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by

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The Components of the Bid-Ask Spread: Evidence from the Corn Futures Market

This paper examines whether USDA announcements and commodity index fund rolling activity has an impact of liquidity costs, measured by the Bid-Ask-Spread. Using Huang and Stoll's (1997) model of liquidity costs, we estimate whether changes to liquidity costs are driven by the adverse selection component, the inventory cost component, or the order processing component. Commodity index fund roll activity reduces the asymmetric information cost component of liquidity cost due to an increased proportion of non-information based trading, but the inventory cost component increases as (mostly long only) commodity index funds sell their nearby position and buy the first deferred contract – raising liquidity providers' risk of building a position. The sum of these two effects is that liquidity costs remain low during index fund roll periods, averaging very near to one 'tick' (0.25 cents). On USDA report release days, we find that informed traders raise the asymmetric information component of liquidity costs in the first hour after release, but the inventory cost component is reduced due to the increase in volume associated with trading the report release. As was the case for commodity index fund roll activity, liquidity costs on USDA report release days remain low, averaging very near to one 'tick' (0.25 cents). Our finding that liquidity costs are very minimally changed during USDA report releases and commodity index fund roll periods is similar to other recent research on liquidity costs, but we show that what drives liquidity costs is very different depending on the circumstances surrounding trading on any given day.

Key words: futures markets, liquidity cost, bid-ask-spread, USDA reports, commodity index funds

Introduction

For more than a decade financial investors have increased their participation in, and exposure to, commodity futures markets via commodity index funds as a means of portfolio diversification. A commodity index fund takes long positions in a number of commodity futures markets; when the futures contract approaches maturity the fund rolls its long positions to the next to expire contract according to a pre-announced schedule.

The rise of the popularity of commodity index funds coincided with commodity price booms and busts, increased volatility, and increased correlation with other instruments like equities and bonds (Singleton 2012, Tang and Xiong, 2012; Cheng and Xiong, 2013). Whether the new behavior of commodity futures markets are driven by, or simply coincident with, increased participation of financial investors has been a topic of heated debate within the academic and public policy spheres (Masters and White, 2001; Irwin and Sanders 2011).

On one hand, many empirical studies have found little impact of commodity index fund activity on prices of commodities futures contracts purchased by the funds (Irwin and Sanders, 2011; Fattouh, Kilian, and Mahadeva, 2013; Hamilton and Wu, 2015; and Robe and Wallen, 2015). Alternatively, there are also several studies that do find an empirical link between index fund positons and futures prices. Tang and Xiang (2012) and Singleton (2012) provided early evidence; while Henderson, Pearson and Wang (2015) recently found that investor flows into and out of commodity linked notes caused futures prices to rise and fall. Basak and Pavlova (2016) provide the first comprehensive theory that links how institutional investors could impact spot and futures prices and inventories, although, they do not provide evidence for or against whether this actually occurs.

Few studies, however, have framed the analysis as a question of whether commodity index funds fall victim to predatory trading practices or whether they are the beneficiaries of sunshine trading policies. Given that commodity index funds roll their outstanding long positions on a pre-announced schedule, such exploration can yield key insights into the impacts commodity index fund investors have on futures markets.

Models of predatory trading predict institutions that have to sell (or buy) within a constrained timeframe attract predatory traders that trade in the same direction before or at the same time as the institution – causing the price impacts of large institutional orders to overshoot equilibrium (Brunnermeier and Pedersen, 2005). In the case of a commodity index fund selling its front month position and buying the next to expire contract, predatory traders would also sell the front month, exacerbating price declines that were not prompted by a change in fundamentals. When the index fund completes its programmatic trading, predatory traders can buy back their short positions for a profit when prices rise back to equilibrium levels.

Alternatively, the theory of sunshine trading says that liquidity providers rush to the market to trade with predictable non-information based orders (Admati and Pfleiderer, 1991). This theory suggests that the public announcement of large upcoming orders is good for the institution as it minimizes the price impact that may arise if its large orders were perceived to be based on private information about future price moves. This theory says that the very act of announcing a large non-information based order brings liquidity to the market, and allows the institution to execute the order without artificially moving the price.

Commodity index funds roll positions during pre-announced windows of time, and thus a central question regarding whether commodity index fund trading impacts commodity futures markets can be posed as a question of whether they consume a fixed supply of liquidity in the market, along with additional demanders of liquidity (the predators). Or whether commodity index funds attract additional liquidity that dampens the price impact of large orders. Few studies have examined the financialization of commodity markets through this lens. Exceptions include Bssembinder et al. (2016) who explore whether the NYMEX crude oil futures market appeared to be resilient to trading during commodity index fund roll periods, and Wang, Garcia, and Irwin, (2012), who examine how liquidity costs are affected by commodity index fund roll activity, and USDA report announcements. Market quality measures such as bid-ask-spread (BAS), depth of the limit order book were at least as good, and in some cases better during the roll period in each of these studies.

This paper extends the work of Bessembinder et al. (2016) and Wang, Garcia, and Irwin, 2012. We consider the CBOT corn futures market, and we extend the analysis to estimate both liquidity costs (BAS) and its components. We use Huang and Stoll's (1997) model (H-S model) of the components of the BAS to break down liquidity costs into an asymmetric information component, an inventory cost component, and an order processing cost component. If we observe changes in the BAS, we can determine what is likely driving changes in liquidity costs.

A long history of research has been devoted to understanding how USDA report announcements on key commodities affect measures of market quality like liquidity costs, volatility, and price discovery. Recent examples include Wang, Garcia, and Irwin (2012), Lehecka, Wang, and Garcia (2014), Adjemian (2012), and Adjemian and Irwin (2016). Our study contributes to this line of research by estimating the effect USDA announcements have on the components of liquidity costs. We observe whether the BAS widens or narrows in the face of USDA report announcements, and we estimate if the observed changes in the BAS are due to changes in asymmetric information, inventory costs, or order processing costs.

Compared to a typical trading day, when new information comes into public knowledge, we expect the asymmetric information component to comprise a larger share of the BAS because traders are likely to be heterogeneous in their ability to process new information and make decisions based on likely future price reactions. Liquidity providers during this time period are at greater risk of trading against an 'informed' trader after the release of key USDA reports.

