Market Depth in Lean Hog and Live Cattle

Futures Markets

by

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Liquidity costs in futures markets are not observed directly because bids and offers occur in an open outcry pit and are not recorded. Traditional estimation of these costs has focused on bid-ask spreads using transaction prices. However, the bid-ask spread only captures the tightness of the market price. As the volume increases measures of market depth which identify how the order flow moves prices become important information. We estimate market depth for lean hogs and live cattle markets using a Bayesian MCMC method to estimate unobserved data. While the markets are highly liquid, our results show that cost- and risk-reducing strategies may exist. Liquidity costs are highest when larger volumes are traded at distant contracts. For hogs the market becomes less liquid prior to the expiration month. For cattle this occurs during the expiration month when the liquidity risk is also higher. For both markets this coincides with periods of low volume. For the nearby contract highest trading volume occurs at the beginning of the month prior to expiration and lowest trading volume occurs in the expiration month. For both commodities the cumulative effect of volume on price change may lead to liquidity costs higher than a tick.

Introduction

Estimation of transaction costs in futures markets is challenging as a portion of the costs is implied by the movement of prices and often is not observed directly. One such cost is related to establishing or closing a position, the cost of liquidity. Numerous studies exist using bid-ask spreads to investigate liquidity costs (see Frank and Garcia 2007 for a review). However, this measure captures only the tightness of the market price for average volume trades, and does not identify how prices change with larger orders which may be substantial for impatient, high-volume traders (Engle 2001).

For a typical market reaction curve which reflects the effect of order size on price, small-size buying or selling orders result in price movements that are commonly referred to as the bid-ask spread. As the order size increases, another dimension of liquidity, market depth identifies how the order flow moves prices (Kyle 1985). In this context, order size and price movements are positively (negatively) related for buy (sell) orders. While market makers influence bid and ask prices, the shape of the market reaction curve is often related to other factors including the supply of standing limit orders (Engle 2001), and the presence of private information (Kyle 1985; Hasbrouck 2004). A steeper curve reflects a shortage of limit orders or accentuated information asymmetries, implying a lack of liquidity and large price changes for an order size.

A natural approach to measure market depth is to estimate the slope in the price-volume relationship. However, in agricultural futures markets this is not straightforward because buy and sell orders occur in an open outcry pit and are not recorded. In order to estimate this relationship unobserved bids and offers need to be estimated first. Estimation of these unobserved data can be done using Hasbrouck's (2004) approach. In his model, a Bayesian Markov Chain Monte Carlo

(MCMC) algorithm, the Gibbs sampler, is used to estimate trade directions (i.e., whether a transaction price was a buy or a sell) conditional on the observed data and the structure of the model. Observed data are transaction prices and volume, and the model is built on Roll's model of market microstructure behavior.

The degree of market depth in agricultural commodity futures markets has not been investigated extensively. Based on Hasbrouck's (2004) limited findings of the pork belly futures market, agricultural commodities seem to be the least liquid markets trading on the CME. For instance, he finds that one pork belly contract moves the price by about 10 basis points whereas 50 S&P contracts move the price by about one basis point. It is evident that further research is needed. Clearly the pork belly contract may not adequately characterize the degree of liquidity that exists in other agricultural markets. Further, research directed to agricultural markets seems warranted as findings may have a great impact in making operational decisions. Knowing how the market will react to incoming trading activity is important for market participants to select cost-reducing trading strategies and to manage liquidity risk. For example, splitting orders or being patient when the market is less receptive (i.e. less deep) may reduce transaction costs significantly (Engle and Lange 2001).

The ability of the market to absorb different levels of trading activity depends on the amount of incoming orders which is often driven by the contract being traded and the time to maturity. Cost-reducing opportunities can arise by trading the most active contracts. In the paper, we investigate the microstructure dynamics of lean hog and live cattle futures markets. In particular, we identify differences in liquidity costs between heavily and lightly traded days, nearby and distant contracts, and examine maturity effects. We estimate market depth using Hasbrouck's (2004) trade impact model, employing the *volume by tick* database from the CME, which provides prices and volume of all trades executed during the day in the open auction with their corresponding time stamps.

Estimates of transaction costs can be used to perform comparative analyses between different trading systems as markets transitioning to electronic trading usually operate side-by-side (Pirrong 1996). Brorsen (1989) argues that liquidity costs should also be considered in research simulating hedging strategies. The price impact of a trade may be the main component, in magnitude, of the liquidity cost. Ignoring this portion of the cost may therefore yield misleading results when different hedging scenarios are compared. For institutions, price impact functions can be used for regulation purposes. For example, using estimated price impact reaction curves Pennings et. al (1998) recommend to incorporate scalpers on the floor of the Amsterdam Agricultural Futures Exchange (ATA) to increase market absorption, to improve order book information to help traders adjust quickly to new information, and to implement a reporting system of order imbalances to reduce large price changes.

Background

Kyle's (1985) definition of liquidity involves three dimensions. The first one is the tightness of the market which is the difference between buy and sell quotes at low trade volumes. This is often referred to as the bid-ask spread and it is by far the most common measure of liquidity used

in futures markets. However, this dimension does not fully characterize the price that a trader will have to pay to buy or sell a particular number of contracts. Large-size orders arriving to the market transmit information that helps traders and exchange locals update their beliefs and modify their quotes accordingly. A second dimension of liquidity, market depth is the amount by which prices increase (decrease) in response to a large buy (sell) order. This amount may be considerable larger than the bid-ask spread. The third dimension of liquidity is resiliency which is defined as the speed of prices to return to the equilibrium. Here we focus on market depth as much of the research performed for equities has shown this is a large portion of the liquidity cost.

