Bid-Ask Spreads, Volume, and Volatility:
Evidence from Livestock Markets

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Abstract

Understanding the determinants of liquidity costs in agricultural futures markets is hampered by a need to use proxies for the bid-ask spread which are often biased, and by a failure to account for a jointly determined micro-market structure. We estimate liquidity costs and its determinants for the live cattle and hog futures markets using alternative liquidity cost estimators, intraday prices and micro-market information. Volume and volatility are simultaneously determined and significantly related to the bid-ask spread. Daily volume is negatively related to the spread while volatility and volume per transaction display positive relationships. Electronic trading has a significant competitive effect on liquidity costs, particularly in the live cattle market. Results are sensitive to the bid-ask spread measure, with a modified Bayesian method providing estimates most consistent with expectations and the competitive structure found in these markets.

Key words: Bayesian estimation, bid-ask spread determinants, liquidity cost

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In agricultural futures markets, traders face a variety of transaction costs including brokerage fees, exchange fees, and liquidity costs which influence the effectiveness of marketing decisions. The first two costs are available, but estimation of liquidity costs is challenging, and is often performed using a measure of the bid-ask spread (BAS). Regardless the measure, there is evidence that the liquidity costs change over time and with market conditions. Identifying the factors that influence liquidity costs is of substantial value for participants and decision makers operating in the market. For instance, the cost of placing an order on a lightly traded day may be higher than the same order a few days later if trading activity increases. Hence, understanding the determinants of liquidity costs can help identify cost-reducing opportunities in marketing decisions.

Our understanding of the factors that influence liquidity costs in agricultural futures markets is limited for several reasons. In most agricultural markets, liquidity costs are not directly observed and proxies must be used. Also, previous research in agricultural markets generally has been performed for short periods of time, mainly due to data availability and computational complications associated with high frequency intraday data (e.g. Thompson and Waller 1988, Brorsen 1989). These short-term investigations make it difficult to identify the presence of contract and time-to-maturity effects. Further, in light of the increase in electronic trading in agricultural markets, relationships may have changed and its effect on pit-trading liquidity costs is not clear. For instance, Bryant and Haigh (2004) provide evidence in cocoa and coffee markets that bid-ask spreads widened with electronic trading, a result that contrasts with Pirrong's (1996) findings for financial futures. Cocoa and coffee markets are thinly traded, and it is not clear whether more actively traded agricultural markets follow a similar pattern. In addition, both studies examined the effect of electronic trading on a combined bid-ask spread, and did not identify the effect of electronic trading on pit trading. While electronic trading has increased markedly, in many agricultural markets pit trading is still a viable alternative, and the effect of electronic trading on the cost of liquidity is of interest to decision makers. Finally, previous work has not accounted for the potential simultaneity between the factors influencing liquidity costs and bid-ask spread measures. Reported determinants of liquidity costs may not totally reflect causal relationships, but rather be a result of a common dependence on latent information flows which influence volume, price variability, and BAS measures. Modeling agricultural futures markets in a simultaneous framework may permit a better understanding of their structure and dynamics (Wang and Yau 2000).

The paper estimates liquidity costs and its determinants in lean hogs and live cattle markets using several bid-ask spread measures, taking into account the simultaneous relationship between market information and BAS. To our knowledge, no research on the determinants of BAS in these livestock markets exists. We use the *volume by tick* database from the CME group which provides prices and volume of all trades executed during the day in the open outcry. We estimate liquidity costs for the period 2005-2008 using different estimators including recently developed Bayesian methods. The period of analysis covers almost all contracts traded in 2005 to 2008. We use a generalized-method-of-moments instrumental variable (GMM IV) estimator which permits consistent and efficient estimation in the presence of simultaneity, autocorrelation, and heteroscedasticity. In the analysis we examine the effects of days to maturity, day of the week, volume per transaction, and the relative proportion of electronic trading as well as volume and volatility variables identified in the literature.

Our findings suggest that volume and volatility are endogenous variables and significantly related to the bid-ask spread. Consistent with expectations, volume and volatility are simultaneously determined and significantly related to the bid-ask spread. Daily volume is negatively related to the spread while volatility and volume per transaction generally display positive relationships. In live cattle we also find electronic trading and day of the week effects to have a significant effect. Results are sensitive to the measure of the bid-ask spread, with Bayesian methods providing estimates of liquidity costs and its determinants consistent with a competitive structure found in these markets. These findings should be of interest to decision makers seeking to implement cost-reducing marketing strategies and to manage their liquidity risk.

Background

Few studies have investigated the relationship between the bid-ask spreads and its determinants in agricultural futures markets. Most of this research has analyzed the effect of trading volume, volatility, and time to contract maturity of grains on a measure of BAS, often using the Roll (*RM*) or Thompson-Waller (*TW*) measures. Recent studies have incorporated structural changes in trading mechanisms such as the opening of electronic markets.

An impediment to studying the relationship between BAS and its determinants is the measurement of the BAS. A lack of bid-ask quotes in U.S. exchanges makes it difficult to estimate these relationships directly. Even when estimators exist, their differences may distort the BAS-determinant relationship (Bryant and Haigh 2004). For instance, analyzing liquidity costs for corn and oats contracts traded in the Chicago Board of Trade (CBOT), Thompson and Waller (1988) find a positive relationship between trading volume and BAS when Roll's measure is used, but a negative relationship when the *TW* estimator is used.

Nevertheless, several studies provide insights into the determinants of liquidity costs in agricultural markets. Thompson and Waller (1988) find that price volatility explained bid-ask spread movements. Using the first difference of the variance of prices, price volatility consistently has a positive effect on the BAS, indicating that an increase in market uncertainty translates into higher cost of holding risky positions for scalpers.

Brorsen (1989) identified factors affecting liquidity costs in corn for six contract months between 1983 and 1984. Liquidity costs are measured as the standard deviation of log price changes and scalpers' returns using naïve trading rules. Maturity (number of months prior to expiration), volume and seasonality are the factors examined. Volume and seasonality are significant in explaining liquidity costs; however volume is negatively related to the standard deviation whereas it is positively related to scalpers' returns.

Further evidence of the negative relationship between volume and liquidity costs is provided by Thompson, Eales, and Seibold (1993) who compare liquidity costs of wheat futures contracts from two exchanges with different trading activity, Chicago and Kansas City. Liquidity costs estimated using *RM* and *TW* measures in Kansas City (the exchange with the lowest volume) were found to be higher than in Chicago. In addition, liquidity costs at both exchanges also increased during the expiration month. Other corroborative evidence on the importance of volume was identified by Thompson and Waller (1987) who examined the level of trading activity in coffee and cocoa contracts on the New York Board of Trade (NYBOT) and found lower execution costs in actively traded nearby contracts relative to thinly traded more distant contracts. It is important to note that none of the above studies use volume per transaction to explain BAS. Thompson and Waller (1988), and Brorsen (1989) recognize that the volume per transaction should be included as a determinant of the BAS, however these data were not available.

In a more recent study, Bryant and Haigh (2004) find a negative and significant relationship between volume and BAS and a positive relationship between volatility and BAS for LIFFE coffee. In cocoa these same relationships appear only after moving to electronic trading. Bryant and Haigh (2004) also find the spread widened after the introduction of electronic trading which they attribute to an adverse selection problem. An important difference in this study for agricultural markets is that Bryant and Haigh use actual bids and asks for which these relationships are expected to be reliable.

Findings financial futures markets are more extensive. Here, we discuss several salient studies that focus on issues related to our research. Ding and Chong (1997) study the determinants of the BAS of the Nikkei stock index futures trading in the Singapore Monetary Exchange (SIMEX) using tick bid and ask quotes. The BAS is found to be positively correlated with volatility and negatively correlated with trading activity. Volatility is measured as the standard deviation of transaction prices and the positive relationship is explained by the risk that market makers face. Trading activity is measured by the number of transactions and its negative relationship is explained by the existence of scale economies which result in a lower BAS as trading activity increases. Daily percentage BAS is found to be at a minimum and flat from 13 days to 3 days prior to maturity which coincides with active trading in the nearby contract, but increases slightly in the last two days. In another study, Ding (1999), investigating the foreign exchange (FXF) futures market, also finds a negative relationship for number of transactions and a positive relationship for volatility. The findings show that there are differences in BASs by delivery months, suggesting the presence of a seasonal effect in BASs, and reveal that it may be less costly to transact in specific contracts.

