The Informational Impact of USDA Reports on The Trading Costs of Agricultural Commodities Futures

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Abstract

We examine the role of information asymmetry on the changes in bid-ask spreads during major United States Department of Agriculture (USDA) announcements. Comparing the information asymmetry component of spread during days with the pre-scheduled USDA announcements and non-announcement days, we find that information asymmetry increases significantly during days with USDA news releases. We further observe that the increase in information asymmetry prior to the news announcement is driven by the divergence in private information possessed by market participants. Finally, we show that, once the USDA news is released, both analysts' forecasts dispersion and news surprises contribute to increased information asymmetry and wider bid-ask spread.

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1. Introduction

The question of whether USDA (United States Department of Agriculture) announcements still contain information about agricultural commodities has been an issue of debate for many years. While many early studies suggested that these announcements indeed carried some information (see e.g. Sumner and Mueller, 1989), more recent studies question the "newsworthiness" of the USDA announcements. Several studies suggest that with the advent of some private agencies that produce their own forecast, the news content of the USDA announcements has decreased (e.g. Garcia et al., 1997; Egelkraut et al., 2003; Good and Irwin, 2006). However, even though the forecast accuracy of private agencies is very high, we still observe reactions in the market (e.g. McKenzie, 2008; Adjemian, 2012), and more interestingly, we observe that not only prices respond, but we also observe substantial increases in traded volume, volatility around the USDA announcement. This has been related to the increase in uncertainty before the announcement and resolution of uncertainty after the announcement (see McNew and Espinosa, 1994).

Recent studies that focus on the cost of trading, measured by the bid-ask spread (BAS) document that the BAS increases around the USDA report releases and attribute the wider BAS to increased volume and price volatility. For example, Wang et al. (2013) find that BAS widens due to the increase in volatility on the day of the news release, as uncertainty may exist about the direction and magnitude of subsequent price adjustments. Similarly, Lehecka et al. (2014) observe that market participants are more actively trading in the last minutes before the report release, resulting in excess volume, volatility and BAS. However, what, to date, is missing from the literature is a clear understanding of why spreads widen.

In this paper, we focus on what drives the widening in the BAS around USDA announcements. Our sample comprises transaction-level data of agricultural commodities futures on corn, wheat and soybean from January 2013 to July 2016. We focus on the bid-ask spread around major USDA announcements such as the World Agricultural Supply and Demand Estimates (WASDE), Grain Stocks, Prospective Planting and Acreage reports. We then employ a spread decomposition model (Madhavan et al., 1997) to decompose the BAS into its two components, a part that is due to information asymmetry and a part that is due to order processing costs. We document that there is a significant difference between the components of the BAS during days with scheduled USDA announcements and non-USDA announcement days, and find that while the information asymmetry component of the spread increases around the USDA announcement, the order processing component decreases. This suggests that in the period around the USDA announcement, there is an increase in trading on the basis of private information (which causes the increase in the information asymmetry component), but also an increase in liquidity trading (which reduces the order processing costs).

When we further examine the reaction of the BAS pre- and post-announcement, we observe that the information asymmetry component increases in both the period before and after the announcement. To examine what drives the increase in information asymmetry before and after the announcement, we focus on the resolution of uncertainty that comes at the time of the news release (McNew and Espinosa, 1994). Specifically, we focus on the surprise in the USDA announcement (measured as the absolute difference between the consensus expectation and actual announcement), and the degree of dispersion in analyst forecasts (measured as the cross-sectional standard deviation of the forecasts of different analysts prior to the USDA announcement).

When we examine the impact of the news surprise and the dispersion in analyst forecasts on the information asymmetry component of the spread, we document that prior to the news announcement, the dispersion in analyst forecasts is a strong determinant of the degree of information asymmetry. This implies that when there is a high disagreement about the content of the upcoming USDA announcement, there is a large amount of trade based on private information prior to the announcement. This finding is in line with e.g. McNichols and Trueman (1994) who argue that a high degree of uncertainty about a public disclosure before the announcement provides for an environment, where the acquisition of private information is beneficial. In other words, when there is a large amount of uncertainty prior to the announcement it pays to acquire private information.

Finally, we find that once the news is released, both analyst forecasts dispersion and news surprises (the difference between actual figures and market expectations) are responsible for increased information asymmetry and wider bid-ask spread. This again is in line with investors trading on private information signals, but also implies that when the announcement comes as a big surprise, it will take some time for the market to absorb this new information.

Smart investors who can process this information and its implications fast, have a short-term informational advantage over slower traders.

Our work contributes to the literature in several ways. First, we examine the transmission channel which can explain the changes in spreads during USDA announcements. Most studies in agricultural commodities focus on volume and volatility as the main driver of increased spread. Here, we focus on information asymmetry as the main driver. Second, we explore what causes the increase in information asymmetry. We consider two determinants, both related to the information content of USDA news. Specifically, we consider the surprise component of news, and the dispersion in analysts' forecasts prior to news releases. The underlying idea is that if the announcement contains a surprise element that was not anticipated, it will have a significant impact on information asymmetry. Moreover, if the dispersion in analyst forecasts prior to the announcement is high, we can expect information asymmetry to increase during news release. Both factors will result in a wider BAS.

We structure the remainder of this paper as follows. Section 2 discusses the related literature on USDA announcements and how they could affect the various components of spread. Section 3 contains the methodology used in the paper. Section 4 describes the data. Section 5 reports our empirical findings and their interpretations. Finally, Section 6 concludes.

2. Literature Review

In this section, we first discuss the literature on the impact of USDA reports in the agricultural futures markets. We then discuss how the information from the reports may be related to information asymmetry and widen the bid-ask spread.

It is generally accepted that public news releases affect trading costs. With regards to agricultural futures, several studies relate the widening of BAS to the release of public news, particularly during USDA announcements. Several empirical studies suggest that bid-ask spread widen due to increased volatility on the day of the release. Active trading during the release of extensive new information may exacerbate price volatility and could present challenges for some producers seeking to manage risk, hence resulting in wider spreads (Garcia et al. 1997; Isengildina-Massa et al. 2008; McKenzie 2008; Adjemian 2012).

A channel which has been sparsely explored is the impact of information asymmetry on bid-ask spreads. Spreads may increase due to traders having different information sets or different speeds at which they can process information. In particular, because the USDA reports are released while markets are open, small agricultural enterprises may not have the resources to process new information quickly enough to place trades in competition with large trading firms (Kauffman, 2013). Our study extends the literature by focusing on the informational impact of news on the bid-ask spreads.

In this study, we conjecture that spreads widen during prescheduled USDA announcement times due to increased information asymmetry. The asymmetric information argument suggests that spreads widen to compensate liquidity providers for dealing with informed counterparties, i.e. traders who are able to react more timely to the release of new information, or those who simply have superior information (Glosten and Milgrom, 1985, and Glosten, 1987). Trading with informed counterparties leads to losses for the liquidity provider. Hence, to offset those losses, liquidity providers widen their bid-ask spreads. An indication of this is documented in Wang et al. (2013) who find that the USDA reports have significant effects on corn bid-ask spreads. They suspect that this increase may be due to uncertainty in the direction and magnitude of subsequent price adjustments following report release. In addition, Lehecka et al. (2014) observe strong reactions in corn futures prices during the USDA report releases. They find that strongest reaction to news release are found immediately after the market opens and market reactions persist for about ten minutes with little evidence of systematic under- and overreactions.

Information asymmetry, itself, may arise during the USDA announcements for several reasons. First, it may arise due to the informational content of the news itself. Particularly, if the content of the announcement was not anticipated, it will result in information asymmetry and significantly affect the spread. The difference between the actual figures reported in the news and the market expectations is often considered as an important determinant of information asymmetry (Balduzzi et al., 2001; Anderson et al., 2003). Second, information asymmetry may also rise if the dispersion in market beliefs prior to the announcement is high, i.e. traders hold different beliefs on the content of the announcement. This dispersion in beliefs prior to the announcement can lead to an increase in information asymmetry in the pre-news period, because when uncertainty about public news announcements is high, acquisition of private information may be more beneficial (McNichols and Trueman, 1994;

Riordan et al., 2013). Post-news period, information asymmetry remains high because different traders have varying capabilities to interpret the news in relation to the assets being traded (Kim and Verrecchia, 1994).

The above discussions suggest that information asymmetry plays an important role in determining the bid-ask spread. To measure this information asymmetry cost, we decompose the bid-ask spread into its various components. In the next section, we discuss the methodology used to decompose the spreads.

3. Methodology

To decompose the spread into it various components we employ the model of Madhavan, Richardson and Roomans (1997) model (MRR, hereafter). This model decomposes spread into two components: information asymmetry and non-information asymmetry (inventory-holding and order processing cost).

3.1. Model Framework

In the market microstructure literature, changes in public beliefs come from two sources. First, it is due to arrival of new public information. Public news announcements may cause revisions in beliefs of market participants without any trading occurring. Here, we denote ϵ_t as the innovation in beliefs due to new public information.[1] Second, changes in public beliefs can also be due to order flow. If liquidity providers believe that some traders may possess private information about fundamental values, a buy (sell) order is associated with an upward (downward) revision of beliefs. Therefore, the revision in beliefs is positively correlated with the innovation in the order flow. Let x_t be the trade indicator variable, +1 if the trade is buyer-initiated, -1 if the trade is seller-initiated, and 0 otherwise (some pre-negotiated trades can be viewed as both buyer- and seller initiated). The change in beliefs due to order flow can be expressed as $\theta(x_t - E[x_t|x_{t-1}])$, where $(x_t - E[x_t|x_{t-1}])$ is the surprise in order flow and $\theta \geq 0$ measures the degree of information asymmetry or the so-called permanent impact

[1] We assume that ϵ_t is an independent and identically distributed random variable with mean zero and variance σ_ϵ^2.

of order flow innovation. Higher values of θ indicate larger revisions for a given innovation in order flow.