An obstacle to studying liquidity costs in US agricultural futures markets is that trading occurs in open outcry pits and bids and offers are not recorded, making it difficult to disentangle bid-ask price movements from reactions to order size. Perhaps, because of this difficulty indirect methods have been used to assess market depth and only a few studies have been performed in agricultural markets: Brorsen (1989) for corn, Bessembinder and Seguin (1993) for cotton and wheat, Pennings (1998) for potatoes and hogs, and Hasbrouck (2004) for pork bellies.

Brorsen (1989) uses the standard deviation of the log intraday price changes as a proxy for market depth. For the CBOT corn market, he finds that as volume increases price changes are smaller because the amount of information conveyed between transactions declines. Price changes are also influenced by seasonality which captures the amount of new information arriving to the market and the composition of traders. For example, during the critical growing period for corn price changes were found to be large.

Bessembinder and Seguin (1993) use daily open interest as a proxy for market depth in various futures markets, including wheat at the CBOT and cotton at the New York Cotton Exchange (NYCE). They investigate the effects of open interest, a proxy for hedging activity reflecting uninformed trading, and volume, a proxy for informed trading, on daily price changes. Relative to other future markets (including metal, currency, and financial markets), agricultural markets are less active and prices move more with changes in volume. They also demonstrate that price effects of unexpected order flows are smaller in more active markets.

Pennings et al. (1998) estimate a market depth curve for potato and hog contracts at the ATA with intraday prices. Their procedure involves fitting a Gompertz growth curve using ordinary least squares regression, allowing for asymmetries between buy and sell price impacts. They find that while there are no asymmetries for the hogs market, potato buy orders have a larger impact on prices than sell orders, meaning that the market is deeper for sell orders. They indicate that the differential behavior is due to differences in the structure of the market. Stop-loss buy orders placed by large potato processing firms exceed the number of stop loss sell orders placed by small potato farms and traders. Relative to the hog market, potato prices have larger increases and declines. Pennings et. al (1998) suggest that large price impacts in the potato market could be attenuated by the presence of scalpers. They also find for the hog market that the more distant maturity is deeper for small orders and the nearby contract is deeper for large orders.

Using a different approach Hasbrouck estimates trade impact curves for different futures markets of the Chicago Mercantile Exchange (CME). In Hasbrouck's approach, unobserved variables reflecting whether a trade was buyer or seller initiated are estimated and incorporated in the

model using Bayesian techniques. Hasbrouck derives conditional distributions for the parameters and unobserved data, and iteratively obtains the posterior bid-ask spread and price impact coefficients. All distributions are conditional on observed transaction prices and volumes. Consistent with expectations and Bessembinder and Seguin's (1993) results, the pork belly market has the highest liquidity costs, as measured by the bid-ask spread and depth, relative to currency and financial markets. For the pork belly market, his estimates imply that more than half of the short-term price volatility is attributable to the private information contained in the trades. The non-informational portion of the liquidity costs, the bid-ask spread, is relatively smaller.

To date, most studies that have attempted to estimate price impact curves have assumed a linear function. Some exceptions are Hasbrouck (1991), Pennings et. al (1998), Kempf and Korn 1999, Engle and Lange (2001), and Hasbrouck (2004). Engle and Lange (2001) argue that the shape of the price impact curve is mostly determined by the supply of standing limit orders, and non-linearity is generated because the number of limit orders changes over time as orders are submitted, canceled, and executed. Theoretical and empirical studies in stocks and in futures markets have found that the shape of the price impact curve is usually concave, meaning large orders convey more information than small orders but exhibit decreasing marginal information content (Iori et. al 2003; Kempf and Korn 1999; Hasbrouck 2004). Hasbrouck (1991) argues that the underlying cost and information structure of trade size and information are unlikely to be linear. Engle and Lange (2001) indicate that market participants' trading behavior (trading high volumes together or splitting orders) may also play a significant role in the shape of the curve. Pennings et. al hypothesize that the market depth curve has an S-shape. For low volumes, price changes are small and the cost of liquidity is basically given by the bid-ask spread. As the number of market buy (sell) orders increase, the rate of price changes increases as offers (bids) gradually increase (decrease) to find a match. At higher order sizes, participants are more informed and therefore small price changes are expected.

Methods

We use Hasbrouck's (2004) model of information to estimate the price impact coefficients. This is an extension of previous work by Frank and Garcia (2007) but here we incorporate the volume corresponding to each price. In the extended model, the evolution of the log efficient price m_t is,

$$m_t = m_{t-1} + \alpha + \sum_{i=0}^{2} q_{t-i} \lambda_i \sqrt{V_{t-i}} + u_t \qquad u_t \sim N(0, \sigma^2_u) \tag{1}$$

where V_t is the volume of the trade at time t, λ_i are the impact coefficients, and q_t is the trade direction indicator (+1 for a buy and -1 for a sell). The observed price is the same as in the Roll model,

$$p_t = m_t + cq_t \tag{2}$$

where p_t is the observed log transaction price and c is the half bid-ask spread.

In the Bayesian approach the transaction cost, c, the impact coefficients λ_i, and the variance of the price changes, σ^2_u, are the unknown parameters from the regression specification

$$\Delta p_t = \alpha + \sum_{i=0}^{2} q_{t-i} \lambda_i \sqrt{V_{t-i}} + c\Delta q_t + u_t \qquad u_t \sim N(0, \sigma^2_u). \qquad (3)$$

In equation (3), λ_0 represents the instantaneous impact of a change in volume on prices. Because the equation is estimated in logs, the coefficients in (3) can be interpreted as the proportional price change associated with a purchase (sale) of a given number of contracts.
The instantaneous liquidity cost a trader would incur at time t would then be $\alpha + \lambda_0 + c$. The lags on volume represent a distributed effect of a particular piece of new information on price change. We include two lags based on Hasbrouck's (2004) findings for pork bellies and other currency and stock index contracts trading on the CME. Therefore, an aggregate effect of new information entering the market through volume can be measured by $\lambda_0 + \lambda_1 + \lambda_2$, and a cumulative liquidity cost is $\alpha + \lambda_0 + \lambda_1 + \lambda_2 + c$. For the shape of the price impact function we use a concave curvature as suggested by previous studies in stocks and futures markets. New information translated into a large buy (sell) order would drive prices up (down) at a decreasing rate, as even larger orders would convey only limited extra information.

