The Electronic Live Cattle Futures Market Bid Ask Spread Behaviors and Components

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Commodity futures markets play an important role in price discovery by synthesizing information from buyers and sellers, and in the management of risk by hedgers (Working 1970). However, the recent live cattle futures price behavior has raised doubts about market quality and raised speculation about what is behind high market volatility (e.g., Mulvany 2016; Meyer 2016). The live cattle futures price went from \$1.20/pound or below in 2013 to more than \$1.70/pound in late 2014. However, it fell sharply to around \$1.20/pound from late 2014 to 2015 (Figure 1). In this paper, we study the market quality of the Chicago Mercantile Exchange (CME) live cattle futures market by analyzing volatility and the components of liquidity costs – adverse selection, inventory, and order processing costs.

The difference between the best ask and bid on the market limit order book, the Bid-Ask Spread (BAS), has long been of interest to liquidity providers, traders, and market regulators. Since the true fundamental value of an underlying asset is usually presumed to be the midpoint of the BAS, one-half the BAS is often regarded as the market liquidity cost. Previous studies have shown that market liquidity cost changes across different trading hours and days. More informative than the BAS itself, however, is what drives liquidity costs in the first place. Liquidity costs can arise due to the presence of informed traders, liquidity providers' inventory risks, or costs related to order processing, and knowing the magnitude and behavior of these liquidity cost components has important implications for market design and efficiency.

Speculators in the futures market can provide liquidity by posting a buy/sell limit order at a specific price, they can also demand liquidity by submitting a market order to buy/sell against the best sell/buy price at the top of the order book. Since orders from both sides seldom arrive in the market simultaneously, liquidity providers quickly absorb market orders that are otherwise not absorbed. In Working (1967), floor traders generate profits by providing liquidity to markets and temporarily absorbing hedging orders. After observing quote revisions and transactions, they will post new quotes to cover their costs to supply liquidity. In the presence of informed traders, liquidity providers may increase their quotes and widen the BAS to cover the costs of trading against informed traders, as the adverse selection component increases in the electronic markets (Bryant and Haigh 2004). The liquidity provider's costs also include inventory and order processing cost components. The inventory cost component captures the liquidity provider's inventory risks as higher price volatility dramatically affects their inventory values. In addition, it also reflects the liquidity provider's waiting cost as we expect relatively low inventory cost component under more liquid market conditions. The order processing is the third source of trading friction, it is mainly affected by programming and other types of fixed costs. If order processing is the only source for the BAS, the transaction price will bounce between the ask and bid price, which induce negative serial correlation in transaction price changes.

This is the first paper to study the liquidity cost and BAS components in the live cattle futures market based on the observed market BAS. Our period of study, January 1st, 2012 to October 31st, 2015, contains tumultuous price behavior, volatility, and liquidity costs, and our findings provide clues to the market factors that created such an environment. The remainder of the article is structured as follows. Section 1 discusses previous literature of related studies. Section 2 provides a brief explanation on the Huang and Stoll model as well as the procedures taken to estimate the model. Section 3 describes the dataset we used in this research. Our empirical results are presented in section 4. The conclusion is in section 5.

Literature Review

Studies have researched liquidity costs in agricultural commodity futures markets (e.g., Bryant and Haigh 2004; Frank and Garcia 2010; Wang, Garcia, and Irwin 2014). Before intraday bid and offer quote data were available, research relied on BAS estimators to approximate market liquidity costs. These utilize successive price changes or price volatility. Bryant and Haigh (2004) examine the performance of different BAS estimators using data from the LIFFE agricultural futures markets.[1] They also divided each trading day into six equal length time intervals, and conclude that the intraday spread appears to be a weak “reverse-J” pattern. In other words, the BAS tends to be the highest at the market opening then sharply declines during midday trading hours. The BAS has a U-shaped pattern throughout a contract’s life. The BAS is wide when the delivery date is distant, then it gradually decreases as liquidity and high volume enters the contract. As expiration approaches and volume rolls to the next-to-expire contract, the BAS increases again. With a modified Bayesian method, Frank and Garcia (2010) advance the BAS studies by investigate U.S. live cattle futures markets. They find that the BAS in the CME live cattle market is generally around 0.03 to 0.05 cents per pound regardless of the BAS estimator considered.[2] They also identified that BAS has a strong negative correlation with the volume and positive correlation with the price volatility. With the availability of the tick data, Wang, Garcia, and Irwin (2014) study BAS behavior in the electronic corn futures market. Their findings are consistent with previous studies that BAS responds positively to volatility and negatively to trading volume.

