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The value of public information: Market microstructure noise and price volatility spillovers in agricultural commodity markets

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After 2013, major grain-related USDA announcements have been rescheduled to be released at 11:00 am CDT. Such a change granted researchers a great chance to study market volatilities and spillovers react to significant USDA information on real time. Also, with new statistical methods, researchers now can separate efficient volatility from noise volatility. In this paper, we adopt a recently developed method, which is called Markov Chain estimator (MC estimator), to study intraday volatility and volatility spillover between corn and soybean futures during USDA announcement days. Our results suggest that volatilities in both corn and soybean would response to USDA announcements immediately after the news being published. The elevated level of volatilities would not settle down within the first hour after announcements. Also, more persistent spillover occurs at equilibrium level, which is measured by efficient return spillover, than at noise level, which is measured by noise return spillovers.

Key words: futures markets, volatility spillover, Markov Chain estimator, USDA reports

Introduction

The economic value of public information is a question of interest in the financial and agricultural commodity literature and is usually measured through the impacts that information has on market prices. News announcements are considered to carry informational value for market participants if they trigger a response from market prices (Campbell, Lo and MacKinlay 1997). Market participants will update their expectations and perceptions in light of newly released information, which is likely to result in market price adjustments and increased volatility levels (Summer and Mueller 1989; Isengildina-Massa et al. 2008b; Lehecka, Wang and Garcia 2014; Lehecka 2014).

The United States Department of Agriculture (USDA) releases different periodic reports such as the Grain Stocks (GS), Prospective Plantings (PP), Crop Production (CP), Acreage, or World Agricultural Supply and Demand Estimates (WASDE) that have been shown to have significant effects on market prices (Summer and Mueller 1989; Garcia et al. 1997; Isengildina-Massa et al. 2008a; Adjemian 2012). Research has focused on the impacts that these announcements have on the first and second moments of the price distribution in specific markets but has almost ignored how these effects spillover to other related markets. Failure to account for spillover effects underestimates the value of USDA information and limits understanding of market structure and price behavior. Garcia et al. (1997) used daily information to examine spillovers in price levels between corn and soybean futures market given USDA harvest forecasts. Summer and Mueller (1989) show that USDA harvest forecasts, especially those released on August, September and October, impact on both the means and variances of soybean and corn daily futures prices. Lehecka (2014) finds CP reports to affect soybean and corn daily return variances, especially during July and August, when weather conditions become critical for these crops. Isengildina-Massa et al. (2008a) find releases of WASDE reports to increase return variance in corn and soybean futures markets, relative to return variance during non-announcement sessions. By allowing for spillover effects, Karali (2012) uses a generalized autoregressive conditional heteroskedasticity (GARCH)-BEKK model to study how the covariance structure between both corn-meal-hog and soybean-meal-oil futures prices responds to announcements. Karali finds that the average conditional changes of covariance in selected announcement days over non-announcement days between corn and soybean meal range between 18.84% and 63.95% with daily level data.

Several agricultural commodity futures markets are interrelated, either through the supply chain (related production processes, substitutability in either production or consumption, etc.) or through hedging strategies. Consistently, the release of public information may not only alter the prices within a market, but also price interactions across related markets, which may in turn affect hedging ratios and portfolio returns. Karali (2012) studies the spillover of USDA announcement effects across related agricultural markets. Her findings suggest that USDA reports have significant effects on agricultural commodity daily futures returns, and the volatilities caused by these reports spill over to related markets. Karali (2012)'s conclusions are however based on daily returns that may not fully reveal the extent of the market response, especially given recent structural changes in agricultural futures markets such as the emergence of electronic trading in 2006. The new trading platform has significantly reduced trading latency. Lehecka et al. (2014) have recently shown that the market response to USDA announcements usually fades in about 10 minutes. It is thus important to revisit this research question using intraday high frequency data.

Increasing availability of high frequency futures price data on derivatives has boosted methodological proposals in the financial economics literature to measure covariance, by allowing for the properties of intraday data. Many of them build upon the model-free realized variance (Sheppard 2006). In the absence of noise (Andersen et al. 2003), the model-free realized covariance measurements constitute rigorous measures of integrated covariance and their precision increases with the frequency of sampling. However, high frequency data is usually affected by market microstructure noise caused by market imperfections such as the tick size, asynchronous trading, bid-ask bounce, market closure, trading halts, high-frequency traders, or market herd behavior (Hasbrouck 2014; O'Hara 2015; Shapira, Berman and Ben-Jacob 2014). Recent research has proposed several adjustments to realized variance that are robust to different forms of noise (Sheppard 2006). First approaches involved the assumption of additive noise that is independent from the efficient price. As opposed to realized variance, realized covariances are generally biased towards zero in the presence of noise. This is mainly due to the Epps (1979) effect that involves that the correlation between returns of different markets declines as the sampling frequency increases due to non-synchronous trading (i.e., returns being observed at different irregular times).

Recent proposals have challenged the models based on the assumption of exogenous noise. Hansen and Lunde (2006) show that noise does depend on efficient price levels and is serially correlated. Further, the additive noise assumption does not account for asynchronous trading. In order to reduce biasness in covariance caused by the synchronization problem, researchers either propose a covariance estimator that is robust to the Epps (1979) effect (Hansen et al. 2015), or try to synchronize the different assets with re-sampling schemes (Barndorff-Nielsen et al. 2011). Hansen (2015) and Hansen et al. (2015) have recently proposed a Markov chain framework that allows for serially correlated and asynchronous trading, endogenous noise, as well as for the decomposition of the observed returns covariance into its different components: efficient price returns covariance, noise returns covariance and cross-correlations.

The primary goal of our article is to use high frequency data to assess the impact of USDA information releases on the covariance matrix of corn and soybean futures price returns. More specifically, attention is paid to intraday return volatility and volatility spillovers. Identification of USDA announcement effects on the spillovers between the two commodities will be based upon the works of Hansen et al. (2015) and Hansen (2015). By assuming that noise is additive and endogenous (i.e., it depends on efficient price levels), we will build an empirical model to investigate to what extent observed return volatility spillovers across two commodities are due to spillovers in the quadratic variation of efficient price returns, the quadratic variation of noise returns, or the cross-correlations between the efficient price and noise returns.

Relevant Literature

The value of USDA reports for agricultural commodity markets is an important research question (Colling and Irwin 1990; Garcia et al. 1997; Isengildina-Massa et al. 2008b; Karali 2012; Lehecka 2014; Lehecka et al. 2014). If agricultural commodity markets were perfectly efficient, prices in these markets would adjust to shocks and reports immediately (Fama 1970). However, researchers have found evidence suggesting that agricultural markets are characterized by semi-strong efficiency or even weaker condition (Lehecka et al. 2014). The less-than-perfect efficiency condition means that not all new information from USDA reports is absorbed immediately, leading to serially correlated returns.

McNew and Espinosa (1994) show that USDA crop reports have significant impacts on investors' perception of risk and dramatically reduce implied volatility of both corn and soybean futures. Similar responses to WASDE reports are identified by Isengildina-Massa et al. (2008a), which is a sign of USDA reports resolving uncertainty issues. Adjemian (2012) finds releases of WASDE reports to be quickly incorporated into market prices and to originate overnight and close-to-close conditional price volatility of approximately 0.23%, while the average and level of price volatility being less than 0.05%, respectively (Adjemian 2012).

As noted, the question of volatility spillovers has been hardly investigated, with Karali (2012) being an exception. Karali (2012) uses daily trade data on corn, lean hogs, soybeans, soybean meal and soybean oil futures prices for the period from January 1995 to April 2009 and considers a wide array of USDA reports. Using a parametric GARCH specification (with announcement days being captured through dummies in the conditional GARCH model) she shows that the largest movements in covariances occur with releases of Crop Progress, Feed Outlook, Grain Stocks, and Hogs and Pigs reports. All these reports increase conditional covariance between corn and soybean meal by at least 25.26%. Crop Progress, Grain stocks, and Hogs and Pigs also increase variances of both corn and soybean meal.

With the emergence of electronic trading in agricultural futures markets in 2006, trading in the electronic platform increased substantially reaching 94% by 2014 (Haynes and Roberts 2015). This facilitated an increase in the speed of market operations. As a result, daily frequency is not likely to properly reflect the market adjustment to new information. Recently, new players, such as pension funds, large financial institutions, and high-frequency traders, have joined agricultural commodity markets with different trading goals and tools. Another recent important change concerns the release time of several USDA reports that since January 2013 was rescheduled to take place at noon.[2] One possible outcome of mid-day released USDA information is that market participants would need absorb the information within the announcements and respond to real time changes in the market at the same time. These changes have reshaped the futures market landscape (Irwin and Sanders 2011; Lehecka et al. 2014) and made commodity market experts worry about using daily close or open prices to study announcement effects. To the extent that announcements take place within the trading session, their intraday impacts might be stronger than inter-day effects. Consistently with this argument, Lehecka et al. (2014) study announcement effects on corn futures market using an intraday data set. Using minute-level nearest-to-maturity corn contract prices observed from September 2009 until July 2012, the authors assess the impacts of announcements on returns variability and average trading volume. Return variability is measured as the average absolute deviation of log futures prices. Their major finding is that USDA reports have a significant impact on both variables. The abnormal levels of return variability and volume cannot be classified as either over- or under-response to the information as they oscillate for roughly 10 minutes and disappear after that. Joseph and Garcia (2017) study the intraday effects of USDA reports released at 11:00 and find they persist for about an hour after the release.

Most research on USDA announcement effects has relied on methods that are especially useful to study data with relatively low levels of noise such as daily or lower frequency data. However, with the increasing availability of high frequency data and its complex nature, parametric techniques have been progressively set aside in favor of nonparametric methods (Andersen et al. 2003). Barndorff-Nielsen and Shephard (2002) suggest the use of realized volatility (RV), which is the square root of the sum of intraday square returns or realized variance, as an estimator for integrated volatility (IV). Integrated volatility measures the volatility caused by shocks to equilibrium prices and is free from market microstructure noise. Hence, while realized volatility is based on observed prices, integrated volatility reflects the volatility of efficient price returns.

Since efficient prices are unobservable, their returns can only be approximated through observed prices that are contaminated by microstructure noise. Barndorff-Nielsen and Shephard (2002) establish the asymptotic unbiasedness of realized volatility in relation to the integrated volatility when a semi-martingale is observed without noise. Several research papers have followed and proposed improved approximations to integrated volatilities based on refined estimates of realized volatilities. Zhang, Mykland and Aït-Sahalia (2005) show that, due to market microstructure noise, realized volatility explodes as sampling frequency approaches zero. They propose to sample over longer horizons to address this problem. As an alternative, Jacod et al. (2009) recommend a pre-averaging approach for estimating IV. In a similar fashion, wavelet analyses can compute long-run variances using short-run averages and are used by Hasbrouck (2014) and Wang (2014) to approximate IV. The use of realized kernels has also been shown to mitigate the impacts of noise (Hansen and Lunde 2006; Barndorff-Nielsen et al. 2008; Barndorff-Nielsen et al. 2009).