Estimation of equation (3) is performed using Markov chain Monte Carlo techniques. We use the Gibbs sampler to obtain sample values $(q^{(i)}, \lambda^{(i)}, c^{(i)}, \sigma^2_u{}^{(i)}) \sim F(q, \lambda, c, \sigma^2_u | p, vol)$ based on known conditional distributions for a known set of transaction prices $p=\{p_1,p_2,...,p_T\}$ and $vol=\{vol_1, vol_2, ... vol_T\}$. For the vector variable $\boldsymbol{\Theta}=(q, \lambda, c, \sigma^2_u)$, a Markov chain is used to make n random draws which converge in distribution to the joint distribution after a sufficiently large number of iterations. Here, the parameter vector is based on $n = 2,000$ of which we discard the first 20% as burning time. The liquidity cost c and the price impact coefficients λ_i are then computed drawing from the marginal distribution $f(c, \lambda \mid p, vol)$. The specific implementation process is:

1. Draw $c^{(1)}, \lambda^{(1)}$ from $f(c, \lambda \mid \sigma_u^{(0)}, q^{(0)}, p, vol)$ $\qquad$ $c, \lambda \mid p, vol \sim N^+(\mu^{post}, \Omega^{post})$

2. Draw $\sigma^2_u{}^{(1)}$ from $f(\sigma^2_u \mid c^{(1)}, \lambda^{(1)}, q^{(0)}, p, vol)$ $\qquad$ $\sigma^2_u \mid p, vol \sim IG(\alpha^{post}, \beta^{post})$

3. Draw $q^{(1)}$ from $f(q \mid c^{(1)}, \lambda^{(1)}, \sigma_u^{(1)}, p, vol)$ $\qquad$ $q_t \mid p, vol \sim Bernoulli(p_{buy})$

Where: c and λ are restricted to $[0,+\infty)$, $\mu^{post}=Dd$, $\Omega^{post}=\sigma^2_u(X'X)^{-1}$, $D^{-1}=X' \sigma^2_u{}^{-1}X+(\Omega^{prior})^{-1}$, $d=X' \sigma^2_u{}^{-1}p+(\Omega^{prior})^{-1} \mu^{prior}$, $X=[\Delta q_t]$, $\mu^{prior}=\boldsymbol{0}$, $\Omega^{prior}=10^6*I$, I is a 2x2 identity matrix, $\alpha^{post}= \alpha^{prior}+T/2$, $\beta^{post}= \beta^{prior}+\Sigma u_t^2/2$, $\alpha^{prior} =\beta^{prior} =10^{-12}$, $q_t^{prior} \sim Bernoulli(1/2)$, $q_t^{post} \mid p \sim Bernoulli(p_{buy})$, p_{buy} is the probability that $q = +1$,

$$P_{buy} = e^{\dfrac{-(m_{t-1}-m_{t+1}+L(V_t+q_{t+1}V_{t+1}))^2-2\left\{p_t-c-\frac{1}{2}[m_{t-1}+m_{t+1}+L(q_{t-1}V_t-q_{t+1}V_{t+1})]\right\}^2}{4\sigma^2_u}}$$

Data

Liquidity costs are estimated for lean hog and live cattle futures contracts. During this period trading in these commodities was fundamentally open outcry. We use the *volume by tick*

database from the CME, which provides prices of all trades (including zero price changes) executed during the day in the open auction with their corresponding time stamps and volumes.

To permit flexibility in investigating liquidity cost behavior, we estimate the model daily beginning the month prior to expiration of the nearby contract through its expiration. For the live cattle market, we estimate liquidity costs starting in January 2005 through expiration of the nearby February 05 contract. For the same period, we also estimate costs for the April 05 and June 05 contracts. For the hog market, we begin in July 2005 and estimate the liquidity costs through expiration of the nearby contract, using August 05, October 05, and December 05 contracts. The January contract for the live cattle market, and the July contract for lean hog market both reflect monthly trading volumes near the yearly average for their respective markets. To analyze the effect of trading at more distant contracts, we focus on the trading activity in January 2005 for live cattle and July 2005 for lean hogs to examine liquidity costs for the nearby and differed maturities. This allows us to investigate costs independent of expiration month effects. Table 1 presents descriptive summary statistics for each contract for the month prior to expiration, the most actively traded month. For both commodities, the nearby contract has the highest average price and trading activity, and the most distant contract shows the lowest average price and trading activity. In general live cattle contracts are more actively traded than the lean hog contracts. To examine differences in liquidity costs on heavily and lightly traded days, we select days in the top and bottom quartiles of total daily volume traded using the nearby contract. Days in the top quartile of volume occur at the beginning of the month prior to expiration and days in the bottom quartile appear immediately before expiration. Figure 1 shows this pattern for both commodities.

