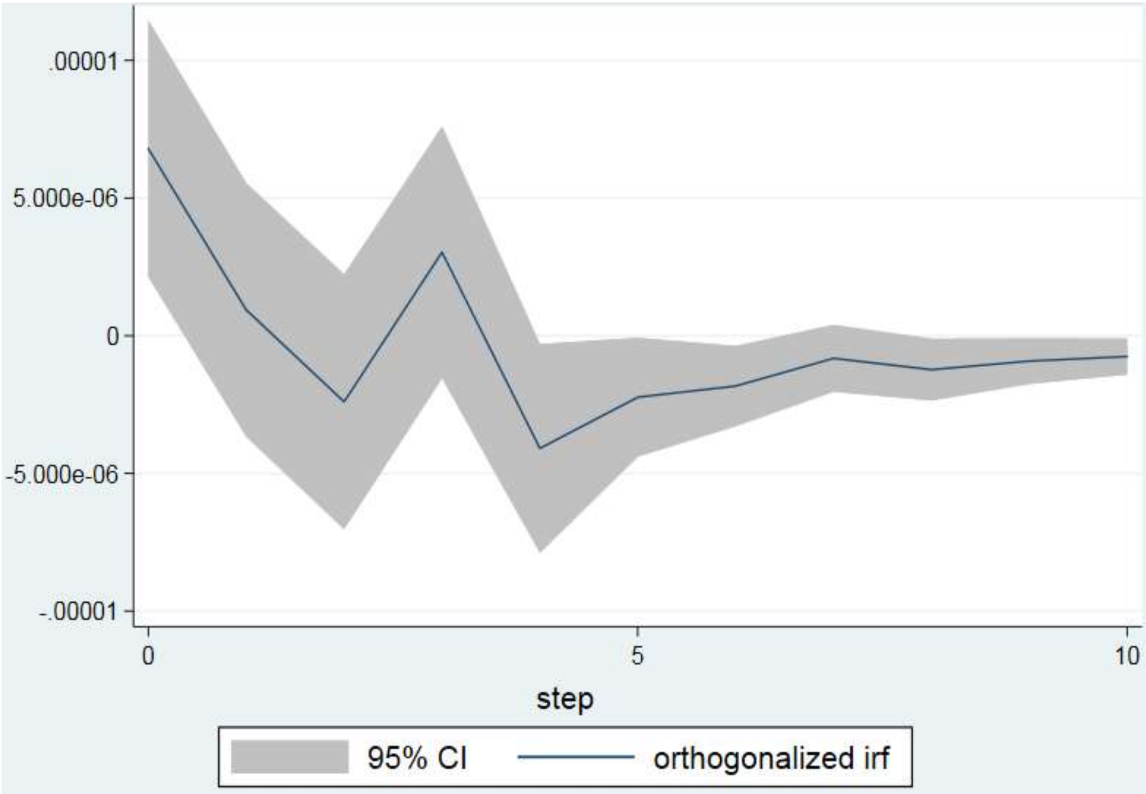


Figure 12.3: The effect of AT on RS- Corn

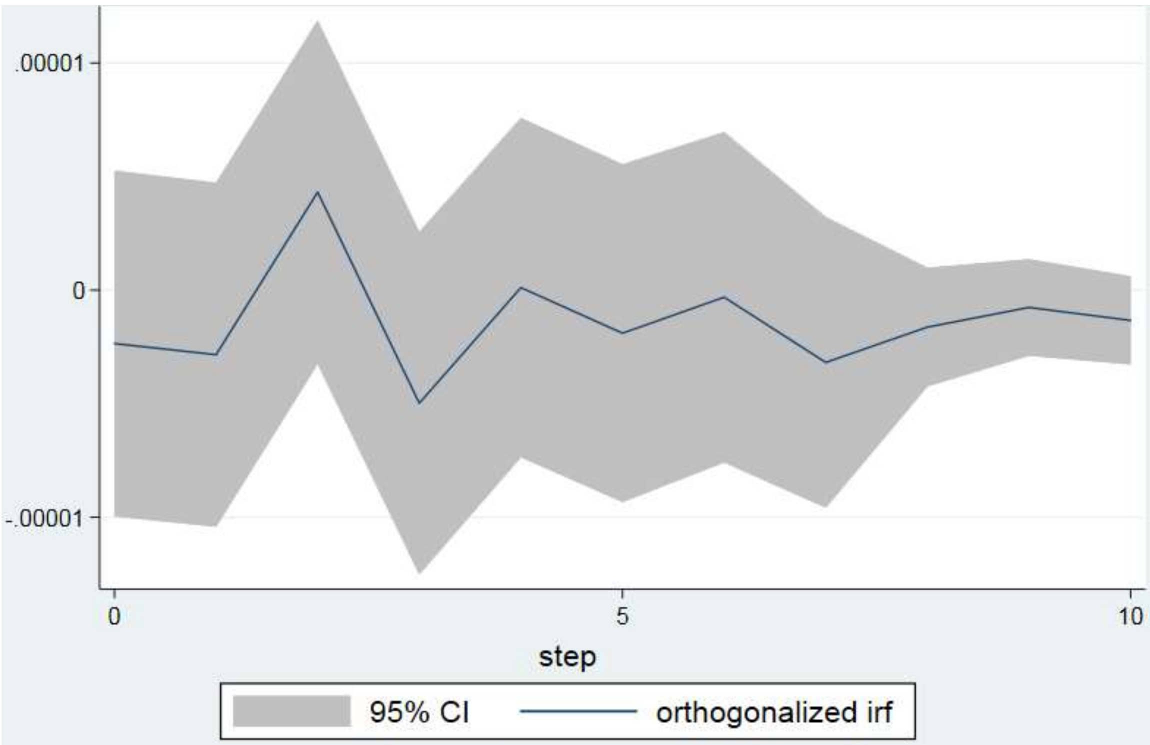


Figure 12.4: The effect of AT on RS- Lean hogs

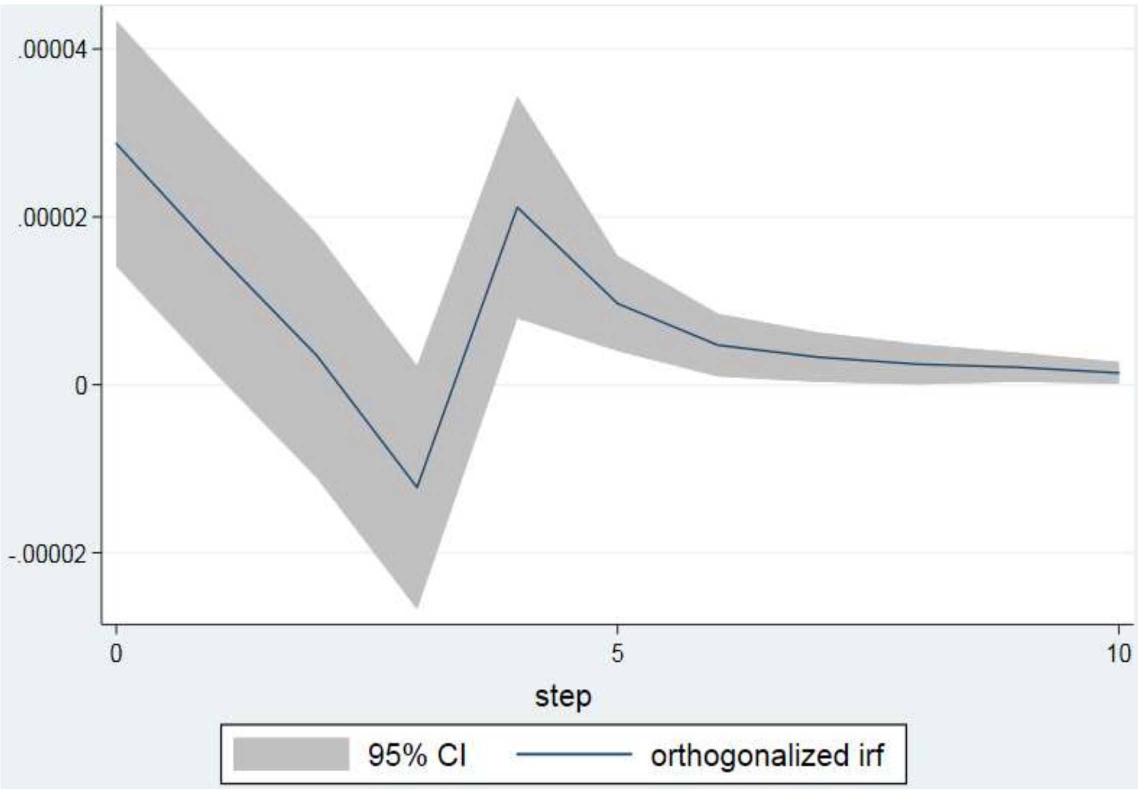
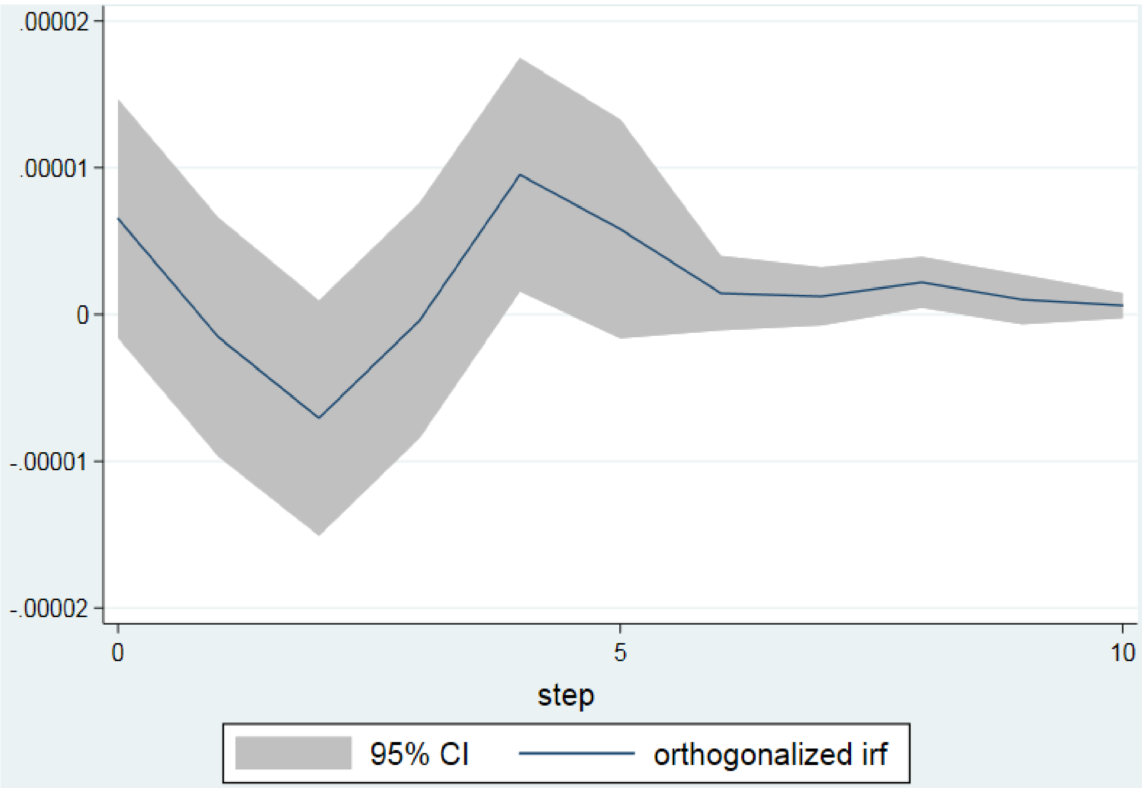


Figure 12.5: The effect of AT on RS- Live cattle



6. Conclusions

Using the CME Group data for wheat, soybean, corn, lean hogs and live cattle for the period of December 2015 to March 2016, we examine the impact of AT on market quality. As the dataset from the CME Group does not identify whether an order is generated manually by a human or by a computer algorithm, we use Hendershott, Jones and Menkveld's (2011) measure of AT which is commonly used in previous studies. We study the relationship between AT and different measures of market quality, such as bid-ask spread, effective spread, adverse selection and realized spread, as well as trade size and volatility. AT, measures of market quality, trade size and volatility are determined jointly, so we estimate a VAR model. Our control variables are the USDA announcements, day of the week, and time of the day.

In general, we find that AT improves market quality by narrowing the EHS. This effect is even stronger in lean hogs and live cattle markets where AT also decreases adverse selection. AT also decreases volatility in all commodities. The inverse relationship between AT and EHS and PI shows that ATs are more active if transaction costs and information asymmetry are lower. In the soybean market, AT appears to increase adverse selection and decrease RS. We also perform an impulse response analysis. We find that the effect of AT on QHS and RS is positive, on EHS and PI is negative and, in all cases, it is temporary.

QHS and RS affect AT positively. EHS and PI affect AT negatively except in lean hogs where EHS is positive, and in corn where PI in not significant. Size and volatility affect AT positively except in live cattle. The USDA announcements are significant and negative only in the soybean market. The effect of the day of the week on AT is only significant in corn where Thursdays and Fridays are negative. The effect of the opening time on AT is positive in soybean and corn, and negative in live cattle. The closing time is negative in all markets except in live cattle, where it is not significant. The midday is significant and negative in soybean and live cattle.