These empirical results also agree with research in equity markets. From the liquidity providers’ inventory perspective, asset risk becomes relatively high as price volatility increases. In order to manage their inventory risk, liquidity providers widen the BAS with a hope to recoup their losses from holding inventories (Stoll 1976; Ho and Stoll 1983). The positive relationship

[1] Bryant and Haigh (2004) estimate the BAS with five different estimators, which are Roll’s measure (RM), Chu, Ding, and Pyun measure (CDP), Thompson-Walker measure (TWM), Commodity Futures Trading Commission estimator (CFTC), and the Smith and Whaley estimator (SW).

[2] The tick size for the CME live cattle futures contract is 0.025cents/pound.

between volume and BAS has been studied and explained by different researchers (e.g. Copeland and Galai 1983; Stoll 1989). Stoll (1989) conjectures that the inventory cost arises not only due to liquidity provider's uncertainty of the inventory returns but also due to the uncertainty of when the next transaction will occur. When a market is liquid with high trading volume, it is easier for liquidity providers to balance their inventory positions. Under such circumstances, there will be less uncertainty on both their inventory returns and liquidity.

Irwin and Sanders (2012) identify that the electronic trading volume of live cattle futures contract has grown from 7% of the total volume in 2004-2008 to 62% in 2009-2011. There have been multiple studies that compare the liquidity cost between the open outcry and electronic trading platforms. Empirical evidence from Pirrong (1995) suggests that the adoption of electronic trading does not reduce the market liquidity because of the superior capability of modern computers to handle exceedingly large trading volume. With deeper and more liquid market conditions, positive volume shocks have less price volatility effects on electronic trading markets. As the electronic trading volume goes up with declining pit trading volume, Frank and Garcia (2010) also find that the competitive pressure from electronic trading drives the BAS lower in the pit. Despite the huge price volatility in 2008-2009, Wang, Garcia, and Irwin (2014) demonstrate that the BAS in the electronic corn futures market is low and stable, often only slightly above one tick.[3] In contrast, Bryant and (Haigh 2004) hypothesize that the BAS tends to widen in the electronic market because of anonymous trading. In effect, they argue that liquidity providers face more severe adverse selection in the electronic market than in the open outcry.

[3] The tick size for the CME corn futures contract is 0.25 cents/bushel.

However, their study did not use the observed quoted BAS and they did not conduct empirical analyses to quantify the actual market adverse selection cost.

The majority of studies on liquidity costs in agricultural futures markets focus on the BAS patterns of different time intervals and the BAS determinants inside the markets. Not much research exists on BAS in agricultural futures market from a market microstructure point of view since Working (1967), who was the first one to study agricultural futures market in this context. Working noted that floor traders are willing to stand ready to absorb hedging orders that are otherwise not absorbed immediately. Public buy/sell orders are generally executed at liquidity providers' bid/ask prices. The ask price is usually slightly higher than the previous equilibrium value while the bid price is usually lower than the previous equilibrium value. With rounds of buying and selling, liquidity providers recover their cost of standing ready. In the absence of new information arrival that moves the price, transaction price can bounce between the ask and bid quotes, which cause the trade directions to be negatively correlated.

According to existing literature, there are three different cost components in the BAS, adverse selection cost, inventory cost, and order processing cost. Liquidity providers are often assumed to be uninformed, who supply liquidity to markets and receive the BAS as their compensation. Among the transactions liquidity providers make, there is a probability that liquidity providers will trade against informed traders. With new and exclusive information on hand, informed traders buy/sell if the true fundamental value is higher/lower than the current price level. Liquidity providers can lose money by trading against informed traders, and such loss is mainly due to information asymmetry (e.g. Glosten and Milgrom 1985; Grossman 1986). Such phenomenon has been verified by various empirical studies. Working (1967) discovers that professional scalpers tend to lose money when becoming the counterparty of larger hedging orders, and larger hedging orders sometimes cause more long-lived market volatility than researchers previously assumed. Stoll (1976) investigates liquidity providers' inventory behavior in stock markets. His study suggests that liquidity providers inventory levels decline prior to price increases, and increase prior to price declines. These empirical results support the idea that liquidity providers lose money against informed traders. The second BAS cost component is the inventory cost. Market buy/sell orders do not always arrive simultaneously with market sell/buy orders. When liquidity providers stand ready to supply liquidity, it is very difficult for them to balance their inventory positions consistently. Amihud and Mendelson (1980) suggest that liquidity providers operate to maintain their inventory level at a specific level. The inventory cost component increases as their current inventory levels deviate from their preferred levels. Although inventory cost component is connected with price volatility, market liquidity also has strong effects on inventory costs. Stoll (1989) points out that inventory cost components rise not only due to liquidity providers' uncertainty of the return of their inventory but also due to the uncertainty of when the next transaction will occur. In a liquid market environment, liquidity providers can balance their inventory positions easier than under illiquid markets. The last BAS cost component is the order processing cost, which reflects labor, programming, exchange clearing fees, and other types of physical and fixed costs. Order processing costs can be a large portion of the BAS. For instance, Huang and Stoll (1997) find that more than 50% of the stock markets BAS is attributable to the order processing cost, while adverse selection cost component is only less than 15%. Lin, Sanger, and Booth (1995) conclude that order processing cost has a strong negative relationship with transaction sizes.