Results

Table 2 provides average parameter estimates and their standard deviations for the three contracts in the month prior to expiration, the nearby and two distant for each commodity. Posterior means and standard errors are averages of the daily estimates. In Hasbrouck's framework, the half bid-ask spread (c) is the non-informational portion of the cost (i.e., not related to volume) and represents the net gains of locals (market makers) regardless of the new information contained in the trade. Market depth is the informational price change which is embedded in the efficient price and is reflected by the price impact coefficients (λ_i). For both markets, the half bid-ask spread (c) is smaller in the nearby contract which is consistent with expectations as the nearby contracts for both commodities are more highly traded (Table 1), meaning the difference between bids and offers is smaller in more active markets. For all contracts the half spread for live cattle is smaller than for lean hogs, also consistent with the notion that more actively traded markets exhibit smaller liquidity costs. For both commodities the contemporaneous price impact coefficients (λ_0) are also the lowest for the nearby contracts, indicating a higher capacity to absorb incoming orders. This is also consistent with the higher volumes traded observed in the nearby contract as any incoming order has a higher probability of finding a match in more active markets. The lagged effects of volume (λ_1 and λ_2) on price changes in general are close in magnitude to the contemporaneous effect, but slightly smaller. This means that the information contained in trades not only affects the contemporaneous transaction but carries over to subsequent transactions.

Using the average posterior mean coefficients in Table 2 we compute the trade impact function for the range of buy sizes that are most commonly traded in the market (1 to 20 contracts). Figure 2 and Figure 3 provide the impact of a buy order on log price changes for the lean hog and live cattle contracts respectively. The figures also show the tick computed using the average price of all three contracts for each commodity as reported in Table 1. For both commodities the reaction curve of the most distant contract is higher and steeper than the nearby and distant contracts, indicating that a trader using the distant contract incurs higher transaction costs. Further, trading in the most distant contract can lead to liquidity costs higher than the tick. For the lean hog market, the cumulative impact of a trade of more than three contracts moves the liquidity cost to a level higher than the tick, whereas in live cattle this occurs when trading more than nine contracts.

As maturity approaches and traders close positions, the market may become less absorbent of new incoming orders. Figure 4 shows the contemporaneous price impact coefficient (λ_0) for each day starting in the month prior to maturity through expiration for the nearby lean hog (August) and live cattle (February) contracts. For the lean hog contract, the contemporaneous effect increases just before the beginning of the expiration month and then declines slightly. For the live cattle contract, the contemporaneous effect increases near the beginning of the expiration month, and becomes more variable, indicating high liquidity risk in the market as expiration approaches. For both commodities the increase in the trade impact coefficients appears to be associated with the decrease in volume observed in the market as we get closer to expiration (Figure 1).

To identify the effects of volume more clearly, we examine the average liquidity cost for a trader ($\alpha + \lambda_0 + c$) and the cumulative liquidity cost with two lags ($\alpha + \lambda_0 + \lambda_1 + \lambda_2 + c$) for the top and bottom daily volume quartiles for the nearby lean hog and live cattle contracts (Figures 5 and 6). The days of maximum and minimum volumes are not included to represent general high and low levels of market activity. As expected, liquidity costs on heavily traded days are smaller at the trader and market levels for both commodities. Cost differences between heavily and lightly traded days are larger for the live cattle contract than for lean hog contract. Notice that volume traded and average order sizes and their distribution differ in each market. Average volume on heavily traded days is 10,394 and 14,740 for lean hogs and live cattle, while on lightly traded days it is 2,743 and 3,372 for hogs and cattle. This means that the difference between heavily and lightly traded days is more pronounced in the cattle market, leading to a larger difference in the reaction curves. The distribution of order size may also reinforce this pattern. Table 3 shows the average distribution of order sizes for the days represented in Figures 5 and 6. Volumes and their distribution are more similar for the lightly traded days. For the heavily traded days the cattle market has larger volume and a relatively larger number of large-size orders. These differences are reflected in Figures 5 and 6 as a wider gap between highly and lightly traded days in the cattle market.

For both commodities, only cumulative liquidity costs surpass the tick. On heavily traded days, both markets reach the tick at around 12 contracts. However, on lightly traded days they differ with the live cattle contract reaching the tick with around 5 contracts while the hog market did not change much from the 12 contracts registered on heavily traded days.

In Figure 1, heavily and lightly traded days were identified at the beginning of the month prior to expiration and at expiration respectively. These results together with Figures 5 and 6 suggest that trading at the beginning of the month prior to expiration can lead to lower liquidity costs. Further, during the expiration month not only are liquidity costs higher but also the liquidity risk increases as reflected by the higher variability of the trade impact coefficient in Figure 4. Liquidity risk seems to be particularly high in the live cattle contract shortly after the expiration month starts.

Conclusions

Liquidity costs are implied by price movements and cannot be observed directly. Estimation of liquidity costs have focused on bid-ask spreads using transaction prices. However, the bid-ask spread does not completely characterize liquidity costs as it only captures the cost for low volume trades. As the volume increases, measures of market depth should be used to better characterize the microstructure dynamics of the market. Very few studies have attempted to estimate market depth in agricultural commodities. Here we estimate market depth for the lean hog and live cattle futures markets, and identify cost- and risk-reducing opportunities based on the contract used (nearby or distant), the timing (maturity effects), and the volume being traded on a particular day. We use Hasbrouck's (2004) model of trade effects and a Bayesian MCMC method to estimate unobserved data. Consistent with previous studies we use a concave trade impact function—larger orders convey more information than small orders but exhibit decreasing marginal effect.

In general, the lean hog and live cattle futures contracts appear to be very liquid. However, high-volume traders may want to still select strategies to reduce cost and manage liquidity risk. For nearby contracts liquidity costs are less than a tick. For both lean hogs and live cattle liquidity costs are higher than a tick when larger volumes are traded in distant contracts.

For hogs the market becomes less liquid prior to the expiration month. For cattle this occurs later in the expiration month, and is accompanied by larger liquidity risk as evidenced by the wide fluctuations in daily costs. For both markets this coincides with periods of low volume. Avoiding trades during these periods or splitting orders may help high-volume traders reduce transactions costs and manage their market risk.