Given the above two sources, the post-trade expected value of an asset, μ_t, conditional on new public information and order flow innovations can be expressed as

$$\mu_t = \mu_{t-1} + \theta(x_t - E[x_t|x_{t-1}]) + \epsilon_t. \tag{1}$$

Liquidity providers' quotes reflect their compensation for their service in providing liquidity. As such, liquidity providers' bid and ask prices are conditioned on a trade being buyer- or seller-initiated. Let $\phi \geq 0$ be the liquidity provider's compensation for transaction costs, inventory costs, risk bearing and possibly the return to their unique position. The ask price will therefore be $p_t^a = \mu_{t-1} + \theta(x_t - E[x_t|x_{t-1}]) + \phi + \epsilon_t$ and the bid price be $p_t^b = \mu_{t-1} - \theta(x_t - E[x_t|x_{t-1}]) - \phi + \epsilon_t$. Thus, ϕ captures the temporary effect of order flow on prices. Note that u_t is the conditional expected value given that x_t is observed. Even though liquidity providers fix their quotes before the trade is observed, they can condition on the incoming trade's sign because buys execute at the ask price while sells execute at the bid price. In addition, liquidity providers must also incorporate the transaction cost, ϕ, into the quotes. For this reason, the transaction price p_t can be written as

$$p_t = \mu_{t-1} + \theta(x_t - E[x_t|x_{t-1}]) + \phi x_t + \epsilon_t. \tag{2}$$

Equation (2) suggests that liquidity providers are compensated for the probability of trading with investors with private information (captured by θ) and the order processing costs (captured by ϕ). This compensation is reflected in the bid-ask spread.

To estimate Equation (2), we must incorporate the temporal behaviour of order flow. The MRR model assumes a general Markov process for the trade indicator variable, x_t. Let γ be the probability that a transaction at the ask (bid) following a transaction at the ask (bid). As large traders may break their orders into smaller components for easier execution, continuations are more likely than reversals, so that $\gamma > 0.5$. Let λ be the probability of trade occurring at the midquote. We can prove that the first-order autocorrelation coefficient of the trade indicator variable is $\rho = 2\gamma - (1 - \lambda)$. Notice that when there is no possibility of transacting within the quotes (i.e., $\lambda = 0$) and order flow is independent (i.e., $\gamma = 0.5$), order flow is serially uncorrelated, and $\rho = 0$. Subsequently, the conditional expectation of the trade indicator variable given public information can be expressed as $E[x_t|x_{t-1}] = \rho x_{t-1}$.

Using the fact that $p_{t-1} = \mu_{t-1} + \phi x_{t-1}$ and $E[x_t|x_{t-1}] = \rho x_{t-1}$, we can re-write Equation (2) as

$$p_t - p_{t-1} = (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + \epsilon_t. \tag{3}$$

Equation (3) expresses the transaction price changes as a linear function of contemporaneous and past order flows. It forms the basis for the MRR model to investigate of intraday price movements. In the absence of market frictions, the model reduces to the classical description of an efficient market where prices follow a random walk. However, in the presence of frictions (i.e., the transaction costs, ϕ and information asymmetries, θ), transaction price movements reflect order flow and noise induced by price discreteness, as well as public information shocks.

3.2. Model Estimation

Recall that the four parameters governing the behaviour of transaction prices and quotes are θ (the asymmetric information parameter), ϕ (the cost of supplying liquidity), λ (the probability of a transaction takes places inside the spread), and ρ (the autocorrelation of order flow). Let $\beta = \{\theta, \phi, \lambda, \rho\}$ be the parameter vector. The parameters in β can be estimated using Generalized Method of Moments (GMM) method. Specifically, we let $u_t = p_t - p_{t-1} - (\phi + \theta)x_t + (\phi + \rho\theta)x_{t-1}$. Then the following moment conditions can be employed to exactly identify the parameter vector in β and a constant drift, α:

$$E\begin{pmatrix} x_t x_{t-1} - x_t^2\rho \\ |x_t| - (1-\lambda) \\ u_t - \alpha \\ (u_t - \alpha)x_t \\ (u_t - \alpha)x_{t-1} \end{pmatrix} = 0. \tag{4}$$

The first equation is simply the definition of the autocorrelation in trade indicator, the second equation defines the crossing probability, the third equation defines the drift term as the average pricing error, and the last two equations are the OLS normal equations. The idea behind GMM is to choose parameter values for β such that the moment conditions are satisfied.

4. Data and Sample Description

4.1. United States Department of Agriculture (USDA) Report and Survey

For the news announcements, we focus on major USDA reports such as the World Agricultural Supply and Demand Estimates (WASDE), Grain Stocks Report (GSR), Prospective Planting Report (PPR), and Acreage report (AR).[2] The WASDE report provides monthly USDA forecasts of U.S. and global supply-use balances of major agricultural commodities. The GSR is issued quarterly in January, March, June and September (the January report is released together with January WASDE), and contains estimated agricultural stocks on a state and national level, as well as by their on- and off-farm storage. The PPR and AR are announced annually in March and June, respectively, (both reports are released together with the March and June GSRs, respectively) and contain the expected plantings as of March 1 and acreage by planted and/or harvested areas, respectively, for crops such as wheat, corn, and soybean.

To obtain a measure of the surprise in the announcement and a measure for dispersion in forecasts, we focus on analyst forecasts. In particular, we collect the expected and actual end inventories figures for the USDA reports from Bloomberg. Bloomberg conducts surveys of various analyst firms which cover these agricultural commodities. These surveys are conducted one week prior to the announcement of the USDA reports, covering as many as 32 analysts and traders each time as listed in Appendix B.[3] The market expectation is then

[2]We do not consider the weekly Crop Progress Report because it is released at 4:00pm (CST) which coincides with the break time between the daytime and the evening trading sessions.

[3]Isengilda et al. (2016) focus on two companies that provide private crop forecasts to capture the unanticipated news in the USDA announcement. We focus on analyst forecasts, as we need a wider range of forecast in order to calculate a measure of forecast dispersion. In addition, the properties of the Bloomberg News have been investigated, for example, by Gay et al. (2009) and Chen et al. (2013), who find that, on average, Bloomberg forecasts are more consistent with the market consensus view.

calculated as the median estimate across these surveys. We follow Balduzzi et al. (2001) and Anderson et al. (2003) in the way we compute the standardized news surprise by dividing the news surprise by its in-sample standard deviation. The standardized news surprise associated with report type i = *{WASDE, GSR, PPR, AR}* at announcement time t is

$$S_{i,t} = \frac{A_{i,t} - E_{i,t}}{\sigma_i}, \tag{5}$$

where $A_{i,t}$ and $E_{i,t}$ are the actual and expected value of report i, and σ_i is the standard deviation of $A_{i,t} - E_{i,t}$.

Apart from providing a consensus view, these surveys also provide us with a measure of the dispersion in market expectations. To measure the dispersion in expectations, we compute the cross-sectional standard deviation among the different analysts ($SD_{i,t}$) and normalize this by the average inventories forecast ($\mu_{i,t}$), i.e.,

$$DISP_{i,t} = \frac{SD_{i,t}}{\mu_{i,t}}. \tag{6}$$

Table 1 provides an overview of the USDA announcements, including the time of the release, the frequency of the release, the number of observations, and several summary statistics on the content of the announcements. In total, there are 902 trading days that we consider in our sample. Of these, 53 contain USDA announcements. For the majority of the announcements, surprises are non-zero, i.e., the expected end inventory figures differ from the actual figures, which may suggest that there is unanticipated news in the USDA announcements. The table also reports the degree of analysts' forecast dispersion. The average degree of dispersion varies across the different announcements, but appears to be highest for the WASDE for Soybean and lowest for the AR on corn.

INSERT TABLE 1 HERE

Before we can use these data in our analysis, it is important to recognize that there may be seasonal patterns in these data. We illustrate this seasonality effect in Figure 1, where the coefficients of a regression between the analyst dispersion variables and monthly dummies from January 2013 to July 2016 across the three commodities are shown. We observe that particularly in the months of May, July and August, dispersion tends to be high across all the commodities. High dispersion in May is due to the end of the planting season, which makes inventory level more difficult to forecast (Lehecka, 2014). Dispersion is also high in July-August because crop yield during this growing season is sensitive to northern-hemisphere summer weather conditions (Tannura et al., 2008; Lehecka, 2014). In contrast, dispersion is low from October to November during the harvesting season when analysts have greater degree of certainty about their crop inventory forecasts. To ensure that our results are not driven by these seasonalities, we control for seasonalities in analysts' dispersion, by using a deseasonalized measure of analyst dispersion.

INSERT FIGURE 1 HERE

4.2. Futures Contracts

Our data consist of corn, wheat and soybean futures, which constitute the three most actively traded agricultural commodities at the Chicago Mercantile Exchange (CME). These futures are electronically-traded on the Chicago Board of Trade's GLOBEX trading platform. Our sample period is from January 1, 2013 to July 31, 2016. The start of the sample is chosen to match the change in USDA announcement time from 8:30am to 11:00am (Central Standard Time).[4] Trading in these futures is divided into a daytime (8:30am to 13:20pm) and evening session (19:00pm to 7:45am). We focus on the daytime session as the majority (approximately 90%) of trading occurs during this period (see e.g. Wang et al., 2013; Lehecka et al., 2014). Corn and wheat futures contracts have five maturities a year: March,

[4]From January 2013, the release time of major USDA reports was changed to occur during the most active trading session at 11:00am (CST), allowing markets the best chance to absorb news at a time of ordinarily high liquidity (Abbott, 2012). This change allows us to assess the impact of news since market participants can rapidly adjust their positions during this time.