Wang and Yau (2000) find that trading volume, BAS, and price volatility are jointly determined in two financial (S&P500 and deutsche mark) and two metal (silver and gold) futures contracts, and that failure to account for simultaneity leads to downward biased parameter estimates. Using a GMM estimation procedure, their results indicate trading volume and BAS are negatively related, and price volatility and BAS are positively related. While their findings are intuitive, the strength of the results may be compromised because their procedures do not account for the autocorrelation and heteroscedasticity often found in these markets.

Pirrong (1996) argues that the cost of liquidity in the open outcry and the electronic systems are different. Scalpers in the open outcry are less vulnerable to adverse selection because they observe information on the floor and they know which brokers are bidding and offering so they can anticipate incoming orders. In contrast to liquidity suppliers in the computerized system, scalpers in the pit do not have real time access to fundamental information. Using *RM* and *TW* measures and computerized DTB and LIFFE Bund contracts, he finds that the computerized system is more liquid than the open outcry, a finding that contrasts with Bryant and Haigh's (2004) results in cocoa and coffee markets where the spread has widened after the trading was automated.

Bid-Ask Spread Measures

To develop an improved understanding of the relationship between liquidity costs and their determinants, we use four bid-ask spread estimators, Roll's (*RM*) serial covariance (Roll 1984), Thompson-Waller's (*TW*) mean absolute price change (Thompson and Waller 1987), Hasbrouck's (*HAS*) Bayesian (Hasbrouck 2004), and a modified Bayesian estimator (ABS) using absolute price changes. Previous research has identified rather large differences in bid-ask costs using various measures (e.g. Bryant and Haigh 2004), but none has examined systematic differences using Bayesian methods and their effect in identifying the determinants of liquidity.

The *RM* estimator is based on the negative serial dependence of successive observed price changes. Its main assumptions are that the market is informationally efficient and that each transaction is equally likely to be a purchase or a sale. The estimator for the half BAS is computed as follows,

(1) $$RM = \sqrt{-\operatorname{cov}(\Delta p_{\tau}, \Delta p_{\tau-1})}$$

where Δp_{τ} are observed log transaction price changes at time τ, $\tau = 1, \ldots \tilde{\tau}$. The *TW* estimator captures the changes induced by the placement of buy and sell orders. Buy (sell) orders increase (decrease) the average price level and therefore the mean absolute price change would reflect the execution cost of trading,

(2) $$TW = \frac{1}{\tilde{\tau}} \sum_{\tau=1}^{\tilde{\tau}} \left| \Delta p_{\tau}^{*} \right|$$

where Δp_{τ}^{*} are the non-zero price changes.

The Bayesian estimators are based on Roll's model,

(3) $$p_{\tau} = m_{\tau} + cq_{\tau}$$

where m_{τ} is the log efficient price. Buyers announce the highest price they are willing to pay (bid) and sellers announce the lowest price they are willing to accept (ask), c is the half BAS, $q_{\tau} = \{+1$ for a buy, -1 for a sell$\}$ is the trade direction indicator so that the (log) ask price is $a_{\tau} = m_{\tau} + c$, the (log) bid price is $b_{\tau} = m_{\tau} - c$, and the difference is the BAS, or $2c$. Assuming that the efficient price follows a random walk, and taking differences in (3), the BAS is the estimated coefficient in the model,

(4) $$\Delta p_{\tau} = c\Delta q_{\tau} + u_{\tau} \qquad u_{\tau} \sim N(0, \sigma_u^2)$$

The Bayesian methods to estimate c use a Markov Chain Monte Carlo simulation, the Gibbs sampler, where sample values of c, $q = (q_1, \ldots, q_{\tilde{\tau}})$, and σ_u^2 are drawn from their conditional distributions based on observed (log) transaction prices $p = (p_1, \ldots, p_{\tilde{\tau}})$. After a sufficiently large number of iterations the sample values converge in distribution to the joint distribution $F(q, c, \sigma_u^2 | p)$. In the *HAS* estimator, the conditional distribution of c is truncated and restricted to positive values, $c|p \sim N^+(\mu_c^{post}, \Omega_c^{post})$, $\mu_c^{post} = Dd$, $\Omega_c^{post} = \sigma_u^2 (\Delta q' \Delta q)^{-1}$, $D^{-1} = \Delta q' (\sigma_u^2)^{-1} \Delta q + (\Omega_c^{prior})^{-1}$, and $d = \Delta q' (\sigma_u^2)^{-1} \Delta p + (\Omega_c^{prior})^{-1} \mu_c^{prior}$. The truncation imposes non-negativity of costs and permits identification in a sampling framework.

The *ABS* is similar in structure to *HAS* estimator, but uses absolute values to ensure non-negative costs. Specifically, in the *ABS* estimator the conditional distribution of c uses the absolute values of Δp and Δq, $c|p \sim N(\mu_c^{post}, \Omega_c^{post})$, $\mu_c^{post} = Dd$, $\Omega_c^{post} = \sigma_u^2 (|\Delta q|'|\Delta q|)^{-1}$, $D^{-1} = |\Delta q|' (\sigma_u^2)^{-1} |\Delta q| + (\Omega_c^{prior})^{-1}$, $d = |\Delta q|' (\sigma_u^2)^{-1} |\Delta p| + (\Omega_c^{prior})^{-1} \mu_c^{prior}$. The priors and the conditional distributions of q and σ_u^2 for both *HAS* and *ABS* are as in Hasbrouck (2004), $\mu_c^{prior} = 0$, and $\Omega_c^{prior} = 10^6$, $\sigma_u^2 | p \sim IG(\alpha^{post}, \beta^{post})$, $\alpha^{post} = \alpha^{prior} + \tilde{\tau}/2$, and $\beta^{post} = \beta^{prior} + \Sigma u_\tau^2/2$, with $\alpha^{prior} = \beta^{prior} = 10^{-12}$, and $q_\tau^{post} | p \sim Bernoulli(p_{buy})$, where

$p_{buy} = e^{4cp_t/\sigma_u^2} \left(e^{2c(m_{t-1}+m_{t+1})/\sigma_u^2} + e^{4cp_t/\sigma_u^2} \right)^{-1}$ is the probability that $q = +1$, and

$q_t^{prior} \sim Bernoulli(1/2)$.

Based on previous findings we expect differences among estimators (Bryant and Haigh 2004, Hasbrouck 2004). When the assumptions of informational efficiency and equal probability of buy and sell incoming orders do not hold the *RM* estimator will be biased. Hasbrouck (2004) demonstrates that *RM* is upward biased for several futures markets including pork bellies. Also, when the covariance between successive price changes is positive the *RM* estimator cannot be computed. The *TW* measure has been criticized because it does not distinguish true price change from bid-ask spread, and therefore may provide an upward estimate of the BAS (Smith and Whaley 1994). The Bayesian estimators do not have these limitations since they do not assume efficient incorporation of information, and the probability of buy and sells are computed conditional on the transaction prices. In addition, since the Bayesian methods are estimated using a Markov Chain Monte Carlo simulation, they permit a more precise identification of liquidity costs. Findings suggest that the *HAS* estimator tends to generate unexpectedly small measures of liquidity cost. Hasbrouck argues that the procedure more accurately reflects market dynamics because it does not impose efficiency in equation (4), which is assumed in the *RM*, but rather estimates the autocorrelation and incorporates it into the liquidity cost measure. However, it is uncertain whether the autocorrelation incorporated into the liquidity is due to market dynamics or a function of the truncation imposed. It is clear that truncation influences the mean and variance of a distribution and the degree to which observations are autocorrelated, and in a sampling framework the direction of the effects and their magnitude are not evident. Here, we circumvent these issues by using absolute values in the *ABS* measure that also ensures non-negativity and may allow the observations to reflect more accurately the distribution of liquidity costs.

Determinants of the Bid-Ask Spread

Scalpers supply liquidity to the market by providing quotes and standing ready to buy contracts at a bid price and to sell them at an ask price. Holding an outstanding long or short position for a period of time means the scalper is subject to risk. If bad news enters the market after a large buy, the scalper may have to sell the contracts at a much lower price than the purchase price. For bearing this risk a scalper earns the spread, the difference between bid and ask prices.