For the nearby contracts, highest trading volume occurs at the beginning of the month prior to expiration and lowest trading volume occurs in the expiration month. For the lean hog contract, liquidity cost differences between heavily traded and lightly traded days are smaller than for the live cattle. This suggests that trading on lower rather than higher volume days may be more disadvantageous for the cattle trader. For both commodities the cumulative effect of volume on price change may lead to liquidity costs larger than the tick size. The results suggest that for live cattle waiting until expiration to close a position can increase liquidity costs and risk incurred by a trader.

Risk managers seeking ways to measure liquidity costs and risk should find the predictions of market reaction curves useful. Research using the procedures presented here to compare liquidity costs between different trading systems and other commodities and time periods would also be of value. Specifically, further work might identify the effect of large changes in expected and unexpected information on liquidity costs and market depth.

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Table 1. Summary Descriptive Statistics.

Commodity	Lean hogs			Live cattle		
Trading month	Jul 05	Jul 05	Jul 05	Jan 05	Jan 05	Jan 05
Expiration month	Aug 05	Oct 05	Dec 05	Feb 05	Apr 05	Jun 05
Avg. price (cents/lb.)	67.25	58.17	55.64	89.78	87.95	82.02
Standard deviation	0.26	0.26	0.22	0.28	0.24	0.21
Min price (cents/lb.)	64.85	56.20	54.50	87.40	85.65	83.78
Max price (cents/lb.)	69.10	59.80	56.65	93.00	90.30	83.78
Avg. daily volume	7725	5971	1007	11597	8798	2117
Avg. daily trades	611	335	93.8	634.2	550.8	201
Avg. transaction size (median)	5	5	3	8	6	5

Table 2. Average daily posterior means and standard errors for lean hog and live cattle contracts.

| Commodity	Lean hogs		Live cattle	
Trading month	July 2005		January 2005	
Nearby	**Aug**		**Feb**	
c	0.49	(0.012)	0.30	(0.007)
α	0.19	(0.008)	0.11	(0.006)
λ_0	0.32	(0.006)	0.24	(0.004)
λ_1	0.37	(0.007)	0.23	(0.004)
λ_2	0.33	(0.006)	0.18	(0.003)
Distant 1	**Oct**		**Apr**	
c	0.94	(0.021)	0.38	(0.009)
α	0.36	(0.013)	0.09	(0.009)
λ_0	0.45	(0.009)	0.32	(0.005)
λ_1	0.53	(0.009)	0.40	(0.006)
λ_2	0.52	(0.009)	0.26	(0.004)
Distant 2	**Dec**		**Jun**	
c	1.58	(0.034)	0.69	(0.015)
α	0.64	(0.027)	0.29	(0.009)
λ_0	1.00	(0.019)	0.57	(0.005)
λ_1	1.15	(0.020)	0.49	(0.006)
λ_2	1.08	(0.021)	0.47	(0.004)

Means and standard errors in parentheses are averages of daily estimates for the trading month, July 2005 for the lean hog market and January 2005 for the live cattle market.

Table 3. Average distribution of order sizes for heavily and lightly traded days in lean hog and live cattle contracts.

Order size	Lean hogs		Live cattle	
	High	Low	High	Low
1-20	141	185	462	206
21-40	15	25	80	30
41-60	6	7	40	8
61-80	4	3	17	4
81-100	1	2	13	2
101-120	1	1	7	1
121-140	0	1	4	0
141-160	0	0	3	1
More	1	0	10	0

High and low are the top and bottom daily volume quartiles. Numbers in the table are for the lean hog August contract and the live cattle February contract.