Empirical Methods

Prior to Huang and Stoll's (H-S) (1997) framework, there were several empirical models to decompose the BAS (e.g. Glosten and Harris 1988; Madhavan, Richardson, and Roomans 1997). But none provided a complete decomposition into the BAS's three components. For example, Glosten and Harris (1988) developed one of the earliest BAS decomposition model, but it only decomposes the BAS into adverse selection cost and transitory cost. In allowing for liquidity providers inventory behavior and trade direction reversal based on Roll (1984), H-S is the first model to decompose the market effective BAS into three different components.

The empirical H-S model depicts market microstructure and liquidity provider inventory behavior based on a study by Stoll (1989). In the first scenario, the BAS only reflects the order processing cost. At "time 0" (t_0), liquidity providers purchase at the bid price then sell at the ask price at t_1. Buy orders at the bid prices will be ultimately offset by sell orders at asks. The market asks and bids always straddle the true equilibrium price, and the effective BAS in this scenario is equal to the quoted BAS. In the second scenario, BAS only reflects liquidity providers' inventory costs. After a public sell, liquidity providers lower the bid and ask quotes to induce a public buy and impede additional public sells, which help liquidity providers to manage their inventory risks. The new quotes are set such that the liquidity provider is indifferent in absorbing an addition public sell at the bid and absorbing a public buy at the ask. Such liquidity providers' behavior were modeled by Ho and Stoll (1981) and (Stoll 1978). In the third scenario, the BAS only reflects adverse selection costs. As Copeland and Galai (1983) and Glosten and Milgrom (1985) suggest that liquidity cost still exists even when liquidity providers have zero inventory and fixed costs, because liquidity cost is also affected by adverse selection. Liquidity providers are generally assumed to be uninformed but they have ex ante expectations on the probability that the next trader is informed. New information is conveyed to the marketplace after an informed transaction, liquidity providers post new quotes to match their new beliefs on the true asset value. For example, liquidity providers lower their bid and ask quotes after a public sell if the previous transaction conveys new information that the expected asset equilibrium value is lower. Once private information is revealed immediately after a trade, liquidity providers revise their belief on the asset fundamental value then post new quotes, so that the new quotes straddles the new equilibrium value. The fundamental value is hypothetical since we cannot directly observe it. In the H-S model, they model the adverse selection and inventory costs by observing the quote midpoint changes.[4]

The H-S (1997) model is also named the "three-way" decomposition model because it decomposes the effective BAS into three different components. The basic version of the H-S model is shown in equations (1) and (2).

(1) $Q_{t-1} = (1 - 2\pi)Q_{t-2} + \delta_{t-1}$

(2) $\Delta M_t = \frac{1}{2}(\alpha + \beta)(S_{t-1}Q_{t-1}) - \frac{1}{2}\alpha(1 - 2\pi)S_{t-2}Q_{t-2} + \varepsilon_t$

The subscript (t) in the model denotes occurrences of consecutive events, ΔM_t is the quoted midpoint change, S_t is the observed BAS, α is the proportion of the half effective BAS that is due to adverse selection, β is the proportion of the half effective BAS that is due to inventory cost, π is the probability of a trade reversal, and Q_{t-1} is the trade indicator. $Q_t = 1$ denotes a public buy and $Q_t = -1$ denotes a public sell. Liquidity providers revise their quotes after observing the trade indicator from t-1. In this model, $(1 - \alpha - \beta)$ is the proportion of order processing cost component of the effective BAS. Equation (1) derives the expectation of Q_{t-1} after observing Q_{t-2},

[4] For a more detailed explanation and an illustration of the mechanism see Stoll (1989).