With low trading activity, the time between trades is longer, and the risk that the scalper faces is higher (Brorsen 1989). Similarly, high trading activity is associated with lower risk, lower liquidity costs and lower spreads. Consequently, volume is negatively related to the bid-ask spread. In contrast, large individual orders may have an opposite effect on spreads. For instance, a scalper buying a large order may have trouble liquidating the position quickly, thus increasing risk. Volume per transaction is therefore a dimension of volume that we expect to positively influence bid-ask spreads. This notion of market depth identifies price movements due to an increase in the order flow (Kyle 1985). The cost of transacting of larger orders will be higher as they increase the risk incurred by the scalper.

The volatility of prices represents another dimension of risk. Volatility reflects new information in the market. With new information, prices are more variable and the risk associated with scalper's inventories increases, resulting wider spread. Information entering the market may also induce changes in the volume of contracts transacted which in turn influence the scalpers' exposure to risk. Hence, volatility is jointly determined with volume and spreads, and information shocks cause a reaction in all three variables jointly.

The effect of electronic trading on liquidity costs and the bid-ask spread is uncertain. Electronic trading can be a source of competition to pit trading, reducing the pit spread to a more competitive level. However in the presence of adverse selection identified by Bryant and Haigh (2004), a competitive effect of electronic trading on pit spreads is less likely to exist.

Finally, research shown that liquidity costs can change as a function of contract months, days of the week, and time to maturity. Contract months may have a significant effect in the presence of seasonality not captured in daily volume, and days of the week may reflect the characteristics of cash markets and their interaction with volume traded. A time-to-maturity effect may exist if daily volume does not adequately identify the changing nature of market activity.

Based on our discussion, we model liquidity costs using (5),

$$(5) \qquad BAS_{iht} = \beta_0 + \beta_1\, EXP_{ht} + \beta_2\, SD_{ht} + \beta_3\, VOL_{ht} + \beta_4\, VOL/TRAN_{ht} + \beta_5\, ET_t + \beta_6\, D_{1ht} + \beta_7\, D_{2ht} + \beta_8\, MON_t + \beta_9\, TUE_t + \beta_{10}\, WED_t + \beta_{11}\, THU_t + u_{iht}$$

where BAS_{iht} is the half bid-ask spread for day t, for contract h, using BAS estimator $i = \{RM, TW, HAS, ABS\}$, EXP_{ht} is the number of days to expiration for contract h, SD_{ht} is the log standard deviation of transaction prices for contract h, VOL_{ht} is the log of volume of contract h, $VOL/TRAN_{ht}$ is the log volume per transaction for contract h, ET_t is the proportion of electronic trading volume (e-volume/(pit-volume + e-volume)), D_{1ht} and D_{2ht} are dummies for contract months, MON – THU are dummy variables that take the value of 1 for the particular day of the week and 0 otherwise, β are parameter estimates, and u_{iht} is a random error.

We first estimate (5) using OLS and perform diagnostic tests, including error misspecification (autocorrelation and heteroscedasticity) and endogeneity tests for the variables that may be jointly determined with the BAS. For autocorrelation we use the Breusch-Godfrey test and the autocorrelation and partial autocorrelation functions of the error term. For heteroscedasticity we use the Breusch-Pagan test. Endogeneity tests are performed on total volume, average volume per transaction, and volatility to assess their common dependence on latent information flows.

The endogeneity test is based on an instrumental variables (IV) approach. The standard test Durbin-Wu-Hausman compares the resulting coefficient vectors $\beta = (\beta_0 \ldots \beta_k)$ of both the OLS and IV models. The test statistic is the difference between the two coefficient vectors scaled by a precision matrix $\mathbf{D} = \mathrm{Var}[\beta^{IV}] - \mathrm{Var}[\beta^{OLS}]$ and is distributed as χ^2 with degrees of freedom equal to the number of regressors being tested for endogeneity (Hausman 1978). However, identifying endogeneity becomes more complicated in the presence of heteroscedastic and autocorrelated errors which are commonly found in time series data. Below we present the specification of the IV model, error specification tests, and the modification of the endogeneity test accounting for misspecified errors.

For the specification of the IV model we need at least one instrument for each endogenous variable satisfying two conditions: i) the instrument is highly correlated with the endogenous variable, and ii) the instrument is uncorrelated with u_{it}. For instruments, we select lag values of the endogenous variables except for volatility where we use the first difference of the log standard deviation of prices as suggested by Thompson, Eales, and Seibold (1993) and our own preliminary results. We examine the first condition with a simple OLS regression where the dependent variable is the endogenous variable and the independent variable is its instrument, and check the significance of the parameter estimate. We also perform tests for relevance of instruments by computing the F-test of the joint significance of the excluded instruments in the first-stage regression. In order to avoid misleading conclusions about the F-statistic when one instrument is highly correlated with more than one instrumented variable, we compute Shea's (1997) partial R^2 that takes into account intercorrelations among instruments. For instance, if the system has two endogenous variables and two instruments, and one instrument is highly correlated with both endogenous variables, then the joint F-statistic will be highly significant but the Shea partial R^2 will be low, indicating that the model may be unidentified, biasing the IV model coefficients.

The IV model is estimated using the two stage least square (2SLS) estimator. In matrix form, (5) can be written as,

(6) $\mathbf{y} = \mathbf{X}\beta + \mathbf{u}$

where β is the vector of coefficients $(\beta_0 \ldots \beta_k)'$ and $\mathbf{X}$ is T x k. Defining a matrix $\mathbf{Z}$ of the same dimension as $\mathbf{X}$ in which the endogenous regressors (VOL_t, $VOL/TRANS_t$ and SD_t) are replaced by the instruments ($VOL_{t\text{-}1}$, $VOL/TRANS_{t\text{-}1}$, and ΔSD), the IV estimator and its variance under *iid* disturbances are,

(7) $\hat{\beta}_{2SLS} = (\mathbf{X}'\mathbf{P}_Z\mathbf{X})^{-1}\mathbf{X}'\mathbf{P}_Z\mathbf{y}$

(8) $\quad \mathrm{Var}[\hat{\beta}_{2SLS}] = \hat{\sigma}^2 (\mathbf{X'P}_Z\mathbf{X})^{-1}$

where $\mathbf{P}_Z$ is the projection matrix $\mathbf{Z}(\mathbf{Z'Z})^{-1}\mathbf{Z'}$, and $\hat{\sigma}^2 = \hat{\mathbf{u}}'\hat{\mathbf{u}}/T$. If the disturbances in (6) are not *iid*, then the 2SLS estimates will be consistent but inefficient, and the model variance should be estimated using a robust method. Here we use a generalized-method-of-moments (GMM) estimator that will give consistent and efficient estimates in the presence of non-*iid* errors (Hayashi 2000).

When we define the covariance matrix of $\mathbf{u}$ in (6) as $E[\mathbf{uu}'|\mathbf{X}] = \mathbf{\Omega}$ where $\mathbf{\Omega}$ is a TxT matrix with heteroscedastic and/or autocorrelated errors, the (feasible) efficient GMM estimator is,[1]

(9) $\quad \hat{\beta}_{FEGMM} = (\mathbf{X'Z}\hat{\mathbf{S}}^{-1}\mathbf{Z'X})^{-1}\mathbf{X'Z}\hat{\mathbf{S}}^{-1}\mathbf{Z'y}$

where $\mathbf{S}^{-1}$ is the optimal weighting matrix that produces the most efficient estimate, and $\hat{\mathbf{S}}$ is the estimator of $\mathbf{S} = E[\mathbf{Z'\Omega Z}]$ which will take different forms depending on the specification of $\mathbf{u}$ in (6). When the disturbance in (6) is *iid*, and $\mathbf{\Omega} = \sigma^2\mathbf{I}_T$, then (9) reduces to (7), and the 2SLS estimator is the efficient GMM estimator (Hayashi 2000). When the disturbance in (6) cannot be assumed to be homoscedastic, a heteroscedastic-consistent estimator of $\mathbf{S}$ is given by the standard "sandwich" Huber-White robust covariance estimator (Huber 1967, White 1980),

(10) $\quad \hat{\mathbf{S}} = \frac{1}{T}(\mathbf{Z}'\hat{\mathbf{\Omega}}\mathbf{Z}) = \frac{1}{T}\sum_{t=1}^{T}\hat{u}_t^2\mathbf{Z}_t'\mathbf{Z}_t$

where $\hat{\mathbf{\Omega}}$ is the diagonal matrix of squared residuals $\hat{u}_t^2$ from the first-stage estimation.