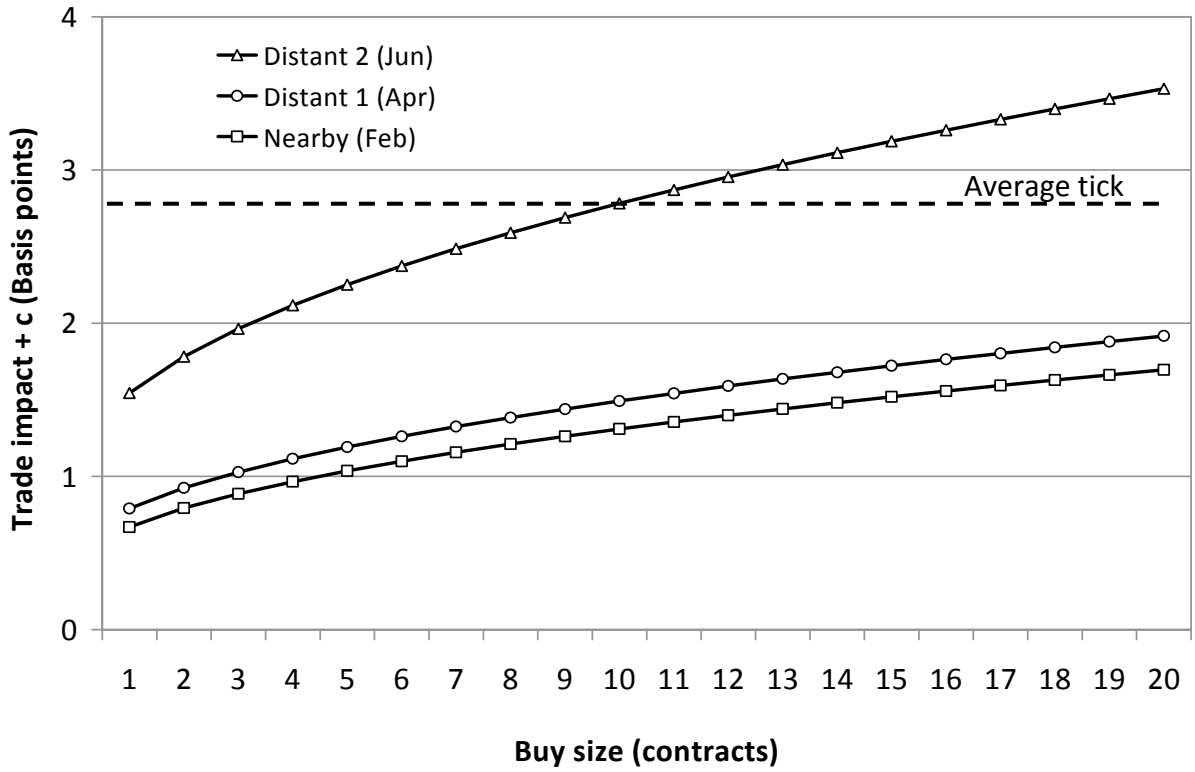**Figure 1. Total daily volume of nearby contracts for lean hog and live cattle contracts.**
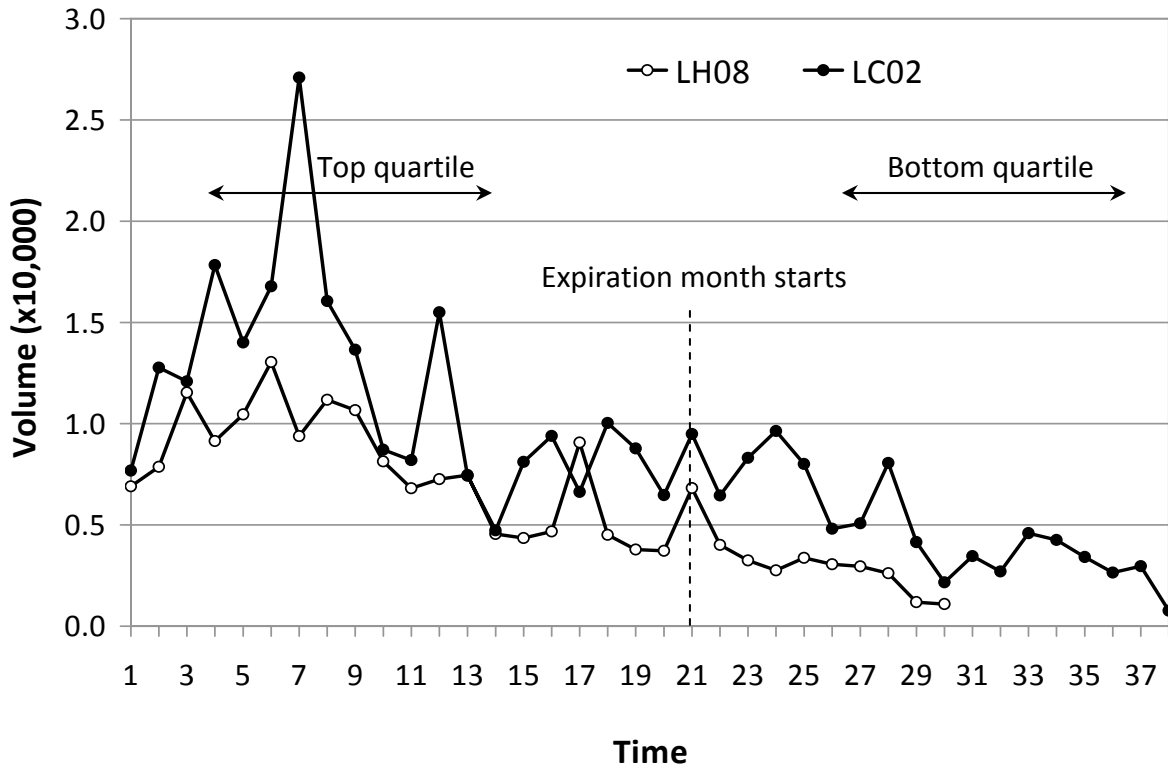
LH08 is the lean hog August contract trading in July 2005 through expiration, and LC02 is the live cattle February contract trading in January 2005 through expiration.