While the literature has made considerable progress in measuring volatility using high frequency data, proposals measuring covariance are much scarcer. Covariance measurement using high frequency data needs to address two major issues. First, the asynchronous trading problem,

[2] The reports subject to this reschedule event are World Agricultural Supply and Demand Estimates ("WASDE"), Acreage, Crop Production, Grain Stocks, Prospective Plantings, and Small Grains Summary.

which will be especially relevant when the time interval considered is sufficiently small and will lead to downward biased covariances. A second important issue in high frequency covariance measurement is endogenous microstructure noise (Hansen and Lunde 2006). The endogeneity of microstructure noise means that noise and efficient returns variances are not independent. The negatively correlation between noise and efficient returns indicates that the increase in noise return variance would likely to reduce efficient return variance, and vice versa. Third, noise estimates depend on sampling time schemes (Hansen and Lunde 2006), which makes the estimation processes even more complicated. Lower sampling frequency would result in less noise, while higher sampling frequency would retain more noise in realized volatility estimation.

In order to overcome the obstacles mentioned above, Barndorff-Nielsen et al. (2011) propose a multivariate realized kernel that is robust to serially dependent and endogenous noise and that can accommodate non-synchronous trading. Markov chain estimators have been proposed as alternative robust measures of covariance in the presence of market microstructure noise both at the univariate (Hansen and Horel 2009) and multivariate level (Hansen 2015; Hansen et al. 2015). The Markov Chain estimator uses the discreteness of high frequency data (resulting from the tick size) and does not require the synchronization of the observation times for the different prices considered (Hansen et al. 2015). This estimator is shown to perform similarly to the multivariate kernel estimator. However, in contrast to the multivariate kernel, the Markov estimator has readily available standard errors for the different elements of the covariance matrix.

Method

This paper uses the Markov chain covariance estimator proposed in Hansen et al. (2015) to assess corn and soybean futures returns covariance. Let X_t be a 2-dimensional process of observed intraday futures prices of corn and soybean at time *t*. The vector of high-frequency returns ΔX_t is assumed to be ergodic and distributed as an order $k < \infty$ homogenous Markov chain, with $S < \infty$ states. The finite S assumption implies that the returns vector takes a finite number of values at time *t*. This is compatible with the tick size, which imposes a minimum price movement for soybean and corn futures prices, and the daily price limits that restrict the maximum change that these prices can experience within a day. Let $\Delta\mathcal{X} = \{\Delta X_{t-k+1,\dots}, \Delta X_t\}$ be an ordered set whose possible values are indexed $\boldsymbol{x}_s$, $s=1,\dots,S^k$, with $\Delta\mathcal{X}_t = \boldsymbol{x}_s$ being a vector representing the *observed* state for $\Delta\mathcal{X}$ at time *t*.

The transition matrix P is a $S^k \times S^k$ matrix that identifies the probabilities of price returns moving from one state to another and is given by equation (1)

$$P_{r,s} = Pr(\Delta\mathcal{X}_{t+1} = \boldsymbol{x}_s | \Delta\mathcal{X}_t = \boldsymbol{x}_r), \text{for } r,s = 1, \dots S^k. \quad (1)$$

The homogenous Markov chain assumption implies that the transition probability is stationary. The Markov chain estimator becomes robust to heterogeneity as *k* increases (Hansen and Horel 2009). The stationary distribution of P is denoted using its corresponding eigenvector $\mathbb{R}^{S^k}$, assumed to be uniquely defined as $\pi' P = \pi'$. The matrix containing π in its main diagonal is $\Lambda_\pi = diag(\pi_1, \dots, \pi_{S^k})$. Following Kemeny and Snell (1983), the fundamental matrix (Z) can be derived as:

$$Z = (I' - P + \Pi)^{-1}, \tag{2}$$

where $\Pi = l\pi'$, $l = (1, \dots, 1)'$ and π' representing each row of Π. Matrix f of order $S^k \times 2$ contains the last 2 columns of $\Delta\mathcal{X}_t$, with f_s the realization of ΔX_t in state s. The Markov chain filtered process can be computed as

$$E(X'_{t+h}|\Delta\mathcal{X}_t) = X'_t + e'_{st} \sum_{j=1}^{h} P^j f \tag{3}$$

with e_r denoting the r^{th} unit vector. By subtracting the deterministic trend, μ_{t+h} with $\mu = E(\Delta x_\tau)$, from X_{t+h}, the filtered process of X_t is derived as $Y_t = \lim_{h\to\infty} E(X_{t+h} - \mu_{t+h}|\mathcal{F}_t)$. The process $\{Y_t, \mathcal{F}_t\}$ can be defined as a martingale with initial value $Y_0 = X_0 + f'(Z' - I)e_{s0}$ and whose increments are given by: $\Delta Y_t' = e'_{s_t} Zf - e'_{s_{t-1}} PZf$. The following martingale decomposition for X_t is assumed:

$$X_t = Y_t + \mu_t + U_t \tag{4}$$

where Y_t represents the efficient latent price vector, and U_t, $U'_t = e'_{s_t}(I - Z)f$, is a stationary, ergodic and bounded process representing noise. Following Hansen (2015) the autocovariance of the terms in the martingale decomposition can be expressed as follows. First, the covariance of ΔY_t is derived as:

$$var(\Delta Y_t) = f'Z'(\Lambda_\pi - P'\Lambda_\pi P)Zf. \tag{5}$$

The covariance of noise is:

$$cov\left(U_t, U_{t+j}\right) = f'Z'P'\Lambda_\pi P\left(P^{|j|} - \Pi\right)Zf, \tag{6}$$

while the cross-correlations are

$$cov\left(\Delta Y_t, U_{t+j}\right) = \begin{cases} f'Z'(-\Lambda_\pi + P'\Lambda_\pi P)P^{j+1}Zf, for\ j \geq 0 \\ 0, for\ \forall j < 0 \end{cases}. \tag{7}$$

Finally, the covariance of observed returns equals:

$$\begin{aligned} var(\Delta X_t) &= var(\Delta Y_t) + cov(\Delta Y_t, U_t) + cov(U_t, \Delta Y_t) + var(\Delta U_t) \\ &= f'Z'(I-P)'\Lambda_\pi(I-P)Zf \end{aligned} \tag{8}$$

Given observed prices, P can be estimated by maximum likelihood (Hansen and Horel 2015) as follows:

$$\hat{P}_{\mathrm{r,s}} = \frac{\sum_{\mathrm{t=1}}^{\mathrm{n}} 1_{\{\mathrm{s_{t-1}=r, s_t=s}\}}}{\sum_{\mathrm{t=1}}^{\mathrm{n}} 1_{\{\mathrm{s_{t-1}=r}\}}} \quad r,s=1,\ldots,S. \tag{9}$$

$\hat{\pi}$ is obtained as the eigenvector of $\hat{P}$, the maximum likelihood estimator in (9), which allows us to derive $\widehat{\Pi} = l\hat{\pi}'$, $\widehat{\Lambda}_\pi = diag(\hat{\pi}_1, \ldots, \hat{\pi}_{S^k})$ and $\hat{Z} = \left(I - \hat{P} + \widehat{\Pi}\right)^{-1}$. The terms of the martingale decomposition (equations 1 to 8) can then be estimated based on $\hat{Z}$ and $\widehat{\Lambda}_\pi$. A potential problem in the estimation is that the number of possible states grows exponentially with the lags considered and the number of states. For example, with k=3 and returns ranging from -4 to +4 cents, the transition matrix will be of order $\left(S^2\right)^k \times \left(S^2\right)^k = \left(9^6\right) \times \left(9^6\right)$, which involves substantial computational burden. Therefore, Hansen et al. (2015) propose several techniques, such as removing jump states and truncating extreme moves, to keep computations manageable. These techniques are described in the next section.

Data

Data used in the analysis consist of mid-quotes derived from CME market depth dataset for corn and soybean traded on the electronic platform. Mid-quotes carry substantially less noise than transactions prices, as they are free from the well-known bid-ask bounce effect (Couleau, Serra and Garcia, 2017). Data are time-stamped to the nearest millisecond, which results in quotes and prices having the same time-stamp when they occur within the same millisecond. The day trading session starts at 8:30 and finishes at 13:20 central time, but we conduct our analysis from 9:00 to 13:20, as we are not interested in the opening and closing sessions. For the announcement days, we derive the MC estimator for the covariance matrix of the martingale decomposition of observed returns for each consecutive 5 minutes, and we pay special attention to the 10:40 to 11:20 interval, i.e. the 40 minutes surrounding the announcement, where we expect to observe most of the effects.

The soybean futures contract is traded with seven maturities per year: January, March, May, July, August, September and November. The corn futures contract is traded with five maturities per year: Mach, May, July, September, and December. We choose the first nearby futures contract and rollover to the next nearby at the beginning of the delivery month. Since nearby contracts are more highly traded than deferred contracts, they are more likely to respond more and quicker to new information in USDA reports. The analysis focuses on the period from January 2014 to May 2017. We investigate volatility spillover effects before, during and after the announcement takes place following sampling methods used in Lehecka et al. (2014), i.e. we use data from the announcement day, five days preceding and five days following the announcement. This allows to compare the market during announcements and non-announcement days and thus to identify the announcement effects. The announcements studied in this paper are Acreage, Crop Production, Grain Stocks, Prospective Planting, and World Agricultural Supply and Demand Estimates (“WASDE). Details of each announcement are presented in Table 1 in Appendix.

High frequency data are usually affected by several issues that need to be addressed due to their potential to bias research results. Barndorff-Nielsen et al. (2009) data cleaning procedures are applied in this article. Any zero-priced quote or transaction price is removed from the dataset. The Markov estimator used in this research does not require data to have a time-stamp. Hence the fact that several quotes and transactions prices are likely to have the same time-stamp does not pose any problem for this research.

Empirical Analysis

We study the intraday impact of USDA announcements on the covariance of corn and soybean mid-quote returns. The covariance is estimated using MC methods in Hansen et al. (2015). Since we use an intraday lens that requires high frequency data, our MC estimator is affected by market microstructure noise and thus does not reflect efficient mid-quote returns. To disentangle noise from observed returns, we derive the covariance martingale decomposition proposed by Hansen et al. (2015).

To estimate the model, we define the state space S, which requires identification of the minimum change that returns can experience. Since we derive returns from mid-quotes, returns can change by at least half a tick. Therefore, we take half a tick (0.125 cents per bushel for both corn and soybean) as the finest granularity to define the observed returns state space. Returns are expressed in numbers of half ticks. For example, if corn mid-quote returns are 0.25 cents, they are made equal to 2 half ticks in our model. In order to keep the size of P manageable, we follow

Hansen and Horel (2009) and truncate large returns to reduce the number of possible states, which does not diminish the consistency of the Markov chain estimator. We truncate those returns beyond +/- 3 half ticks to +/- 3. Truncated returns represent less than 1 percent of sample observations.[3] We also eliminate unobserved states from the transition matrix to further reduce its size. According to simulation results presented in both Hansen and Horel (2009) and Hansen et al. (2015), under different noise assumptions, k = 3 or k = 4 minimize the root mean square error. Also, as discussed in Hansen et al. (2015), time homogeneity of the Markov process is unlikely to be valid for high-frequency data[4]. Since selecting larger k values will make the Markov estimator more resilient to inhomogeneity, we generate our results with k = 4.