When the disturbance in (6) exhibits both heteroscedasticity and autocorrelation, $\hat{\mathbf{S}}$ can be estimated using the Newey-West (1987) heteroscedasticity and autocorrelation consistent covariance matrix as implemented by Baum, Schaffer, and Stillman (2007),

(11) $$\hat{\mathbf{S}} = \hat{\mathbf{\Gamma}}_0 + \sum_{j=1}^{q} \kappa \left(\hat{\mathbf{\Gamma}}_j + \hat{\mathbf{\Gamma}}_j^{'} \right)$$

where $\hat{\mathbf{\Gamma}}_0 = \frac{1}{T}\sum_{t=1}^{T} \hat{u}_t^2 \mathbf{Z}_t^{'} \mathbf{Z}_t$, $\hat{\mathbf{\Gamma}}_j = \frac{1}{T}\sum_{t=1}^{t-j} Z_t^{'} \hat{u}_t \hat{u}_{t-j} Z_{t-j}$ is the sample autocovariance matrix for lag j, $\hat{u}_t$ and $\hat{u}_{t-j}$ are consistent residuals from the first-stage estimation, and $\kappa = (1 - j/q_T)$ if $j \leq q_T - 1$ and 0 otherwise is the Bartlett kernel function with bandwidth q_T which weights each term of the summation with decreasing weights as j increases. We select the bandwidth using Newey and West's (1994) procedure.

In the IV model we perform error specification tests for heteroscedasticity and autocorrelation using extensions of OLS tests. For heteroscedasticity we use the Pagan and Hall (1983) test which relaxes the assumption of homoscedasticity in the system equations that are not explicitly estimated (i.e., regressions of endogenous variables with the instruments) and which is required by most of other standard tests for OLS regression. In the test we use p variables, the instruments, their squares, and cross-products to compute the test statistic that under the null of homoscedasticity is distributed as χ_p^2. In the presence of heteroscedasticity we estimate the IV model using (9) and (10). For autocorrelation we use the Cumby-Huizinga (1992) test which is a generalization of the Breusch and Godfrey test used above for OLS regressions because this and other standard tests for OLS such as Box-Pierce and Durbin's h test are invalid in the presence of endogenous regressors. In the presence of heteroscedasticity and autocorrelation we estimate the GMM IV model using (9) and (11).

When the GMM IV model is estimated in the presence of heteroscedasticity and/or autocorrelation, the Durbin-Wu-Hausman test for endogeneity needs to be modified. We use the *C* statistic or GMM distance test implemented by Baum, Schaffer and Stillman (2007). The test uses the GMM objective function $J\,(\hat{\beta}) = T\ \bar{g}(\hat{\beta})'\ \hat{S}^{-1}\ \bar{g}(\hat{\beta})$ where $\bar{g}(\hat{\beta})$ = 1/T **Z'u** are the orthogonality conditions and $\hat{S}$ is the weighting matrix defined in (10) and (11). The test statistic is defined as (J - J_A) and is distributed as χ^2 with degrees of freedom equal to the number of regressors being tested, where J is the value of the GMM objective function for the efficient GMM that uses the full set of orthogonality conditions, and J_A is the value of the efficient GMM that uses only the number of orthogonality conditions for the variables known to be exogenous.

Data

The analysis is performed for lean hogs and live cattle futures contracts trading in the CME group. The open-outcry prices and volume of all trades executed during the day are taken from the *volume by tick* database. For both commodities we use February, April, June, August, October, and December contracts trading between January 2005 and October 2008. We compute liquidity costs on a daily basis to more carefully identify factors influencing its behavior.

We use a period of 80 trading days prior to maturity to study expiration effects, as suggested by Cunningham (1979), and Brorsen (1989). To account for expiration, *EXP* has a value of zero on the expiration day, a value of 1 the day before, a value of 2 two days before, and so forth to the 80th day. As we switch to another contract, the first day takes a value of 80, and the variable declines to expiration. Depending on holidays and weekends in different months, some contracts may have as many as 85 days prior to maturity.

To construct a daily dataset with approximately 80 trading days for each contract and no overlapping observations we use three contracts per year. We built two datasets of three contracts each which include most of the contracts trading for each commodity. For both commodities, a first dataset uses prices from the April, August, and December contracts (AAD), and the second uses prices from the February, June, and October contracts (FJO).

Our determinants are measured on a daily basis. Volatility is computed as the standard deviation of transaction prices for a specific contract each day. Volume is the total number of contracts for a specific contract, and volume per transaction is the total volume divided by the number of transactions on that day. Daily data on the proportion of electronic trading (ET) comes from the CME group. In hogs and cattle markets the open outcry regular trading hours are 9:05am to 1:00pm. The CME GLOBEX electronic platform operates side-by-side with extended hours, opening at 9:05 am on Mondays and closing at 1:30 pm on Fridays.[2] The relative volume of electronic trading (ET) is computed as a proportion of the volume of transactions traded electronically (for all contracts) over the total volume (for all contracts) in both the pit and electronic markets. Figures 1 and 2 show the total daily volume for hogs and cattle, respectively, traded in the pit and in the electronic platform. As can be seen, electronic trading in these markets was negligible during the early part of the period, but has increased recently.[3]

Results

Table 1 shows the average values of the spread estimators identified, Roll serial covariance (*RM*), Thompson-Waller (*TW*), Hasbrouck's Bayesian (*HAS*), and modified Bayesian (*ABS*) for each commodity and set of expiration months. *TW* yields the highest estimates, followed by *RM* and *ABS*, and then by *HAS*. In the presence of negative correlation and noise, the efficiency assumption in *RM*'s measure does not hold and the *RM* measure overestimates the liquidity cost (Hasbrouck 2004).[4] The *TW*, based on all price changes, also seems to be upwardly biased, a finding consistent with Bryant and Haigh (2004) and others. The *ABS* estimates are the closest to the tick level—the minimum price changed allowed by the exchange—of 0.025 cents/lb. The *HAS*' estimates are always the smallest, and consistently below tick changes. Table 2 presents the correlation between the different measures. *ABS* and *TW* appear to be the most correlated while *HAS* seems to be the least correlated with other measures. These results are consistent across contract months and commodities. Across commodities, liquidity costs are always lower in cattle with consistent higher volume traded. No differences in liquidity costs and the other summary statistics appear to exist.

Tables 3 and 4 present the estimation results for lean hogs, and tables 5 and 6 for live cattle. Each table contains the results of the estimation for the four measures of bid-ask spread, *RM*, *TW*, *HAS*, and *ABS*. All four measures were computed in log differences and thus represent percentage price changes. In almost all cases the endogeneity test for total volume, volume per transaction, and volatility was significant, indicating these variables should be treated as endogenous. Only for the AAD live cattle when we use the *RM* and *HAS* measures do we fail to reject the null hypothesis of no endogeneity. In light of the evidence of endogeneity we perform IV estimation for all cases. Error specification tests also indicate the presence of heteroscedasticity and autocorrelation in all cases analyzed. Therefore, the estimation for all models in tables 3 through 6 was performed using the GMM IV model with heteroscedastic and autocorrelated standard errors.

Results for lean hogs demonstrate that volume, volatility, and volume per transaction consistently stand out as determinants of the BAS. As expected and consistent with Thompson and Waller (1987), Thompson, Eales, and Seibold (1993), and Bryant and Haigh (2004), the volume has negative sign in all cases, showing that higher volumes imply less risk of holding contracts for scalpers which results in lower liquidity costs. When volume decreases buyers (sellers) have difficulty filling their orders and scalpers provide the necessary liquidity at a higher cost *c*. While the direction of the volume effect is consistent for all measures, the magnitude of the effect varies considerably across measures. The coefficients for volume range from -26.42 for *RM* (table 4) to -3.80 for *HAS* (table 3), which means that when volume increases by 1%, the cost of liquidity decreases by 0.02642% and 0.0038% respectively.[5] For an average price of 65 cents/lb, this translates into a decrease of $6.90 and $1.00 per contract.

For all bid-ask spread measures, the log volume per transaction (VOL/TRANS) has a positive sign, with the magnitudes following a similar pattern as the results for volume. The highest coefficient is for *RM* and the lowest for *HAS*. The coefficient which can be viewed as a measure of market depth supports the notion that a larger volume per transaction means that traders must pay a price for immediacy. For the *ABS* estimate, an average price of 65 cents/lb and an average volume of 380 contracts per transaction (table 1), an increase of 10 contracts (approximately a 2.6% increase) would lead to an increase of $5.88 per contract, or roughly half a tick.