Figure 2. Liquidity cost in nearby and two distant lean hog contracts trading in July 2005.
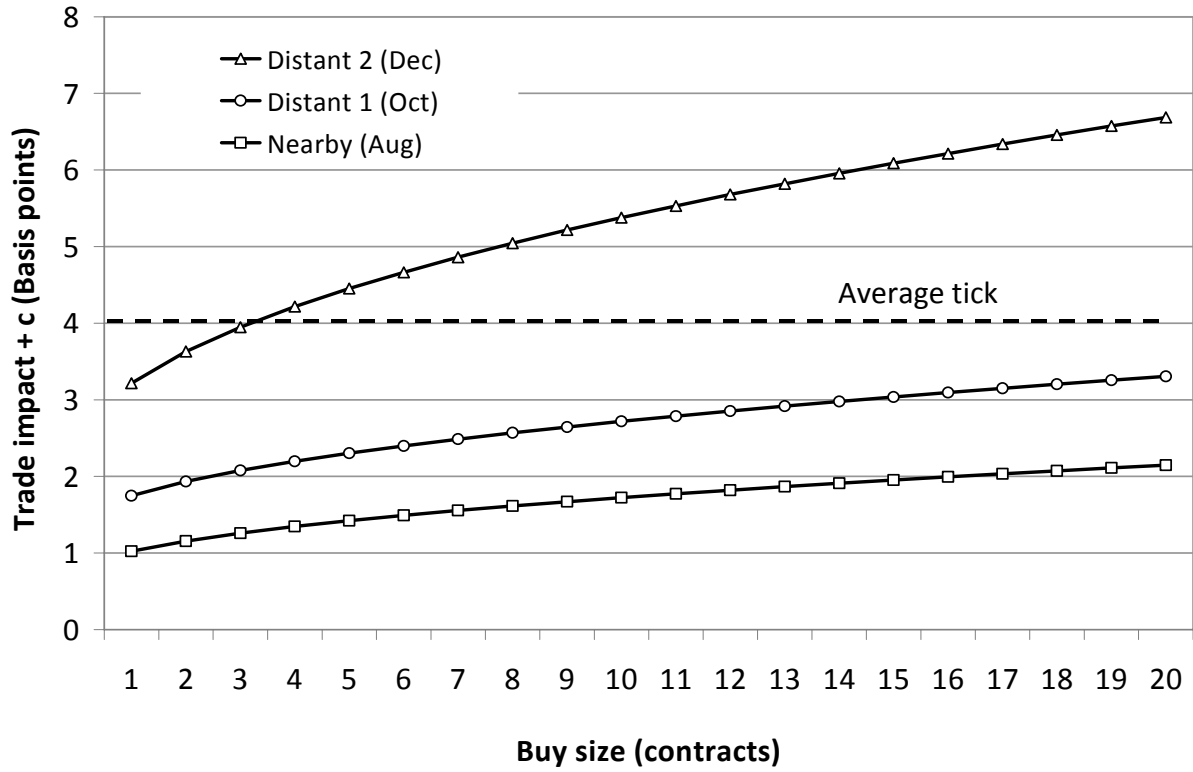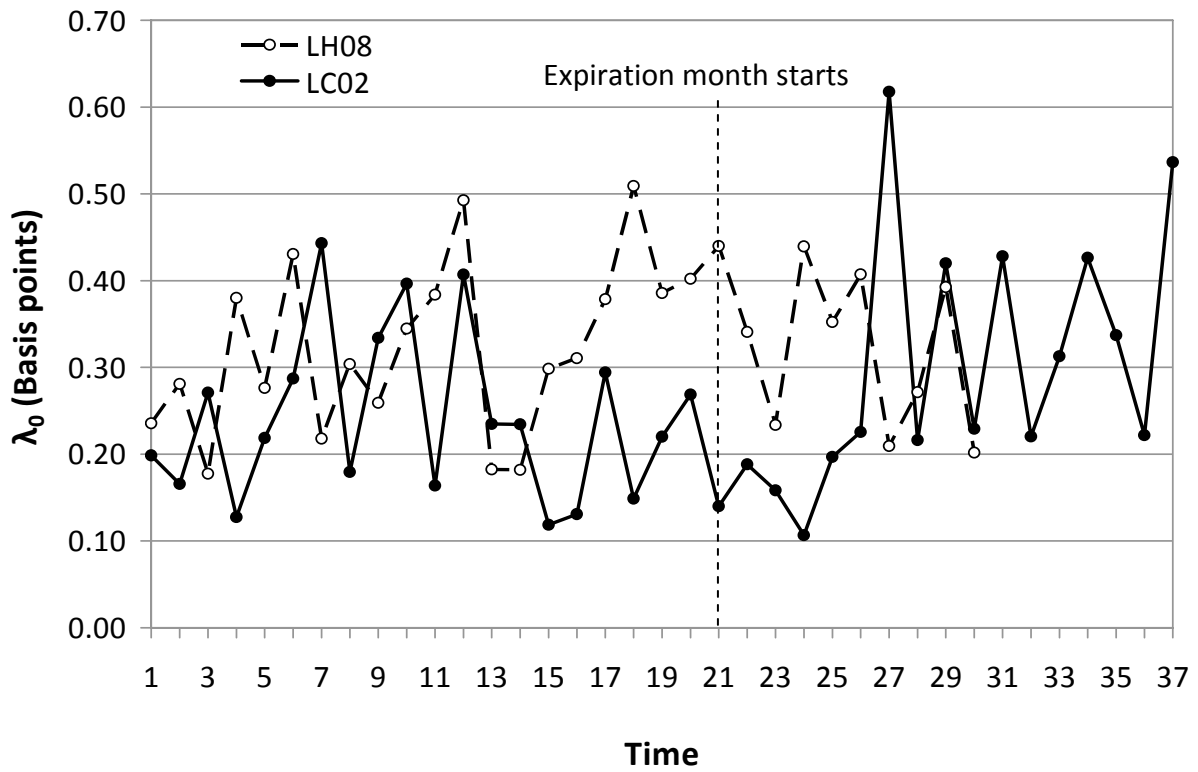

The trader liquidity cost ($\alpha + \lambda_0 + c$) is presented here.

Figure 3. Liquidity cost in nearby and two distant live cattle contracts trading in January 2005.


The trader liquidity cost ($\alpha + \lambda_0 + c$) is presented here.