May, July, September, and December, while soybean futures contracts have seven maturities: January, March, May, July, August, September and November. Each futures contract is for 5,000 bushels to be delivered on the second business day following the last trading day of the delivery month. On each trading day, about ten to twenty contracts are traded with different levels of activity. We focus on the nearby contracts as they are the most liquid, which should allow for an accurate assessment of market response (Isengildina-Massa et al., 2008; Karali, 2012). Each contract is rolled over to the next expiration when the volume of the second-nearby contract exceeds the volume of the front-end contract.

We obtain tick-level data (time-stamped to the nearest millisecond) for prices, volume, bid-ask quotes and bid-ask depths from Thomson Reuters Tick History maintained by the Securities Industry Research Centre of Asia-Pacific. Following Chordia et al. (2001) we clean our data of outliers by removing observations using the following filters: (i) Quoted Spread > \$5; (ii) Effective Spread/Quoted Spread > 4.0; (iii) Quoted Spread/Transaction Price > 0.4; (iv) Price is higher (lower) than the daily mean plus (minus) 5 times the daily standard deviation. Trades that are executed at the exact same time are treated as one trade. In this case, we assign the use the value-weighted average price and aggregate the traded volume.

Table 2 presents summary statistics for the futures contracts in our sample. It reports the average contract price, quoted spread, number of trades per day, daily trading volume, volume per trade and the bid and ask depths. As can be seen from the table, the average dollar spread is similar for the different contracts. However, since the average price levels differ across the three commodities, the average percentage spread varies, with corn contracts having the highest percentage spread at 5.99 bps, followed by wheat (4.65 bps) and soybean (2.38 bps). While the average number of trades is highest for the soybean futures, the average trading volume and volume per trade are highest for corn futures. Finally, we note that the average quantity offered at the bid and ask prices are roughly equal, but these figures are substantially higher for corn contracts.

INSERT TABLE 2 HERE

5. Empirical Results

In this section, we present our empirical results. First, we compare the spreads surrounding the USDA announcements on days with news versus non-USDA announcement days. Second, we decompose the spread in its different components to assess how the different components of the spread are affected by the USDA announcements. Finally, we conduct regression analyses to study the effect of news surprises and analysts' forecasts dispersion on information asymmetry components of the bid-ask spread. We also provide a robustness test for our results.

5.1. Spreads and USDA announcements

To assess whether spreads respond to USDA announcements, we plot the bid-ask spread during the day session on days with USDA announcements in Figure 2. Specifically, we show the abnormal spread, which is the difference between the spread during announcement days and non-announcement days, along with the 95% confidence interval. We observe that abnormal spreads are relatively constant throughout the trading day except during the period surrounding the announcements. Spreads start to widen shortly prior to the news release and peak at 11:00am (CST) when the USDA report is announced. Following the announcement, spreads decline gradually until the daytime trading session closes. Thus, we observe a clear reaction in bid-ask spreads in the period surrounding the USDA announcements.

INSERT FIGURE 2 HERE.

In Table 3, we report the results of a more formal test of the behavior of the futures in the 40-minute window surrounding the USDA announcements (20 minutes prior and after). We report averages for non-announcement and announcement days and conduct t-tests of the difference in means between announcement and non-announcement days.[5] Panels A to C report the statistics for the corn, wheat and soybean futures, respectively. We find that quoted spreads (both in dollar and percentage terms) increase significantly during the USDA announcements for each commodity. Daily number of trades and trading volume also

[5]We also employ a non-parametric Wilcoxon test for differences in medians. These results lead to the same conclusions as the t-test.

increase significantly. However, there is no significant change in volume per trade, indicating that trade size is not affected by USDA announcements. The last two rows show that bid and ask depths decrease significantly, suggesting that less market participants are willing to provide liquidity during announcement periods.

INSERT TABLE 3 HERE

To decompose the bid-ask spread, we estimate Equation (4) by GMM for each day over the 40 minute window around the announcement time of 11:00am.[6] Table 4 presents statistics for the average quoted spread, the effective spread[7] and implied spreads, computed as $IS_t = 2(\phi_t + \theta_t)$ during days with and without USDA announcements. The implied spread consists of the information asymmetry and order processing components, which we report in U.S. cents, as well as in percentages.[8] We also provide the difference in means and medians, along with their respective test statistics.[9]

INSERT TABLE 4 HERE

Panel A of Table 4 presents the results for the period from 10:40am to 11:20am. The first two rows show the average quoted and effective spreads as the basis for comparison. Both spreads are significantly higher (at the 1% level) during days with announcement compared to days without announcements. These results are consistent with Figure 2. The third row reports the implied spread estimated using the MRR model. Similar to the quoted and effective spreads, implied spreads are significantly higher during announcement days. When we consider the two components of the spread, we observe that the increase in spread is largely due to the increase in the information asymmetry component. The order processing component decreases during announcement days, which is expected as the increased trading

[6]We also consider information asymmetry and order processing components during the day before and after the announcement days with non-announcement days. On these days, we find no significant differences between the components from those days and non-announcement days.
[7]Effective spreads are computed as twice the difference between the transaction price (p_t) and the standing midquote (m_t), i.e., $ES_t = 2(p_t - m_t)$.
[8]We only report the results for the percentage spread due to information asymmetry, as the percentage of order processing costs makes up the remainder of the spread.
[9]We conduct a similar analysis for the four different USDA announcements. In general, our findings are consistent with previously reported results and can be found in Table A.1. in the Appendix.

activity around the announcement times leads to a lower per-trade cost of processing a transaction (Copeland and Stoll, 1990). Overall, these results are in line with studies from the finance literature, such as Krinsky and Lee (1995) and Riordan et al. (2013), who show that information asymmetry increases surrounding important news events.

Panel B reports the results for the period before the news release (10:40am – 11:00am).[10] We observe that the quoted, effective and implied spreads increase significantly during this period. This increase is attributed to information asymmetry, given that the order processing component remains relatively unchanged. These results suggest that traders may put some effort into private information acquisition, and this is reflected in their trades prior to the news announcement.

Panel C reports the results for the period after the news release (11:00am – 11:20am). The increase in spread after news releases is stronger than what is observed in the period before the news release. Again, this increase in spread is driven by the increase in the asymmetric information component of the spread. We attribute this finding to the increased divergence in interpretation of news. Kim and Verrechia (1994) explain that some market participants are inherently more informed than others. Information asymmetry may rise following the USDA announcements because those informed market participants are now able to faster make an assessment on the agricultural commodity futures on the basis of the newly-released reports relative to other traders in the market. This leads to increased information asymmetry among market participants.

5.2. Determinants of Increased Information Asymmetry.

While so far we have demonstrated that the increase in quoted spreads around the USDA announcements is primarily driven by the increase in information asymmetry, we have not considered the information content of the news. In this section, we consider the impact of two important aspects of news on information asymmetry: (i) the news surprise; and (ii) the dispersion in analysts' forecasts.

[10] Release dates and times for are published on the USDA website. Using Bloomberg news platform as source of precise news release (considering the precise release time as the first time when the news is mentioned in Bloomberg), we observe that the 90% of news releases of our sample are during the first second after 11am. There are no news releases before 11:00am.

We study the impact of news surprises and analysts' forecasts dispersion on information asymmetry using regression analyses.[11] The regressions are estimated using the full sample period, which includes announcement and non-announcement days. In the first specification, we examine the impact of news surprises measured by the absolute value of the surprise, $|S_t|$.[12] In the second specification, we separate the positive and negative news surprises. We do this by constructing a dummy variable I_t^+ which is equal to +1 if the surprise is positive and 0 otherwise, and I_t^- which is equal to -1 if the surprise is negative and 0 otherwise. Here, a positive (negative) surprise reflects an inventory announcement which is bigger (smaller) than expected by analysts. For the third specification, we examine the impact of analysts' forecasts dispersion, $DISP_t$, on information asymmetry. Finally, for the fourth and fifth specification, we include both the news surprises and analysts' forecasts dispersion variables in the same equations.

We include several control variables in our regressions. First, we control for time effects similar to Frank and Garcia (2011) and Wang et al. (2013). Specifically, we control for seasonalities and day-of-the-week effects by including monthly and daily dummies. We also include roll-day dummies (5^{th} to 9^{th} day of the month prior to maturity). Second, to control for market conditions, we include lagged information asymmetry, θ_{t-1}, and the roll returns (log front-end futures settlement price minus log second-end futures settlement price). We also include the lagged daily depth difference (average daily ask depth minus average daily bid depth), the lagged (log) changes in daily volume and lagged (log) changes in daily realized volatility (at 1-minute frequency) volatility, all lagged by one day to avoid endogeneity issues as pointed out in Wang et al. (2013).

INSERT TABLE 5 HERE.

[11] Prior to estimating the regression model, we test for non-stationarity of the dependent variable using Augmented Dickey-Fuller tests. We found that the information asymmetry component, θ_t is stationary. For brevity, we only report the regressions for information asymmetry.

[12] Given that the quarterly GSR is released together with WASDE, PP or AR in some quarters, we use the surprises of GSR on those days, as Wang et al. (2014) found that GSR reports have the biggest influence on the bid-ask spread.