For the effect of AT on spreads, we find that grains behave the same, and meats seem to have similar behavior, except for PI in soybean, and QHS and size in live cattle where the results are unexpected and different than the other markets. In live cattle, the unexpected results may be in part due to the low quality of the data. The sample in this study included four months of data. A larger sample may bring some more light to the results.

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Appendix

Tables A.1 to A.4 show the VAR estimates of equations 6-1 to 6-4 for each measure of market quality (QHS, EHS, PI and RS), size and volatility.

Table A.1: VAR model estimates using QHS as a measure of market quality

		Wheat	Soybean	Corn	Lean hogs	Live cattle
AT						
	AT					
	L1	0.4486***	0.5182***	0.4281***	0.4605***	0.2550***
	L2	0.1058***	0.0309	0.1812***	0.0543	0.1346***
	L3	0.0621**	0.0506	0.0225	0.0364	0.0735**
	L4	0.0133	0.0168	0.0098	0.0307	0.1583***
	L5	-0.0306	0.0121	0.0311	0.0328	-0.0672**
	L6	0.0273	0.0413	0.0435	0.0557*	0.0071
	L7	0.0656**	0.0621**	0.0863***	0.0009	-0.0187
	L8	-	-0.0152	-	0.0197	-0.0273
	L9	-	0.0636**	-	-0.0068	-0.0096
	L10	-	-	-	-	0.0482
	L11	-	-	-	-	0.0318
	L12	-	-	-	-	0.0003
	L13	-	-	-	-	0.0167
	QHS					
	L1	94524.29***	159375.1**	263364.2***	-269161.5	35400000***
	L2	-24512.67	-21362.21	-148180*	177884	-10600000
	L3	-33254.28	-9049.609	-133660.4*	-702150.1	-30900000***
	L4	13760.1	58011.67	201477.2**	522565.3	1119806
	L5	66365.26**	-43277.29	-50633.96	1516243	9612625
	L6	3486.623	-63959.34	-51789.72	-1510939	638986.1
	L7	-650.2828	27409.71	34533.07	3019124*	5481953
	L8	-	173152.3**	-	1536271	-4971423
	L9	-	-99137.32	-	-581681.7	12400000
	L10	-	-	-	-	1877990
	L11	-	-	-	-	1079612
	L12	-	-	-	-	938297.3
	L13	-	-	-	-	-12100000
	Size					