Summary of Market Conditions: Announcement Days vs. Non-Announcement Days

Before digging into covariance matrix estimation results, we first characterize the market conditions on announcement days using both mid-quote returns, time stamped to the second, as well as mid-quote return volatility, trade volume and quote updates time-stamped within each minute. For comparison purposes, we present the same information for the 10 days surrounding the announcement day (i.e. 5 days before and after). Compatible with previous research, we expect real-time trading on USDA crop announcements to cause volatility spikes in agricultural futures prices around the announcement time (11:00 central time), that dissipate within a few minutes (Adjemian and Irwin, 2017).

Figures 1 and 2 present mid-quote returns in both announcement and non-announcement days for both corn and soybean futures from 9:00 to 13:00. Our mid-quote returns are time stamped to the second. For each second t, mid-quote returns are generated as the difference between the median value of all mid-quotes within this second (t) and within second t-1. A comparison between Figures 1 and 2 shows that corn mid-quote return volatility in non-announcement days is rather constant and much lower than in announcement days. Volatility in announcement days changes substantially. The nervousness in the market is patent from the market opening, as volatility levels are above non-announcement days. Huge spikes in both positive and negative directions are observed immediately after the USDA report release at 11:00 am. During the 20 minutes following the announcement, volatilities quickly fall from the extreme high levels, but remain clearly above both non-announcement day volatilities until the end of the trading session. Similar patterns can be seen in the soybean market in Figures 1 and 2. Compared to corn mid-quote volatilities on announcement days, soybean volatilities tend to be larger in absolute magnitude and more symmetric.

Figure 3 presents corn and soybean mid-quote returns Average Absolute Deviation (AAD). We plot the relative AAD results by computing the ratio AAD in announcement to AAD in non-announcement days. Following Lehecka et al. (2014) and Joseph and Garcia (2018), we define AAD as follows: $AAD_m = \frac{1}{M}\sum_{m=1}^{M}\left|r_{t,m} - median_m\right|$, where t denotes seconds and m denotes

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[3] We test the robustness of our results by alternatively truncating returns beyond +/- 3 half ticks and results show no significant differences.

[4] A time-homogeneous Markov chain has the same transition matrix P after each step.

minutes, $p_{t,m}$ is the median mid-quote in second *t* in minute m = 1…M, $r_{t,m} = ln\left(\frac{p_{t,m}}{p_{t-1,m}}\right) \times 100$ is the log returns of $p_{t,m}$, and $median_m$ is the median value of $r_{t,m}$ within each minute m. After calculating AAD, we test for the null hypothesis that return variability in announcement and non-announcement days is identical by using both the two-tailed F test on the variance and Kruskal-Wallis χ^2 on absolute returns. Statistical significance is represented by the red dots in Figure 3. Results suggest that from 09:00 am to 10:55 am, absolute volatilities are not significantly different between announcement and non-announcement days. After 10:55 am, volatilities in both corn and soybean markets begin to increase significantly, reaching levels that are 40 and 25 times larger than non-announcement days for corn and soybeans, respectively. The absolute volatilities in both markets decline until 12:00 and remain at a level significantly larger than in non-announcement days until the end of the trading day.

Transactions volume (as the sum of the number of contracts per minute) for both announcement and non-announcement days is presented in Figure 4. In the time slot between 10:55 am and 11:00 am, we observe several minor jumps in transactions volume in announcement days. After 11:00 am, transactions volume jumps to an extremely high level and progressively declines to between 300 and 400 contracts per minute 60 minutes after the release, remaining at levels comparable to both non-announcement days and the volume before the announcement. Mid-quote updates (as the sum of the number of updates per minute) for both announcement and non-announcement days are presented in Figure 5 and behave very similarly to transaction volumes. In the following subsection we present the results of the Markov Chain (MC) estimators and their martingale decompositions.

Martingale Decomposition Estimation: Announcement vs. Non-Announcement

Compared to other methods, MC estimators and their martingale decompositions have two main advantages. First, they do not require any data cleaning techniques to align asynchronous trading activities. Second, they allow to disentangle volatility due to noise and fundamental price volatility (Hansen et al. 2015). As noted above, we divide the time window between 9:00 to 13:00 into 48 5-minute intervals and results are presented graphically. The length of the 5-minute interval is chosen as a compromise between granularity and minimum data requirement to estimate the MC. The MC estimation results are generated per 5-minute interval, which means we estimate each MC estimation result independently with data from corresponding 5-minute interval. As most changes occur around announcement time, we want to zoom in the period from 10:40 to 11:20 am on announcement days. As a complement to the plots covering the 9:00 to 13:00 time frame, Tables 2 and 3 only present the numerical results for this time window. Table 2 summarizes the MC covariance estimator and its decomposition for the entire 40-minute window. Table 3 presents the detail for the 5-minute bins.

Table 2 presents the variance of observed returns (VAR(dX)) and its decomposition into the variance of efficient returns (VAR(dY)), the variance of noise returns (VAR(dU)), and the covariance between efficient returns and noise returns (Cov(dU, dY)) for announcement (Table 2A) and non-announcement days (Table 2B). The tables show that mean values for observed, efficient and noise returns are higher on announcement days than on non-announcement days in both markets. The average of observed return volatility in corn and soybean markets jumps from 0.037 to 0.0950 and from 0.0835 to 0.2029, respectively. These results are compatible with the plots from Figures 1 to 4 and with the increased number of transactions taking place during announcement days (figure 5), impounding new information into the market. However, our results cannot be directly compared to the AAD volatility measure presented in Figure 3 in the previous subsection. First, because our volatility measures are defined in half ticks, instead of dollars. Second, because the methodologies to derive the two measures are different. As a result, only the patterns and duration of the effects may be compared.

The average of the efficient price return volatility in corn and soybean markets jumps from 0.0312 to 0.0771 and from 0.079 to 0.1959, respectively, which involves public information shocks inducing relevant changes in the efficient price. An interesting result is that the observed return volatility is higher than the efficient price volatility, both during announcement and non-announcement days, being the difference especially relevant for corn. Differences between the two measures point towards the existence of microstructure noise that biases volatility measures based on observed returns. The average of the covariance between noise and efficient price returns in corn and soybean markets is negative and moves from -0.1933 to -0.1330 and from -0.1553 to -0.1718, respectively. The negative sign of the covariance is compatible with previous research results and is attributed to possible nonsynchronous revisions of bid and ask quotes as a response to efficient price changes (Hansen and Lunde, 2006, Couleau et al., 2017).

The average of noise return volatility in corn and soybean markets jumps from 0.0115 to 0.0347 and from 0.0179 to 0.0733, respectively. During this frantic period, it may be difficult to cancel or take positions due to increased liquidity demand, which may result in higher market frictions and noise. The last column in both tables 2A and 2B suggests that the correlation between the (observed, efficient, noise) returns in the corn and the soybean markets increases from (0.98%, 8.27%, 2.74%) in non-announcement days to (1.99%, 12.98%, 4.64%) in announcement days. The higher correlation levels on announcement days signals that mid-quote changes between corn and soybean market are more linked together on announcement days, when fundamental information shocks the market.

To further examine the time sequence of the impacts of announcements on the market, we now present the results for the 5-minute time intervals between 10:40 and 11:20 in Table 3. Tables 3A, 3B and 3C present, respectively, information on observed, efficient and noise return volatilities. Results show that the time-pattern of the volatility measures has an ‘n’ shape in both corn and soybean markets, that involves an increased volatility specially during the 5 minutes preceding the announcement, reaches its peak right after the announcement, to decline afterwards, though not to the lower pre-announcement levels. For corn, (observed, efficient, noise) returns volatility increase from (0.0463, 0.0394, 0.0145) during 10:50 am and 10:55 am to (0.0848, 0.0607, 0.0333) during 10:55 am and 11:00 am. For soybean, the same combination changes from (0.1204, 0.1184, 0.0247) to (0.1902, 0.1694, 0.0865). Within the first five minutes after announcements at 11:00 am, (observed, efficient, noise) returns volatility in the corn market further increase to (0.2302, 0.1893, 0.1112), while the same numbers in the soybean market increase to (0.4435, 0.4323, 0.2278), reaching their maximum. For the following 15 minutes, observed and efficient price volatility in both markets decrease by about 50% and remain at levels above pre-announcement periods. As for noise volatility, the values decrease more than 50% and remain at levels above pre-announcement periods.

The patterns described in Table 3 can be visually observed in Figures 6 and 7 with an extended time horizon (from 9:00 to 13:00) and thus allow to refine research conclusions. Figures 6 and 7 contain observed, efficient and noise return variances for corn and soybean, respectively and for both announcement and non-announcement days. For non-announcement days, we present the average of the estimation for the 10 days around the announcements. Each bar in the figures represents a time interval of 5 minutes. Figures 6 and 7 show something that was not evident from Table 3, i.e., that differences in observed, efficient and noise volatilities between announcement and non-announcement days start to be relevant just a few minutes before the release. In contrast, after the release volatility measures stay at levels clearly above non-announcement days, which suggests that announcement effects persist until the end of the day. This is consistent with the information in plots 1 to 5. It is also consistent with results for soybean futures market in Joseph and Garcia (2018). However, Joseph and Garcia (2018), found the observed return variance to drop to the non-announcement levels before 12:00 pm, while our results point towards a longer duration of announcement effects.

Unlike the 'n' shape patterns in volatilities in the 40 minutes surrounding announcement time, the time sequences of the correlations between corn and soybean observed, efficient and noise returns have a 'v' shape. Correlations decline until 11:00, reaching the lowest point 5 minutes before the announcement (Table 3). For (observed, efficient, noise) returns, the correlation decreases from (2.11%, 12.92%, 6.21%) during the time bin 10:40 – 10:45, to (0.75%, 5.5%, 2.32%) 5 minutes before the release. After reaching their minimum, the correlations increase during the first 10 minutes following the release, reaching maximum values between 11:05 and 11:10 am (2.76%, 17.83%, 5.55%). After 11:10 am, the correlations remain at relatively higher levels. The time-pattern of correlation points towards markets being less connected during the minutes before the announcement and then responding in a more synchronous manner after announcement takes place. Figure 8 complements the information on correlations in Table 3 by showing that the correlations of observed, efficient and noise returns in announcement days are generally larger than in non-announcement days and are highly volatile. Correlation of observed and efficient returns reaches its maximum right after the release. Noise return correlation, in contrast, presents important spikes throughout the day.