which allows the probability of trade reversal to be different from 0.5. The right-hand side of equation (2) can be rewritten as: $\frac{1}{2}\alpha(S_{t-1}Q_{t-1} - (1-2\pi)S_{t-2}Q_{t-2}) + \frac{1}{2}\beta S_{t-1}Q_{t-1}$. The term $(S_{t-1}Q_{t-1} - (1-2\pi)S_{t-2}Q_{t-2})$ is the observed trade direction at t-1 minus its expectation after observing Q_{t-2}, which expresses the unpredictable trade innovation at t-1. This unpredictable trade innovation is attributable to the private information that results in adverse selection cost. Therefore, after observing Q_{t-2} and S_{t-2} at time t-2, the non-surprise proportion is not considered in the estimation of the adverse selection component (α) in the H-S model. In equation (2), the second term on the right hand side represents the proportion of information that is not a surprise.[5]

We estimate the H-S model with the generalized method of moments (GMM), the same procedure used by t H-S. Unlike the maximum likelihood or least square estimations, the GMM procedure imposes weak distributional assumptions on error terms, which is often unknown and hard to identify. Under weak assumptions, Hansen (1982) shows that the GMM estimators are consistent and normally distributed. In addition, both Newey and West (1994) and Andrews and Monahan (1992) show that applying the pre-whitening process with the first-order vector auto-regression prior to the application of the Newey and West (1994) procedure can produce more consistent and efficient estimators. With unknown forms of disturbance autocorrelation and heteroscedasticity, we apply the Newey-West error terms in our statistical analysis.

Data

The empirical analysis is based on the BBO dataset from the CME electronically-traded live cattle futures market from January 1st, 2012 to October 31st, 2015. The BBO data contains all transactions and top-of-book quote revisions for all active contracts in the Globex trading

[5] For more detailed model derivation, see Huang and Stoll (1997). Shang, Mallory, and Garcia (2016) also provide a more elaborated interpretation of the H-S model.

platform. Each best bid price is paired with another best ask price, the number of contracts available to trade is also recorded with the corresponding quotes. A new record is updated and recorded if either the BBO quote or size changes. All quotes and transactions are recorded in chronological order, and each record has a time stamp to the nearest second. We use nearby contracts that are rolled to the first deferred contract on the first day of the contract maturity month. We also limit our study to the day time trading session.

In this study, the observed quotes BAS is the best offer minus the best bid. The volatility measure is the standard deviation of quote midpoints, which is the same used by Wang, Garcia, and Irwin (2014) and Shang, Mallory, and Garcia (2016). When applying the H-S model, the trade direction indicator is generated with the method provided by Lee and Ready (1991). The Lee and Ready classifies trades above the quote midpoint to be buy orders and trades below quote midpoint to be sell orders. Transactions executed at the midpoint are classified to be buy/sell orders if the transaction price is above/below the previous transaction price. If there is no price change on midpoint-executed trades, then the trade indicator is classified to be the same as the last transaction.

Results

Figure 1 shows the nearby futures contract settlement prices and the daily volatility in the live cattle futures market. The daily settlement price was relatively stable in 2012 and 2013, then the price volatility increased in 2014 and 2015. The live cattle price reached its highest 3-year record at $1.71/pound in 2014, it then experienced a sharp slump reaching nearly $1.20/pound in 2015. Daily market volatility is measured by the standard deviation of quote midpoints. From 2012 to 2015, daily volatility changes sharply throughout the period, with numerous observed spikes. Overall, the price volatility is slightly lower in 2012 and 2013 than 2014 and 2015. The market volatility is especially high during late 2014 and early 2015, which is also the same time period that live cattle price reached record highs.

Table 1 provides the live cattle market liquidity measures for each year. The live cattle market quoted BAS is generally between one to two ticks (one tick is 0.025 cents/pound). For example, in 2012, the daily mean BAS is 0.035 cents/pound in the live cattle market, which is about 33% higher than the minimal tick. With higher price volatility in 2014 and 2015, the market quoted BAS also increases. From 2012 to 2015, the highest BAS is 0.041cents/pound in 2015, which is about 50% higher than the minimal tick and 16% higher than the BAS in 2012. The second column in Table 1 shows average daily volatility year by year. It provides us further evidence that live cattle prices are more volatile during the period of 2014 to 2015. In addition, we also see that the day-time electronic trading volume increases from 2012 to 2015. The increment of trading volume can be due to the positive relationship between volume and volatility and may also be due to the trend of volume transferring from pit to electronic system. From 2012 to 2015, the daily mean transaction size is only between one to two contracts, the standard deviation of the transaction size further indicates that majority of the transactions are made with a size of one contract.