Panel A in Table 5 reports the regressions for the period surrounding the news release (10:40am to 11:20am). In the first column, we observe that the coefficients for the absolute surprises, $|S_t|$ are positive and significant at the 1% level, indicating that the bigger the surprise, the larger the information asymmetry component. In the second column, we observe that both positive and negative surprises increase the information asymmetry component at the 1% level. In the third column, we replace news surprises with the dispersion in analysts' forecasts. We observe that the adjusted R^2 increases across all commodities, suggesting that this model is better in explaining the degree of information asymmetry. The coefficients are positive and highly significant, suggesting that a higher dispersion in analysts forecasts leads to increased information asymmetry surrounding the USDA announcement. In the fourth and fifth columns, we add back the news surprise. With the addition of the dispersion variable, the magnitudes of the news surprise coefficients decline substantially, although they remain statistically significant. Nevertheless, a large portion of information asymmetry is explained by the dispersion variable.

In Panel B of Table 5, we report the results for the 20-minute period prior to the news release. The first two columns show that coefficients for the news surprises are positive and statistically significant. This observation, that the surprise in the news is related to the degree of information asymmetry prior to the release of that news, suggests that some market participants are informed about the content of the announcement, and suggests that some market participants are able to acquire private information. When we replace news surprises with analyst dispersion, the adjusted R^2 increases, suggesting that the latter model provides better fit. The dispersion variable is highly significant, showing that if there is a high dispersion in forecasts about the upcoming USDA announcement, then the information asymmetry prior to the news announcement is higher. The most striking result of Panel B is that when we include both the news surprises and the dispersion variables, much of the significance of the news surprise coefficients disappears. This shows that it is not the surprise in the news announcement that drives the degree of information asymmetry prior to the announcement, but the degree of dispersion among analysts. These findings suggest that if dispersion among analyst forecasts is high, then it pays for market participants to engage in the acquisition of private information.

Panel C of Table 5 reports the results for the 20-minute period following the USDA announcement. The results suggest that both news surprises and analyst's dispersion are important determinants of information asymmetry. Here, the news surprises coefficients are statistically significant despite the inclusion of the dispersion variable because different traders have varying capabilities to interpret news announcements with relation to the commodity futures. Hence, information asymmetry remains high post-news, a finding which is consistent with Kim and Verrecchia (1994).[13]

5.3. Robustness Test

Although the results reported for the full sample in Table 5 are appealing, we cannot rule out the possibility that the increased information asymmetry is due to the news-day effect rather than surprise and/or analysts' dispersion effects. To eliminate the news-day effect, we focus our analysis on days with news releases, i.e. the 53 USDA announcement days. However, due to the reduced sample size, we face insufficient degrees of freedom if we add all the control variables. Hence, to control for the seasonality effects and obtain meaningful t-statistics, we first run a regression of $DISP_{i,t}$ on month-dummy variables. We collect the residual from this regression, which we call the *deseasonalized analyst dispersion*, $DDISP_{i,t}$. We then use $DDISP_{i,t}$ for regression analyses similar to Table 5.[14]

Table 6 reports the results of the new regression analyses. In general, the results are consistent with those reported in Table 5. In particular, the coefficients for the analysts' forecasts dispersion variable are positive and highly significant across all the periods. The coefficients, however, are larger in the 20-minute period prior to the news release. This observation suggests that the increase in information asymmetry prior to the news announcement is driven by the dispersion in analysts' forecasts. We therefore conclude that liquidity providers widen the bid-ask spread during the pre-news period as compensation for

[13]Consistent with Wang et al. (2013), we find that seasonality, day-of-the-week, and the roll days dummies are significant in explaining information asymmetry. The coefficient for the lagged information asymmetry is positive and significant, suggesting that there is persistence in information asymmetry. The roll-returns coefficient is positive and significant which may indicate strong backwardation in agricultural commodities futures, i.e., more information about the fundamentals are released to the market. We also observe that lagged volume and lagged realized volatility are significant determinants of information asymmetry. These results are available from the corresponding author.
[14]Unlike the dispersion variable, we do not observe seasonality effect in the news surprises nor in the information asymmetry component. Hence, we only deseasonalize the analysts' dispersion.

increased information asymmetry due to disagreement among traders and investors about the end-inventory figures of the USDA reports.[15]

INSERT TABLE 6 HERE.

6. Conclusion

In this paper, we assess the role of information asymmetry on the changes in bid-ask spreads. We focus on the bid-ask spread around major USDA announcements and employ the spread decomposition model of Madhavan et al. (1997) to decompose the bid-ask spread into information asymmetry and the order processing components. We compare these components during days with the scheduled USDA announcements and non-USDA announcement days.

We observe that information asymmetry is significantly higher during the USDA announcement days than on non-announcement days. We also find that the increase in information asymmetry prior to the news announcement is driven by divergence in private information possessed by market participants, obtained using Bloomberg analysts' survey. This information was obtained one week or more, prior to the USDA report announcements. Once the news is released, both analysts' forecasts dispersion and news surprises (the difference between actual figures and market expectations) are responsible in increased information asymmetry and widening of the bid-ask spread. These results remain after controlling for the variables known to affect the bid-ask spread and for the news-day effect.

[15] We also test using various approaches to measure dispersion such as the interquartile dispersion (IQD) and median absolute dispersion (MAD). The results are qualitatively similar to those reported in Table 6 and are available from the corresponding author.

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7. Appendix A

Table A.1. Spread Decomposition by Announcements (in US cents)

This table reports the estimates from the MRR decomposition model during the 40-minute period surrounding the USDA report announcement time (10:40am to 11:20am). It includes the quoted and implied spreads, the various spread components, the autocorrelation of order flow, and the inside quote probability, during announcement days(A), non-announcement days (NA), and their differences. Panels A, B, C, and D report the components during the WASDE, Grain Stocks reports, Prospective Plantings reports and Acreage reports, respectively. Figures in parentheses are the t-statistics. *** and ** denote statistical significance at 1% and 5% levels, respectively.

	Corn Futures				**Wheat Futures**				**Soybean Futures**			
	NA	*A*	*Diff*	*t-stat*	*NA*	*A*	*Diff*	*t-stat*	*NA*	*A*	*Diff*	*t-stat*
Panel A: WASDE												
Quoted spread	0.252	0.282	0.030***	(31.62)	0.259	0.302	0.043***	(23.51)	0.260	0.319	0.059***	(33.23)
Implied spread	0.189	0.199	0.011***	(2.43)	0.161	0.209	0.049***	(11.31)	0.171	0.239	0.069***	(20.18)
-Information asymmetry, θ (in cents)	0.008	0.032	0.024***	(23.57)	0.027	0.056	0.030***	(14.56)	0.030	0.063	0.032***	(15.35)
-Order processing, φ (in cents)	0.086	0.067	-0.019***	(-7.01)	0.053	0.048	-0.005**	(-1.98)	0.055	0.057	0.002	(0.92)
-Information asymmetry, θ (in %)	90.9%	68.1%	-22.8%***	(-17.98)	65.9%	46.7%	-19.1%***	(-7.77)	64.4%	48.6%	-15.8%***	(-7.02)
-Order processing, φ (in %)	9.1%	31.9%	22.8%***	(17.98)	34.1%	53.3%	19.1%***	(7.77)	35.6%	51.4%	15.8%***	(7.02)
Panel B: Grain Stocks Reports												
Quoted spread	0.252	0.294	0.042***	(27.71)	0.259	0.329	0.070***	(23.27)	0.260	0.348	0.088***	(31.44)
Implied spread	0.189	0.218	0.029***	(3.99)	0.161	0.240	0.080***	(11.25)	0.171	0.270	0.099***	(17.97)
-Information asymmetry, θ (in cents)	0.008	0.035	0.027***	(16.34)	0.027	0.064	0.037***	(11.15)	0.030	0.071	0.040***	(11.85)
-Order processing, φ (in cents)	0.086	0.073	-0.013***	(-2.85)	0.053	0.056	0.003	(0.64)	0.055	0.064	0.009***	(2.54)
-Information asymmetry, θ (in %)	90.9%	68.6%	-22.3%***	(-10.69)	65.9%	47.3%	-18.6%***	(-4.56)	64.4%	48.0%	-16.4%***	(-4.38)
-Order processing, φ (in %)	9.1%	31.4%	22.3%***	(10.69)	34.1%	52.7%	18.6%***	(4.56)	35.6%	52.0%	16.4%***	(4.38)
Panel C: Prospective Plantings Reports												
Quoted spread	0.252	0.292	0.040***	(20.51)	0.259	0.328	0.069***	(13.51)	0.260	0.372	0.112***	(24.76)
Implied spread	0.189	0.221	0.032**	(2.31)	0.161	0.244	0.084***	(6.20)	0.171	0.282	0.111***	(10.90)
-Information asymmetry, θ (in cents)	0.008	0.033	0.025***	(7.87)	0.027	0.063	0.036***	(5.69)	0.030	0.076	0.045***	(6.95)
-Order processing, φ (in cents)	0.086	0.078	-0.009	(-0.99)	0.053	0.059	0.006	(0.68)	0.055	0.065	0.010	(1.44)
-Information asymmetry, θ (in %)	90.9%	72.1%	-18.7%***	(-4.69)	65.9%	49.1%	-16.8%**	(-2.13)	64.4%	47.1%	-17.3%**	(-2.39)
-Order processing, φ (in %)	9.1%	27.9%	18.7%***	(4.69)	34.1%	50.9%	16.8%**	(2.13)	35.6%	52.9%	17.3%**	(2.39)
Panel D: Acreage Reports												
Quoted spread	0.252	0.324	0.072***	(32.76)	0.259	0.355	0.096***	(19.19)	0.260	0.381	0.121***	(27.80)
Implied spread	0.189	0.233	0.045***	(3.20)	0.161	0.256	0.096***	(7.13)	0.171	0.312	0.141***	(13.74)
-Information asymmetry, θ (in cents)	0.008	0.045	0.037***	(11.99)	0.027	0.073	0.046***	(7.21)	0.030	0.078	0.048***	(7.34)
-Order processing, φ (in cents)	0.086	0.072	-0.015*	(-1.69)	0.053	0.055	0.002	(0.23)	0.055	0.078	0.023***	(3.23)
-Information asymmetry, θ (in %)	90.9%	61.7%	-29.2%***	(-7.33)	65.9%	44.0%	-21.9%***	(-2.77)	64.4%	49.6%	-14.8%**	(-2.05)
-Order processing, φ (in %)	9.1%	38.3%	29.2%***	(7.33)	34.1%	56.0%	21.9%***	(2.77)	35.6%	50.4%	14.8%**	(2.05)