	L1	2.3987***	6.5935***	2.8303***	718.5896***	-217.4498
	L2	-0.9755*	-2.4364***	0.3275	12.6482	827.2154*
	L3	0.2793	0.1585	-0.0728	80.0159	150.5349
	L4	0.2219	-1.5669*	-0.9029**	-160.4701	-302.6445
	L5	-0.4175	-0.0875	-0.3421	398.4595**	-1433.316***
	L6	-0.5863	0.5858	0.1088	-91.1491	-239.4082
	L7	0.3234	0.3668	0.2241	0.6463	-278.9926
	L8	-	-0.4889	-	58.5467	531.1465
	L9	-	-0.2430	-	-212.6551	442.9464
	L10	-	-	-	-	1035.736**
	L11	-	-	-	-	265.8416
	L12	-	-	-	-	-65.6828
	L13	-	-	-	-	-78.6874
	Vol					
	L1	-0.0178	6.6583**	5.5119	-2.2169	-1.1488
	L2	-0.5445	6.6583	-3.3830	-0.9926	1.1431
	L3	-1.1740	1.5953	1.3967	0.6889	3.8925
	L4	-1.1132	5.3201**	-1.7745	-0.8957	2.9630
	L5	-2.0574	1.5951	-2.1664	-0.6495	-0.5529
	L6	0.9139	-0.6218	2.5746	0.1708	-5.1497*
	L7	-1.6894	-5.4945**	8.9182	1.0701	3.8128
	L8	-	1.5353	-	0.5917	-1.6816
	L9	-	3.2772	-	-0.8851	-0.1731
	L10	-	-	-	-	-1.8551
	L11	-	-	-	-	-1.7209
	L12	-	-	-	-	-0.1153
	L13	-	-	-	-	2.5916
	DN	-0.0739	-5.5106*	-0.7368*	66.2304	371.7342
	DW2	-1.9705	-1.8912	-3.6399	-2.4128	518.6788
	DW3	-0.1699	0.9385	-3.3809***	-93.2919	-518.9047
	DW4	-1.6602	-2.7463	-6.4774**	-192.5755	-257.6456
	DW5	0.8741	-0.0644	-4.4998	40.8046	-22.1322
	DI1	1.9756	8.6916***	4.7829*	113.6183	-897.903**
	DI2	-1.0147	-7.4618***	-0.5864	-157.6851	-681.5882*

	DI3	-15.8343***	-18.9986***	-21.1597***	-1432.38***	68.9459
QHS						
	AT					
	L1	0.0000001***	0.0000000052	-0.0000000029	0.00000000017	-0.00000000011
	L2	0.000000006	0.000000013	0.000000028***	0.00000000043	-0.00000000019**
	L3	-0.0000000017	-0.0000000094	0.000000013	-0.00000000019	-0.00000000013
	L4	-0.000000022	-0.0000000021	-0.000000014	0.00000000011	0.00000000017*
	L5	0.0000000002	-0.0000000077	-0.000000023***	0.00000000023	-0.00000000018**
	L6	0.0000000084	-0.0000000076	-0.0000000033	-0.00000000015	-0.0000000001
	L7	-0.000000031	-0.0000000069	-0.0000000091	-0.00000000015	0.00000000016*
	L8	-	-0.00000000093	-	-0.00000000045	0.000000000059
	L9	-	-0.0000000036	-	-0.00000000042	-0.00000000011
	L10	-	-	-	-	0.000000000096
	L11	-	-	-	-	-0.00000000013
	L12	-	-	-	-	-0.000000000084
	L13	-	-	-	-	0.00000000011
	QHS					
	L1	0.2319***	0.3089***	0.1874***	0.2357***	0.2866***
	L2	0.1243***	0.0945***	0.1017***	0.1599***	0.1479***
	L3	0.0908***	0.1032***	0.1425***	0.1058***	0.1002***
	L4	0.0404	0.0748***	0.0987***	0.0416*	0.0406
	L5	0.0189	0.0297	0.1126***	0.1214***	0.0426*
	L6	0.0674***	0.0264	0.0926***	0.0759***	0.0189
	L7	0.0819***	0.0864***	0.0961***	0.0509**	0.0203
	L8	-	0.0352	-	0.0853***	0.0209
	L9	-	0.0927***	-	0.0768***	0.0459*
	L10	-	-	-	-	0.0150
	L11	-	-	-	-	0.0285
	L12	-	-	-	-	0.0524**
	L13	-	-	-	-	0.0526**

	Size					
	L1	0.0000011**	0.00000035	0.00000011	0.00000036	-0.0000029**
	L2	-0.00000038	-0.000000035	0.00000029***	0.0000038	-0.0000016
	L3	0.000000072	0.000000047	-0.000000007	0.0000024	-0.0000004
	L4	-0.00000033	-0.0000001	-0.00000025**	0.0000013	0.000001
	L5	0.00000034	-0.000000053	-0.00000013	0.0000036	-0.0000017
	L6	0.00000014	-0.0000006**	0.00000002	-0.0000032	0.00000073
	L7	-0.00000033	-0.00000027	-0.00000014	-0.0000021	0.0000014
	L8	-	-0.000000052	-	-0.0000039	0.0000027*
	L9	-	-0.00000019	-	0.0000016	-0.00000069
	L10	-	-	-	-	0.00000089
	L11	-	-	-	-	-0.0000033**
	L12	-	-	-	-	-0.00000023
	L13	-	-	-	-	-0.00000018
	Vol					
	L1	0.0000062***	0.0000024***	0.0000061***	0.000000075***	0.000000056***
	L2	-0.0000043**	-0.00000086	-0.00000093	-0.000000053**	0.0000000065
	L3	-0.0000013	-0.0000011	-0.0000022	-0.0000000019	-0.0000000065
	L4	-0.00000018	0.0000016**	-0.00000069	-0.0000000071	-0.0000000014
	L5	0.0000009	-0.00000031	-0.00000048	-0.000000073***	-0.0000000073
	L6	0.0000021	-0.00000016	-0.0000043**	0.000000016	-0.00000001
	L7	-0.0000044***	-0.00000096	-0.000001	-0.000000022	0.0000000069
	L8	-	-0.00000031	-	0.0000000073	-0.0000000079
	L9	-	0.00000064	-	-0.000000014	0.0000000019
	L10	-	-	-	-	0.0000000053
	L11	-	-	-	-	-0.000000012
	L12	-	-	-	-	0.0000000079
	L13	-	-	-	-	0.0000000078
	DN	0.0000029	0.00000061	0.0000031***	0.0000039	0.0000082***
	DW2	0.00000021	0.00000039	-0.00000073	-0.00000055	0.0000012
	DW3	0.0000019*	0.00000097**	0.00000088	0.0000021	0.0000011
	DW4	0.0000021*	0.000001**	0.00000026	0.0000012	0.000000073
	DW5	0.0000012	0.00000061	0.000000019	0.000001	0.000001
	DI1	0.0000089***	0.0000062***	0.0000069***	0.0000203***	0.0000022*

	DI2	0.00000027	-0.00000017	0.00000034	0.0000027	-0.0000011
	DI3	-0.000012***	-0.0000055***	-0.0000044***	-0.000015***	-0.0000113***
Size						
	AT					
	L1	-0.0034**	-0.0018**	-0.0044**	-0.000018***	-0.0000012
	L2	-0.00075	0.0019**	-0.000047	0.0000062	-0.0000022
	L3	-0.00022	0.00033	0.00607***	0.0000078	-0.00000063
	L4	0.00035	-0.00039	-0.00041	-0.0000035	-0.0000019
	L5	0.0014	-0.00032	-0.0017	-0.0000049	0.0000029
	L6	0.0012	-0.00029	0.0024	0.0000059	0.0000014
	L7	0.00103	-0.000601	-0.0065***	0.0000037	0.000000081
	L8	-	0.0022**	-	-0.000001	0.0000028
	L9	-	-0.00205**	-	0.000011*	0.0000016
	L10	-	-	-	-	-0.0000033*
	L11	-	-	-	-	0.00000049
	L12	-	-	-	-	0.0000019
	L13	-	-	-	-	-0.0000018
	QHS					
	L1	-2496.718**	-3371.219	-15581.03**	-344.374	-1249.247***
	L2	747.889	-574.426	6758.566	-146.227	-348.568
	L3	1473.38	583.100	5229.963	-111.698	551.397
	L4	-74.2853	-1899.685	-12564.9**	24.765	-925.814*
	L5	-2829.239**	-2118.77	5094.429	-164.892	-290.316
	L6	-1372.281	2796.125	1570.205	226.056	-426.387
	L7	-505.669	-2725.393	5873.527	-144.686	593.483
	L8	-	-6129.751**	-	-381.201	-350.179
	L9	-	2069.178	-	244.962	-289.053
	L10	-	-	-	-	343.832
	L11	-	-	-	-	-236.976
	L12	-	-	-	-	334.540
	L13	-	-	-	-	0.0217
	Size					
	L1	0.1454***	0.1749***	0.1672***	0.1388	0.1979***
	L2	0.1109***	0.1729***	0.0989***	0.1177	0.0036