Figure 2 provides the market quoted BAS and the daily trading volume. Prior to sharp price increases in mid-2014, the market BAS is slightly above a tick. This result is in line with Frank and Garcia (2010), who finds that the BAS in the live cattle futures market is usually between 0.03-0.05 cents/pound. As price volatility increased, the quoted BAS also increased and has been relatively high since mid-2014. On occasion, the quoted BAS was more than two ticks. Daily electronic trading volume has increased sharply with a number of regular and dramatic declines. Irwin and Sanders (2012) demonstrate that monthly electronic trading volume in the live cattle market increased sharply from 2000 to 2011. From 2012 to 2014, the daily average trading volume only changes slightly year by year. However, the daily average trading volume in 2015 is at least 10% higher than any of the three other years. In addition, from Table 1, we see a slight decrease in average trade size in 2015 in comparison to previous years. With larger trading volume and smaller transaction size, we suspect there may be more noise transactions in 2015.

BAS Components

For each of the 953 trading days from January 2012 to October 2015, we estimate the BAS components. Our empirical results show that only a small proportion of the BAS is due to adverse selection cost, and the largest BAS cost component is the order processing cost. The mean adverse selection cost component (α) is only 1.8% of the BAS, while the mean inventory cost component (β) is 15.6%. The order processing cost component is 82.6%. Our finding of large order processing cost component is in line with the study by Huang and Stoll (1997); their research from the stock markets show that market BAS is mainly due to order processing cost, while adverse selection and inventory cost components are both small. The findings differ from Shang, Mallory, and Garcia (2016), who find larger adverse selection cost in the CBOT corn futures market and inventory cost is the largest cost component there. A low adverse selection cost component also contrasts with Bryant and Haigh (2004) view that anonymous trading in the electronic futures market can lead to more severe adverse selection issues.

From our empirical results (Figure 3), it is clear that most of the adverse selection component estimations are not statistically different than zero in the live cattle futures market. With increasing number of transactions per day and low market adverse selection cost component, one might infer that there is relatively more uninformed liquidity trading in the live cattle futures market. As the number of market participants has increased, perhaps the number of informed traders may not have increased as fast as uninformed traders. Therefore, the probability of liquidity providers facing informed traders becomes low, which is reflected by low adverse selection cost component.

The inventory cost component seems to have a slight upward trend from 2012 to 2015 (Figure 3). A vast majority of the inventory cost component estimates are statistically significant at 5% significance level which contrasts with the adverse selection component. In a four-year average, 15.6% of the BAS is attributable to the inventory cost component. The inventory cost components in 2012 and 2013 are mostly below the four-year average, while the inventory cost component in the latter two years are greater than the four-year average. The liquidity provider's inventory cost component reflects both market volatility and liquidity. Higher price volatility indicates higher inventory risk for liquidity providers, because unbalanced inventory positions can cause huge loss to liquidity providers. Considering the fact that live cattle price was exceedingly volatile during 2014 and 2015, it is reasonable that the inventory cost component is relatively higher during that time than other years. In addition, it is important to keep in mind that the quoted BAS increases dramatically in 2014 and 2015 in comparison with the other years, a small increment in the inventory cost component is still a large dollar amount per traded contract than would have been the case in 2012 and 2013.

Figure 3 also provides the daily order processing cost component. We use the Delta Method to calculate the significance of the daily order processing cost component with the use of the coefficient variance-covariance matrix. Nearly all of the order processing estimations are significant at 5% significance level. This is similar to Huang and Stoll (1997), who find a large proportion of the BAS is due to order processing cost. Research has shown that order processing cost declines as the size of order increases, which is due to economies of scale (Lin, Sanger, and

Booth 1995). There is always a fixed amount of cost to match and execute an incoming order regardless of the order size. When a market order arrives at the exchange clearing house, it is matched with an existing limit order, liquidity providers' inventory, or another market order that arrives nearly simultaneously. The amount of fixed cost to match and execute orders can spread over more contracts for a large order, so the order processing cost component per contract declines. In contrast, the small average order size which we observe in our sample can be one explanation for high order processing cost component. In addition, in the H-S model that we adopted here, order processing cost component (1-α-β) captures all costs except adverse selection and inventory costs. Therefore, other than fixed costs, (1-α-β) can also include liquidity providers' risk premium and profit from supplying liquidity. From earlier market microstructure studies, liquidity providers are assumed to be risk neutral. If the liquidity provider becomes more risk averse due to volatile market prices, order processing cost could also increase to cover a risk premium for the liquidity provider. Finally, notice a decreasing pattern of the order processing cost component throughout the period. The order processing cost component contributed more than 80% of the market liquidity cost in 2012, and this number (on average) decreases to below 80% in 2015. The explanation for this modest decline is not completely evident, but appears to be related to increasing market volatility which has raised the inventory costs of BAS.