After examining the intraday pattern on announcement days, we test whether the volatility and correlation measures in announcement days are statistically different from those in non-announcement days. We conduct the test to identify the duration of the announcement impacts. We consider that announcement values that are statistically different from non-announcement values signal that the public information release is still having an impact on the market. We follow Lehecka et al. (2014) and test the significance of the differences using both the t-test and the Wilcoxon test. Let $\mu_{Ann,i}$ ($\mu_{Non,i}$) be the variance or correlation estimation on announcement (average variance or correlation estimation on no-announcement) days during time interval i. Our null and alternative hypotheses are as follows H_0: $\mu_{Ann,i} = \mu_{Non,i}$ and H_1: $\mu_{Ann,i} \neq \mu_{Non,i}$. The test results are presented in Tables 3A, 3B, and 3C for observed, efficient, and noise returns, respectively. Figures 9, 10, and 11 expand the test results over the 9:00 – 13:00 interval. Significance of both tests is indicated by a red dot. In the corn market, differences in observed and efficient return volatilities between announcement and non-announcement days are statistically significant after 10:55 am. The differences in volatilities of noise returns are significant only after 10:55 am. Observed and efficient return volatilities persist at higher levels relative to non-announcement days (figure 9) until 13:00 pm, except for the noise variance that fades at around 11:30. Therefore, USDA announcement effects on observed and efficient corn return volatilities are identified around 5 minutes before the release and persist 120 minutes after the release.

In the soybean market, both tests suggest that differences in observed and efficient return volatilities are already significant after 10:40 am. The differences in volatilities of noise returns are significant after 10:50 am. Observed and efficient return volatilities persist at higher levels than non-announcement days until 12:50 pm, while noise return volatility converges to non-announcements slightly before 12:00. Therefore, USDA announcements effects emerge earlier in the soybean market than in the corn market and last a little less.

The correlations between the two markets have a more complicated pattern of significance. Both tests support an increase in correlations between corn and soybean observed, efficient and noise returns during 10:40 am and 10:45 am. Afterwards and before the announcement takes place, the only significant difference is the correlation between corn and soybean efficient returns during 10:45 – 10:50 and 10:55 – 11:00. Therefore, the pattern identified above consisting of an increase in volatility in both markets and a decrease in cross-correlations right before the announcement is only significant in efficient returns in both corn and soybean markets. With the announcement, correlations between (observed, efficient, noise) returns increase (three, two, five)-fold relative to non-announcement days (Figure 11). The correlation between efficient returns after 11:00 is more persistent than the correlation between observed returns. Correlation between efficient returns lasts almost till the end of the trading session, while correlation between observed returns only lasts for about 30 minutes. The differences in correlation between noise returns are only significant under both tests between 11:05 and 11:15. Our results contrast with Karali (2012) who focuses on USDA announcement volatility spillovers between corn, soybean meal, and lean hog futures prices, using daily prices and a GARCH model. The author finds that USDA announcements increase conditional volatility spillovers between corn and soybean meal by 1.53%. Our results suggest much higher increases and thus point to the need to use an intraday lens to grasp the impacts of announcements on spillovers across related markets.

Conclusion

This paper examines the intraday covariance between the mid-quote returns in corn and soybean markets around USDA announcements from the beginning of 2014 to the middle of 2017. The covariance is estimated using MC methods in Hansen et al. (2015). Since we use an intraday lens that requires high frequency data, our observed return volatility estimator is affected by market microstructure noise and thus does not reflect efficient mid-quote returns. To disentangle noise from observed returns, we derive the covariance martingale decomposition proposed by Hansen et al. (2015).

Previous research has studied USDA announcement effects from different perspectives, with a predominant focus on USDA announcements during the period in which announcements took place outside the trading session and has paid little attention to intraday impacts of announcements. Also, volatility spillovers across related markets during announcement periods have been widely ignored, except for Karali (2012). With the emergence of electronic trading in agricultural futures markets in 2006, the resulting reduced trading latency, the participation of new players in the market, as well as the real-time trading of USDA reports have reshaped the futures market landscape and warrant a reassessment the impacts that these reports have on the market.

Separating efficient return volatilities from noise return volatilities has fundamental value for all researchers who want to understand how USDA announcements affect commodity futures markets. Efficient return volatilities indicate the volatilities in commodity markets that are driven by fundamental information. It is a better measurement of the informational impacts of USDA announcements on market participants' behavior than observed volatilities. On the other hand, noise return volatilities can be categorized as idiosyncratic part of investors' responses that will fade away quickly. A valuable USDA announcement should have large impact on efficient terms.

Research results suggest that USDA announcements elevate intraday mid-quote observed, efficient and noise return volatility between 20 and 10 minutes before the report release. The USDA impacts do not dissipate after the announcement and last till the end of the trading session. Relative to non-announcement days, the magnitudes of the increases are substantial, with volatility in efficient and observed returns increasing five/six-fold and noise volatility increasing 10/12-fold. Correlations between efficient, observed and noise returns increase three, two and five-fold, respectively, which contrasts with the meager effects found in Karali. The martingale decomposition helps us disentangle noise from efficient returns and we find that noise blurs the duration of the return correlation effects, making them appear shorter. Efficient return correlations increase right after announcement and remain about 50% higher than regular days till the end of the session. In contrast, observed returns correlation fades in about 30 minutes after the announcement. Our results are suggestive that intraday effects of announcements are longer than what previous research has found. While effects on noise returns are quick and dissipate in half an hour, effects on observed and efficient returns are specially long, as they extend till the end of the trading session.

Our results have several policy implications. First, while the structural changes that have recently affected futures markets have increased trading latency, the real-time trading of USDA announcements represents a relevant shock that the market cannot absorb in a few minutes and that lasts till the market closes. However, noise disappears much quicker, after about 30 minutes after the announcement. For information arbitragers, increased volatilities and correlations offer relevant profit opportunities, especially during the first 30 minutes after announcement when volatilities reach their peaks. For hedgers, the most relevant information is the one contained in observed return volatility after 30 minutes, when the impact of the announcement on noise has dissipated. Since there is an increased correlation between corn and soybean returns during announcements, arbitrage opportunities are not limited to within but also across markets.

Appendix

Data Cleaning Process:

- Delete entries with a time stamp outside opening trading window
- Delete entries with a bid, ask or transaction price equal to zero
- If multiple quotes had the same timestamp, replacing all these with a single entry with median bid and median ask price
- Delete entries for which the spread is negative

Table 1 Futures Contracts Used for USDA Report Releases, January 6, 2014 ,to May 30, 2017

Report release date	Reports	Corn futures contract	Soybean futures contract
1/10/2014	CP, Grain Stocks	March, 2014	March, 2014
2/10/2014	CP	March, 2014	March, 2014
3/10/2014	CP	May, 2014	May, 2014
3/31/2014	Grain Stocks, PP	May, 2014	May, 2014
4/9/2014	CP	May, 2014	May, 2014
5/9/2014	CP	July, 2014	July, 2014
6/30/2014	Acreage, Grain Stocks	July, 2014	July, 2014
7/11/2014	CP	September, 2014	August, 2014
8/12/2014	CP, WASDE Mix	September, 2014	September, 2014
9/11/2014	CP, WASDE Mix	December, 2014	November, 2014
9/30/2014	Grain Stocks	December, 2014	November, 2014
10/10/2014	CP, WASDE Mix	December, 2014	November, 2014
11/10/2014	CP, WASDE Mix	December, 2014	January, 2015
12/10/2014	CP	March, 2015	January, 2015
1/12/2015	CP, Grain Stocks	March, 2015	March, 2015
2/10/2015	CP	March, 2015	March, 2015
3/10/2015	CP	May, 2015	May, 2015
3/31/2015	Grain Stocks, PP	May, 2015	May, 2015
4/9/2015	CP	May, 2015	May, 2015
5/12/2015	CP	July, 2015	July, 2015
6/10/2015	CP	July, 2015	July, 2015
6/30/2015	Acreage, Grain Stocks	July, 2015	July, 2015
7/10/2015	CP	September, 2015	August, 2015
8/12/2015	CP, WASDE Mix	September, 2015	September, 2015
9/11/2015	CP, WASDE Mix	December, 2015	November, 2015
9/30/2015	Grain Stocks	December, 2015	November, 2015
10/9/2015	CP, WASDE Mix	December, 2015	November, 2015
11/10/2015	CP, WASDE Mix	December, 2015	January, 2016
12/9/2015	CP	March, 2016	January, 2016
1/12/2016	CP, Grain Stocks	March, 2016	March, 2016
2/9/2016	CP	March, 2016	March, 2016
3/9/2016	CP	May, 2016	May, 2016
3/31/2016	Grain Stocks, PP	May, 2016	May, 2016
4/12/2016	CP	May, 2016	May, 2016
5/10/2016	CP	July, 2016	July, 2016
6/10/2016	CP	July, 2016	July, 2016

Note: All contracts are traded in the CBOT. The acronyms used stand for CP = Crop Production; WASDE = World Agricultural Supply and Demand Estimates; PP = Prospective Planting

Table 1 cont. Futures Contracts Used for USDA Report Releases, January 6, 2014 ,to May 30, 2017

Report release date	Reports	Corn futures contract	Soybean futures contract
6/30/2016	Acreage, Grain Stocks	July, 2016	July, 2016
7/12/2016	CP	September, 2016	August, 2016
8/12/2016	CP, WASDE Mix	September, 2016	September, 2016
9/12/2016	CP, WASDE Mix	December, 2016	November, 2016
9/30/2016	Grain Stocks	December, 2016	November, 2016
10/12/2016	CP, WASDE Mix	December, 2016	November, 2016
11/9/2016	CP, WASDE Mix	December, 2016	January, 2017
12/9/2016	CP	March, 2017	January, 2017
1/12/2017	CP, Grain Stocks	March, 2017	March, 2017
2/9/2017	CP	March, 2017	March, 2017
3/9/2017	CP	May, 2017	May, 2017
3/31/2017	Grain Stocks, PP	May, 2017	May, 2017
4/11/2017	CP	May, 2017	May, 2017
5/10/2017	CP	July, 2017	July, 2017

Note: All contracts are traded in the CBOT. The acronyms used stand for CP = Crop Production; WASDE = World Agricultural Supply and Demand Estimates; PP = Prospective Planting

Table 2A Summary Statistics for Martingale Decomposition in Announcement Days (from 10:40 to 11:20)

	Corn	Soybean	Corn vs. Soybean	Correlation
Variance of Observed Returns: VAR(dX)				
Min.	0.0000	0.0141	-0.0033	-5.96%
1st Qu.	0.0440	0.1041	0.0000	0.01%
Median	0.0721	0.1478	0.0019	1.64%
Mean	0.0950	0.2029	0.0028	1.99%
3rd Qu.	0.1189	0.2370	0.0041	3.17%
Max.	0.9619	0.9804	0.0195	18.59%
Variance of Efficient Returns: VAR(dY)				
Min.	0.0000	0.0165	-0.0295	-16.53%
1st Qu.	0.0371	0.0927	0.0044	6.50%
Median	0.0596	0.1331	0.0107	12.53%
Mean	0.0771	0.1959	0.0169	12.98%
3rd Qu.	0.0926	0.2384	0.0231	19.35%
Max.	0.7928	0.9413	0.1524	40.78%
Variance of Noise Return: VAR(dU)				
Min.	0.0000	0.0027	-0.0364	-23.27%
1st Qu.	0.0106	0.0183	0.0000	-0.22%
Median	0.0198	0.0299	0.0007	3.70%
Mean	0.0347	0.0733	0.0028	4.64%
3rd Qu.	0.0373	0.0607	0.0030	8.54%
Max.	0.3259	0.7569	0.1121	61.44%
Covariance between efficient return and noise return: Cov(dU,dY)				
Min.	-0.8172	-0.7339	-0.4869	-0.6146[1]
1st Qu.	-0.2552	-0.3036	-0.1825	-0.1572
Median	-0.1241	-0.2082	-0.1101	-0.0992
Mean	-0.1330	-0.1718	-0.1244	-0.1043
3rd Qu.	0.0078	-0.0447	-0.0463	-0.0383
Max.	0.4070	0.3603	0.1998	0.2494

Note [1]: The last column of the table contains correlations with the exception of the covariances between efficient returns and noise returns, which are asymmetric and thus we present the Cov(dU,dY) for soybean vs corn.