	L3	0.0656**	0.0530**	0.0568**	0.0570	0.0684**
	L4	0.0462*	0.0829***	0.0769**	0.0640	0.0479*
	L5	0.0463*	0.0169	0.0358	-0.0544	0.0754***
	L6	0.0560**	0.0406	0.0639**	0.0692	0.0181
	L7	0.0597**	0.0168	-0.0014	0.0548	0.0559**
	L8	-	0.0516**	-	0.0176	0.0190
	L9	-	0.0031	-	0.1193	-0.0021
	L10	-	-	-	-	-0.0141
	L11	-	-	-	-	-0.00501
	L12	-	-	-	-	0.0705**
	L13	-	-	-	-	-0.0233
	Vol					
	L1	0.1941**	0.0929	1.4221***	0.0000103	-0.000112
	L2	0.0132	-0.0243	0.3581	0.000128	-0.0000728
	L3	-0.0483	-0.0717	0.1681	-0.000412	-0.000222
	L4	0.0441	-0.0868	0.2573	-0.000179	-0.000267
	L5	-0.0043	-0.0635	0.3469	0.000284	0.000463***
	L6	-0.0407	0.0841	-1.1853***	-0.000162	-0.0000431
	L7	-0.0160	0.0521	-1.5125***	0.000126	-0.000178
	L8	-	0.1020	-	-0.000237	-0.0000158
	L9	-	-0.2035***	-	-0.000161	0.000157
	L10	-	-	-	-	-0.0000776
	L11	-	-	-	-	-0.0000541
	L12	-	-	-	-	-0.000255
	L13	-	-	-	-	0.000164
	DN	-0.1651	-0.0327	-0.2151	-0.0102	-0.0164
	DW2	0.0606	0.0669	0.1357	0.0099	0.0335
	DW3	-0.0015	0.0808	0.3217**	-0.0065	0.04403
	DW4	-0.00019	0.1117**	0.4232**	0.0259	0.0529**
	DW5	-0.10084	0.0263	0.2443	-0.0144	0.02501
	DI1	-0.1928**	0.1039	0.5992***	-0.1314***	-0.0526**
	DI2	-0.0835*	0.0189	-0.4641***	0.0293	0.0450**
	DI3	0.0013	-0.0198	0.1022	0.1513***	0.0587*
Vol						

	AT					
	L1	-0.00098^{**}	-0.0012^{***}	-0.00031^{***}	-0.0015^{***}	0.00011
	L2	0.00074^{**}	0.00052^{**}	0.000101	-0.000018	0.00029
	L3	0.00024	0.00055^{**}	0.00032^{***}	0.00052	-0.00051^{**}
	L4	-0.00029	0.00036	-0.000052	-0.00018	-0.00048^{**}
	L5	0.000058	0.000017	-0.00015	-0.00037	0.000069
	L6	0.00057	-0.00019	0.00013	0.00062	-0.00029
	L7	-0.00072^{**}	-0.00011	-0.00014	0.000094	0.00024
	L8	-	0.00023	-	-0.00071	-0.00035
	L9	-	-0.00013	-	0.00048	0.000405
	L10	-	-	-	-	0.000309
	L11	-	-	-	-	-0.00058^{**}
	L12	-	-	-	-	-0.00057^{**}
	L13	-	-	-	-	0.000082
	QHS					
	L1	-621.8941^{**}	1718.402^{**}	-201.6653	8569.725	7042.391
	L2	182.1778	-357.332	-111.3991	-23154.7	91416.79
	L3	897.9963^{***}	1211.228	805.74^{**}	15003.01	136925.3^{**}
	L4	-181.0998	-736.0478	-522.0507	52494.71^{**}	122668^{*}
	L5	-316.7161	-289.3082	7.7147	-6869.535	-161253.7^{**}
	L6	-119.5359	1287.612^{*}	88.2915	47248.51^{**}	60034.67
	L7	263.3728	-1885.42^{**}	125.3228	-12274.39	-84393.13
	L8	-	-593.165	-	-15967.29	-3188.127
	L9	-	768.2978	-	-8304.749	22850.92
	L10	-	-	-	-	-37018.43
	L11	-	-	-	-	8343.077
	L12	-	-	-	-	85602.09
	L13	-	-	-	-	88394.99
	Size					
	L1	-0.0157^{**}	-0.0293^{***}	-0.0029^{**}	-2.3074	1.0025
	L2	0.0064	0.0078	0.00043	-2.4258	0.3344
	L3	0.0035	0.0137^{*}	0.0026^{*}	2.3119	-4.4213
	L4	-0.0074	0.0052	-0.00088	-1.2737	-1.3790
	L5	0.0021	-0.0000025	0.00017	-1.40014	-3.7520

	L6	0.0053	-0.0104	0.00092	5.9017**	-0.7981
	L7	-0.0104	-0.0073	-0.00126	-2.2229	5.0299
	L8	-	0.0071	-	-4.1460*	-0.2962
	L9	-	-0.00101	-	-0.8535	-0.3335
	L10	-	-	-	-	-0.4807
	L11	-	-	-	-	-7.5149*
	L12	-	-	-	-	-6.2729
	L13	-	-	-	-	0.7788
	Vol					
	L1	0.2514***	0.2265***	0.2474***	0.1779***	0.2031***
	L2	0.0489**	0.1205***	0.0775***	0.0773***	0.0867***
	L3	0.0624***	0.0536**	0.0581**	-0.0079	0.0669***
	L4	0.0267	0.0786***	0.0492**	0.0725***	-0.0334
	L5	0.0807***	0.0041	0.0623***	0.0076	0.02002
	L6	0.0416*	0.0202	0.0078	0.0398*	0.0290
	L7	0.0348	0.0124	0.0262	-0.0102	-0.0154
	L8	-	0.0579***	-	0.0316	0.0508**
	L9	-	0.0156	-	0.0589***	0.0298
	L10	-	-	-	-	-0.0169
	L11	-	-	-	-	0.0208
	L12	-	-	-	-	0.0252
	L13	-	-	-	-	-0.0365
	DN	0.0979***	0.1607***	0.0564***	-4.0373	13.4838**
	DW2	-0.0098	-0.0054	0.0039	-4.7050*	3.3006
	DW3	0.00046	0.0017	0.0059	-2.6358	-5.3048
	DW4	-0.00091	0.0253	0.0102	-2.1279	2.8739
	DW5	0.0078	-0.0049	0.00047	-0.7559	4.5888
	DI1	0.2333***	0.1768***	0.1072***	18.9335***	20.9196***
	DI2	0.0103	0.0128	0.0124*	6.1322***	4.8571
	DI3	0.1103***	0.1109***	0.0505***	17.8542***	21.0118***

Significant at 1%***, 5%**, and 10%* levels

Table A.2: VAR model estimates using EHS as a measure of market quality

		Wheat	Soybean	Corn	Lean hogs	Live cattle
AT						
	AT					
	L1	0.4665***	0.5301***	0.4286***	0.4558***	0.2974***
	L2	0.1028***	0.0157	0.1584***	0.0559*	0.1202***
	L3	0.0779**	0.0472	0.0309	0.0305	0.0279
	L4	0.01902	0.0139	0.0092	0.0339	0.1543***
	L5	-0.0025	-0.0124	0.0178	0.0433	-0.0434
	L6	0.0295	0.0485	0.0416	0.0463	-
	L7	0.0659**	0.0571*	0.0532*	0.0179	-
	L8	-	-0.03203	0.0181	0.0266	-
	L9	-	0.07001**	0.02147	-0.01104	-
	EHS					
	L1	-49044.5**	-55407.03	-93046.47***	-759161.4	11800000
	L2	12790.33	-36005.95	12876.81	-69212.25	3284024
	L3	42614.47**	-21094.38	72184.69**	-688982.9	-3022731
	L4	-5181.824	-50718.26	-81578.21**	1084254	-13700000*
	L5	-9402.08	-85474.33	-2695.151	2091120	908496.8
	L6	-515.603	54163.36	34192.07	-517808.6	-
	L7	-2997.82	-38508.54	-79463.43**	2864601*	-
	L8	-	-199287.1***	-20165.82	2280001	-
	L9	-	91761.34	-1634.617	690130.5	-
	Size					
	L1	2.3433***	6.6820***	2.9372***	709.1596***	-293.2124
	L2	-0.8899	-2.6764***	0.1806	14.8977	895.6039*
	L3	0.5265	0.1395	0.1112	73.3088	72.6735
	L4	0.1942	-1.6584*	-0.8453**	-167.6997	-183.905
	L5	-0.2815	-0.4278	-0.4052	385.9544**	-1204.913**
	L6	-0.5568	0.8099	0.2217	-100.8702	-
	L7	0.2983	0.1891	0.0359	-34.7211	-
	L8	-	-0.9209	-0.2828	26.1948	-
	L9	-	0.0377	-0.0623	-225.5659	-
	Vol					
	L1	1.1454	7.3933***	6.8159	-1.9934	0.7456