Conclusion

The CME Group closed most of its pit trading in July 2015; electronic trading is now the only platform for live cattle futures trading. Under a more efficient and fast trading environment, there are numerous concerns about the live cattle futures market liquidity and volatility, especially after unprecedented price fluctuation in 2014 and 2015. A particular concern is that the presence of informed traders who can execute quotes and transactions rapidly have an unfair advantage in the electronic futures markets (Meyer 2016) .In this research, we study the magnitude of the BAS in the electronically traded live cattle futures market. Furthermore, in order to study the market adverse selection issue, we decompose the BAS into three different components with the H-S model, which are adverse selection, inventory, and order processing cost components, to examine this extraordinary period in the live cattle futures market.

The evidence suggests that the electronic live cattle futures market has maintained relatively low liquidity cost during most of the period. From 2012 to 2013, the live cattle price was relatively stable, the market quoted BAS was generally not much more than the minimal tick (0.025 cent/pound). Since late 2014 when the daily nearby live cattle futures price became more volatile, we also see large volatility in the bid-ask revisions. Consistent with previous literature that volatility and BAS has a strong positive correlation, our empirical results show that the market BAS during 2014 and 2015 is higher than the other two years. During 2014 and 2015, live cattle futures market BAS increased to nearly two ticks and almost reached three ticks on some trading days. When price is extremely volatile, liquidity providers may become more cautious so that they post quotes with relatively wide BAS to the public. As the statistical evidence shows that the inventory cost component increased slightly from 2012 to 2015, this indicates that liquidity providers post wider BAS in order to cover higher inventory return risk under more price volatile conditions.

Overall, the adverse selection cost component is small and the order processing cost is the largest cost component. Throughout the entire period, market quoted BAS remains between one to two ticks with a few exceptions during times of high price volatility. These findings provide important implications on the live cattle futures market quality. The market is able to incorporate private information rapidly because relatively high market liquidity and sufficient amount of noise traders can better absorb new information shocks. In addition, low liquidity cost can also stimulate trading on information about fundamentals. With the market efficient enough to quickly find the new price equilibria after information shocks, it can act relatively well on the price discovery role.