Alternatively, commodity index fund roll days are not more associated with new information about market fundamentals than a typical trading day, but index fund roll days have been shown to result in slight 'trade imbalances', defined by the number of buyer-initiated trades minus the number of seller initiated trades during index fund roll periods (Bessembinder el al. 2016). During the roll period, we expect an increase in the inventory cost component of liquidity costs, since the trade imbalance that results from a large seller in the market makes it more difficult for a liquidity provider to maintain a neutral position as they supply liquidity to buyer and seller initiated market orders.
Previous studies on the BAS in agricultural futures markets have observed intraday patterns of the BAS that are described as "L-shaped" in corn futures (Wang, Garcia, and Irwin, 2012) and "reverse J-shaped" in coffee and cocoa futures (Bryant and Haigh 2004). Since strong intraday patterns have been documented, we also estimate the components of the BAS over 30 minute intervals during the daytime trading session to determine if the effects of commodity index roll trading and USDA announcements are concentrated during the open, close, or distributed throughout the trading day.

Empirical Model and Estimation

The H-S model decomposes the BAS into three components, adverse selection, inventory, and order processing costs. Under Huang and Stoll (1997) and Ho and Stoll (1981), liquidity providers operate in a competitive environment. They observe order flows and transaction prices and place standing orders to buy and sell. The difference between the best offer to sell and the best offer to buy at any given time is the BAS, S_t. Liquidity providers earn S_t from trading with liquidity demanders as long as the fundamental value (defined here to be ΔM_t, the midpoint of the BAS) does not change. In a competitive market where liquidity providers are risk-neutral, S_t just covers costs, the components of which are inventory, order processing, and adverse selection.

The adverse selection component covers the cost of potentially trading against an informed liquidity demander, who trades via market orders that execute immediately against the liquidity provider's limit order. The inventory cost component covers the price risk of holding a position when the fundamental value changes. If the number of market orders to buy are approximately equal to the number of market orders to sell, then the liquidity cost component is low because it is easy for the liquidity provider to maintain a neutral position in the market.

The remaining costs of providing liquidity are called order processing costs because they are thought to mainly be comprised of fixed costs associated with computing and communication costs that arise from order execution and processing. The reduced form of the three-way decomposition equation system of the H-S model is as follows:[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 variable π is the probability of trade reversal, which means a market order to buy is followed by a market order to sell, and vice versa. The variable Q_{t-1} denotes the trade indicator at t-1; Q_{t-1} equals -1 if it is a market order to sell and +1 if it is a market order to buy. The variable α is the percentage of the half-spread attributable to adverse selection cost, and β is the proportion of the half-spread that is attributable to the inventory cost. The model provides direct estimates of α and β; the remainder of the spread is assumed to be attributable to the order processing cost.

Estimation Procedure of the H-S Model

Following Huang and Stoll (1997), we use GMM to estimate the empirical model. Hansen (1982) proves that the GMM estimators are asymptotically normally distributed. An advantage of opting the GMM procedure is that it imposes weak distributional assumptions on the errors terms, δ_t and ε_t. The GMM procedure chooses parameter values, $\Phi = (\alpha\beta\pi)'$, such that the moment conditions closely approximate the underlying population moments. The moment conditions are defined by $g_T(\Phi)$ in equation 4. The estimated covariance matrix of $\hat{\Phi}$ equals $V_{\hat{\Phi}} = [D_0 S_0^{-1} D_0]^{-1}$, where $D_0 = E[\frac{\partial g_T(\Phi)}{\partial \Phi}]$ and $S_0 = \sum_{l=-\infty}^{l=+\infty} E\,[f_t f_{t-1}]$, and f_t is the vector of arguments that defines the expectation of moment conditions. For the three-way decomposition H-S model, the corresponding moment conditions are:

[2] In the interest of brevity we only present the reduced form equations of the H-S model. For development of the full model and intuition, see Huang and Stoll (1997), and earlier work including Ho and Stoll (1981), Glosten and Milgrom (1985), and Copeland and Galai (1983).

$$(4)\quad g_T(\Phi) = \begin{Bmatrix} \delta_{t-1}Q_{t-2} \\ \varepsilon_t S_{t-1} \\ \varepsilon_t S_{t-2} \\ \varepsilon_t Q_{t-1} \\ \varepsilon_t Q_{t-2} \end{Bmatrix} = 0$$

The Newey and West (1994) estimator is used to correct for heteroscedasticity and autocorrelation in the standard errors.

Data

The data are from the CBOT BBO database that include electronic Globex trading records for each corn futures contract from January 14, 2008 to October 31, 2011.[3] Best bid and offer quotes and volume, along with transaction prices and volume are recorded with time-stamps to the second. We focus on this date range for three specific reasons. First, this covers the period of highest recent concern regarding the role of speculation in general, and commodity index funds in particular, in futures markets.

Second, there was some concern about the role of index funds prior to 2008, but since the BBO dataset only only contains trades and quotes that were conducted on Globex, it is important to truncate the beginning of the sample to a time when the vast majority of volume had already migrated from the open outcry pit to Globex. Irwin and Sanders (2012) showed that as of 2006 electronic volume was still negligible, but began to steadily increase around that time. By January 2008 more than 80% of the volume was transacted on Globex, and this percentage remained steady thereafter until the CME Group closed the open outcry pits in 2015. Therefore, we begin our sample in January of 2008.

Third, a technical change that occurred on November 4th, 2011 in the way trades are recorded precludes us from extending the sample beyond October 31, 2011 for this analysis. A plot of the average trade size per day reveals a distinct shift from October 31 to November 4, 2011, which were a Friday and Monday respectively. Since the H-S model is sensitive to the sequence of orders, this structural change in the data architecture precludes us from conducting analysis on estimates of the H-S model across these dates. Since the heat of the controversy over financialization of futures markets occurred before the end of 2011, the period from 2008 through 2011 is of primary concern for us anyway.

The BAS, S_t, is the best offer minus the best bid. The spread midpoint, M, is the arithmetic mean of the best bid and offer prices. Daily volatility is defined as the standard deviation of M at times when a transaction occurs. We use M rather than trade prices so that the volatility measure is not

[3] Data are missing on 04/15/09. In addition, we exclude 07/07/08 and 07/05/11 because of low trading volumes following the July 4 holidays. Two other days, 10/08/10 and 03/31/11 have identical trade indicators throughout the day; both days were locked at the limit after the release of USDA reports (10/08/10 – WASDE and CP, 03/31/11 - PP).

subject to bid-ask bounce effect, as did Chung and Kim (2009). The trade indicator is generated by the Lee and Ready (1991) procedure. If the transaction price is higher than the quote midpoint, it is coded as a buyer-initiated transaction, or a market order to buy. Seller-initiated transactions are transaction prices that are lower than the quote midpoints.