	L2	-0.5171	-3.80053	-5.7337	-0.8694	1.8114
	L3	-1.4158	1.7271	0.7953	0.7203	1.5319
	L4	-0.8967	5.1679**	-1.5437	-1.1590	2.1982
	L5	-0.9229	1.0352	-3.1829	-0.8141	-0.3340
	L6	1.3856	-1.1316	1.6112	0.1281	-
	L7	-1.3931	-5.5265**	6.7982	0.7774	-
	L8	-	1.6542	0.0369	0.7487	-
	L9	-	2.292375	-0.5985	-0.7805	-
	DN	0.1423	-5.4809*	-1.1151	77.4489	672.4262
	DW2	-1.5958	-1.8719	-3.4398	7.6273	569.152
	DW3	0.3317	1.2674	-3.1323	-74.6671	-429.2106
	DW4	-0.7579	-2.7817	-6.2185***	-153.2212	-227.7276
	DW5	1.1438	-0.1701	-4.9286*	74.5497	17.7369
	DI1	2.1383	8.5789***	4.7647	194.3292	-837.549**
	DI2	-0.8806	-7.1795***	-0.3182*	-161.353	-895.9487**
	DI3	-15.5608***	-19.5878***	-21.3459***	-1377.458***	45.9476
EHS						
	AT					
	L1	-0.00000014***	-0.000000028***	-0.000000031*	-0.0000000013***	-0.00000000028***
	L2	0.000000044	0.0000000015	-0.000000031	0.00000000069	-0.000000000055
	L3	0.000000019	-0.000000001	-0.000000025	0.00000000058	0.00000000022**
	L4	0.000000021	0.000000011	0.000000024	0.00000000034	-0.00000000039***
	L5	0.0000000082	0.000000017	0.000000026	0.00000000038	0.000000000026
	L6	0.000000043	-0.0000000088	-0.000000027	-0.0000000002	-
	L7	0.000000057*	0.000000011	0.000000021	0.00000000066	-
	L8	-	-0.0000000072	0.0000000089	-0.00000000077	-
	L9	-	0.000000013	0.000000019	0.00000000077*	-
	EHS					
	L1	0.2288***	0.2341***	0.1394***	0.1117***	0.2163***
	L2	0.0940***	0.0667***	0.0911***	0.1182***	0.1008***
	L3	0.1096***	0.0722***	0.1105***	0.1060***	0.0432*
	L4	0.0370	0.0815***	0.0778***	0.0694***	0.0552**
	L5	0.0191	0.0313	0.0139	0.0983***	0.0597***

	L6	0.0557**	0.0261	0.0528**	0.0602***	-
	L7	0.1096***	0.0519**	0.0492**	0.0561**	-
	L8	-	0.0595**	0.1043***	0.0603***	-
	L9	-	0.0773***	0.1128***	0.0802***	-
	Size					
	L1	-0.00000093	-0.00000086***	-0.00000061**	-0.0000044*	-0.000003**
	L2	0.0000012*	0.00000024	-0.00000039	0.0000013	-0.0000022
	L3	0.00000033	-0.00000019	0.000000029	0.0000011	0.0000011
	L4	-0.0000000089	0.00000035	0.00000063**	0.0000014	-0.0000032**
	L5	-0.000000081	0.00000047	0.0000000016	-0.0000018	-0.00000089
	L6	0.000000084	-0.000000032	-0.00000039	-0.0000026	-
	L7	0.0000012*	0.00000058*	0.00000043	-0.000000035	-
	L8	-	0.00000011	0.00000042	-0.0000047**	-
	L9	-	0.0000005	0.00000043*	0.0000035	-
	Vol					
	L1	-0.0000094***	-0.0000029***	-0.000017***	0.000000014	0.000000048***
	L2	0.0000027	-0.00000023	-0.0000032	-0.000000018	0.0000000076
	L3	0.00000095	-0.00000049	0.0000029	0.000000012	-0.0000000096
	L4	-0.00000065	-0.0000013	-0.000000092	-0.00000001	0.0000000018
	L5	-0.0000015	-0.00000062	-0.0000014	-0.00000004*	-0.000000011
	L6	0.000000096	-0.00000029	0.0000031	0.00000001	-
	L7	0.0000041**	0.0000012	-0.0000017	-0.000000026	-
	L8	-	-0.0000016*	-0.000001	0.0000000025	-
	L9	-	0.00000023	0.0000075**	0.000000022	-
	DN	-0.0000017	0.00000024	-0.0000051**	0.0000026	0.0000029
	DW2	0.00000019	-0.00000036	0.00000058	-0.0000016	0.00000081
	DW3	-0.0000017	-0.00000083	-0.00000095	-0.0000017	0.0000018
	DW4	-0.00000062	-0.00000099	-0.00000024	-0.0000014	-0.000000079
	DW5	-0.00000065	-0.00000066	-0.0000013	-0.00000085	-0.00000046
	DI1	-0.0000014	-0.0000038***	-0.0000071***	0.000019***	0.0000033***
	DI2	0.0000024**	0.0000015***	0.00000049	0.0000048**	0.00000052
	DI3	0.000018***	0.0000085***	0.000011***	0.000018***	0.0000014
Size						
	AT					

	L1	-0.0052***	-0.0021**	-0.0048**	-0.000019***	-0.0000021
	L2	-0.000011	0.0025***	0.0016	0.0000058	-0.0000018
	L3	0.00017	0.00031	0.0058**	0.0000061	0.00000044
	L4	-0.00034	-0.00034	0.00034	-0.000003	-0.0000014
	L5	0.00091	0.00012	-0.0012	-0.0000063	0.0000036**
	L6	0.0022	-0.00059	0.0036	0.0000065	-
	L7	0.0012	-0.00027	-0.0038*	0.0000035	-
	L8	-	0.0024**	-0.0021	-0.0000023	-
	L9	-	-0.0024***	-0.0012	0.000012**	-
	EHS					
	L1	-14.9902	721.3551	4800.043*	25.6694	-1111.181***
	L2	646.5928	2283.886	1009.496	-87.8563	-578.384
	L3	-81.4489	-309.9688	-2069.288	-342.1831	169.2512
	L4	-449.3884	1630.043	7589.298***	62.3885	219.0162
	L5	1527.314	3500.477*	-1998.332	-434.4608	-143.2692
	L6	2579.949***	-2915.756	1088.599	-164.1972	-
	L7	1085.832	3421.056	2425.113	-15.9257	-
	L8	-	4904.536**	-396.9661	-107.6351	-
	L9	-	-2963.474	-1543.824	-25.5757	-
	Size					
	L1	0.1259***	0.1765***	0.1560***	0.1467***	0.2168***
	L2	0.1135***	0.1850***	0.1074***	0.1226***	0.0296
	L3	0.0635**	0.0531**	0.0458	0.0569*	0.0964***
	L4	0.0381	0.0885***	0.0833***	0.0666**	0.0830***
	L5	0.0482*	0.0275	0.0365	-0.0531*	0.1097***
	L6	0.0696**	0.0342	0.0689**	0.0687**	-
	L7	0.0613**	0.0293	0.0179	0.0619**	-
	L8	-	0.0633**	-0.0026	0.0261	-
	L9	-	-0.0039	0.0088	0.1241***	-
	Vol					
	L1	0.1639**	0.0747	1.3605***	0.000015	-0.00025
	L2	0.0243	-0.0295	0.5092	0.0000801	-0.0002003
	L3	-0.0022	-0.0816	0.2621	-0.000405	-0.00029*
	L4	0.0494	-0.0909	0.3749	-0.00023	-0.00044***