Table 2B Summary Statistics for Martingale Decomposition in Announcement Days (from 10:40 to 11:20)

	Corn	Soybean	Corn vs. Soybean	Correlation
Variance of Observed Returns: VAR(dX)				
Min.	0.0010	0.0017	-0.0062	-33.05%
1st Qu.	0.0161	0.0527	0.0000	-0.03%
Median	0.0310	0.0769	0.0000	0.00%
Mean	0.0370	0.0835	0.0006	0.98%
3rd Qu.	0.0518	0.1070	0.0008	1.18%
Max.	0.2625	0.3416	0.0122	40.68%
Variance of Efficient Returns: VAR(dY)				
Min.	0.0000	0.0021	-0.0253	-33.13%
1st Qu.	0.0151	0.0483	0.0000	0.03%
Median	0.0274	0.0700	0.0029	6.88%
Mean	0.0312	0.0790	0.0042	8.27%
3rd Qu.	0.0428	0.0990	0.0067	14.13%
Max.	0.1660	0.5162	0.0554	70.05%
Variance of Noise Return: VAR(dU)				
Min.	0.0000	0.0000	-0.0133	-75.75%
1st Qu.	0.0036	0.0088	-0.0001	-2.15%
Median	0.0085	0.0147	0.0000	0.85%
Mean	0.0115	0.0179	0.0005	2.74%
3rd Qu.	0.0162	0.0227	0.0008	8.08%
Max.	0.1595	0.1897	0.0157	100.00%
Covariance between efficient return and noise return: Cov(dU,dY)				
Min.	-1.0000	-0.9995	-0.9985	-0.6492
1st Qu.	-0.3839	-0.3254	-0.1562	-0.1368
Median	-0.1631	-0.1632	-0.0422	-0.0389
Mean	-0.1933	-0.1553	-0.0837	-0.0702
3rd Qu.	0.0223	0.0189	0.0011	0.0025
Max.	0.6222	0.6892	0.5416	0.6932

Note [1]: The last column of the table contains correlations with the exception of the covariances between efficient returns and noise returns, which are asymmetric and thus we present the Cov(dU,dY) for soybean vs corn.

Table 3A Martingale decomposition in five-minute bins around announcement time.

Variance of Observed Return (VAR(dX)) For Corn					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.0461	0.0378	1.22	1.66	335716
10:45 - 10:50	0.0446	0.0393	1.13	1.13	311849
10:50 - 10:55	0.0463	0.0375	1.24	2.05*	346049*
10:55 - 11:00	0.0848	0.0386	2.20	6.9**	476437**
11:00 - 11:05	0.2302	0.0350	6.57	9.7**	566431**
11:05 - 11:10	0.1166	0.0367	3.17	9.6**	514591**
11:10 - 11:15	0.1002	0.0361	2.78	8.25**	522729**
11:15 - 11:20	0.0910	0.0352	2.59	10.85**	525762**
Variance of Observed Return (VAR(dX)) For Soybean					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.1058	0.0819	1.29	3.04**	372923**
10:45 - 10:50	0.1030	0.0835	1.23	3.43**	377553**
10:50 - 10:55	0.1204	0.0853	1.41	4.97**	412457**
10:55 - 11:00	0.1902	0.0841	2.26	6.02**	511360**
11:00 - 11:05	0.4435	0.0857	5.18	13.24**	542256**
11:05 - 11:10	0.2498	0.0829	3.01	7.23**	518634**
11:10 - 11:15	0.2247	0.0808	2.78	6.27**	529677**
11:15 - 11:20	0.1957	0.0838	2.34	6.47**	506492**
Correlation of Observed Return (Corr(dX)) Between Corn and Soybean					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.0211	0.0092	2.28	2.17*	362283**
10:45 - 10:50	0.0171	0.0118	1.45	1.32	337212*
10:50 - 10:55	0.0139	0.0095	1.46	1.07	334402*
10:55 - 11:00	0.0075	0.0108	0.69	-1.44	316355
11:00 - 11:05	0.0252	0.0111	2.27	7.65**	468838**
11:05 - 11:10	0.0276	0.0090	3.05	7.9**	471400**
11:10 - 11:15	0.0234	0.0074	3.15	6.89**	466238**
11:15 - 11:20	0.0237	0.0094	2.51	5.79**	449801**

Note: means significant at p-value = 0.05;** means significant at p-value = 0.01; W statistic is the Wilcoxon test; Report mean is the average across announcement days of the martingale decomposition estimation during each five minutes interval; Pre/Post Report Mean is the average across non-announcement days (5 days before and 5 days after the announcement) of the martingale decomposition during each five minutes interval. Ratio equals Report Mean divided by Pre/Post Report Mean.*

Table 3B Martingale decomposition in five-minute bins around announcement time.

Variance of Efficient Return (VAR(dY)) For Corn					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.0393	0.0318	1.24	1.92	336940
10:45 - 10:50	0.0377	0.0335	1.13	1.21	324646
10:50 - 10:55	0.0394	0.0313	1.26	2.45*	354401**
10:55 - 11:00	0.0607	0.0312	1.95	6.6**	461106**
11:00 - 11:05	0.1893	0.0306	6.18	8.74**	566466**
11:05 - 11:10	0.0974	0.0304	3.20	8.67**	514261**
11:10 - 11:15	0.0822	0.0308	2.67	7.31**	520074**
11:15 - 11:20	0.0710	0.0300	2.36	10.27**	516295**

Variance of Efficient Return (VAR(dY)) For Soybean					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.1069	0.0772	1.38	3.14**	382075**
10:45 - 10:50	0.0998	0.0788	1.27	3.63**	388086**
10:50 - 10:55	0.1184	0.0799	1.48	4.63**	411287**
10:55 - 11:00	0.1694	0.0794	2.13	5.89**	487828**
11:00 - 11:05	0.4323	0.0822	5.26	11.85**	548771**
11:05 - 11:10	0.2385	0.0792	3.01	7.21**	507842**
11:10 - 11:15	0.2204	0.0763	2.89	5.84**	512604**
11:15 - 11:20	0.1861	0.0789	2.36	6.14**	495800**

Correlation of Efficient Return (Corr(dY)) Between Corn and Soybean					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.1292	0.0818	1.58	3.22**	370948**
10:45 - 10:50	0.1191	0.0883	1.35	2.16*	336699*
10:50 - 10:55	0.1052	0.0883	1.19	1.26	332252*
10:55 - 11:00	0.0550	0.0875	0.63	-3.12**	246994*
11:00 - 11:05	0.1506	0.0765	1.97	6.74**	426454**
11:05 - 11:10	0.1783	0.0830	2.15	9.45**	439559**
11:10 - 11:15	0.1615	0.0808	2.00	7.52**	440313**
11:15 - 11:20	0.1385	0.0748	1.85	6.1**	417603**

Note: means significant at p-value = 0.05;** means significant at p-value = 0.01; W statistic is the Wilcoxon test; Report mean is the average across announcement days of the martingale decomposition estimation during each five minutes interval; Pre/Post Report Mean is the average across non-announcement days (5 days before and 5 days after the announcement) of the martingale decomposition during each five minutes interval. Ratio equals Report Mean divided by Pre/Post Report Mean.*

Table 3C Martingale decomposition in five-minute bins around announcement time.

Variance of Noise Return (VAR(dU)) For Corn					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.0141	0.0116	1.21	1.63	339909*
10:45 - 10:50	0.0136	0.0117	1.16	1.07	312188
10:50 - 10:55	0.0145	0.0114	1.27	1.91	343669*
10:55 - 11:00	0.0333	0.0122	2.74	5.33**	462170**
11:00 - 11:05	0.1112	0.0107	10.37	9.1**	545818**
11:05 - 11:10	0.0370	0.0117	3.16	5.2**	467408**
11:10 - 11:15	0.0298	0.0114	2.61	3.89**	467969**
11:15 - 11:20	0.0257	0.0111	2.31	6.01**	469262**
Variance of Noise Return (VAR(dU)) For Soybean					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.0216	0.0173	1.25	1.48	324634
10:45 - 10:50	0.0203	0.0173	1.17	1.91	352476**
10:50 - 10:55	0.0247	0.0191	1.30	2.74**	375568**
10:55 - 11:00	0.0865	0.0186	4.66	4.15**	516986**
11:00 - 11:05	0.2278	0.0186	12.25	9.37**	550554**
11:05 - 11:10	0.0811	0.0178	4.55	3.71**	484509**
11:10 - 11:15	0.0736	0.0171	4.30	3.17**	481551**
11:15 - 11:20	0.0536	0.0177	3.03	3.35**	452650**
Correlation of Noise Return (Corr(dU)) Between Corn and Soybean					
Time	**Report Mean**	**Pre/Post Report Mean**	**Ratio**	**t statistic**	**W statistic**
10:40 - 10:45	0.0621	0.0141	4.39	2.45*	353912**
10:45 - 10:50	0.0577	0.0323	1.79	1.34	316030
10:50 - 10:55	0.0381	0.0339	1.12	0.24	289299
10:55 - 11:00	0.0232	0.0476	0.49	-3.53**	291388
11:00 - 11:05	0.0461	0.0343	1.34	1.42	340105*
11:05 - 11:10	0.0555	0.0196	2.84	4.29**	346447**
11:10 - 11:15	0.0478	0.0096	4.96	3.88**	352202**
11:15 - 11:20	0.0416	0.0271	1.53	1.40	325005