Selection of Contracts and Trading Days

We exclude all the September contracts from 2008 to 2011. Due to the uncertainty of the timing of new crop delivery, the September corn futures contract is lightly traded (Smith 2005; Wang, Garcia, and Irwin 2013). For the analysis we construct a series of nearby contracts by rolling the nearby to the first deferred contract on the first trading day of the contract settlement month.

We filtered the data to ensure that the trading volume in the BBO dataset (containing only transactions that occur on Globex) were greater than 20% of the volume reported by the Commodity Research Bureau for that day. Although Globex's share of volume steadily increased during our sample period, the share is highly volatile day-to-day (Gousgounis and Onur 2016). Details about the number of trading days filtered out by this condition and its effect on our results are provided in the supplement.

Bunching Sequential Trades

The H-S model postulates Q_t should exhibit negative serial correlation because uninformed trades arrive on both sides of the market; in fact, this variable can exhibit positive serial correlation. Huang and Stoll (1997) postulate that informed traders split large orders to disguise private information; further, they show positive serial correlation in Q_t biases downward α. Huang and Stoll (1997) proposed 'bunching' sequential trades when the transactions have the same bid or ask, execution price, and trade direction. Because trading is less active in commodity futures than in the equity markets H-S examined, we bunch sequential transactions only if they occur within the same minute.[4] We estimate the H-S three-way decomposition model on bunched data.

USDA Announcement and GSCI Roll Days

The USDA regularly releases reports on market fundamentals that convey a large amount of information at once. Focusing on USDA report releases allows us to specifically assess the impact information has on liquidity costs. In our sample, all reports were released at 8:30 EST before the daytime trading session. We consider the same USDA reports as Lehecka, Wang, and Garcia (2014): World Agricultural Supply and Demand Estimates (WASDE), Crop Progress (CP), Grain Stocks (GS), Prospective Plantings (PP), and Acreage (AR).

[4] See the supplement for an example.

Our analysis also considers roll dates of the GSCI. Component contracts that expire in the next month are always rolled on the fifth through the ninth of the month prior to expiration. Our analyses will separate out these trading days to explore the effect commodity index funds have on futures markets. Aulerich, Irwin, and Garcia (2013) showed that total commodity index trader open interest begins to decline before, and continues to decline after, the GSCI index roll period. However, they show that the GSCI index roll period is the most intense in terms of rolling activity and it captures 50% or more of all commodity index fund rolling activity. Like Wang, Garcia, and Irwin (2013) we use the GSCI index roll period to define the index roll period.

Corn Price Behavior and Summary Statistics

Figure 1 shows nearby corn futures contract daily settlement prices. The price of corn increased substantially from January to early July 2008. Soon after the rapid price increase, it slumped from above $7/bushel to around $4/bushel by the end of 2008. It remained relatively low and stable in 2009 and 2010, compared to 2008. By the end of 2010, corn price started a new and abrupt upward trend. From late 2010 to summer 2011, the corn price more than doubled from around $3.5/bushel to more than $7.5/bushel. In 2011, the corn price moved up and down several times and the overall price level was generally much higher than 2009 and 2010.

Table 1 provides daily average of selected metrics over the 763 trading days in the sample. Average daily electronic trading volume increased 30.8% from 2008 to 2011. The highly volatile years of 2008 and 2011 had higher mean BAS than 2009 and 2010. The 2008 average BAS, 0.271 cents/bushel, of corn nearby futures is the highest in the sampled period, which is 6.06%, 6.45%, and 3.36% higher than the BAS in 2009, 2010, and 2011 respectively. The volatile years of 2008 and 2011 have a similar mean BAS, while the stable prices years of 2009 and 2010 are similar to one another but have smaller average BAS than the volatile years.

From 2008 to 2011, the BAS and volatility measurements are highly correlated; years with high BAS are also years with high volatility. This is in line with Wang, Garcia, and Irwin (2013). They postulate that high volatility can be explained by large information inflows into the market. We can test if the periods of high volatility are dominated by the asymmetric information components of the BAS.

Effects of the bunching procedure are provided in columns 5 to 8. Before sequential transactions are bunched, the day session average transaction size is approximately 5.84 contracts/transaction from 2008 to 2011. The average transaction sizes are not significantly different across years. After bunching sequential transactions the average transaction size increases in all years in a range from about 12 to 19 contracts per transaction. The transaction size in 2010 is the highest both before and after data bunching. The last two columns in Table 1 are numbers of transactions during daytime trading sessions. Before bunching, the 2011 daily average transaction count is highest, which corresponds to the largest annual trading volume. After bunching, the 2008 daily average number of transactions decreases by 53.81%. The transaction counts in 2010 decrease by 65.28%, the largest decrease in the four years considered. This fact indicates that in 2010, a period of price stability, many sequential transactions are executed at the same price and with the same bid and offer quotes.

Daily Bas Decomposition Results

Figure 2 plots the three BAS cost components for each trading day in our sample, and table 3 provides the empirical 25%, 50%, 75%, and 90% quantiles of the series plotted in figure 2. In figure 2, days with statistically significant estimates are denoted by a circle, and days with estimates that are not statistically significant are denoted by x's. USDA announcement days that result in statistically significant estimates are demarked by an 'A', while announcement days that do not result in statistically significant estimates are demarked by an 'a'. Similarly, GSCI roll days that result in statistically significant estimates are demarked by an 'R', and roll days that do not result in statistically significant estimates are demarked by an 'r'. A quick glance at figure 2 makes clear that USDA announcement and GSCI roll days generally produce estimates of BAS components that fall within the range of estimates produced from typical trading days, and paired sample t-tests could not reject that the estimates from USDA announcement and GSCI roll days came from the same distribution as typical trading days.