	L5	-0.0472	-0.0640	0.4251	0.00035	0.00025
	L6	-0.0474	0.0854	-1.0085**	-0.00011	-
	L7	0.0062	0.0419	-1.1849***	0.000072	-
	L8	-	0.0879	0.0816	-0.000322	-
	L9	-	-0.1941**	-0.9036**	-0.00019	-
	DN	-0.0953*	-0.0179	-0.1876	-0.0134	-0.0115
	DW2	0.0555	0.0654	0.1298	0.0073	0.0331
	DW3	-0.0063	0.0649	0.3150**	-0.0122	0.0382
	DW4	-0.0152	0.10054*	0.4238**	0.0163	0.0509**
	DW5	-0.0953	0.0135	0.2866	-0.0202	0.0304
	DI1	-0.1817**	0.1113*	0.5637***	-0.1448***	-0.0284
	DI2	-0.0862*	0.0123	-0.4717***	0.0290	0.0457**
	DI3	0.0302	-0.000093	0.1105	0.1369***	0.0569*
Vol						
	AT					
	L1	-0.00088**	-0.00086***	-0.00031***	-0.0013***	0.000033
	L2	0.00096***	0.00047*	0.00011	-0.00019	0.00028
	L3	0.00015	0.00047*	0.00036***	0.00056	-0.00041*
	L4	-0.00048	0.00034	-0.000033	0.000098	-0.00056**
	L5	0.00014	0.0000904	-0.00012	-0.00053	-0.00017
	L6	0.00036	-0.00034	0.00012	0.00088*	-
	L7	-0.00085**	-0.00015	-0.00016	-0.0000304	-
	L8	-	0.00017	0.000026	-0.00087*	-
	L9	-	-0.00025	-0.00012	0.00051	-
	EHS					
	L1	474.2008**	521.2752	82.7529	69496.78***	91145.52
	L2	165.6538	183.4136	66.0766	-6684.876	-16844.97
	L3	-751.2811***	-1192.723**	-284.4895**	5992.084	17457.41
	L4	-191.4205	510.4479	320.7443**	56528.7**	63020.64
	L5	297.0373	371.0988	81.9435	-17295.3	148741**
	L6	-220.7974	-1370.829**	-77.35054	24254.79	-
	L7	-389.7402	1147.117**	-114.9495	-24586.3	-
	L8	-	-68.8889	168.0657	-31904.38	-
	L9	-	-1037.435*	-285.7776**	20292.28	-

	Size					
	L1	-0.0117*	-0.0247***	-0.0026*	-1.9732	-0.9616
	L2	0.00805	0.0069	0.00067	-2.8013	-3.1775
	L3	0.00054	0.0106	0.0029*	1.8388	-6.6797*
	L4	-0.0084	0.0061	-0.00066	-1.8654	-5.2614
	L5	0.0043	0.00095	0.00064	-2.1204	-7.7354**
	L6	0.0029	-0.0139*	0.00078	5.5294**	-
	L7	-0.0121*	-0.0065	-0.0015	-2.320005	-
	L8	-	0.00604	-0.00021	-4.2366*	-
	L9	-	-0.0047	-0.0017	-0.5379	-
	Vol					
	L1	0.2435***	0.2387***	0.2446***	0.1671***	0.2148***
	L2	0.0524**	0.1284***	0.0769***	0.0777***	0.0999***
	L3	0.0717***	0.0566**	0.0618***	-0.0101	0.0949***
	L4	0.0211	0.0766***	0.0496**	0.0712***	-0.0079
	L5	0.0762***	0.0059	0.0652***	0.0155	0.0232
	L6	0.0382*	0.01876	0.0019	0.0465**	-
	L7	0.0291	0.0065	0.0123	0.0027	-
	L8	-	0.0527**	0.0487**	0.0373	-
	L9	-	0.0136	0.003101	0.0528**	-
	DN	0.1021***	0.1598***	0.0556***	-4.0148	11.7164**
	DW2	-0.0104	-0.0039	0.0039	-4.6309*	2.7709
	DW3	-0.0012	0.0039	0.00602	-2.1909	-5.0952
	DW4	-0.0027	0.0285*	0.0106	-1.4469	3.4579
	DW5	0.0054	-0.0039	0.0012	-0.3722	3.3775
	DI1	0.2279***	0.1747***	0.1087***	17.8438***	17.3327***
	DI2	0.0086	0.0148	0.0134*	5.8334***	6.4881**
	DI3	0.10485***	0.1103***	0.0501***	18.6394***	23.3741***

Significant at 1%***, 5%**, and 10%* levels

Table A.3: VAR model estimates using PI as a measure of market quality

		Wheat	Soybean	Corn	Lean hogs	Live cattle
AT						
	AT					
	L1	0.5054***	0.5536***	0.4866***	0.4656***	0.2941***
	L2	0.1044***	0.0328	0.1835***	0.0645**	0.1167***
	L3	0.079003***	0.0583**	0.0346	0.0512	0.0278
	L4	-	0.0578**	0.0604**	0.0568*	0.1626***
	L5	-	-	-	-	-0.0456*
	PI					
	L1	-11279.82***	-26632.05***	-5221.012	-471789.7***	-1740175**
	L2	-1875.662	45.4365	-6299.464	-29959.05	-797244.9
	L3	-1269.833	40.5224	-3073.205	-99167.67	458348.1
	L4	-	1430.98	2316.866	225094.9	1455953*
	L5	-	-	-	-	-301265.3
	Size					
	L1	2.6874***	6.5358***	3.0949***	687.5205***	-338.9854
	L2	-0.9702*	-2.9113***	0.3236	-7.8768	848.3992*
	L3	0.2722	-0.3938	-0.1936	108.0972	54.6427
	L4	-	-1.3785	-0.7289**	-157.9121	-59.1949
	L5	-	-	-	-	-1164.032**
	Vol					
	L1	4.5073**	11.8209***	14.1233**	0.1050	3.4775
	L2	-0.6357	-2.3055	-3.3514	-0.5196	3.1506
	L3	-2.0809	1.6044	0.4451	1.8385	0.9594
	L4	-	5.6708**	-1.5863	-0.9565	-1.0105
	L5	-	-	-	-	-0.3678
	DN	0.7235	-3.4869	-1.5675	66.0865	662.6363
	DW2	-1.9241	-1.8515	-3.0558	14.5248	557.0644
	DW3	0.0195	1.3939	-2.1061	-69.9139	-440.4342
	DW4	-1.2883	-1.736002	-4.8936**	-186.6517	-258.8326
	DW5	0.6322	0.5595	-3.1303	37.5726	-13.8886
	DI1	2.2879	7.0779***	4.176*	37.9678	-849.1396**
	DI2	-0.9369	-5.9309***	-0.2976	-145.5552	-888.5225**
	DI3	-15.5936***	-20.4583***	-22.0635***	-1397.103***	79.2049