The volatility of transactions prices has the expected positive sign when we use *RM*, *TW*, and *ABS*. The findings are in line with Thompson and Waller (1988) and Bryant and Haigh (2004). However, with *HAS* a negative and significant coefficient emerges which is hard to explain. The higher the volatility in prices, the more uncertainty scalpers face and the higher increase the cost of their service, raising *c*.[6]

Days to maturity has a positive and significant sign only when *HAS* and *ABS* are used, however the coefficients are small. A positive sign implies that the further from expiration the higher the liquidity cost. Here, using the *ABS* measure and for the FJO months increases 0.00007% the liquidity cost each day further away from expiration day. Using the *RM* and *TW* measures the estimated coefficients are negative for AAD months and positive for FJO months, but they are never significant at the 5% level.

In table 3, liquidity costs for the June contract are lower than for other contracts and this is consistent across spread measures. In most cases the coefficient is significant, although the magnitude of the effect varies between -11.68 for *TW* to -3.27 for *HAS*. In our analysis we use trading periods of about four months for each contract and so the June contract effect refers to trading from March to June. This finding suggests longer-term patterns may exist in liquidity costs perhaps associated with seasonality in volume which are not captured by the daily volume variables.

Day-of-the-week and electronic trading displayed little effect on liquidity costs. There is no effect in AAD months (table 3) and only two measures, *RM* and *HAS*, identified a Monday and a Tuesday negative effect on FJO months in table 4.[7] The effect of electronic trading on the pit liquidity cost also is weak. While not significant in most cases, the sign is negative. The recent increase in electronic activity (figure 1) may have increased competitive pressure on trading in the pit. This contrasts with Bryant and Haigh's (2004) findings in the coffee and cocoa markets in which adverse selection problems lead to larger spreads with the introduction of electronic trading. However, they seem to be consistent with Pirrong's (1996) findings in the more liquid Bund market, indicating that electronic trading resulted in lower liquidity costs. Here again, the coefficients of electronic trading display high variability between the different spread measures, ranging from -53.72 for *RM* to -0.84 for *HAS*.

Live cattle liquidity costs follow a similar structure to those described for hogs. Volume is negatively related to liquidity costs, and volatility and volume per transaction increase liquidity costs. Here again the signs of the volatility when using *HAS* are also negative but not significant. Days to maturity has mixed signs but is not significant in either liquidity cost measure and sets of contract months. Here longer-term volume patterns also emerge in the June contract. The day-of-the week effect is stronger in cattle, where the results suggest that liquidity costs are lower during the early part of the week. Notice that cash cattle markets primarily are "early in the week" markets which means more trading activity in futures during this period as market participants offset and establish new positions. The effect of electronic trading is also stronger in cattle than in hogs as all its coefficients are significant. The negative direction of the effect is similar to hogs.

Along with volatility, volume in its two dimensions appears to be the main determinants of liquidity costs. For both hogs and cattle, all three variables are consistently significant across measures and set of contract months. To investigate the relationship between volume and liquidity costs in more depth consider figures 3 and 4 which provide the behavior of volume as a contract approaches maturity and the *ABS* measure.[8] The figures are constructed averaging the volume across contracts for the same number of days to maturity. For hogs there are two peaks occurring approximately 25 and 65 days before expiration. For cattle we also observe two peaks, the main one approximately 35 days before expiration and the second one around 75 trading days prior to maturity. The observed peaks in volume are consistent with the large influx of index fund trading activity—long positions that were rolled on well-defined days—during this period (Sanders, Irwin, and Merrin 2008).[9] Consistent with the estimated relationships, the figures identify a clear pattern of higher liquidity costs during periods of low volume, particularly as expiration approaches. They also are indicative of slightly higher liquidity costs during peak market activity, reflecting market depth and the higher volume per transaction prevalent during these periods.

Concluding Remarks

Estimation of the determinants of liquidity costs in agricultural futures markets is not straightforward. Measurement problems, changes in market conditions, and statistical problems complicate our understanding of the determinants of liquidity costs. We estimate a model for lean hogs and live cattle using commonly used spread estimators, Hasbrouck's Bayesian estimator, and the modified Bayesian estimator using absolute values. We perform the estimation for almost all contracts trading during 2005 and 2008, and estimate coefficients for total volume per day, volume per transaction, price risk, the proportion of electronic trading, days to maturity, day-of-the-week effects, and other explanatory factors.

Our results show that the price, volume, and volatility are jointly determined and the estimation of a GMM IV model for heteroscedastic and autocorrelated errors is needed. Liquidity costs are lower in cattle with consistent higher volume traded. Volume and volatility appear to be the most important determinants of the BAS. For both commodities the direction of the effects of total volume and volatility are consistent with findings by Thompson and Waller (1987), Thompson, Eales, and Seibold (1993), and Bryant and Haigh (2004). The cost of liquidity depends on scalpers' risk of holding positions. Higher traded volume implies lower time between trades and therefore lower risk for the scalper. In contrast, higher price volatility is associated with a higher risk of holding a position. Volume per transaction which is viewed as a measure of market depth has the expected positive sign and is a significant factor explaining liquidity cost movements in both hogs and cattle. Visual inspection of volume and liquidity costs generated by the *ABS* estimator reveals a clear pattern of higher liquidity costs during periods of low volume, particularly as expiration approaches. Slightly higher liquidity costs emerge during observed peaks in volume, reflecting higher volume per transaction prevalent during these periods and the price of immediacy in a competitive environment. Identification of these patterns may help decision makers target low-cost trading days.

Other factors explaining liquidity costs movements are days-of-the week effects, the introduction of electronic trading, and seasonality. Day-of-the-week effects are stronger in cattle, implying lower liquidity costs for transactions performed during the first days of the week. The negative coefficient for the proportion of electronic trading suggests the presence of competitive pressure from electronic to pit markets that decreases liquidity costs in the pit. Here the effect is also stronger for live cattle. The results are more in line with Pirrong (1996) for Bund contracts and contrast with Bryant and Haigh's (2004) findings for coffee and cocoa thin markets. For both commodities seasonality in the June contract also emerges.

Finally, while the determinants of liquidity costs generally seem to emerge regardless of the procedure used, large differences in their magnitudes and, to a lesser extent, differences in their signs exist. When we use the traditional *RM* and the *TW* measures which have shown to provide biased estimates of the spread, estimated liquidity costs and the effects of its determinants are always larger. Bayesian measures which do not impose efficient incorporation of information and allow for more flexibility and efficient estimation, identify appreciably smaller liquidity costs and determinant effects. Consistent with previous findings, the *HAS* estimator generates the smallest liquidity costs—on average below the minimum tick size set by the exchange—and the smallest estimated coefficients. Within the context of the market relationships, the *HAS* estimator provides counterintuitive estimates of the expected positive relationship between price volatility and liquidity costs. In contrast, the *ABS* estimator generates average liquidity costs more compatible with minimum tick size, provides estimated coefficients that correspond to market relationships, and identifies the relationship between the aspects of volume and liquidity costs that would be expected in competitive markets faced with large peaks in market activity. Further research on liquidity costs using Bayesian procedures seems warranted to identify more explicitly the source of the differences between *HAS* and *ABS* estimators, under what conditions they can provide meaningful measures of cost, and their usefulness in different markets which are experiencing a movement to electronic trading.

Endnotes

[1] The term "feasible" arises because the matrix **S** is not known and must be estimated. The estimation of **S** involves making some assumptions about $\mathbf{\Omega}$ (*iid*, heteroscedastic, or heteroscedastic-autocorrelated disturbances) and is a two-step procedure. In the first step, we estimate $\hat{\beta}_{2SLS}$, obtain the residuals and construct $\hat{\mathbf{\Omega}}$. Then we estimate $\hat{\beta}_{FEGMM}$ using $\hat{\mathbf{\Omega}}$ to compute $\hat{\mathbf{S}}$. The efficient GMM estimator is $\hat{\beta}_{EGMM} = (\mathbf{X'ZS}^{-1}\mathbf{Z'X})^{-1}\mathbf{X'ZS}^{-1}\mathbf{Z'y}$, and the feasible efficient two-step GMM is the EGMM using $\hat{\mathbf{S}}$ (Baum, Schaffer, and Stillman 2007).