Appendix B. Frequency of Analysts' Forecasts in the Bloomberg's Survey

Panel A: Forecasts for Corn

Corn	WASDE	GSR	PP	AR		WASDE	GSR	PP	AR
A/C Trading	37	8	4	2	GlobalEqon LLC	0	0	0	0
ABN Amro	3	2	1	0	Goldman, Sachs & Co.	0	0	0	1
ADM Investor Services	42	13	4	3	Grain Service	24	13	3	3
Advance Trading Inc	2	0	0	0	Hightower Report	9	4	3	2
Advanced Economic Solutions	2	2	1	1	Hueber Report	13	3	0	1
Advanced Market Concepts	39	15	4	4	INTL FCStone	41	13	3	4
AgResource	10	3	2	1	Jefferies Bache	27	10	3	2
AgriSource	34	2	3	0	Jefferies Llc	1	0	0	0
AgriVisor Services	34	15	4	4	Linn Group	33	12	4	4
Allendale Inc.	24	6	3	3	Love Consulting	42	15	4	4
Bennett Consulting	8	4	1	2	Macquarie Bank Ltd.	1	0	0	0
Brock Associates	1	0	0	1	Macquarie Group	20	8	2	2
Brugler Marketing	35	11	0	2	Mckeaney-Flavell	35	11	3	3
CHS Hedging Inc	21	8	2	2	Midco Commodities	6	0	0	0
CHS Hedging Llc	11	2	1	1	Morgan Stanley	1	1	0	1
Citi Futures Perspective	5	0	0	0	NewEdge	20	7	2	2
Citigroup	19	7	3	3	Northstar Commodity	41	13	4	4
Citigroup Global Markets Inc	0	1	0	1	Pira Energy Group	12	3	4	3
Commodity Information Systems	29	11	4	4	Price Futures Group	40	15	4	3
Corn & Soybean Advisor	0	0	0	0	Prime Agriculture Consulting	36	15	4	4
Country Hedging	3	1	0	0	R.J. O'Brien & Associates	41	14	4	4
Daniels Trading	1	1	0	1	Rabobank	5	0	2	1
DC Analysis Llc	6	2	1	1	Rabobank Nederland	0	0	1	0
Deutsche Bank Securities	4	1	0	1	Risk Management Commodities	13	1	1	0
Doane Agricultural Services	42	15	2	4	Roach AG	1	0	0	0
ED&F MAN Capital Markets Inc	36	13	3	4	Societe Generale	3	0	3	2
EFG Group	41	14	4	4	Stewart-Peterson Group	38	12	4	4
Farm Direction Llc	7	3	2	1	U.S. Commodities Inc.	36	12	4	3
Farm Futures	39	13	4	4	Vantage RM	36	12	3	4
FC Stone Inc	4	1	0	0	Walsh Trading	14	0	2	1
Fimat Futures	0	1	0	0	Water Street Solutions Inc	3	1	1	1
Fintec Group Inc	4	2	1	0	Western Milling	15	5	2	2
Futures International LLC	35	12	3	3	Zaner Group Llc	29	11	3	3
Global Commodity A&C	7	0	1	0					

Panel B: Forecasts for Wheat

Wheat									
	WASDE	GSR	PP	AR		WASDE	GSR	PP	AR
A/C Trading	26	3	0	0	Grain Service	23	13	2	1
ABN Amro	3	2	1	0	Hightower Report	9	4	3	1
ADM Investor Services	42	13	4	2	Hueber Report	11	3	0	0
Advanced Economic Solutions	2	2	1	1	INTL FCStone	41	13	3	2
Advanced Market Concepts	41	15	4	2	Jefferies Bache	27	10	3	1
AgResource	5	3	2	0	Jefferies Llc	1	0	0	0
AgriSource	28	1	1	0	Linn Group	28	11	4	2
AgriVisor Services	35	15	4	2	Love Consulting	42	15	4	2
Allendale Inc.	25	6	3	1	Macquarie Bank Ltd.	0	1	0	0
Bennett Consulting	5	2	1	1	Macquarie Group	21	7	2	1
Brock Associates	1	0	0	1	Mckeaney-Flavell	32	11	3	2
Brugler Marketing	31	8	0	0	Midco Commodities	6	0	0	0
CHS Hedging Inc	21	8	2	1	NewEdge	20	7	2	1
CHS Hedging Llc	11	2	1	1	Northstar Commodity	41	12	4	2
Citi Futures Perspective	5	0	0	0	Pira Energy Group	5	1	3	1
Citigroup	17	6	3	1	Price Futures Group	39	13	4	1
Commodity Information Systems	18	3	4	1	Prime Agriculture Consulting	35	15	3	2
Country Hedging	3	1	0	0	R.J. O'Brien & Associates	41	13	4	2
Daniels Trading	1	1	0	1	Rabobank	0	0	2	0
DC Analysis Llc	6	2	1	1	Risk Management Commodities	2	1	0	0
Deutsche Bank Securities	1	0	0	0	Roach AG	1	0	0	0
Doane Agricultural Services	35	12	2	2	Societe Generale	3	0	3	0
ED&F MAN Capital Markets Inc	36	13	3	2	Stewart-Peterson Group	38	12	4	2
EFG Group	41	14	4	2	U.S. Commodities Inc.	10	4	2	0
Farm Direction Llc	7	2	2	0	Vantage RM	36	12	2	2
Farm Futures	38	14	4	2	Walsh Trading	14	0	1	0
FC Stone Inc	4	1	0	0	Water Street Solutions Inc	3	1	1	1
Fintec Group Inc	5	2	1	0	Western Milling	14	5	2	1
Futures International LLC	35	12	3	1	Zaner Group Llc	29	11	3	2
Global Commodity A&C	7	0	1	0					

Panel C: Forecasts for Soybean

Soybean									
	WASDE	GSR	PP	AR		WASDE	GSR	PP	AR
A/C Trading	37	8	4	2	GlobalEqon LLC	0	1	0	0
ABN Amro	3	2	1	0	Goldman, Sachs & Co.	0	0	0	1
ADM Investor Services	42	13	4	3	Grain Service	24	12	3	3
Advance Trading Inc	1	0	0	1	Hightower Report	9	4	3	2
Advanced Economic Solutions	2	2	1	1	Hueber Report	13	3	0	1
Advanced Market Concepts	40	15	4	3	INTL FCStone	41	13	3	4
AgResource	8	3	2	1	Jefferies Bache	27	10	3	2
AgriSource	35	2	3	0	Jefferies Llc	1	0	0	0
AgriVisor Services	35	15	4	4	Linn Group	33	12	4	4
Allendale Inc.	24	6	3	3	Love Consulting	42	15	4	4
Bennett Consulting	8	4	1	2	Macquarie Bank Ltd.	2	0	0	0
Brock Associates	1	0	0	1	Macquarie Group	19	8	2	2
Brugler Marketing	35	11	0	2	Mckeaney-Flavell	35	11	3	3
CHS Hedging Inc	21	8	2	2	Midco Commodities	6	0	0	0
CHS Hedging Llc	11	2	1	1	Morgan Stanley	1	1	0	1
Citi Futures Perspective	5	0	0	0	NewEdge	20	7	2	2
Citigroup	19	7	3	3	Northstar Commodity	41	13	4	4
Citigroup Global Markets Inc	0	1	0	1	Pira Energy Group	12	3	4	3
Commodity Information Systems	28	10	4	4	Price Futures Group	40	15	4	3
Corn & Soybean Advisor	1	0	0	0	Prime Agriculture Consulting	36	15	4	4
Country Hedging	3	1	0	0	R.J. O'Brien & Associates	41	14	4	4
Daniels Trading	1	1	0	1	Rabobank	5	1	2	1
DC Analysis Llc	6	2	1	1	Rabobank Nederland	0	0	1	0
Deutsche Bank Securities	4	1	0	1	Risk Management Commodities	13	1	1	0
Doane Agricultural Services	42	14	2	4	Roach AG	1	0	0	0
ED&F MAN Capital Markets Inc	36	13	3	4	Societe Generale	3	0	3	2
EFG Group	41	14	4	4	Stewart-Peterson Group	38	12	4	4
Farm Direction Llc	7	3	2	1	U.S. Commodities Inc.	36	12	4	3
Farm Futures	39	14	4	4	Vantage RM	36	12	3	4
FC Stone Inc	4	1	0	0	Walsh Trading	14	0	2	1
Fintec Group Inc	4	2	1	0	Water Street Solutions Inc	3	1	1	1
Futures International LLC	35	12	3	3	Western Milling	15	5	2	2
Global Commodity A&C	7	0	1	0	Zaner Group Llc	29	11	3	3

Table 1. US Department of Agriculture (USDA) Announcements

This table provides a summary of the USDA announcement releases from the period January 1, 2013 to July 31, 2016. It reports the time of the release (in Central Standard Time), the frequency of the release, and the total number of release. The table also reports statistics for the surveys, actuals, and surprises for each of the agricultural commodities, along with the standard deviation of the surprises and the average analysts' forecasts dispersion.