PI						
	AT					
	L1	-0.00000011	-0.000000081	0.000000057	-0.0000000066	-0.00000000044
	L2	0.000000088	0.0000000013	-0.00000029*	0.0000000055	0.00000000079
	L3	0.0000002	-0.00000008	0.00000019	0.0000000072	0.00000000039
	L4	-	0.00000024**	0.000000052	-0.000000014***	-0.0000000022***
	L5	-	-	-	-	-0.00000000039
	PI					
	L1	0.0627***	0.1331***	0.0086	0.0319	-0.0366
	L2	0.0354	-0.0126	-0.0336	-0.0063	-0.0265
	L3	-0.0056	-0.0157	0.0271	0.0035	0.0049
	L4	-	0.0343	0.0233	-0.0258	-0.0037
	L5	-	-	-	-	-0.0278
	Size					
	L1	0.0000059	-0.0000022	-0.0000015	0.0000054	-0.000013
	L2	0.0000032	-0.0000026	-0.0000025	0.000019	-0.0000066
	L3	0.0000059	0.0000029	0.0000015	0.0000069	0.000013
	L4	-	0.0000018	0.0000019	-0.000042**	-0.0000102
	L5	-	-	-	-	0.0000057
	Vol					
	L1	-0.000026	-0.0000042	0.000093***	-0.0000003	0.000000062
	L2	-0.0000029	-0.000016	0.000017	0.00000042*	0.000000096
	L3	0.000036*	0.000023**	-0.000019	-0.000000072	-0.000000099
	L4	-	-0.0000042	0.000037	0.0000003	0.000000048
	L5	-	-	-	-	-0.00000013
	DN	0.000069***	0.000019	-0.000028	-0.000021	0.000023
	DW2	-0.000014	0.0000025	0.0000078	-0.000045*	-0.0000064
	DW3	-0.000002	-0.0000039	0.000026**	-0.000015	-0.000027**
	DW4	-0.000015	0.00000036	0.000017	-0.000011	-0.000013
	DW5	-0.000018	-0.00000033	0.0000085	-0.000011	-0.000036**
	DI1	-0.000018	0.0000023	-0.0000094	0.000021	0.000011
	DI2	-0.00000087	0.0000067	0.0000073	0.000062**	0.000012
	DI3	-0.000012	-0.000033***	-0.000032**	0.0000039	0.0000077
Size						

	AT					
	L1	-0.00406***	-0.0023***	-0.0073***	-0.000017***	-0.0000018
	L2	-0.00021	0.0019**	-0.00076	0.0000073	-0.0000013
	L3	0.00019	0.00032	0.0063***	0.000008	0.00000072
	L4	-	-0.0012	-0.0024	-0.00000086	-0.0000017
	L5	-	-	-	-	0.000004**
	PI					
	L1	267.101***	575.7417***	762.2736**	64.3698**	101.7472**
	L2	102.1286	281.9732*	665.3034**	9.3191	43.9302
	L3	151.5383*	-87.4674	119.4769	21.3809	-3.1171
	L4	-	71.0094	-236.749	-16.1303	-17.7055
	L5	-	-	-	-	37.2791
	Size					
	L1	0.1608***	0.1937***	0.1566***	0.1743***	0.2241***
	L2	0.1294***	0.2002***	0.1059***	0.1467***	0.0371
	L3	0.0948***	0.0819***	0.0726**	0.0835***	0.1017***
	L4	-	0.1089***	0.0787***	0.0984***	0.080005***
	L5	-	-	-	-	0.1121***
	Vol					
	L1	0.0659	-0.0523	0.6791	-0.00039	-0.00046***
	L2	-0.0243	-0.1084	0.0863	-0.00011	-0.00032**
	L3	-0.0665	-0.0701	0.1914	-0.00059**	-0.00031*
	L4	-	-0.1214	0.0645	-0.00031	-0.00037**
	L5	-	-	-	-	0.00021
	DN	-0.1776*	-0.0508	-0.1491	-0.0239	-0.0155
	DW2	0.0703	0.0728	0.1126	0.0062	0.0325
	DW3	-0.0117	0.0701	0.2559	-0.0046	0.0376
	DW4	-0.0244	0.0793	0.3857**	0.0244	0.0517**
	DW5	-0.1014	-0.0093	0.1914	-0.0063	0.0378
	DI1	-0.1336*	0.1633**	0.7589***	-0.1013***	-0.0314
	DI2	-0.0643	0.0087	-0.4445***	0.0188	0.047004**
	DI3	-0.00048	-0.0049	0.1737	0.1444***	0.050045
Vol						
	AT					

	L1	-0.0015***	-0.00104***	-0.00036***	-0.0015***	-0.000055
	L2	0.00066**	0.00043*	0.0000803	-0.00013	0.00023
	L3	0.00055*	0.00075***	0.00035***	0.00049	-0.00042*
	L4	-	0.00024	-0.000023	-0.00019	-0.00054**
	L5	-	-	-	-	-0.00028
	PI					
	L1	36.1398	39.8764	-39.3527**	4616.048*	-16421.94**
	L2	-9.9298	-28.5618	10.4252	-1814.518	-3226.125
	L3	-86.9705***	-28.4932	-30.2658**	2372.683	-5105.724
	L4	-	50.04803	4.9253	-640.5139	2315.061
	L5	-	-	-	-	10151.36
	Size					
	L1	-0.02103***	-0.0306***	-0.0036**	-3.9458*	-1.98101
	L2	0.0036	0.0047	0.00038	-3.6643	-4.2515
	L3	0.0038	0.0131*	0.0038***	0.5629	-7.9479**
	L4	-	0.00013	-0.00071	-3.7253	-5.9421
	L5	-	-	-	-	-9.0361**
	Vol					
	L1	0.2481***	0.2402***	0.2681***	0.1847***	0.2429***
	L2	0.0635***	0.1347***	0.0756***	0.0996***	0.1054***
	L3	0.1255***	0.0701***	0.0849***	-0.0019	0.10503***
	L4	-	0.0862***	0.0635***	0.1109***	-0.0048
	L5	-	-	-	-	0.0294
	DN	0.0889***	0.1536***	0.0018***	-2.5658	12.1581**
	DW2	-0.0122	-0.0027	0.0062	-4.3781	2.8279
	DW3	0.0012	0.0041	0.008101	-2.9877	-4.8955
	DW4	-0.0053	0.0313**	0.01303	-2.3091	3.6588
	DW5	0.0072	0.000078	0.0018	-1.1453	2.3553
	DI1	0.1961***	0.1632***	0.0943***	16.7262***	17.3462***
	DI2	0.0051	0.01103	0.01013	5.2042**	5.5717*
	DI3	0.0936***	0.1091***	0.0437***	17.6101***	23.8656***

Significant at 1%***, 5%**, and 10%* levels

Table A.4: VAR model estimates using RS as a measure of market quality

		Wheat	Soybean	Corn	Lean hogs	Live cattle
AT						
	AT					
	L1	0.5123***	0.5599***	0.4638***	0.4662***	0.2941***
	L2	0.1043***	0.0321	0.1744***	0.0645**	0.1174***
	L3	0.0792***	0.0581**	0.0168	0.0511	0.0285
	L4	-	0.0572**	0.0311	0.0563*	0.1623***
	L5	-	-	0.0012	-	-0.0457*
	L6	-	-	0.0378	-	-
	L7	-	-	0.0957***	-	-
	RS					
	L1	10987.85***	25702.68***	3153.172	495706.6***	1867172**
	L2	2128.839	-603.4966	6922.123*	62963.26	838816.6
	L3	1730.383	-536.7568	3357.391	121684.9	-508793.6
	L4	-	-2172.101	-3306.481	-186871.4	-1606093**
	L5	-	-	-3443.534	-	300385
	L6	-	-	-3837.885	-	-
	L7	-	-	-6526.773*	-	-
	Size					
	L1	2.7645***	6.6207***	3.1068***	692.6399***	-330.4258
	L2	-0.9814*	-2.9382***	0.3417	-4.3273	849.1693*
	L3	0.2633	-0.4128	-0.2068	111.0347	54.3804
	L4	-	-1.3967*	-0.7666**	-155.772	-59.3819
	L5	-	-	-0.6879*	-	-1162.344**
	L6	-	-	0.1487	-	-
	L7	-	-	0.3027	-	-
	Vol					
	L1	4.5385**	11.7821***	12.5267**	0.0486	3.4665
	L2	-0.4223	-2.2916	-2.1706	-0.4657	3.0376
	L3	-1.9314	1.663003	-0.1909	1.8486	0.8961
	L4	-	5.6703**	-0.8288	-0.8524	-1.0614
	L5	-	-	-4.3073	-	-0.2853
	L6	-	-	2.1275	-	-
	L7	-	-	6.1124	-	-