[2] CME GLOBEX trading is closed from 4:00 to 5:00 pm Monday through Thursday for regularly scheduled maintenance. All times refer to Central Time.

[3] Spikes observed in the total volume figures coincide with roll-overs and options expirations.

[4] In four cases a *RM* measure could not be computed due to positive covariance between price changes.

[5] In general, the determinant effects are larger with the traditional *TM* and *RM* than for the Bayesian measures, in part reflecting their higher liquidity cost estimates.

[6] To assess the effect of endogeneity, the basic model was estimated using OLS and the *ABS* measure of liquidity costs. As expected, OLS coefficient estimates are smaller and consistent with Wang and Yau 's (2000) findings for the S&P500, deutsche mark, silver, and gold futures contracts.

[7] In preliminary estimations we included a full set days of the week. In the final estimation we only include only days with significant coefficients. We also included dummy variables for USDA announcement effects (Hogs and Pigs Reports and Cattle on Feed) in early estimations, but find no significant effects.

[8] Volatility patterns are less well defined.

[9]Index fund activity has increased markedly, reaching over 20 percent of open interest in live cattle and hogs for 2006-2008. The roll period is identified as the "Goldman roll" and refers to the days index funds shift positions from nearby to more distant contracts. In both commodities the main peak coincides with the "Goldman roll" which occurs on the 5th through 9th business day of the month proceeding the expiration month. Note lean hogs expire on the 10th business day of the contract month, and live cattle expires on the last day of the contract month. For details see (www2.goldmansachs.com).

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Table 1: Summary Descriptive Statistics

	Lean hogs		Live cattle	
	Apr-Aug-Dec	*Feb-Jun-Oct*	*Apr-Aug-Dec*	*Feb-Jun-Oct*
Observations	954	951	954	954
Average price (cents/lb)	66.74	67.69	90.94	90.92
Average SD	0.25	0.26	0.23	0.23
Average daily volume	7057	7066	9948	9758
Average daily vol/trans	375	389	439	433
Spread estimators (cents/lb)				
ABS	0.0300	0.0297	0.0245	0.0244
HAS	0.0149	0.0148	0.0104	0.0103
RM	0.0503	0.0504	0.0427	0.0424
TW	0.0714	0.0714	0.0594	0.0591

Table 2: Correlation Coefficients between Estimates of Liquidity Costs

	Lean hogs				Live cattle			
	ABS	*HAS*	*RM*	*TW*	*ABS*	*HAS*	*RM*	*TW*
Apr-Aug-Dec								
ABS	1				1			
HAS	0.69	1			0.71	1		
RM	0.80	0.30	1		0.68	0.27	1	
TW	0.96	0.55	0.86	1	0.96	0.60	0.71	1
Feb-Jun-Oct								
ABS	1				1			
HAS	0.73	1			0.64	1		
RM	0.80	0.35	1		0.69	0.19	1	
TW	0.96	0.61	0.85	1	0.95	0.49	0.74	1

Table 3: GMM IV Estimates for Lean Hogs in April, August, and December Contracts

	RM		*TW*		*HAS*		*ABS*	
CONS	-143.52	**	26.37		45.22	**	5.74	
	(25.80)		(22.50)		(7.13)		(11.60)	
VOL	-19.25	**	-20.48	**	-3.80	*	-8.74	**
	(5.47)		(4.62)		(1.87)		(2.50)	
SD	43.89	**	23.86	**	-4.20	**	10.10	**
	(5.14)		(2.86)		(1.21)		(1.57)	
VOL/TRANS	58.23	**	49.45	**	11.02	**	22.05	**
	(10.00)		(9.19)		(3.16)		(4.97)	
EXP	-0.04		-0.02		0.04	*	0.03	
	(0.07)		(0.07)		(0.02)		(0.03)	
D_1	-8.79	*	-7.34		0.46		-2.27	
	(3.69)		(4.12)		(1.20)		(1.92)	
D_2	-15.41	**	-14.62	**	-0.56		-5.00	*
	(4.70)		(4.90)		(1.34)		(2.37)	
ET	-53.72	**	-20.23		-0.84		-5.48	
	(13.34)		(12.41)		(4.56)		(5.94)	
C Statistic	0.0044		0.0034		0.0240		0.0294	

Note: Standard errors are in parentheses. Coefficients and standard errors are multiplied by 10^5. Significance level at the 5% (*) and 1% (**). CONS: constant, VOL: daily log volume for contract *h*, SD: log standard deviation of transaction prices for each day for contract *h*, VOL/TRAN: daily log volume per transaction for contract *h*, EXP: days to expiration of contract *h*, D_1: 1 for April and 0 otherwise, D_2: 1 for August and 0 otherwise, ET: proportion of daily electronic trading computed as e-volume/(e-volume + pit-volume), and the values for the *C* Statistic are the p-values for the endogeneity test described in the text.

Table 4: GMM IV Estimates for Lean Hogs in February, June, and October Contracts

	RM		*TW*		*HAS*		*ABS*	
CONS	-118.82	**	35.97		47.20	**	8.66	
	(22.64)		(27.25)		(7.91)		(12.25)	
VOL	-26.42	**	-24.67	**	-6.68	**	-10.71	**
	(4.56)		(6.21)		(2.19)		(2.91)	
SD	43.48	**	23.25	**	-2.77	*	9.99	**
	(3.78)		(2.58)		(1.27)		(1.42)	
VOL/TRANS	67.86	**	57.66	**	17.26	**	26.31	**
	(9.35)		(10.22)		(3.86)		(5.17)	
EXP	0.07		0.08		0.05	**	0.07	*
	(0.06)		(0.06)		(0.02)		(0.03)	
D_1	7.47		1.95		0.28		1.41	
	(4.37)		(4.64)		(1.41)		(2.22)	
D_2	-2.46		-11.68	**	-3.27	**	-4.57	**
	(3.16)		(3.55)		(1.17)		(1.65)	
ET	-56.96	**	-35.03	*	-11.10		-12.22	
	(12.06)		(16.21)		(6.06)		(7.21)	
MON	-5.69	*						
	(2.30)							
TUE					-1.24	*		
					(0.58)			
C Statistic	0.0103		0.0131		0.0614		0.050	

Note: Standard errors are in parentheses. Coefficients and standard errors are multiplied by 10^5. Significance level at the 5% (*) and 1% (**). CONS: constant, VOL: daily log volume for contract *h*, SD: log standard deviation of transaction prices for each day for contract *h*, VOL/TRAN: daily log volume per transaction for contract *h*, EXP: days to expiration of contract *h*, D_1: 1 for February and 0 otherwise, D_2: 1 for June and 0 otherwise, ET: proportion of daily electronic trading computed as e-volume/(e-volume + pit-volume), MON: 1 for Mondays and 0 otherwise, TUE: 1 for Tuesdays and 0 otherwise, and the values for the *C* Statistic are the p-values for the endogeneity test described in the text.

Table 5: GMM IV Estimates for Live Cattle in April, August, and December Contracts

	RM		*TW*		*HAS*		*ABS*	
CONS	-88.74	**	61.84	**	49.89	**	29.34	**
	(14.80)		(13.95)		(3.84)		(7.18)	
VOL	-11.68	**	-21.44	**	-7.39	**	-10.48	**
	(3.50)		(3.09)		(1.13)		(1.61)	
SD	31.90	**	20.80	**	-0.33		8.44	**
	(2.96)		(1.79)		(0.95)		(0.89)	
VOL/TRANS	22.97	**	28.64	**	9.98	**	15.57	**
	(7.49)		(5.55)		(2.44)		(3.09)	
EXP	0.08		0.01		0.01		0.01	
	(0.07)		(0.05)		(0.01)		(0.02)	
D_1	-1.09		2.04		0.52		1.04	
	(1.72)		(1.51)		(0.52)		(0.70)	
D_2	0.76		1.72		-0.16		0.82	
	(2.22)		(1.80)		(0.55)		(0.88)	
ET	-30.93	*	-26.70	*	-6.19		-10.29	
	(12.38)		(11.13)		(3.42)		(5.40)	
MON	4.64	*						
	(2.23)							
TUE			-2.12	**	-0.55		-0.86	*
			(0.72)		(0.33)		(0.39)	
C Statistic	0.6377		0.0418		0.1084		0.0009	

Note: Standard errors are in parentheses. Coefficients and standard errors are multiplied by 10^5. Significance level at the 5% (*) and 1% (**). CONS: constant, VOL: daily log volume for contract *h*, SD: log standard deviation of transaction prices for each day for contract *h,* VOL/TRAN: daily log volume per transaction for contract *h*, EXP: days to expiration of contract *h*, D_1: 1 for April and 0 otherwise, D_2: 1 for August and 0 otherwise, ET: proportion of daily electronic trading computed as e-volume/(e-volume + pit-volume), MON: 1 for Mondays and 0 otherwise, TUE: 1 for Tuesdays and 0 otherwise, and the values for the *C* Statistic are the p-values for the endogeneity test described in the text.