No	Agricultural Announcements	CST	Frequency	Obs	Survey (in millions)	Actual (in millions)	Surprises (in millions)	Non-zero surprises	Surprises std dev	$DISP_t$
1	World Agricultural Supply and Demand Estimate	11:00	Monthly							
	- Corn			42	1,722.3	1,699.3	-22.98	40	96.22	0.065
	- Wheat			42	734.6	739.3	4.64	40	37.87	0.047
	- Soybean			42	325.8	327.7	1.95	37	26.78	0.103
2	Grain Stocks Report	11:00	Quarterly							
	- Corn			15	5,877.7	5,893.8	16.13	15	181.66	0.027
	- Wheat			15	1,339.9	1,338.1	-1.80	15	33.77	0.032
	- Soybean			15	1,140.3	1,131.2	-9.07	15	48.96	0.050
3	Prospective Plantings Report	11:00	Annually							
	- Corn			4	92.4	92.9	0.52	4	2.20	0.007
	- Wheat			4	54.8	54.3	-0.50	4	0.67	0.010
	- Soybean			4	82.2	81.4	-0.86	4	0.98	0.012
4	Acreage Report	11:00	Annually							
	- Corn			4	92.2	93.0	0.79	4	1.03	0.006
	- Wheat			2	52.9	55.0	2.11	2	1.55	0.008
	- Soybean			4	82.3	82.8	0.53	4	0.19	0.007
	Total Announcements Days (adjusted)			53						
	Total Non-Announcement Days			849						
	Total Sample Days			902						

Table 2. Summary Statistics

This table provides summary statistics for the agricultural futures contracts. The reported figures are the daily averages over the sample period from January 1, 2013 to July 31, 2016.

	Corn	Wheat	Soybean
Price per bushel (in cents)	513.8	620.1	1214.3
Dollar Quoted spread (in cents)	0.253	0.261	0.262
Percentage Quoted spread (bps)	5.99	4.65	2.38
Trades per day	8,129	5,642	9,979
Volume per day	67,651	26,999	46,658
Volume per Trade	8.6	4.9	4.8
Bid Depth	173	28	28
Ask Depth	177	28	27

Table 3. Summary Statistics (20-minute before and 20-minute after)

This table provides summary statistics for the agricultural futures contracts during the 40min period surrounding USDA report announcements (20min prior to and 20min after 11:00am). The reported figures are the average values over the sample period from January 1, 2013 to July 31, 2016. "NA" and "A" denote Non-Announcement and Announcement days, respectively, while "Diff" is the change, and the t-statistics are in parentheses. *** denotes statistical significance at 1% level.

	NA	*A*	*Diff*	*t-stat*
Panel A: Corn Futures				
Quoted spread (cents)	0.252	0.277	0.0255***	(10.00)
Quoted spread (bps)	5.96	6.73	0.76***	(9.44)
Trade	1,502	7,028	5,526***	(12.50)
Volume	12,376	58,814	46,438***	(12.24)
Volume per Trade	8.4	9.0	0.6	(1.90)
Average Bid Depth	176	77	-100***	(-9.54)
Average Ask Depth	178	86	-92***	(-6.49)
Panel B: Wheat Futures				
Quoted spread (cents)	0.259	0.299	0.0399***	(11.03)
Quoted spread (bps)	4.62	5.47	0.85***	(11.15)
Trade	1,092	4,012	2,919***	(13.19)
Volume	5,206	17,917	12,711***	(12.89)
Volume per Trade	4.8	4.6	-0.2	(-1.55)
Average Bid Depth	29	17	-12***	(-12.36)
Average Ask Depth	29	16	-12***	(-16.86)
Panel C: Soybean Futures				
Quoted spread (cents)	0.260	0.312	0.0514***	(12.53)
Quoted spread (bps)	2.36	2.94	0.58***	(14.04)
Trade	1,883	8,063	6,179***	(15.07)
Volume	8,833	38,248	29,415***	(14.00)
Volume per Trade	4.8	4.9	0.1	(1.39)
Average Bid Depth	28	19	-9***	(-5.28)
Average Ask Depth	27	17	-11***	(-7.55)

Table 4. Spread Decomposition during Announcements (in US cents)

This table reports the estimates from the MRR decomposition model. It includes the quoted, effective and implied spreads, and the various spread components during USDA report announcements (A), non-announcement days (NA), and their mean and median differences. Panel A reports the components during the full 40-minute period surrounding the announcement (10:40am to 11:20am). Panel B reports the components for the 20-minute period prior to the announcement (10:40am to 11:00am). Panel C reports the components for the 20-minute period following the announcement (11:00am to 11:20am). Figures in parentheses are the t-statistics corrected using Newey-West correction. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	Corn Futures						**Wheat Futures**						**Soybean Futures**					
	NA	*A*	*Mean Diff*	*t-stat*	*Median Diff*	*Wilcoxon*	*NA*	*A*	*Mean Diff*	*t-stat*	*Median Diff*	*Wilcoxon*	*NA*	*A*	*Mean Diff*	*t-stat*	*Median Diff*	*Wilcoxon*
Panel A: Full Period (10:40 - 11:20)																		
Quoted spread	0.252	0.279	0.027***	(18.51)	0.021***	(11.37)	0.259	0.301	0.042***	(13.08)	0.041***	(10.73)	0.260	0.318	0.058***	(19.80)	0.058***	(10.99)
Effective Spread	0.249	0.269	0.020***	(20.65)	0.015***	(11.39)	0.252	0.284	0.032***	(19.14)	0.025***	(11.57)	0.253	0.299	0.046***	(25.21)	0.039***	(11.67)
Implied spread	0.189	0.203	0.014**	(2.51)	0.009**	(2.31)	0.161	0.215	0.054***	(7.86)	0.047***	(9.35)	0.171	0.247	0.076***	(12.95)	0.078***	(10.57)
-Information asymmetry, θ (in cents)	0.016	0.066	0.050***	(12.64)	0.026***	(11.48)	0.054	0.116	0.062***	(9.41)	0.068***	(10.54)	0.061	0.129	0.068***	(8.70)	0.069***	(10.46)
-Order processing, φ (in cents)	0.173	0.137	-0.036***	(-3.65)	-0.021***	(-7.48)	0.107	0.099	-0.008	(-1.03)	-0.009*	(-1.86)	0.110	0.118	0.008	(1.11)	0.010**	(1.97)
-Information asymmetry, θ (in %)	9.1%	31.7%	22.6%***	(9.57)	24.9%***	(11.17)	34.1%	53.3%	19.2%***	(5.13)	20.4%***	(8.56)	35.6%	51.4%	15.8%***	(3.81)	16.1%***	(8.11)
Panel B: 20-minutes before (10:40 - 11:00)																		
Quoted spread	0.252	0.258	0.006***	(6.33)	0.004***	(8.01)	0.259	0.270	0.011***	(3.92)	0.008***	(5.89)	0.260	0.273	0.013***	(5.93)	0.014***	(7.46)
Effective Spread	0.249	0.253	0.002***	(6.00)	0.004***	(6.56)	0.252	0.259	0.008***	(5.78)	0.005***	(6.35)	0.253	0.263	0.011***	(8.69)	0.009***	(9.21)
Implied spread	0.187	0.197	0.009*	(1.81)	0.011**	(2.14)	0.161	0.179	0.018***	(2.61)	0.019***	(4.13)	0.170	0.191	0.021***	(3.69)	0.024***	(5.78)
-Information asymmetry, θ (in cents)	0.016	0.025	0.009**	(2.39)	0.009***	(3.79)	0.054	0.078	0.024***	(3.49)	0.029***	(4.51)	0.060	0.082	0.022***	(2.78)	0.020***	(4.90)
-Order processing, φ (in cents)	0.171	0.172	0.000	(0.02)	-0.005	(-0.23)	0.107	0.101	-0.006	(-0.72)	-0.001	(-0.68)	0.110	0.109	-0.001	(-0.07)	0.003	(0.17)
-Information asymmetry, θ (in %)	9.3%	12.9%	3.5%	(1.64)	3.8%***	(3.08)	34.4%	42.8%	8.4%**	(2.02)	10.6%***	(3.13)	35.6%	42.6%	6.9%	(1.61)	4.9%***	(3.11)
Panel C: 20-minutes after (11:00 - 11:20)																		
Quoted spread	0.252	0.283	0.031***	(19.79)	0.025***	(11.56)	0.307	0.259	0.048***	(14.15)	0.039***	(10.95)	0.326	0.260	0.066***	(21.09)	0.066***	(11.14)
Effective Spread	0.249	0.272	0.024***	(21.81)	0.017***	(11.51)	0.288	0.251	0.037***	(20.01)	0.028***	(11.65)	0.305	0.253	0.052***	(26.28)	0.049***	(11.70)
Implied spread	0.191	0.203	0.012**	(1.99)	0.004	(1.53)	0.161	0.221	0.060***	(13.39)	0.053***	(9.14)	0.172	0.257	0.085***	(13.98)	0.086***	(10.63)
-Information asymmetry, θ (in cents)	0.015	0.074	0.057***	(14.09)	0.061***	(11.54)	0.054	0.122	0.069***	(9.76)	0.073***	(10.73)	0.061	0.137	0.076***	(9.27)	0.080***	(10.69)
-Order processing, φ (in cents)	0.176	0.129	-0.046***	(-4.63)	-0.048***	(-8.21)	0.107	0.098	-0.009	(-1.14)	-0.009**	(-1.99)	0.110	0.119	0.009	(1.17)	0.009**	(2.05)
-Information asymmetry, θ (in %)	8.8%	35.9%	26.5%***	(10.96)	28.5%***	(11.33)	34.2%	55.0%	20.9%***	(5.35)	22.9%***	(8.55)	35.8%	52.8%	17.0%***	(3.95)	17.6%***	(8.29)