	DN	0.7708	-3.4961	-0.3743	69.3914	658.1339
	DW2	-1.9132	-1.8556	-3.2438	12.3788	554.1268
	DW3	0.0762	1.39403	-2.8716	-67.1089	-444.8923
	DW4	-1.2371	-1.7022	-5.1149**	-183.415	-258.989
	DW5	0.6662	0.5803	-3.9221*	42.3629	-14.0938
	DI1	2.1899	7.1408***	3.2265	23.41606	-855.0446**
	DI2	-0.9549	-5.9769***	-0.8114	-145.7603	-892.9662**
	DI3	-15.5145***	-20.4096***	-21.5873***	-1398.6***	63.7632
RS						
	AT					
	L1	-0.000000093	0.000000025	-0.00000015	0.0000000055	0.000000000072
	L2	-0.000000065	-0.000000015	0.00000024	-0.0000000049	-0.00000000099
	L3	-0.00000024	0.000000063	-0.00000022	-0.0000000067	-0.00000000028
	L4	-	-0.00000024**	0.000000019	0.000000014***	0.0000000018**
	L5	-	-	-0.00000016	-	0.00000000028
	L6	-	-	0.000000032	-	-
	L7	-	-	0.0000000076	-	-
	RS					
	L1	0.0508**	0.129004***	0.0142	0.0302	-0.0309
	L2	0.0325	-0.0114	-0.02205	0.0013	-0.0164
	L3	-0.0113	-0.0126	0.0359	0.0147	0.0029
	L4	-	0.0316	0.0285	-0.0282	-0.0076
	L5	-	-	0.02099	-	-0.0362
	L6	-	-	0.0124	-	-
	L7	-	-	-0.0107	-	-
	Size					
	L1	-0.0000069	0.0000014	0.00000052	-0.000013	0.0000083
	L2	-0.0000019	0.000003	0.0000021	-0.000023	0.0000019
	L3	-0.000006	-0.0000029	-0.0000012	-0.0000104	-0.000015
	L4	-	-0.0000012	-0.00000059	0.000039*	0.0000059
	L5	-	-	-0.0000024	-	-0.0000081
	L6	-	-	-0.00000036	-	-
	L7	-	-	0.0000016	-	-
	Vol					

	L1	0.000011	-0.00000042	-0.00011***	0.00000039*	0.000000017
	L2	0.0000028	0.000015	-0.000021	-0.00000033	-0.000000053
	L3	-0.000039**	-0.000024**	0.000018	0.00000019	0.0000001
	L4	-	0.00000069	-0.000049	-0.00000025	-0.000000042
	L5	-	-	0.0000103	-	0.00000012
	L6	-	-	0.000033	-	-
	L7	-	-	-0.000039	-	-
	DN	-0.000071***	-0.000019	0.000021	0.000023	-0.000019
	DW2	0.000014	-0.0000028	-0.0000056	0.000043*	0.0000075
	DW3	-0.0000016	0.0000031	-0.000026**	0.000012	0.000029**
	DW4	0.000013	-0.0000024	-0.000018	0.0000069	0.000014
	DW5	0.000016	-0.0000014	-0.000012	0.0000065	0.000035**
	DI1	0.0000203	-0.0000055	0.0000017	-0.0000053	-0.0000064
	DI2	0.0000038	-0.0000051	-0.000006	-0.000058***	-0.000012
	DI3	0.000028	0.000041***	0.000042***	0.000012	-0.0000047
Size						
	AT					
	L1	-0.0042***	-0.0024***	-0.0066***	-0.000017***	-0.0000018
	L2	-0.00027	0.0019**	-0.00061	0.0000073	-0.0000013
	L3	0.00015	0.00035	0.0072***	0.0000079	0.00000067
	L4	-	-0.0012	-0.0017	-0.00000079	-0.0000017
	L5	-	-	0.00013	-	0.000004**
	L6	-	-	0.0019	-	-
	L7	-	-	-0.0056***	-	-
	RS					
	L1	-257.5206***	-547.3825***	-553.0392**	-70.6586**	-116.5721**
	L2	-86.5220	-254.0277	-674.451**	-16.1103	-53.6712
	L3	-139.4729	102.1293	-72.1960	-30.5265	1.7465
	L4	-	-42.1413	314.8415	12.1332	17.4478
	L5	-	-	-61.2416	-	-40.8668
	L6	-	-	-89.0989	-	-
	L7	-	-	542.3384*	-	-
	Size					
	L1	0.1592***	0.19202***	0.1454***	0.1734***	0.2231***

	L2	0.1292***	0.1999***	0.0989***	0.1460***	0.0366
	L3	0.0947***	0.0829***	0.0673**	0.0828***	0.1011***
	L4	-	0.1091***	0.0661**	0.0977***	0.0793***
	L5	-	-	0.0525*	-	0.1113***
	L6	-	-	0.0573**	-	-
	L7	-	-	0.0056	-	-
	Vol					
	L1	0.0651	-0.0507	0.8924**	-0.00039	-0.00046***
	L2	-0.0245	-0.1074	0.084005	-0.00012	-0.00032**
	L3	-0.0691	-0.0722	0.2881	-0.000611**	-0.000302*
	L4	-	-0.1216	0.2479	-0.00031	-0.00037**
	L5	-	-	0.4257	-	0.00021
	L6	-	-	-1.3549***	-	-
	L7	-	-	-1.0931**	-	-
	DN	-0.1774*	-0.0504	-0.2013	-0.0249	-0.0149
	DW2	0.0687	0.0729	0.1293	0.0067	0.0329
	DW3	-0.0137	0.0702	0.2870*	-0.0052	0.0387
	DW4	-0.0277	0.0783	0.3743**	0.0237	0.0522**
	DW5	-0.1038	-0.0099	0.2201	-0.0074	0.0387
	DI1	-0.1335*	0.1605**	0.6891***	-0.0984***	-0.0309
	DI2	-0.0638	0.0103	-0.4744***	0.0185	0.0466**
	DI3	-0.0024	-0.0069	0.1095	0.1447***	0.0507
Vol						
	AT					
	L1	-0.0015***	-0.00104***	-0.000303***	-0.0015***	-0.000052
	L2	0.00068**	0.00044*	0.000075	-0.00013	0.00023
	L3	0.000601**	0.00075***	0.00038***	0.00049	-0.00042*
	L4	-	0.00023	-0.000072	-0.00018	-0.00054**
	L5	-	-	-0.000096	-	-0.00028
	L6	-	-	0.00015	-	-
	L7	-	-	-0.00016	-	-
	RS					
	L1	-34.74001	-38.9184	41.389***	-3361.475	17632.93***
	L2	9.0329	26.5956	-13.7054	2232.28	3693.779

	L3	78.2339***	20.2157	25.6383*	-1766.667	6020.628
	L4	-	-50.5518	-7.2506	1744.49	-966.7296
	L5	-	-	14.5223	-	-7902.069
	L6	-	-	9.2606	-	-
	L7	-	-	8.0934	-	-
	Size					
	L1	-0.0216***	-0.0307***	-0.0031**	-3.9502*	-1.8449
	L2	0.0037	0.0048	0.00024	-3.6234	-4.1442
	L3	0.0045	0.0132*	0.0038**	0.6175	-7.8476**
	L4	-	-0.000039	-0.0015	-3.6829	-5.8876
	L5	-	-	0.00076	-	-9.0086**
	L6	-	-	0.00094	-	-
	L7	-	-	-0.0016	-	-
	Vol					
	L1	0.2487***	0.2403***	0.2635***	0.1902***	0.2426***
	L2	0.0631***	0.1344***	0.0669***	0.0995***	0.1041***
	L3	0.1246***	0.0691***	0.0786***	0.00028	0.1046***
	L4	-	0.0863***	0.0388	0.1136***	-0.0043
	L5	-	-	0.0676***	-	0.0319
	L6	-	-	0.0078	-	-
	L7	-	-	0.0334	-	-
	DN	0.0888***	0.1537***	0.0549***	-2.4501	12.1504**
	DW2	-0.0119	-0.0028	0.0046	-4.4332*	2.8111
	DW3	0.0014	0.0041	0.0085	-2.9596	-5.0629
	DW4	-0.0048	0.0312**	0.0129	-2.2858	3.6051
	DW5	0.0075	-0.000069	0.0022	-1.0897	2.1738
	DI1	0.1959***	0.1636***	0.1026***	16.5386***	17.3161***
	DI2	0.0049	0.0109	0.0129*	5.25201**	5.65402*
	DI3	0.0936***	0.1091***	0.0488***	17.5953***	23.83007***

Significant at 1%***, 5%**, and 10%* levels