Table 6: GMM IV Estimates for Live Cattle in February, June, and October Contracts

	RM		*TW*		*HAS*		*ABS*	
CONS	-97.74	**	50.24	**	40.68	**	22.12	**
	(13.91)		(9.16)		(3.18)		(4.59)	
VOL	-13.04	**	-20.95	**	-6.61	**	-10.71	**
	(3.69)		(3.16)		(1.39)		(1.76)	
SD	29.07	**	17.77	**	-0.94		7.70	**
	(2.95)		(1.96)		(0.64)		(1.04)	
VOL/TRANS	35.83	**	37.56	**	12.06	**	20.45	**
	(6.48)		(6.31)		(2.82)		(3.62)	
EXP	0.01		-0.07		-0.01		-0.03	
	(0.03)		(0.04)		(0.01)		(0.02)	
D_1	0.75		-0.27		0.50		0.30	
	(1.56)		(1.91)		(0.70)		(0.97)	
D_2	7.23	**	6.37	**	0.88		2.55	*
	(1.55)		(2.27)		(0.64)		(1.04)	
ET	-50.83	**	-36.00	**	-6.65	*	-14.78	**
	(9.37)		(11.45)		(2.82)		(5.11)	
TUE			-1.59		-0.58			
			(0.90)		(0.36)			
WED			-1.90	*	-0.98	*	-0.71	
			(0.85)		(0.39)		(0.47)	
C Statistic	0.0025		0.0015		0.0127		0.000	

Note: Standard errors are in parentheses. Coefficients and standard errors are multiplied by 10^5. Significance level at the 5% (*) and 1% (**). CONS: constant, VOL: daily log volume for contract *h*, SD: log standard deviation of transaction prices for each day for contract *h*, VOL/TRAN: daily log volume per transaction for contract *h*, EXP: days to expiration of contract *h*, D_1: 1 for February and 0 otherwise, D_2: 1 for June and 0 otherwise, ET: proportion of daily electronic trading computed as e-volume/(e-volume + pit-volume), MON: 1 for Mondays and 0 otherwise, TUE: 1 for Tuesdays and 0 otherwise. TUE: 1 for Tuesdays and 0 otherwise, WED: 1 for Wednesdays and 0 otherwise, and the values for the *C* Statistic are the p-values for the endogeneity test described in the text.

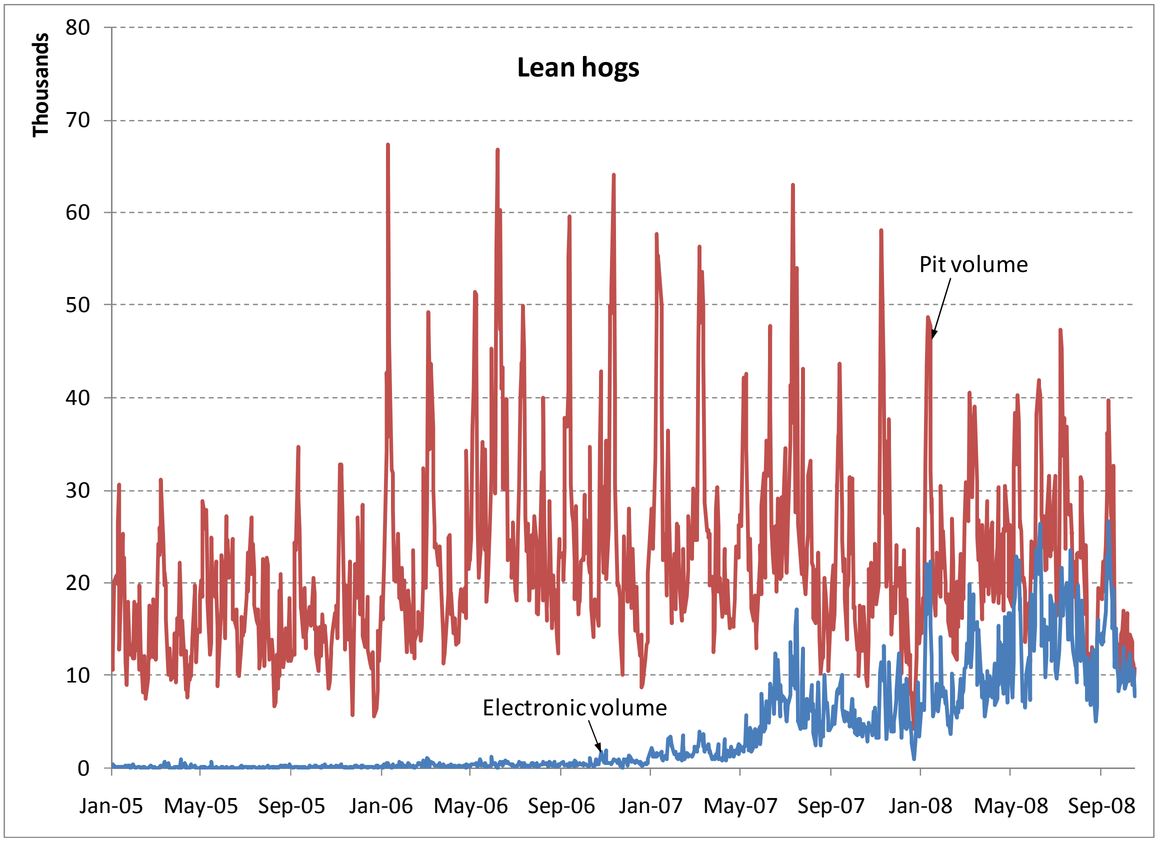


Figure 1: Daily Volume of Lean Hog Contracts Traded Electronically and in the Pit, 2005-2008