Daily Asymmetric Information Component

The daily estimated adverse selection components are shown in the top panel of figure 2. The mean across days is 12.1%, and 70% of trading days resulted in an adverse selection component that was statistically significant. During 2008 and 2011 when prices were volatile most of the estimated adverse selection components (α) are high and statistically significant. This is in contrast to the results from 2009 and 2010 when prices were less volatile. Just over half of the estimated adverse selection components are statistically different from 0 in 2009 and 2010. These results suggest that the adverse selection proportion is usually negligible, except for periods of high volatility.

On USDA announcement days, the daily mean of the adverse selection component, α, is 15.028%, which is larger than the sample average over all days of 12.1%. The average adverse selection component on USDA announcement days and GSCI roll days are also higher in the volatile years of 2008 and 2011, while the values of this measurement are lower in less volatile years of 2009 and 2010.[5]

The day with highest adverse selection component jumps out in figure 2. The date was March 31, 2008 when the GS and PP reports were released revealing unexpectedly low estimates of ending stocks and planting intentions; the asymmetric component on this day is estimated to be 0.61. Along with a huge price spike in many other commodities, the corn price had already increased sharply in March 2008. With strong corn demand outlook due to ethanol production and animal feeding, the significant decline of corn planting acreage and stock level caused prices to move sharply higher. Volatility (standard deviation of quote midpoints) and BAS of March 31, 2008

[5] The supplement contains a table with asymmetric information and inventory cost component estimates on all USDA report days in our sample.

were 6.993 and 0.293, both much higher than the yearly and monthly averages reported in Table 1.

The second highest α coefficient on a USDA announcement day also happened in 2008. The estimated α coefficient was 0.507 on August 12, a WASDE and CP report announcement day. The high adverse selection component of this announcement may have been influenced by the Midwest flood of that year. The June 30, 2008 acreage report preliminary estimates of the flood's impact,[6] but on June 19, 2008 the USDA released a public statement that more extensive and accurate impacts of the flood would be released in the August CP report.[7] In the 2008 August CP report, corn production was around 12.288 billion bushels, 350 million bushels over average market expectations (Good 2008). Although, these are just two anecdotes in the data, it is important to keep in mind that other days on which the most extreme information events occurred were removed from the sample. Days on which prices were locked at the exchange's daily price limit do not appear, since there was not sufficient variation on these days to perform estimation.

These two anecdotes suggest that some traders are able to acquire, interpret, and trade on this information rapidly. Liquidity providers realize some traders can accurately interpret the market impact of information more quickly than they can, and thus they were likely trading against informed traders. The high BAS and asymmetric information component reflect higher market making costs on days when important information is conveyed to the market.

The mean of the asymmetric information component on GSCI roll days is 0.11. From figure 2, it appears that the asymmetric information component on GSCI roll days is not markedly different from a typical trading day.

In table 3 we see that the 25% and 50% quantiles are larger for USDA announcement days than typical trading days, but the 75% and 95% quantiles are much closer for the two types of days. This suggests that in contrast to the anecdotes about March 31 and August 12, 2008, USDA announcement days are no more likely to result in a large estimated asymmetric information component than the typical trading day. However, we found that that USDA announcement days were less likely to result in a small estimated asymmetric information component. This suggests that while there are plenty of typical trading days in which information affects the market as much as USDA announcement days, there are not many USDA announcement days in which information is unimportant.

Comparing the quantiles of the asymmetric information component on GSCI roll days to the typical trading day, we see that all quantiles are markedly smaller. This result is indicative of the fact that GSCI roll days are more likely to contain volume related to liquidity trading (trading for

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[6] The June 30, 2008 estimation is dropped because the recorded volumes from the BBO data is less than 50% of the CRB recorded trading volumes.

[7] For more details, see *http://www.usda.gov/wps/portal/usda/usdahome?navid=LATEST_RELEASES&parentnav=NEWSROOM&navtype=RT&edeployment_target=archived&edeployment_action=latestreleases*

purposes to get into or out of the market for reasons not related to fundamentals or price expectations) and additional suppliers of liquidity appear to be absorbing the increased volume.

Daily Inventory Cost Component

The second panel of figure 2 shows the daily estimated inventory cost components. The mean across days is 53.1%, which is the largest of the three components.[8] This can be seen in table 2, which presents the number of days for which each component is statistically significant. Estimated inventory costs components tend to fall in a wider band than the asymmetric information components, so the relationship between general volatility in prices and the inventory cost component of the BAS is less clear. In general, the adverse selection and inventory components tend to have a negative correlation, with the correlation between the daily adverse selection and inventory components is -0.515.

The daily inventory cost components on USDA announcement days and GSCI roll days tend to fall within the range of estimates for typical trading days; however, it appears that many of the 'R's are higher than the 'A's. Looking at the empirical quantiles for inventory costs in table 3 confirms this observation. Inventory costs at each of the reported quantiles are lower for USDA announcement days and higher for GSCI roll days compared to the typical trading day. Regarding the two noteworthy days discussed above, March 31 and August 12, 2008, the inventory cost components are 0.19 and 0.21, both much lower than the typical estimates for that time period.

Lower inventory costs on USDA announcement days likely reflects an increase in volume as traders respond to the announcement. Some traders can quickly and accurately interpret what the announcement means for price direction, and liquidity providers account for trading against these people in the asymmetric information component. The remaining traders demanding liquidity lower inventory cost because their trades are equally likely to be from the buy or the sell side and so reduces the liquidity provider's risk of building a positon toward one side of the market.

On GSCI roll days, the opposite is true. The increase in trading by individuals and index funds that roll positions to the next to mature contract increases the volume of uninformed trades (trades that are not based on expectations about price direction) on one side of the market (the sell side in the nearby contract). This increases the risk of building a long position, which they must account for in the inventory cost component.

Daily Order Processing Cost Component

The third panel of figure 2 shows the daily estimated order processing cost. The mean across days is 34.8%, and all the estimated order processing cost components are statistically significant. The daily estimates of the order processing cost fall in a band of similar width to that

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8 Statistical significance of the order processing cost is calculated via the delta method. Nearly all days have statistically significant order processing costs.

found for the asymmetric information component. The order processing cost is noticeably higher during the years of 2009 and 2010 when the asymmetric information component was at its lowest and most stable.

USDA announcement and GSCI roll days do not appear very different that the typical trading day after inspecting figure 2. However, table 3 reveals that the empirical quantiles for order processing costs on announcement and roll days are lower than the typical trading day, except for the 25% quantile of USDA announcement order processing cost components.