Note: means significant at p-value = 0.05;** means significant at p-value = 0.01; W statistic is the Wilcoxon test; Report mean is the average of the martingale decomposition estimation during each five minutes interval on an announcement day; Pre/Post Report Mean is the average of the martingale decomposition during each five minutes interval and across the 5 days previous to and following USDA announcements. Ratio equals Report Mean divided by Pre/Post Report Mean*

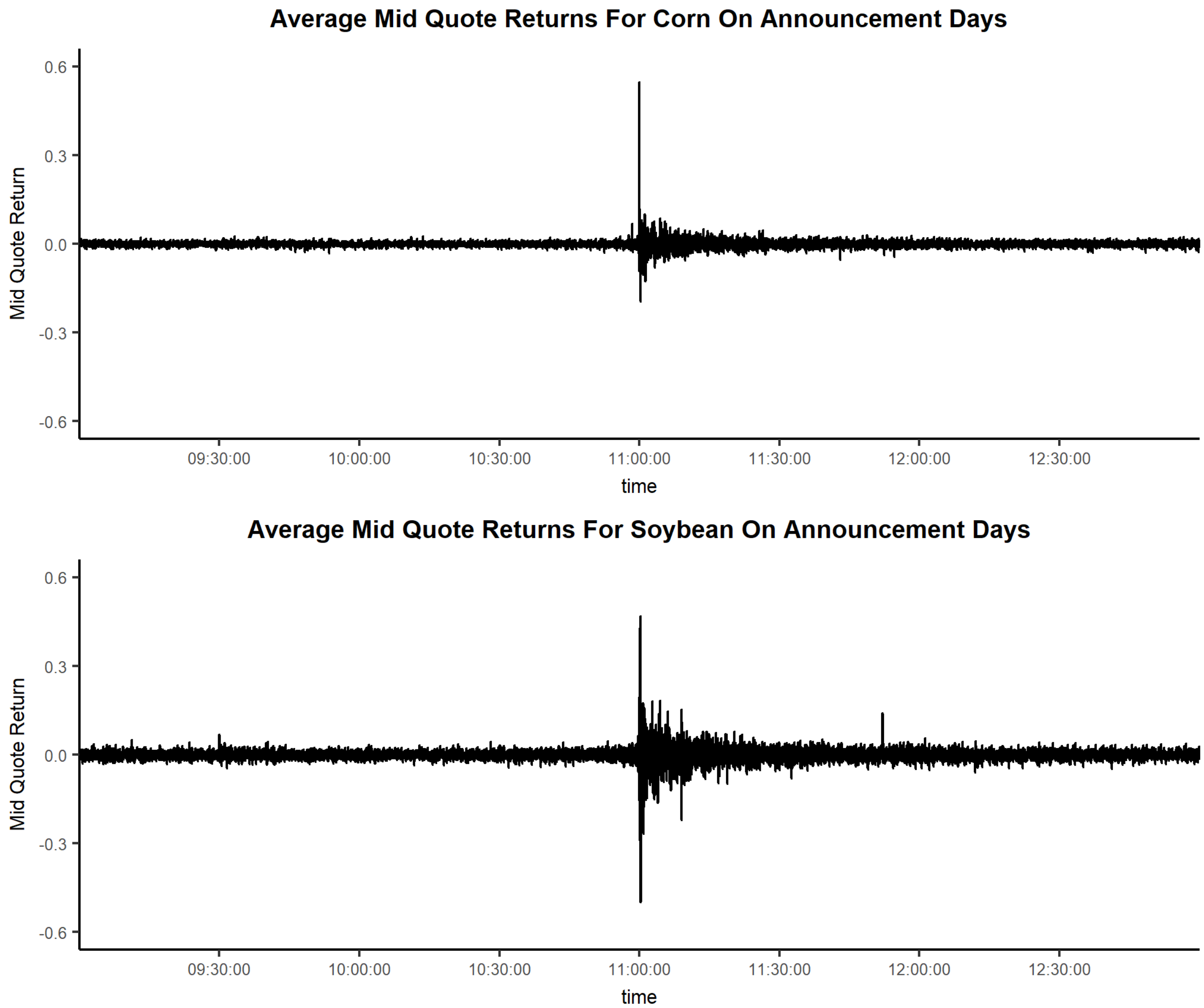

Figure 1: Average Mid Quote Returns on Announcement Days

*Note: All mid quote returns are generated by the difference between the median mid-quote in second t and second (t-*1) and averaged across announcement days *from 9:00 to 13:00.*

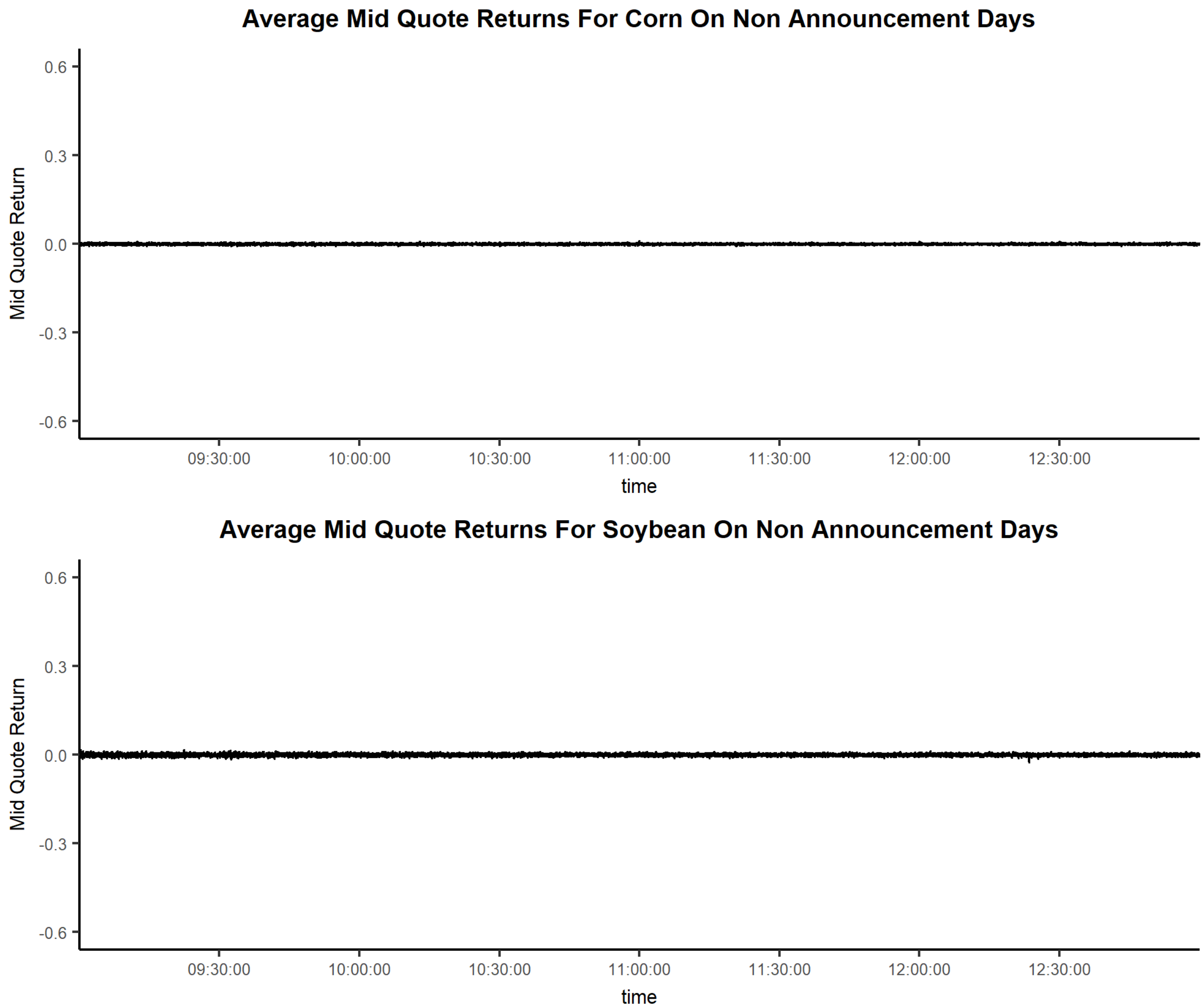

Figure 2: Average Mid Quote Returns on Non-Announcement Days

*Note: All mid quote returns are generated by the difference between the median mid-quote in second t and second (t-*1) and averaged across non-announcement days *from 9:00 to 13:00.*

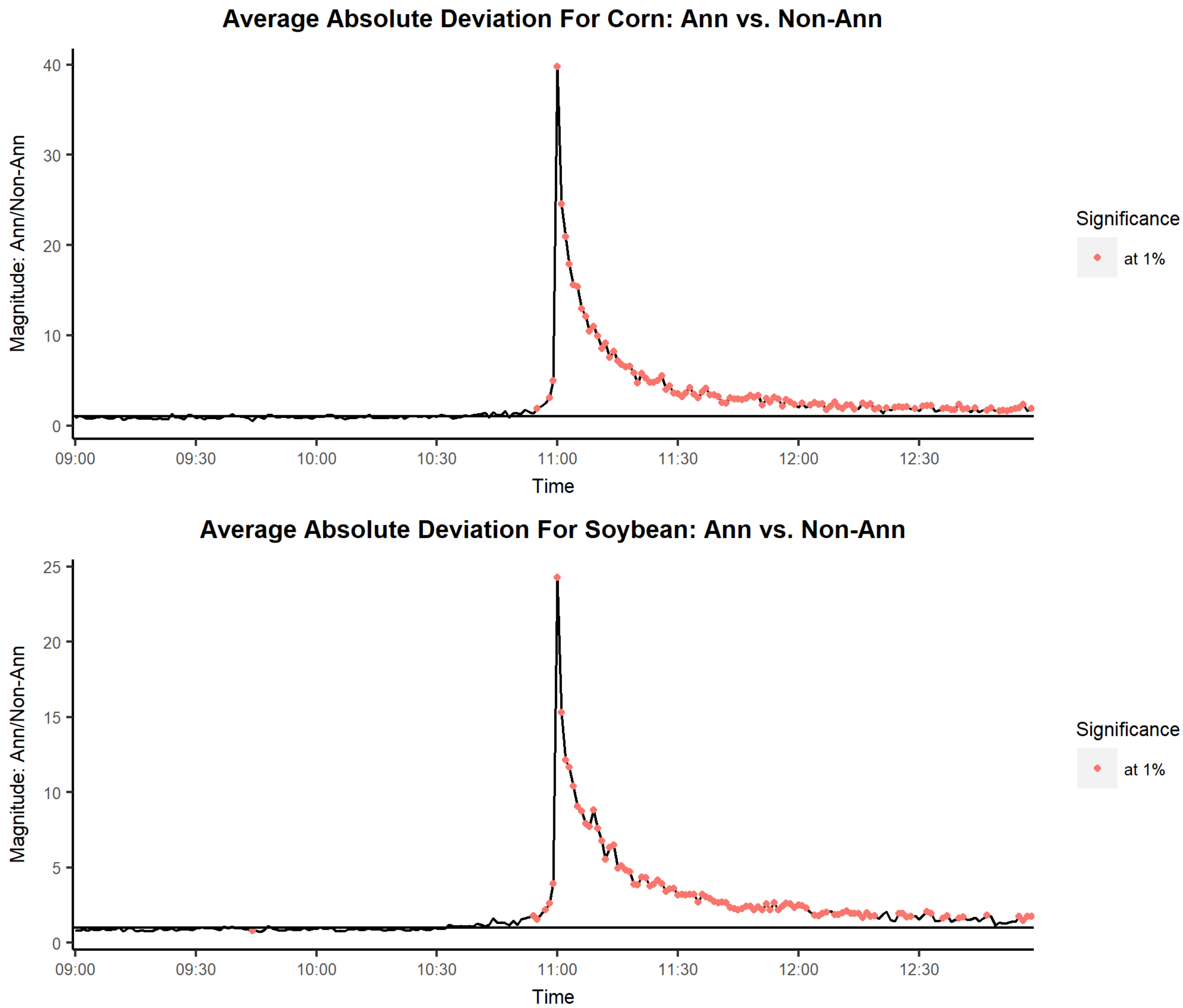

Figure 3: Excess Return Average Absolute Deviation in announcement vs non-announcement days for Corn And Soybean Market