Table 5. The Impact of News Surprises and Analysts' Forecasts Dispersion on Information Asymmetry (Full Sample)

This table reports the regression coefficients of news surprises and analysts' forecasts dispersion on the information asymmetry component of spread. $|S_t|$ denotes the absolute news surprises. $(I_t^+ * S_t)$ and $(I_t^- * S_t)$ denote positive and negative news surprises, respectively. $DISP_{i,t}$ denotes the dispersion variable of Equation (6). The *Control* variables include the lagged information asymmetry component, the lagged market depths, the roll returns, the lagged (log) daily volume and the lagged (log) daily realized volatility. The *Time Effects* variables include the dummies for month, day-of-the-week and roll days. Figures in parentheses are the t-statistics corrected by Newey-West standard error. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	Corn Futures					**Wheat Futures**					**Soybean Futures**				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Panel A: Full Period (10:40 - 11:20)															
Constant	0.0533***	0.0530***	0.0567***	0.0559***	0.0553***	0.0867***	0.0860***	0.0933***	0.0942***	0.0931***	0.1274***	0.1262***	0.1334***	0.1319***	0.1305***
	(4.93)	(4.89)	(5.18)	(5.56)	(5.55)	(3.35)	(3.31)	(3.65)	(3.71)	(3.65)	(4.42)	(4.36)	(4.58)	(4.61)	(4.56)
$\lvert S_t \rvert$	0.0291***			0.0154***		0.0263***			0.0108***		0.0231***			0.0039	
	(10.22)			(5.34)		(7.81)			(2.77)		(4.03)			(0.71)	
$I_t^+ * S_t$		0.0266***			0.0096***		0.0248***			0.0080*		0.0213***			0.0020
		(6.13)			(2.59)		(5.37)			(1.76)		(2.76)			(0.33)
$I_t^- * S_t$		0.0309***			0.0186***		0.0284***			0.0140***		0.0257***			0.0065
		(8.62)			(5.30)		(6.13)			(3.19)		(3.72)			(0.90)
$DISP_t$			0.3457***	0.2369***	0.2459***			0.5709***	0.4137***	0.4210***			0.3026***	0.2751***	0.2752***
			(10.42)	(6.65)	(7.91)			(8.56)	(4.93)	(4.74)			(12.58)	(9.54)	(9.93)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	51.7%	51.8%	56.4%	61.4%	62.1%	30.0%	30.0%	33.6%	34.9%	35.0%	32.8%	32.8%	41.8%	41.9%	42.0%
Panel B: 20-minute before (10:40 - 11:00)															
Constant	0.0453***	0.0453***	0.0467***	0.0465***	0.0464***	0.0758***	0.0751***	0.0815***	0.0815***	0.0808***	0.0749***	0.0743***	0.0782***	0.0780***	0.0773***
	(4.79)	(4.79)	(4.91)	(4.93)	(4.93)	(3.11)	(3.05)	(3.32)	(3.32)	(3.27)	(2.98)	(2.96)	(3.11)	(3.11)	(3.09)
$\lvert S_t \rvert$	0.0064***			0.0033**		0.0086***			-0.0002		0.0074***			0.0006	
	(4.96)			(2.19)		(3.54)			(-0.05)		(3.54)			(0.27)	
$I_t^+ * S_t$		0.0058***			0.0020		0.0060**			-0.0038		0.0062***			-0.0006
		(4.19)			(1.36)		(2.42)			(-1.13)		(4.12)			(-0.34)
$I_t^- * S_t$		0.0069***			0.0041**		0.0121***			0.0038		0.0091**			0.0023
		(3.51)			(2.05)		(2.84)			(0.83)		(2.00)			(0.50)
$DISP_t$			0.0768***	0.0532***	0.0554***			0.2326***	0.2349***	0.2444***			0.1011***	0.0967***	0.0968***
			(5.66)	(3.09)	(3.15)			(4.80)	(3.18)	(3.16)			(6.31)	(4.96)	(5.07)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	41.8%	41.8%	42.3%	42.6%	42.6%	18.4%	18.5%	20.0%	19.9%	20.2%	31.1%	31.0%	32.4%	32.3%	32.3%
Panel C: 20-minute after (11:00 - 11:20)															
Constant	0.0578***	0.0575***	0.0597***	0.0601***	0.0596***	0.1263***	0.1255***	0.1297***	0.1316***	0.1300***	0.2023***	0.2013***	0.2082***	0.2068***	0.2058***
	(4.82)	(4.79)	(4.99)	(5.39)	(5.42)	(3.99)	(3.97)	(4.20)	(4.26)	(4.22)	(6.35)	(6.32)	(6.55)	(6.57)	(6.53)
$\lvert S_t \rvert$	0.0330***			0.0171***		0.0292***			0.0119***		0.0252***			0.0035	
	(10.39)			(5.32)		(7.57)			(2.75)		(4.04)			(0.58)	
$I_t^+ * S_t$		0.0303***			0.0106**		0.0278***			0.0092*		0.0235***			0.0017
		(6.11)			(2.35)		(5.17)			(1.75)		(2.71)			(0.24)
$I_t^- * S_t$		0.0350***			0.0207***		0.0310***			0.0149***		0.0277***			0.0060
		(8.87)			(5.37)		(6.06)			(3.19)		(3.91)			(0.81)
$DISP_t$			0.3955***	0.2745***	0.2848***			0.6340***	0.4619***	0.4689***			0.3356***	0.3112***	0.3113***
			(10.31)	(6.70)	(7.91)			(8.47)	(4.98)	(4.78)			(12.99)	(9.89)	(10.23)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	47.1%	47.1%	52.4%	57.2%	57.9%	25.5%	25.5%	29.0%	30.1%	30.2%	29.0%	29.0%	38.5%	38.5%	38.6%

Table 6. The Impact of News Surprises and Analysts' Forecasts Dispersion on Information Asymmetry (Announcement Days Sample)

This table reports the regression coefficients of news surprises and analysts' forecasts dispersion on the information asymmetry component of spread. $|S_t|$ denotes the absolute news surprises. $(I_t^+ * S_t)$ and $(I_t^- * S_t)$ denote positive and negative news surprises, respectively. $DDISP_t$ denotes the deseasonalized dispersion variable. Figures in parentheses are the t-statistics corrected by White standard error. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	Corn Futures					**Wheat Futures**					**Soybean Futures**				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Panel A: Full Period (10:40 - 11:20)															
Constant	0.0283***	0.0283***	0.0328***	0.0284***	0.0284***	0.0566***	0.0565***	0.0580***	0.0570***	0.0570***	0.0627***	0.0632***	0.0645***	0.0632***	0.0636***
	(10.60)	(10.65)	(18.17)	(10.83)	(10.88)	(14.80)	(14.72)	(24.70)	(14.94)	(14.84)	(19.85)	(19.50)	(26.37)	(20.08)	(19.84)
$\|S_t\|$	0.0084**			0.0082**		0.0018			0.0013		0.0027			0.0020	
	(2.28)			(2.29)		(0.69)			(0.48)		(1.07)			(0.67)	
$I_t^+ * S_t$		0.0061			0.0053		-0.0003			-0.0013		0.0042			0.0032
		(1.42)			(1.32)		(-0.09)			(-0.38)		(1.18)			(0.75)
$I_t^- * S_t$		0.0098**			0.0100**		0.0048			0.0046		-0.0001			-0.0002
		(2.28)			(2.32)		(1.45)			(1.45)		(-0.03)			(-0.08)
$DDISP_t$			0.1293*	0.1240**	0.1325**			0.1574	0.1509	0.1746			0.2579***	0.2520**	0.2471**
			(1.83)	(2.00)	(2.13)			(1.16)	(1.10)	(1.31)			(2.62)	(2.44)	(2.31)
Adj-R2	6.5%	5.6%	2.9%	9.2%	8.9%	-1.5%	-1.4%	0.4%	-1.3%	-0.5%	-0.7%	-1.3%	9.0%	7.9%	7.0%
Panel B: 20-minute before (10:40 - 11:00)															
Constant	0.0105***	0.0105***	0.0126***	0.0106***	0.0106***	0.0428***	0.0427***	0.0391***	0.0437***	0.0437***	0.0413***	0.0413***	0.0412***	0.0416***	0.0416***
	(5.80)	(5.79)	(10.61)	(5.94)	(5.93)	(10.22)	(9.95)	(14.29)	(10.46)	(10.25)	(15.19)	(15.07)	(20.13)	(16.24)	(15.88)
$\|S_t\|$	0.0039			0.0037		-0.005			-0.0059		0.000			-0.0007	
	(1.45)			(1.53)		(-1.36)			(-1.62)		(-0.09)			(-0.39)	
$I_t^+ * S_t$		0.004			0.0030		-0.0085**			-0.0105***		0.0000			-0.0008
		(1.14)			(1.07)		(-2.17)			(-2.50)		(-0.00)			(-0.46)
$I_t^- * S_t$		0.004			0.0041		0.0003			-0.0001		-0.0005			-0.0006
		(0.27)			(1.40)		(0.05)			(-0.01)		(-0.15)			(-0.17)
$DDISP_t$			0.1425**	0.1401**	0.1421**			0.2943*	0.3234**	0.3656**			0.1961***	0.1982***	0.1985***
			(2.19)	(2.32)	(2.27)			(1.75)	(1.93)	(2.29)			(2.77)	(2.77)	(2.75)
Adj-R2	1.9%	0.0%	10.5%	12.2%	10.6%	0.2%	2.7%	3.9%	5.3%	9.9%	-2.0%	-4.0%	7.3%	5.6%	3.7%
Panel C: 20-minute after (11:00 - 11:20)															
Constant	0.0317***	0.0317***	0.0364***	0.0318***	0.0319***	0.0597***	0.0596***	0.0612***	0.0600***	0.0600***	0.0671***	0.0676***	0.0687***	0.0675***	0.0680***
	(11.26)	(11.32)	(18.77)	(11.43)	(11.48)	(15.36)	(15.34)	(25.14)	(15.53)	(15.48)	(20.50)	(20.11)	(27.11)	(20.69)	(20.43)
$\|S_t\|$	0.0086**			0.0084**		0.002			0.0016		0.002			0.0017	
	(2.23)			(2.22)		(0.77)			(0.61)		(0.93)			(0.55)	
$I_t^+ * S_t$		0.006			0.0053		0.0003			-0.0005		0.0041			0.0031
		(1.30)			(1.18)		(0.08)			(-0.15)		(1.10)			(0.69)
$I_t^- * S_t$		0.010**			0.0105**		0.0045			0.0044		-0.0008			-0.0009
		(2.28)			(2.30)		(1.41)			(1.40)		(-0.27)			(-0.32)
$DDISP_t$			0.1157	0.1101*	0.1195*			0.1252	0.1171	0.1366			0.2676***	0.2626**	0.2568**
			(1.56)	(1.68)	(1.82)			(0.89)	(0.83)	(0.99)			(2.56)	(2.40)	(2.26)
Adj-R2	6.0%	5.2%	1.4%	7.2%	7.0%	-1.4%	-2.1%	-0.5%	-2.2%	-2.5%	-1.0%	-1.4%	9.1%	7.7%	7.0%