Intraday Bas and Decomposition Results

Because trading volume and BAS appear to be U-shaped throughout the trading day (Wang and Garcia 2012), we suspect that the components of the BAS are non-constant throughout the trading day as well. In this section we present the results of estimating the components of the BAS during sub-periods of the daytime trading session.

During our sample period, the daytime CBOT corn futures market session was from 9:30 to 13:15 (3 hours and 45 minutes). We separate each trading day into 7 different time intervals — six 30-minute intervals plus a final 45-miunte interval at the end of the trading day (12:30:01-13:15:00). We remove from our sample all days on which any interval contains less than 3 transactions (after bunching), or days on which there is any interval where Q_t, or S_t is constant. After filtering for these conditions there are 707 days out of 763 days left in the sample, 39 of which are USDA announcement days and 38 are GSCI roll days.

After classifying the days as GSCI roll days, USDA announcement days, or typical days as we did in the previous section, we estimate equations 1 and 2 for each time interval on each day. Then, the BAS, the adverse selection component, inventory cost component, and other market measures are averaged across each classification of days and displayed in Figure 3. The dashed lines reflect USDA announcement days, and the dotted line reflects GSCI roll days. Similar to the previous section, table 4 presents the empirical quantiles of the same estimates that are displayed graphically in figure 3.

The right panels of figure 3 show BAS, Volume, and Volatility, respectively. The BAS, Volume, and Volatility (measured by the standard deviation of quote midpoints) are all highest at the open of the trading session. While we observe a slight “L” or “reverse-J” pattern like Wang and Garcia (2012), the average BAS is remarkably close to 0.25, the minimum price fluctuation (one ‘tick’). This means that at any given time during the trading day the BAS was very likely to be one tick, with a small number of instances where the BAS was two ticks or higher. The BAS on USDA announcement days is slightly elevated, although, for all practical purposes the BAS is still mostly one tick for most of these days, with a few more instances of the BAS at two or more ticks during the opening thirty minutes.

The BAS on GSCI roll days is very slightly higher at the open, but still very close to one tick, and the rest of the day the BAS on GSCI roll days is indistinguishable from a typical trading day.

The middle right panel of figure 3 show volume is highest in the first time interval (9:30-10:00). On a typical trading day, the average trading volume in the first 30 minutes of no-announcement trading days is approximately 25,000 contracts and it declines to around 10,000 contracts after 30 minutes. After the first trading hour each day, the trading volume is stable until the last 45 minutes of the trading session. On average, there are less than 10,000 contracts for every 30-minute time interval during the mid-day hours (10:30AM-12:30PM). During the final 45 minutes, volume increases again on average.

The bottom right panel of figure 3 shows that volatility is highest at the market open. On USDA announcement days, volatility is slightly elevated on average. This is expected because during this time period USDA reports were released at 7:30am during a halt of trading. The open of the daytime trading session was the first change the market had to react to new information released in the reports.

The top left plot in Figure 3 shows that the adverse selection component sharply decreases from the first to the second time interval. More than 15% of the BAS is attributable to the adverse selection component at the market open. Then and until the final time interval, 10:00AM-12:30PM, the market adverse selection component is on average less than 10% and very steady throughout this 2.5-hour time interval. In the final 45 minutes of the daytime session, the adverse selection cost is around 15% of the BAS, similar to the market open and much higher than in the mid-day hours. The U-shaped adverse selection pattern indicates that asymmetric information is high during both market opening and closing periods, and the proportion of such cost is stable and lower during the mid-day hours (10:30AM-12:30PM).

We found in the intraday analysis that USDA announcement days appear to correspond to a higher adverse selection component of the BAS, but the effects are greatly reduced within 30 minutes, and disappear after one hour. In the first time interval, the adverse selection component is around 25% of the BAS on USDA announcement days and 15% across other days. In the second time interval (10:00:01-10:30:00), the adverse selection component is about 10% on USDA announcement days and about 5% on other days. By the third time interval, the USDA announcement effect seems to have disappeared. Table 4 shows that all the presented quantiles of the adverse selection component are higher at the market open, but very similar to a typical trading day on the close.

In figure 3, the estimated intraday adverse selection component is effectively the same on GSCI roll days as a typical day. This is reinforced by the fact that the GSCI asymmetric information empirical quantiles are nearly identical to those of a typical trading day at both the open and the close.

In figure 3, the intraday inventory cost component exhibits an inverted U-shape. This particular pattern shows that the liquidity providers' inventory cost is the lowest during market opening and closings. Since a big proportion of informed traders choose to liquidate their positions before market closure, the liquidity providers' inventory cost sharply decreases during the last 45 minutes of each trading day. By the end of each trading day, liquidity providers' net positions are relatively "neutral" so that at the beginning of the next trading day, their net positions are also relatively neutral.

The inventory cost component is around 40% on USDA announcement days and nearly 50% across all days in the first time interval, which also is in line with Krinsky and Lee (1996). By the second time interval and after the USDA announcement days' inventory cost is nearly identical with the average across all days. This suggests that traders start liquidating their positions earlier on USDA announcement days than other days because positions built during the market opening periods. As traders liquidate their inventories earlier, liquidity providers' inventory levels also decline. Therefore, liquidity providers' inventory cost decreases earlier during day-trading hours on announcement days.

On GSCI roll days, inventory costs are higher throughout the day than the typical trading day. Whereas, the impacts of USDA announcements are impacted and processed by the market very quickly, the impacts of commodity index funds and other traders rolling their positions is felt throughout the trading day. The effect is most pronounced on the open when the inventory component is just over 0.50, a nearly 38% increase over the inventory cost component on other days. The increase in inventory cost component during the midday differs only slightly than a usual day and is roughly 0.68, a 10%-12% increase; during the close, the inventory cost component is roughly 0.48, about a 6% increase. It appears the trading activity that comes about from rolling the GSCI positions influences liquidity costs through its effect on the inventory cost component. The effects are largest at market open, and tend to diminish from midday to market close.

Discussion and Conclusions

While exceptions may exist in specific instances, we found liquidity costs on the whole where not strongly influenced by either USDA report releases or commodity index fund roll periods. The average BAS spread was close to one tick in all cases. The largest increase in average BAS was on USDA report days during the first thirty minutes of the daytime trading session, even in this case, the BAS is closer to one tick (0.25 cent) than to two ticks (0.50 cents). During commodity index fund roll periods, the average BAS is nearly identical to the BAS on a typical trading day. By this measure we have to conclude that liquidity costs are not largely affected by USDA report releases and commodity index fund rolls.