Note: The plot is the ratio of mean values of Average Absolute Deviation ("AAD") on announcement days divided by the same measures on non-announcement days. The black horizontal line equals 1, which means equality between AAD on announcement and non-announcement days; the red dots are the differences that are statistically significant according to both F test and Kruskal-Wallis χ^2 *test at 1% level.*

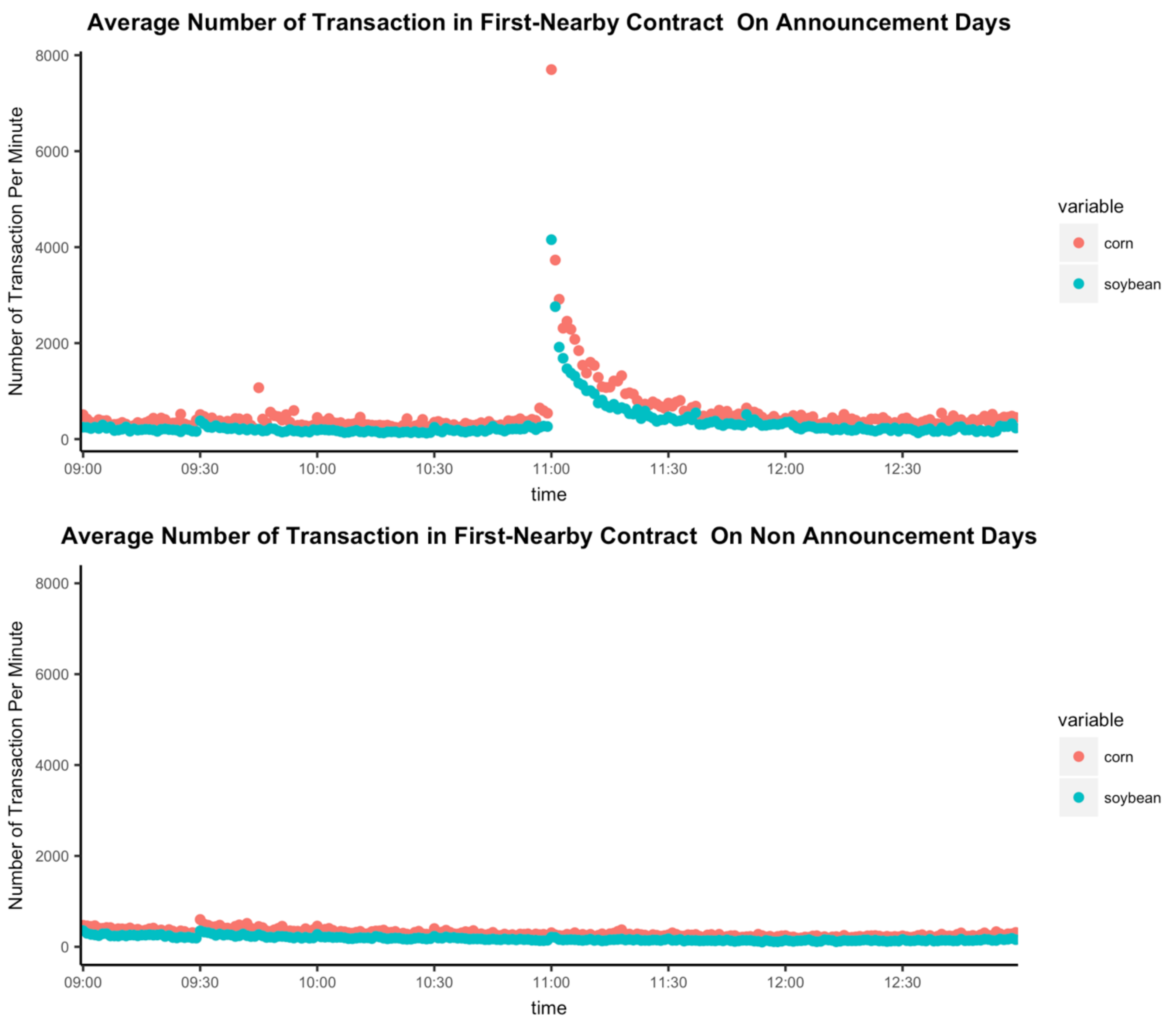

Figure 4: Average Transaction Volume on Announcement Day And Non-Announcement Day

Note: All transaction volumes are generated by the sum of transaction in each minute across all announcement from 09:00:00 to 13:00:00 on announcement and non-announcement days.

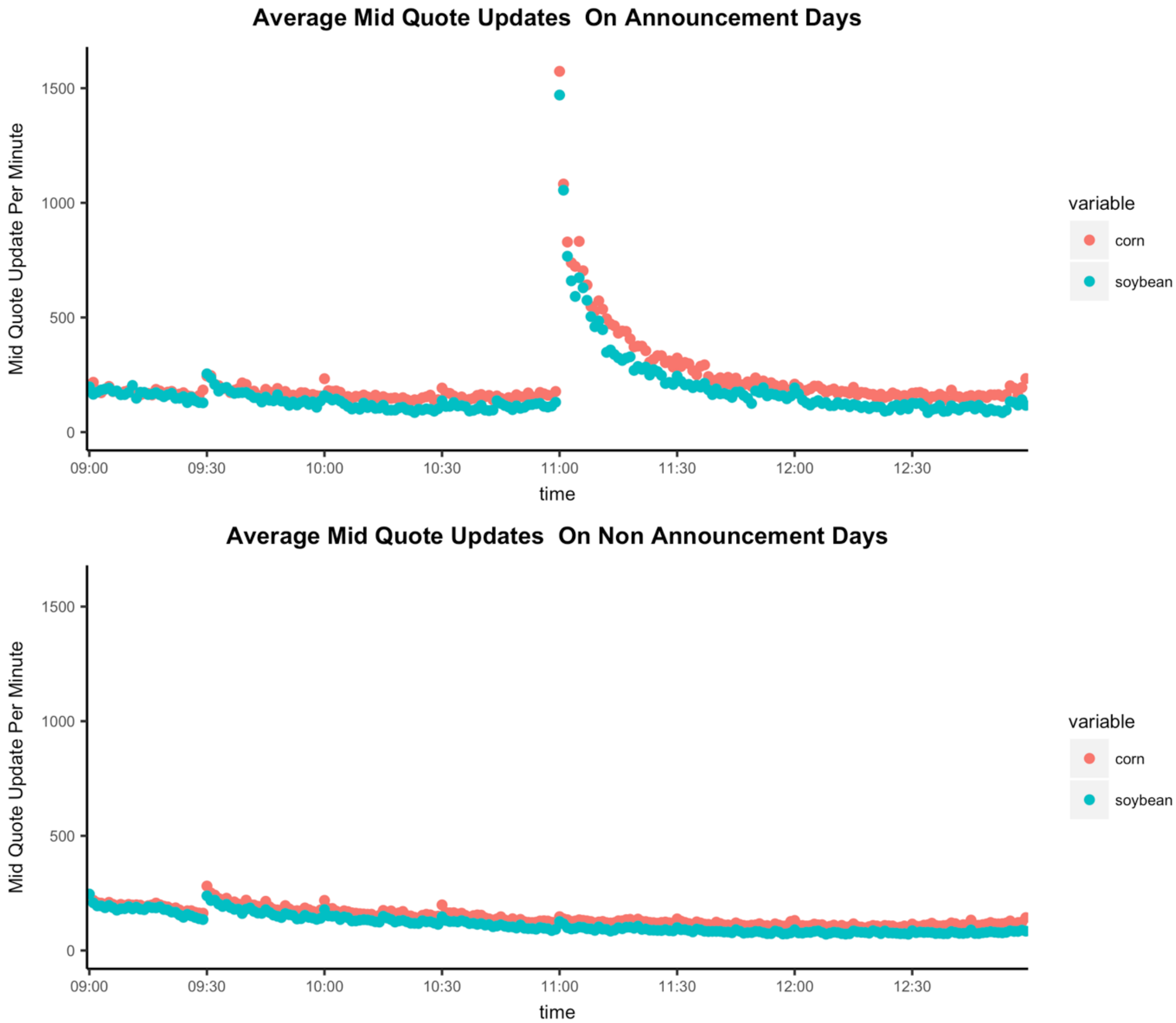

Figure 5: Average Mid-Quote Updates on Announcement Day and Non-Announcement Day

Note: All transaction volumes are generated by the sum of number of mid-quote updates in each minute from 09:00:00 to 13:00:00 on announcement and non-announcement days.