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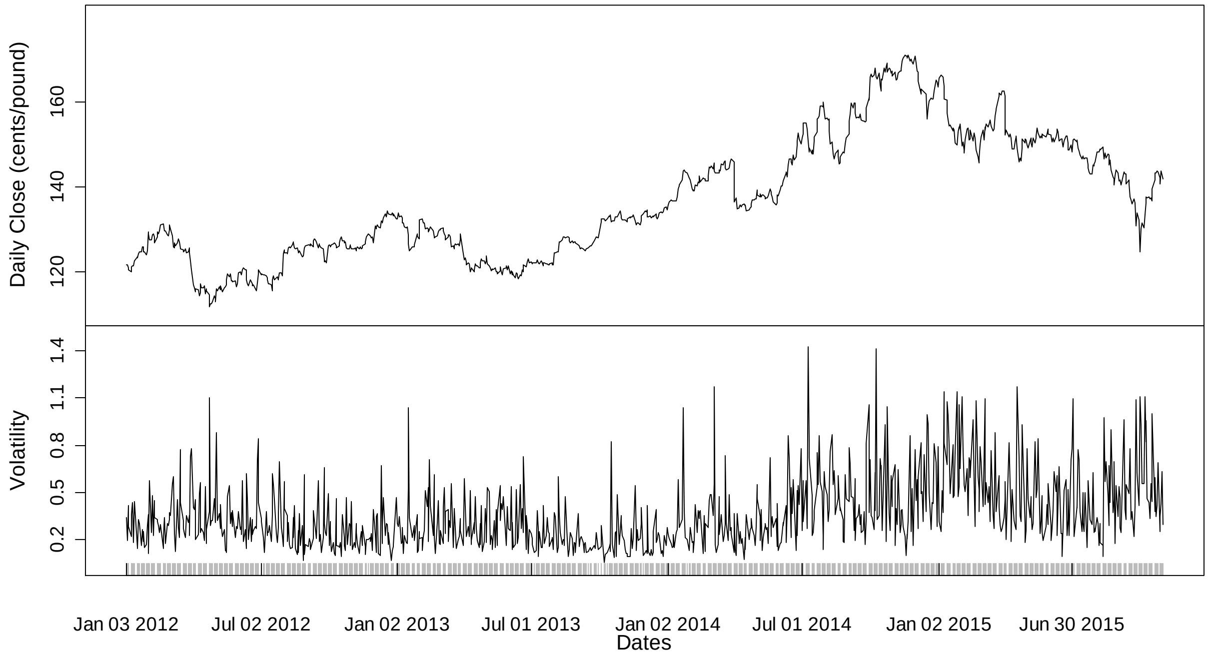
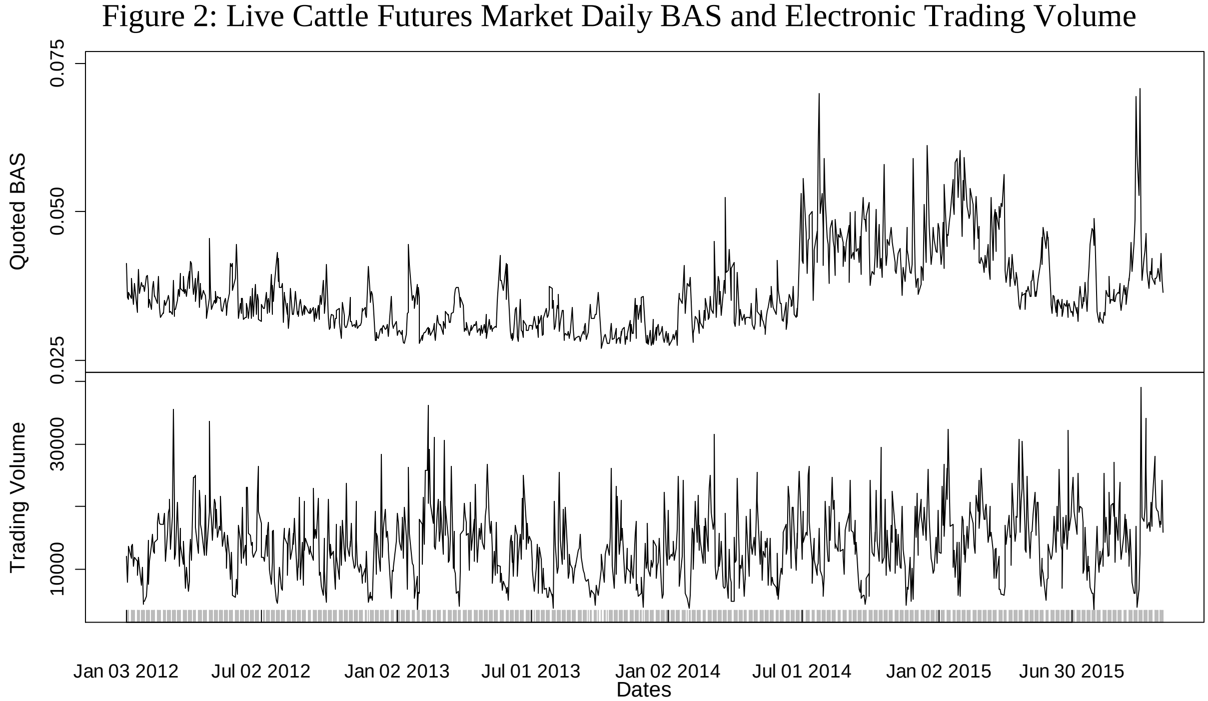
Figure 1: Live Cattle Nearby Futures Daily Settlement Price and Market Volatility