Regarding the question of whether index funds are the beneficiaries of sunshine trading policies or the victims of predatory trading, it appears that they are the beneficiaries of sunshine trading policies because we cannot find a discernable increase in liquidity costs (as measured by the BAS) during the period when the funds are most actively rolling positions.

However, the components of liquidity costs differ on commodity index fund roll days compared to typical trading days. During roll days the inventory cost component of the BAS is larger and the asymmetric information component is smaller than the typical trading day. On roll days, liquidity providers appear to be concerned about building a position because of the large trader on one side of the market compared to the typical trading day.

Also, the components of liquidity costs appear to be quite different on USDA announcement days compared to typical trading days. On USDA report days during the first thirty minutes to one hour after the report is released, we find that the asymmetric information component of the BAS is larger and the inventory cost component is smaller than on the typical trading day. This means that liquidity providers use the spread offered as compensation for trading against the traders who can process and interpret the information in the USDA reports more quickly than others.

In sum, the liquidity costs as measured by the BAS are not different across these three categories of trading days, but by measuring the components separately, we see that the costs of liquidity are influenced by very different things across these days.

Also, the duration of the effects on liquidity costs differed by type of day. While there are modest effects on liquidity costs (BAS), and large effects on the asymmetric information component of liquidity costs, the effects are short lived and gone after one hour. This is similar to the finding of Lehecka, Wang, and Garcia (2014) who argue that after the release of USDA reports, the rapid transmission of information into the corn futures market takes place in ten minutes.

Once a report is released, it becomes common public information; however some traders appear to have superior ability to assess new information and trade as though they have private information, causing liquidity providers to increase the BAS and increase the component designed to compensate them for trading against informed traders (Kim and Verrecchia 1994).

Our asymmetric information result is also similar to Chung, Elder, and Kim (2013) who find that the monetary policy announcement effects are short lived, lasting about 1.5 hours, in the U.S. stock markets. Also, the magnitude of our estimates for the asymmetric information component is similar to what Huang and Stoll's original (1997) study found.

We found that the adverse selection component of liquidity cost is U-shaped throughout the trading day. This is similar to previous studies from the foreign stock markets and foreign futures market (e.g., Ryu 2011, Ahn et al. 2002). Anh et al. (2002) explain that the U-Shaped pattern of the adverse selection cost could arise from informed traders taking advantage of high liquidity and low transacting cost during market opening and closing periods. Offering another point of view, they argue that informed traders who tend to close their intraday positions before market closure could drive the adverse selection component to a U-shaped pattern.

However, our results differ from Madhavan, Richardson, and Roomans (1997), who find that the intraday adverse selection cost appears to have an L-shape, so it consistently declines throughout each trading day. They claim the intraday L-shaped adverse selection cost in the NYSE stock markets is due to liquidity providers' learning process. By the end of each trading day, liquidity providers learn more about the fundamental values of each stock, so they become less dependent on only surmising information from the order flow patterns. What drives an exchange traded market to exhibit a U-shaped versus L-shaped pattern of adverse selection remains an open question.

We find that the largest liquidity cost component of the BAS is inventory cost, and that it has an inverted U shape throughout the trading day. This deviates from the H-S conclusion that order processing cost is the largest component. On average, from 2008 to 2011, around 34.8% of the BAS is attributable to the order processing cost — larger than the adverse selection cost but smaller than the inventory cost. This is likely due to the innovation in information technology since with Huang and Stoll (1997) was written. The cost of technology services related to electronic trading has sharply declined since then.

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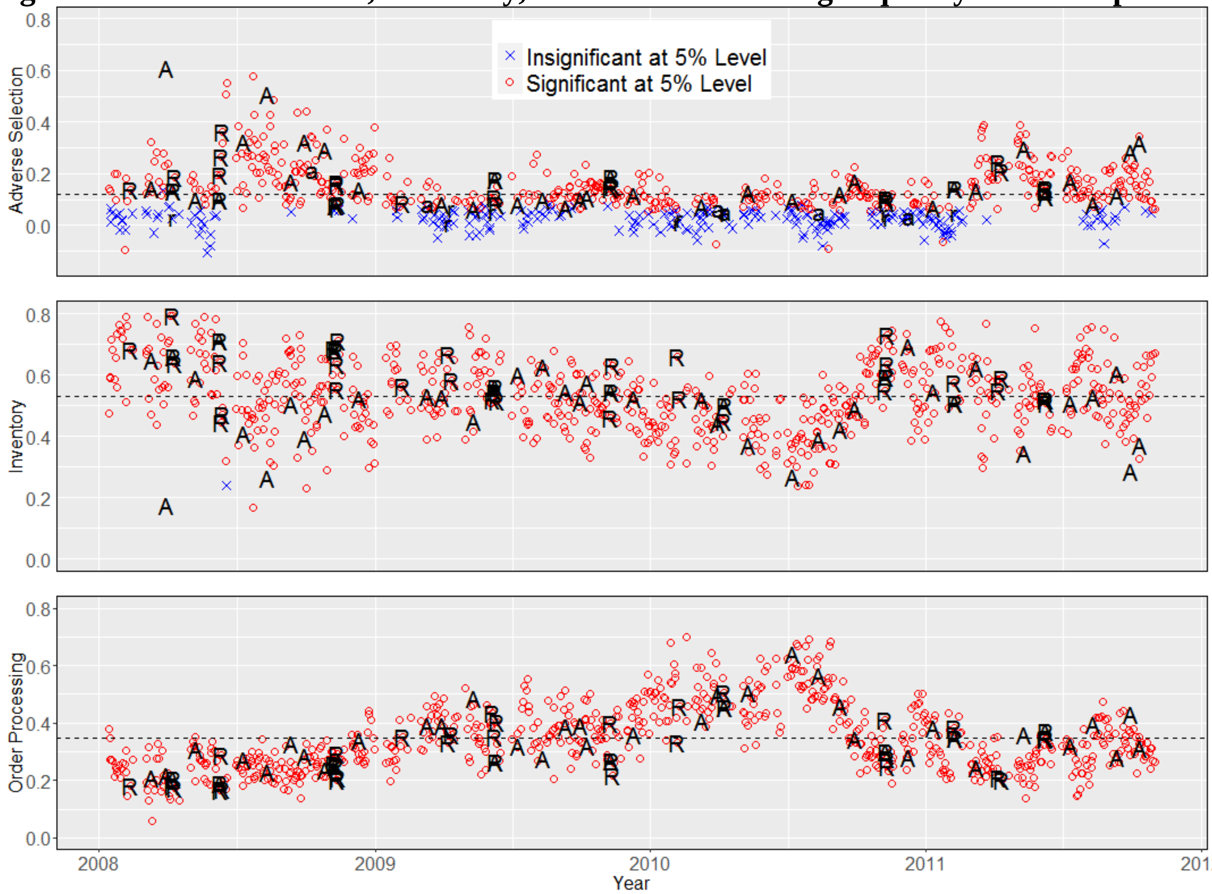
FIGURES