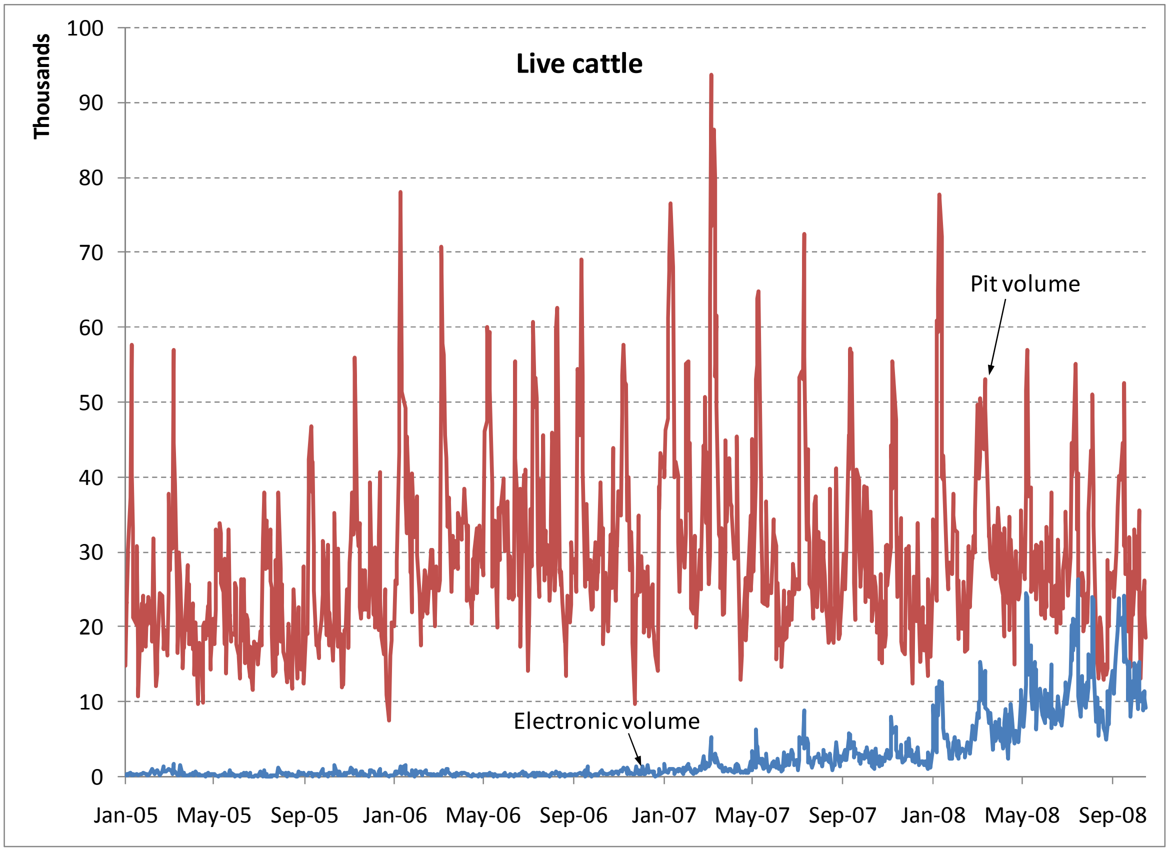
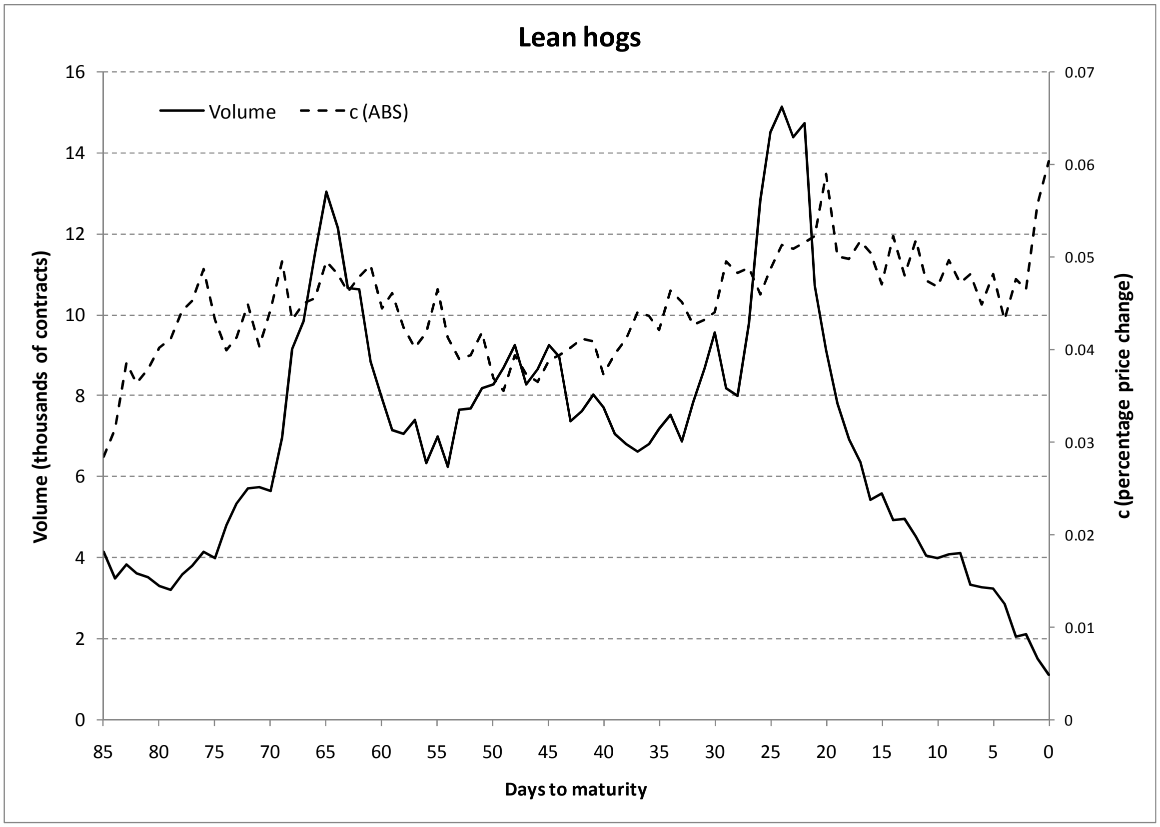
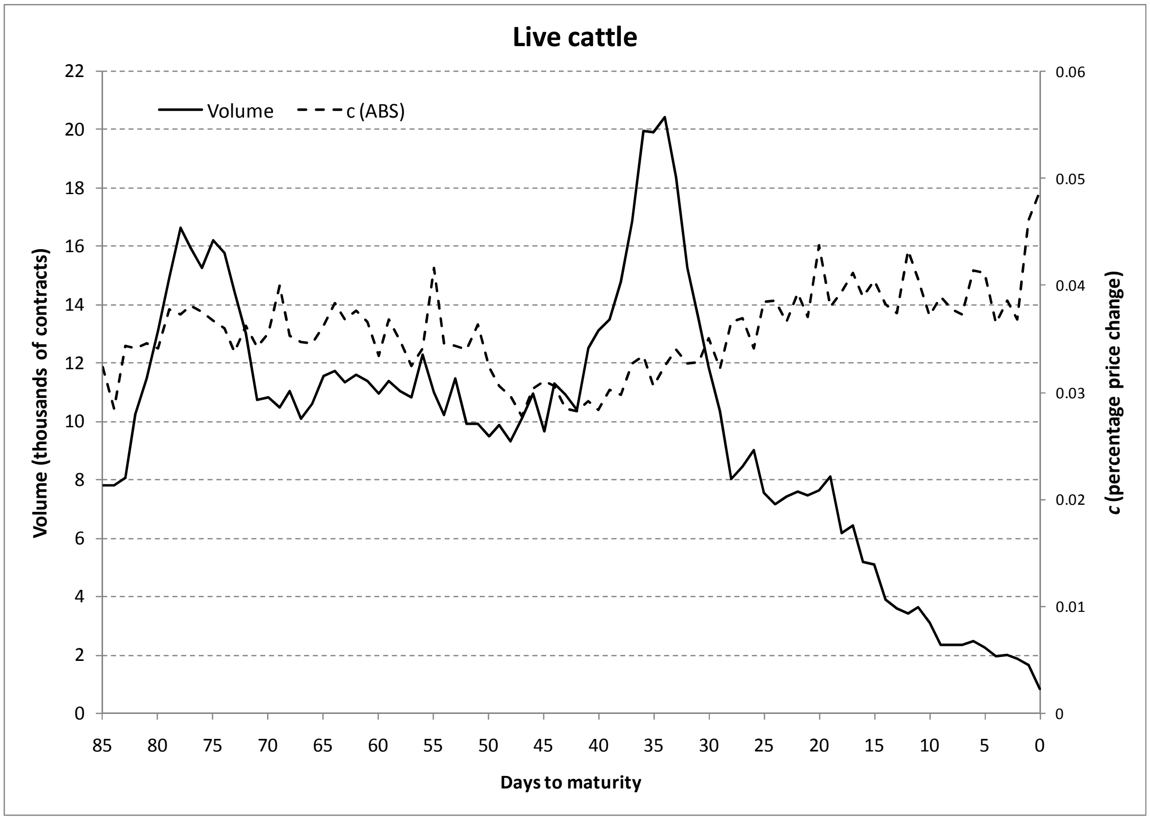


Figure 2: Daily Volume of Live Cattle Contracts Traded Electronically and in the Pit, 2005-2008



Note: Volume is the average number of contracts traded for each day prior to maturity for all maturities in the period 2005-2008. The half BAS is the *ABS* measure of *c.* For *c*, a value of 0.04 in the figure would translate to a half BAS of 0.026 cents/lb for a price 65 cents/lb (0.0004 × 65 cents/lb = 0.026 cents/lb).

Figure 3: Volume and Pit Bid-Ask Spreads for Lean Hogs Prior to Maturity, 2005-2008



Note: Volume is the average number of contracts traded for each day prior to maturity for all maturities in the period 2005-2008. The half BAS is the *ABS* measure of *c.* For *c*, a value of 0.04 in the figure would translate to a half BAS of 0.034 cents/lb for a price 85 cents/lb (0.0004 × 65 cents/lb = 0.034 cents/lb).

Figure 4: Volume and Pit Bid-Ask Spreads for Live Cattle Prior to Maturity, 2005-2008