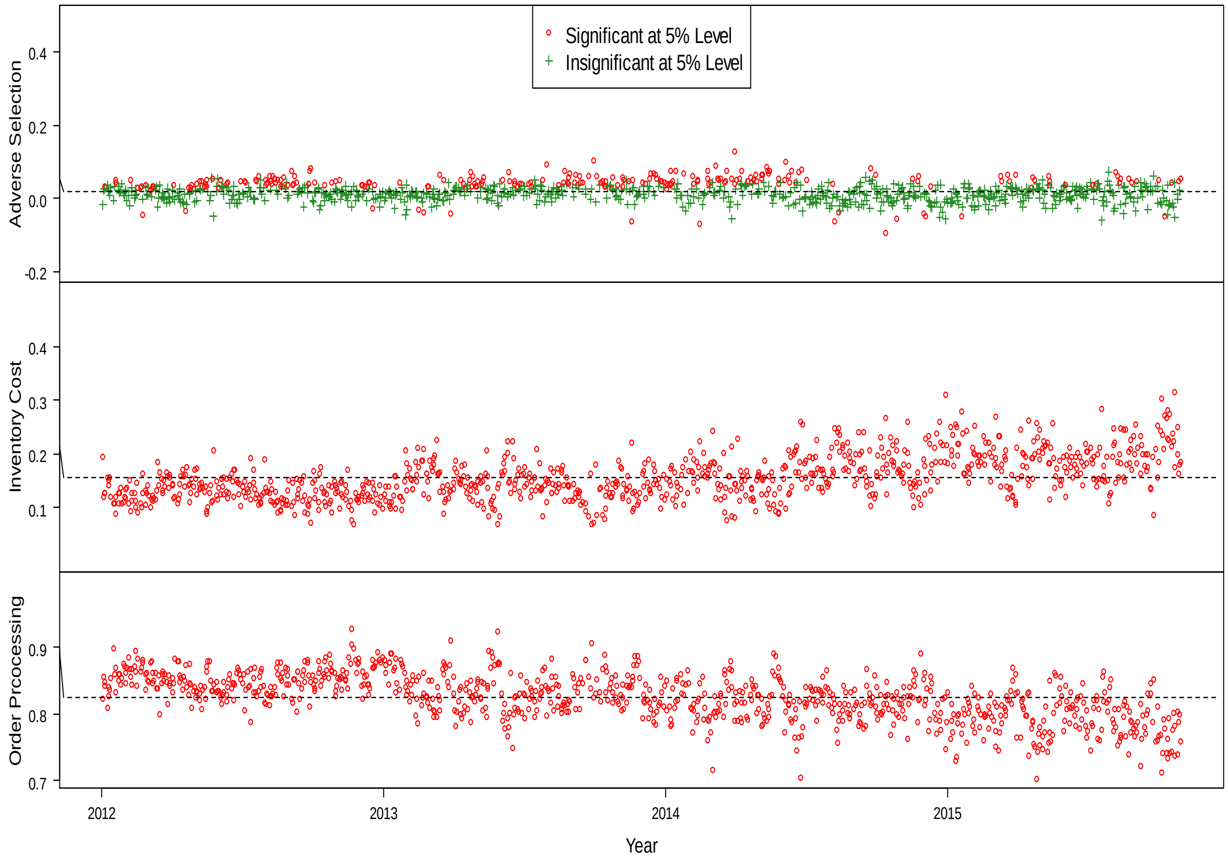
Notes: Figure 1 are daily estimates for the daily settlement price and volatility. *Volatility* is measured by the standard deviation of quote midpoints of all transactions of each trading day.

Figure 2: Live Cattle Futures Market Daily BAS and Electronic Trading Volume



Notes: Figure 2 are daily estimates for the daily quoted BAS and trading volume. *Quoted BAS* is the average BAS on each trading day. *Trading volume* is the total number of contracts traded during daytime trading hours on each trading day.

Figure 3: Live Cattle Futures Market BAS Components



Notes: Figure 3 are daily estimates for the adverse selection cost component (α), inventory cost component (β), and order processing cost component (1-α-β). The dash line on each panel represents the mean value of the α and β, and (1-α-β). Each circle/cross represents a day, and we use crosses and circles to distinguish from significant days (circles) from non-significant ones (crosses) at the 5% significance level. We use the Delta Method to calculate the standard errors and statistical significance of the daily order processing cost components.

Table 1: Summary Statistics

Year	QBAS	Volatility	Volume	Average Trade Size	Number of Trades
Mean					
2012	0.035	0.295	13517	1.539	8731
2013	0.031	0.255	13086	1.523	8536
2014	0.040	0.402	13685	1.493	9118
2015	0.041	0.508	15925	1.404	11281
Maximum					
2012	0.046	1.103	35621	1.882	20813
2013	0.045	1.035	36165	1.813	21448
2014	0.070	1.428	31559	1.869	20354
2015	0.071	1.173	39082	1.952	27887
Minimum					
2012	0.028	0.069	4366	1.251	2982
2013	0.027	0.055	2992	1.305	2051
2014	0.027	0.072	3821	1.260	2673
2015	0.031	0.090	3084	1.235	2012
Standard Deviation					
2012	0.003	0.157	5048	0.121	3050
2013	0.003	0.143	5657	0.102	3446
2014	0.007	0.234	5381	0.098	3390
2015	0.007	0.251	6080	0.086	4097

Notes: This table shows the daily average of market measures from each year. *QBAS* is the observed quoted spread. *Volatility* is the standard deviation of the quote midpoints. *Volume* is the number of contracts traded per day. *Average Trade Size* represents the average size of the transactions from each trading day. *Number of Trades* is a measures the number of trade occurrences for each trading day.