Figure 4. Contemporaneous price impact effect through maturity in nearby contracts.
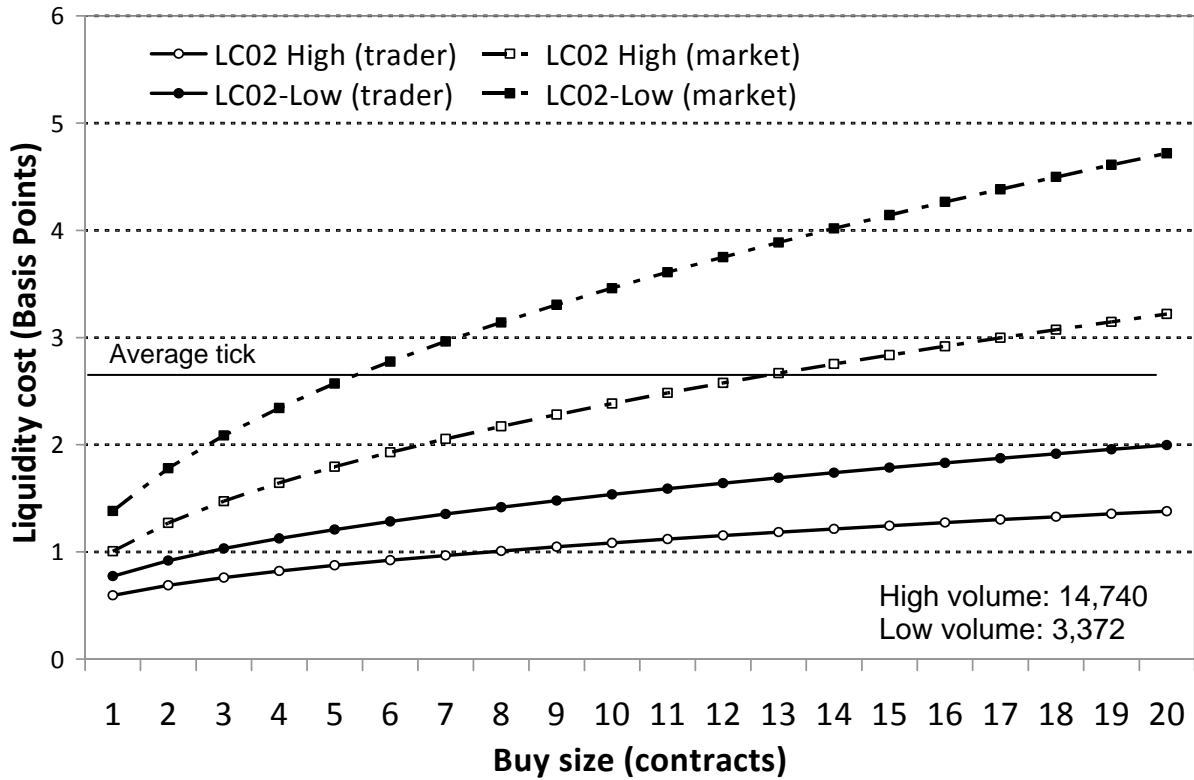

LH08 is the lean hog August contract trading in July 2005 through expiration; LC02 is the live cattle February contract trading in January 2005 through expiration.

Figure 5. Liquidity cost for the highest and lowest volume traded days for lean hog August contract.
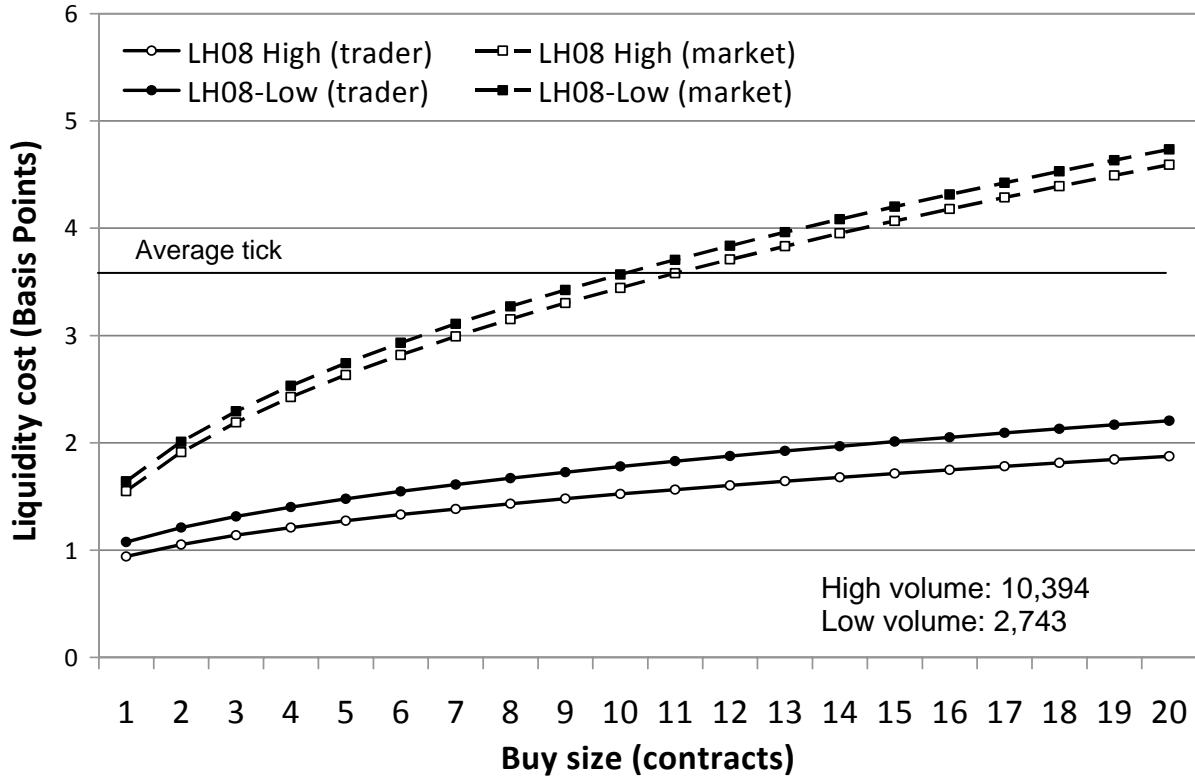
LH08 is the lean hog August contract trading in July 2005 through expiration; trader is the contemporaneous liquidity cost ($\alpha + \lambda_0 + c$) and market is the cumulative liquidity cost ($\alpha + \lambda_0 + \lambda_1 + \lambda_2 + c$); high and low are the top and bottom daily volume quartiles.

Figure 6. Liquidity cost for the highest and lowest volume traded days for the live cattle February contract.

LC02 is the live cattle February contract trading in January 2005 through expiration; trader is the contemporaneous liquidity cost ($\alpha + \lambda_0 + c$) and market is the cumulative liquidity cost ($\alpha + \lambda_0 + \lambda_1 + \lambda_2 + c$); high and low are the top and bottom daily volume quartiles.