Figure 1. Seasonality in Analysts' Forecast Dispersion

This figure plots the coefficients of a regression between the analysts' forecast dispersion and monthly dummies for each agricultural commodity from January 2013 to July 2016.

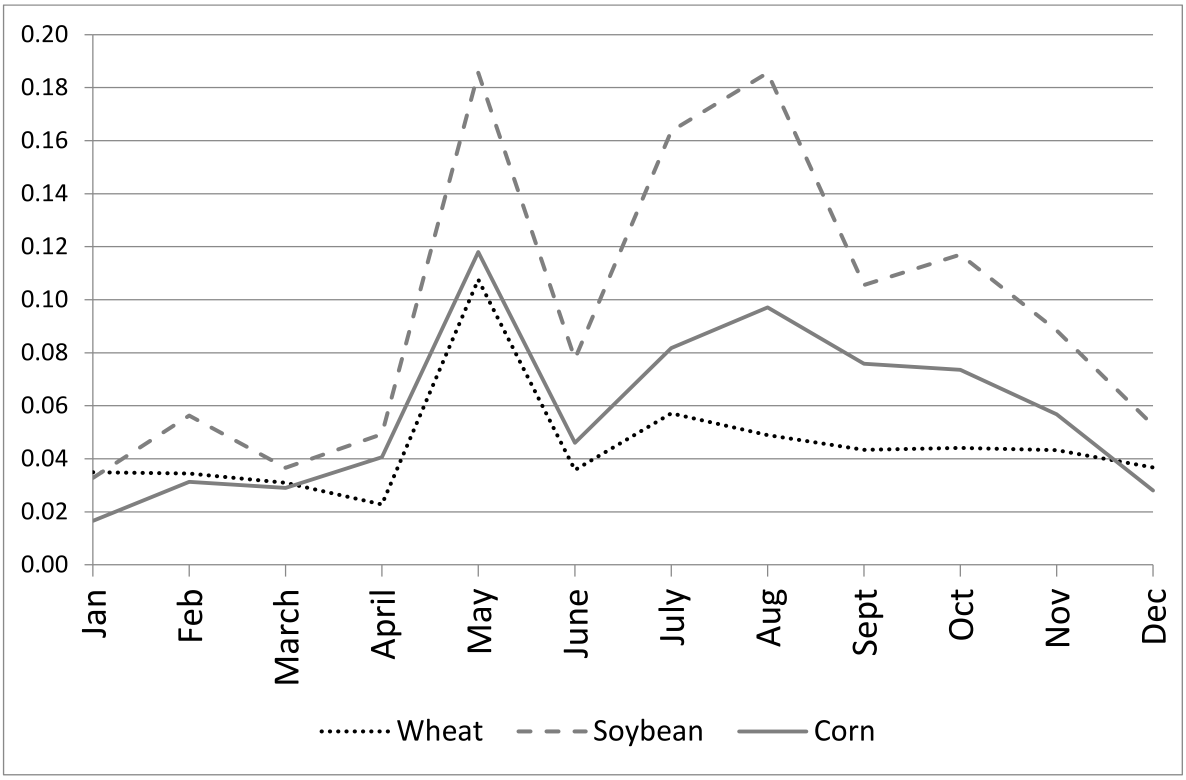

Figure 2. Abnormal Quoted Spreads

This figure plots the abnormal quoted spread (quoted spread during USDA report announcement less non-announcement days) for the agricultural futures contracts, along with the 95% confidence intervals. The plots are the average spreads across the sample period from January 1, 2013 to July 31, 2016.

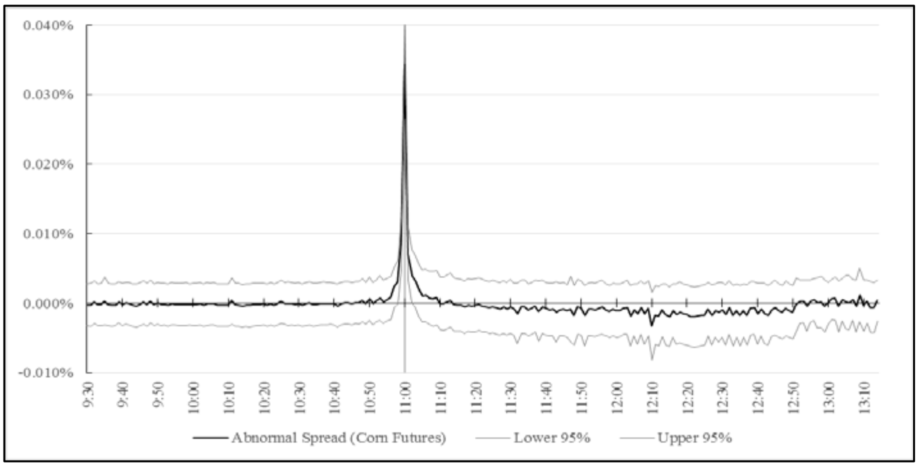

Figure 1.A: Corn Futures Abnormal Spread

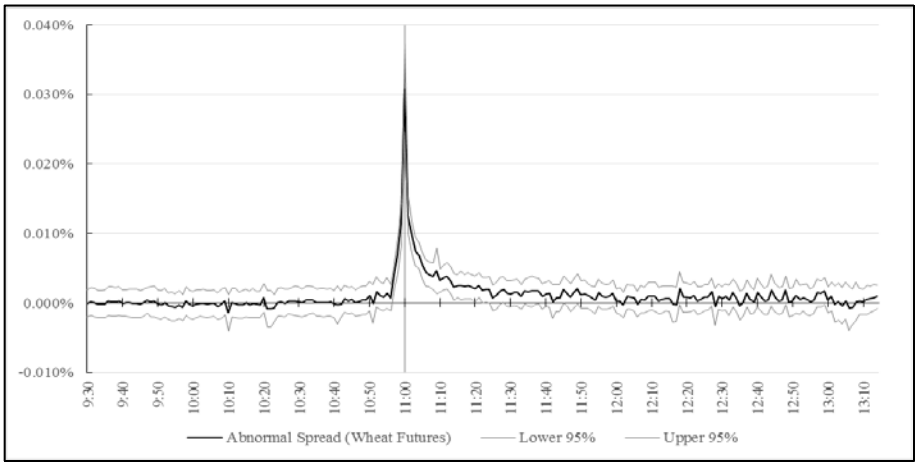

Figure 1.B: Wheat Futures Abnormal Spread

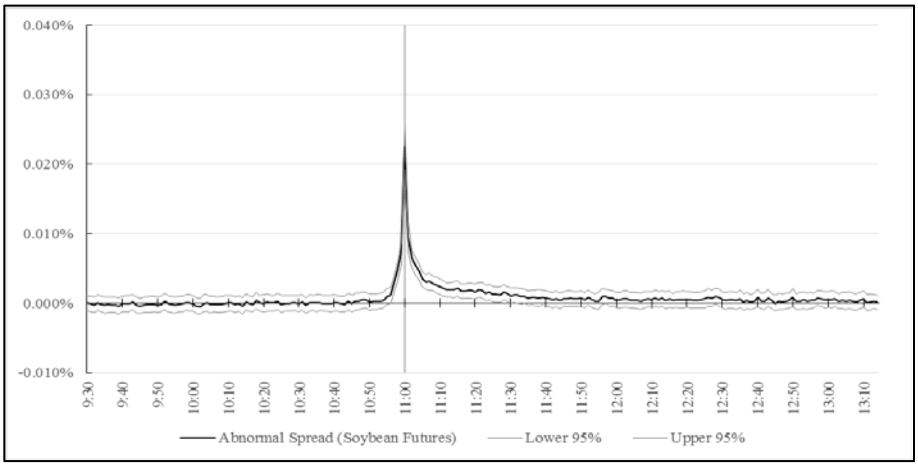

Figure 1.C: Soybean Futures Abnormal Spread