Figure 1: Daily Nearby Corn Futures Settlement Price

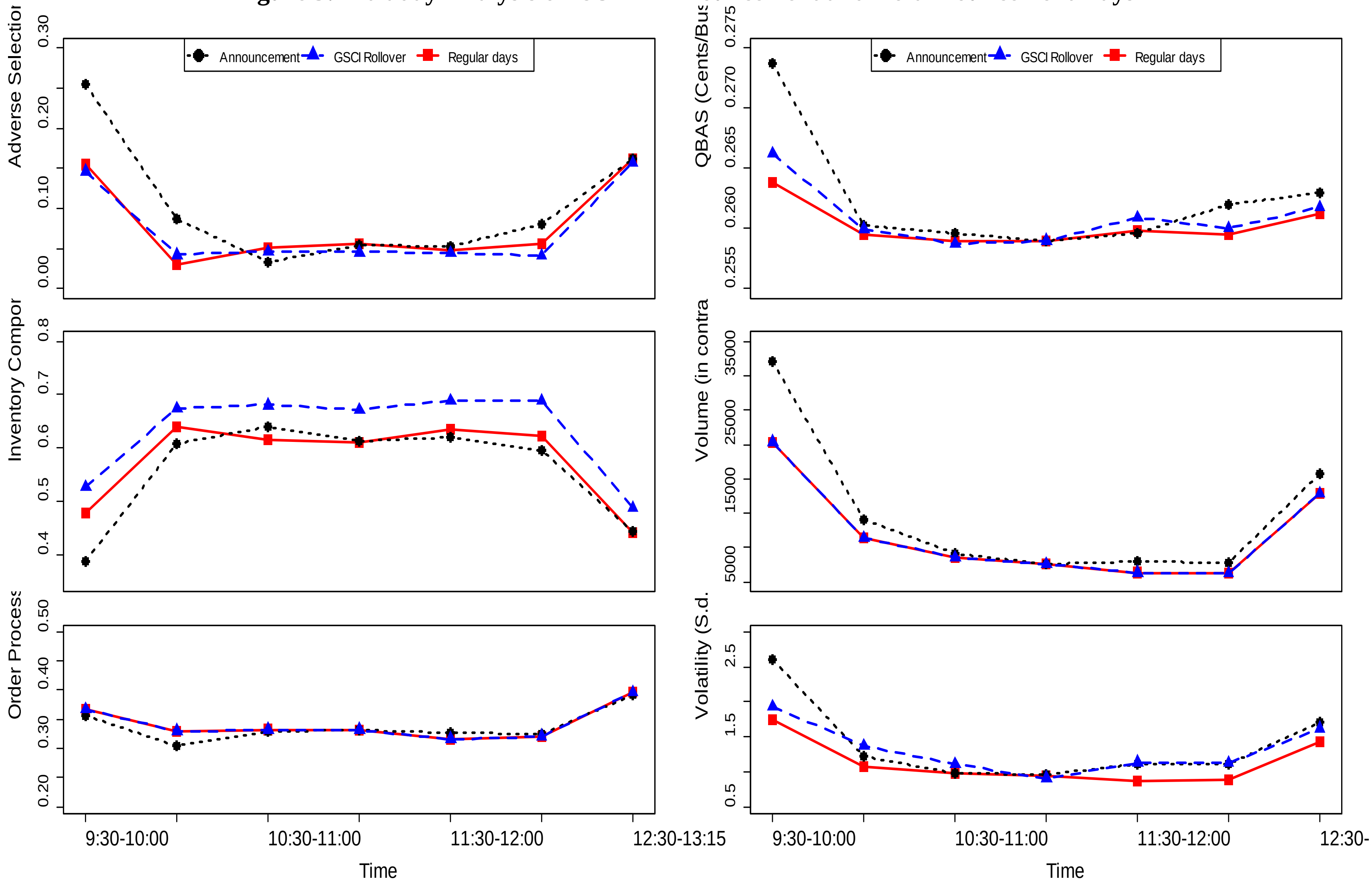
NOTES: Daily nearby corn futures settlement prices are obtained from the CRB database. The nearby contract is rolled over to the first deferred on the first trading day of nearby expiration moth. The time horizon is from January 14, 2008 to October 31, 2011.

Figure 2: Adverse Selection, Inventory, and Order Processing Liquidity Cost Components



NOTES: The three panels show daily estimates for the adverse selection cost component (α), inventory cost component (β) and the order processing cost component (1-α-β). The dash line on each panel represents the mean value of the α and β, where the mean for α is 0.121 and 0.531 is the mean of all β's. 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. In each plot, each letter "A/a" represents an estimation of an USDA announcement trading day; "R/r" represents a GSCI roll day. The statistical significance of announcement day estimations is distinguished by "A" or "R" (significant at 5% level) and "a" or "r" (insignificant at 5% level).

Figure 3: Intraday Analysis on USDA Announcement and No-announcement Days



NOTES: Figure 3 is the result of intraday analysis. The x-axis represents 7 time intervals, which are 9:30:00-10:00:00, 10:00:01-10:30:00, 10:30:01-11:00:00, 11:00:01-11:30:00, 11:30:01-12:00:00, 12:00:0-12:30:00, and 12:30:01-13:15:00. In each plot, the dash line represents estimation of a variable on USDA announcement days, the solid line is a no-announcement day estimation. The 3 plots on the left (from top to bottom) are intraday adverse selection component (α), liquidity providers' inventory cost component (β), and the market volatility. The volatility is the standard deviation of all quote midpoints. The 3 plots on the right (from top to bottom) are the BAS, number of transactions (without bunching data), and the trading volume.

TABLES

Table 1: Summary Statistics

	BAS	Volume	Volatility	Average Transaction Size (not bunched data)	Average Transaction Size (bunched data)	Daily Transaction Counts (not bunched data)	Daily Transaction Counts (bunched data)
Mean							
2008	0.271	75389	3.925	5.598	12.385	13735	6343
2009	0.256	69280	2.443	5.595	15.835	12209	4368
2010	0.254	85991	2.342	6.475	18.794	13215	4687
2011	0.261	102385	4.040	5.726	13.875	17643	7392
Maximum							
2008	0.325	149940	12.173	12.554	30.692	26046	14313
2009	0.274	196443	7.419	7.278	20.947	26775	9876
2010	0.276	217849	8.382	8.938	29.027	31739	12638
2011	0.316	167019	11.853	7.150	21.935	27497	13349
Minimum							
2008	0.218	9897	0.472	4.009	6.603	643	263
2009	0.248	15519	0.614	4.238	9.938	3258	1521
2010	0.250	35619	0.460	4.679	10.874	6396	1885
2011	0.254	43956	1.146	4.424	9.106	6745	2763
Standard Deviation							
2008	0.011	21825	2.101	1.174	3.117	4332	2287
2009	0.003	21650	1.267	0.566	2.198	3398	1354
2010	0.004	32080	1.382	0.742	3.374	4986	2039
2011	0.007	23503	2.065	0.484	2.034	3541	1781

NOTES: The BAS is the best Ask minus the best Bid, which is estimated directly from all transactions of each day. Volume is the total counts of transacted futures contracts of each daytime session. The volatility measurement is the average daily standard deviation of the quote midpoints, *M*. The 4th column is the average transaction size (by number of contracts) before the applying the data bunching process. After bunching all sequential trades, the average size per transaction (by number of contracts) is shown in the 5th column. The 6th and 7th columns are number of non-zero-size transactions for both bunched and not bunched data.

Table 2: GMM Estimation Coefficients Significance Summary

Year	Number of Trading Days	0< α <1	10%	5%	1%	0< β <1	10%	5%	1%
2008	197	187	162	158	148	195	195	194	193
2009	188	176	135	127	103	188	188	188	188
2010	203	184	117	108	80	204	204	204	204
2011	175	162	140	138	129	175	175	175	175
Total	763	709	554	531	460	762	762	761	760

NOTES: We present the daily BAS component estimations in section 6. This table complements

Figure ***2***. The second column in this table shows the sample size in each year after the filtering process by comparing the electronic volume and CRB trading volume. The third column is the number of adverse selection component estimations that are between 0 and 1. Columns 4 to 6 are number of α's that are significant at 10%, 5%, and 1% significance levels respectively. The last four columns are descriptive statistics for β estimations, and the structure of those columns are same as columns 3 to 6 of α's.

Table 3. Quantiles of the Daily BAS, Asymmetric Information (α), Inventory Cost (β), and Order Processing Cost ($1 - \alpha - \beta$).

Daily	25%	50%	75%	90%
BAS	0.254	0.257	0.265	0.273
BAS - Announcement	0.257	0.261	0.272	0.283
BAS - GSCI Roll	0.256	0.259	0.267	0.275
α	0.053	0.106	0.168	0.314
α - Announcement	0.080	0.115	0.171	0.311
α - GSCI Roll	0.048	0.105	0.155	0.197
β	0.459	0.525	0.609	0.732
β - Announcement	0.419	0.521	0.578	0.641
β - GSCI Roll	0.521	0.569	0.656	0.695
$1 - \alpha - \beta$	0.263	0.428	0.420	0.557
$1 - \alpha - \beta$ - Announcement	0.274	0.333	0.393	0.496
$1 - \alpha - \beta$ - GSCI Roll	0.208	0.290	0.358	0.417

NOTES: There were 690 typical trading days, 44 USDA Announcement, and 38 GSCI roll days in our sample. The empirical quantiles represent the number, X, such that 25%, 50%, 75%, and 90% of the estimates fall below X, respectively.

Table 4. Quantiles of the Intraday BAS, Asymmetric Information (α), Inventory Cost (β), and Order Processing Cost (1 – α – β) for the Market Open and Market Close Sub-periods.

	25%	50%	75%	90%
9:30-10:00				
BAS	0.256	0.261	0.269	0.279
BAS Announcement	0.261	0.270	0.284	0.299
BAS GSCI Roll	0.257	0.264	0.269	0.284
α	0.067	0.129	0.213	0.328
α Announcement	0.139	0.194	0.275	0.456
α GSCI Roll	0.103	0.149	0.218	0.265
β	0.408	0.486	0.570	0.646
β Announcement	0.352	0.443	0.499	0.578
β GSCI Roll	0.476	0.531	0.575	0.606
1 – α – β	0.297	0.351	0.421	0.500
1 – α – β Announcement	0.313	0.345	0.399	0.427
1 – α – β GSCI Roll	0.272	0.303	0.355	0.444
12:30-1:15				
BAS	0.254	0.257	0.264	0.275
BAS Announcement	0.255	0.258	0.263	0.284
BAS GSCI Roll	0.256	0.259	0.265	0.272
α	0.073	0.141	0.214	0.321
α Announcement	0.094	0.131	0.200	0.300
α GSCI Roll	0.076	0.114	0.254	0.326
β	0.361	0.446	0.529	0.625
β Announcement	0.385	0.448	0.521	0.619
β GSCI Roll	0.424	0.495	0.588	0.647
1 – α – β	0.306	0.380	0.476	0.557
1 – α – β Announcement	0.295	0.380	0.458	0.555
1 – α – β GSCI Roll	0.271	0.348	0.425	0.477

NOTES: There were 640 typical trading days, 39 USDA Announcement, and 36 GSCI roll days in our sample. The empirical quantiles represent the number, X, such that 25%, 50%, 75%, and 90% of the estimates fall below X, respectively. The time periods 9:30-10:00am and 12:30-1:15pm represent the 30 minutes after the daytime trading session opens and 30 minutes before the daytime trading session closes, respectively. We show quantiles for these sub-periods of the session because they contain the most evident differences across the types of days.