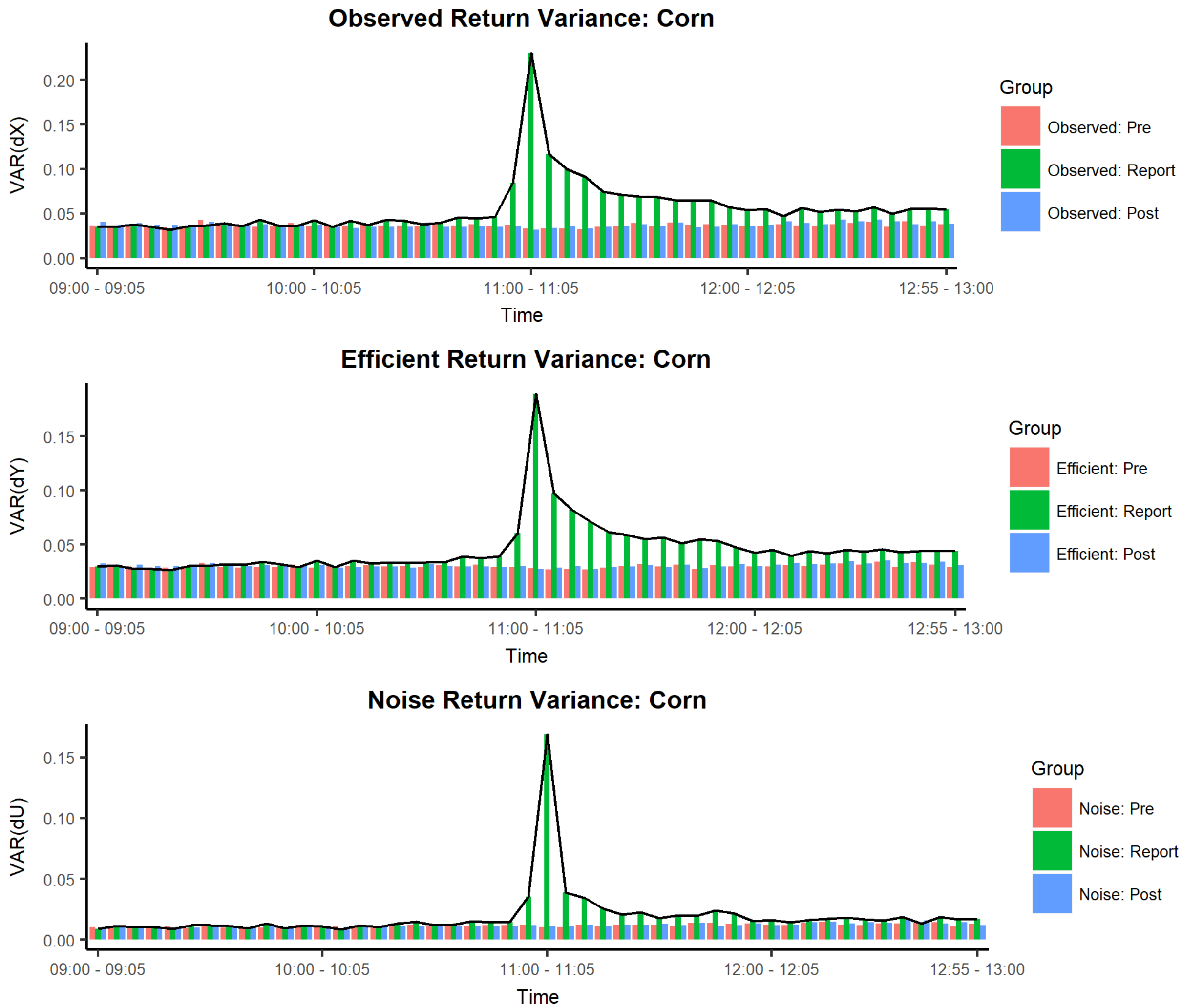

Figure 6: Martingale Decomposition Estimation of Variance Terms for Corn

Note: Each bar corresponds to a five-minute bin estimate, averaged across the announcement days (green bars), five days prior to announcements (orange bars) and five days following announcements (blue bars).

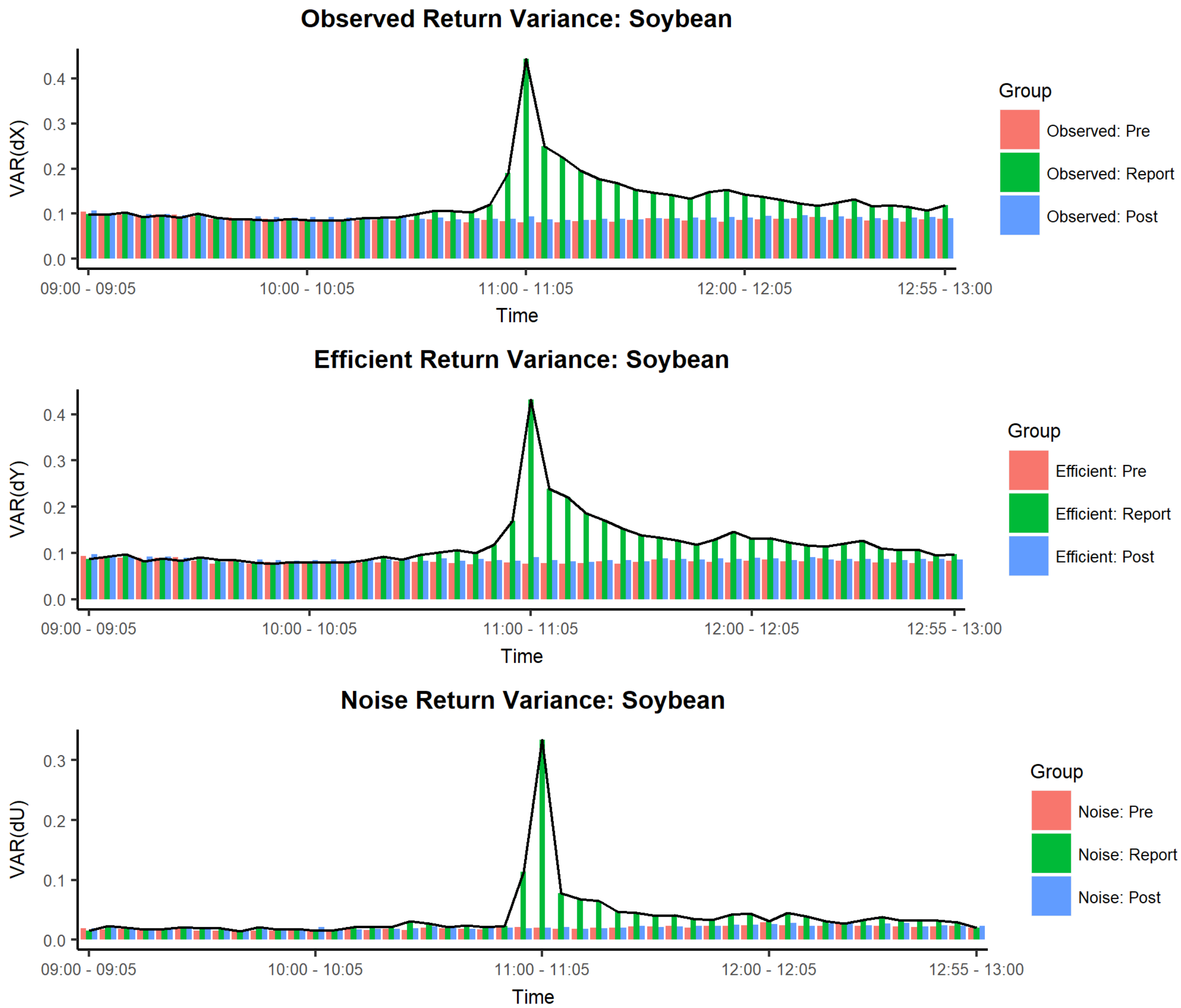

Figure 7: Martingale Decomposition Estimation of Variance Terms for Soybean

Note: Each bar corresponds to a five-minute bin estimate, averaged across the announcement days (green bars), five days prior to announcements (orange bars) and five days following announcements (blue bars).

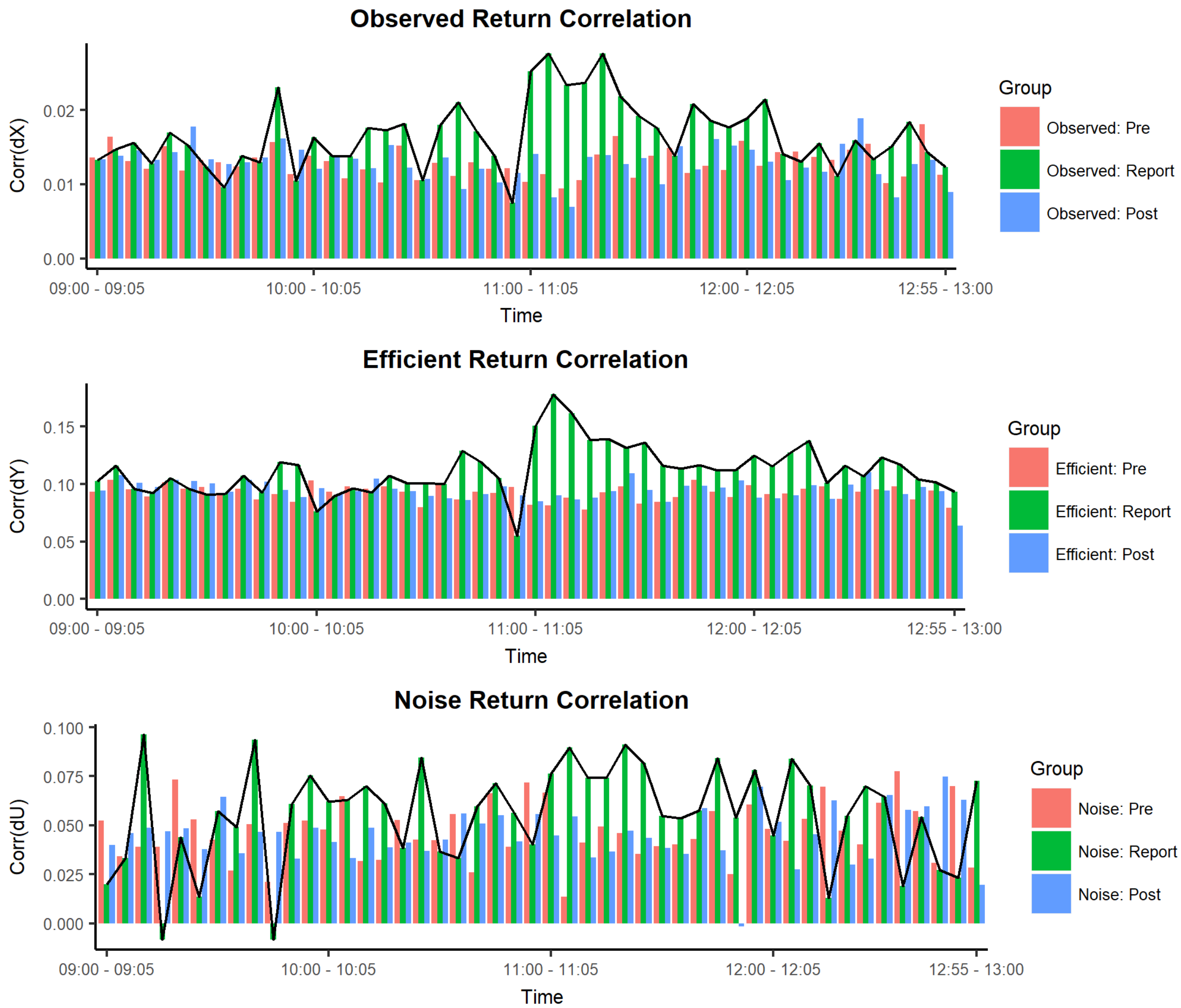

Figure 8: Martingale Decomposition Estimation of Correlation Terms Between Corn and Soybean

Note: Each bar corresponds to a five-minute bin estimate, averaged across the announcement days (green bars), five days prior to announcements (orange bars) and five days following announcements (blue bars).

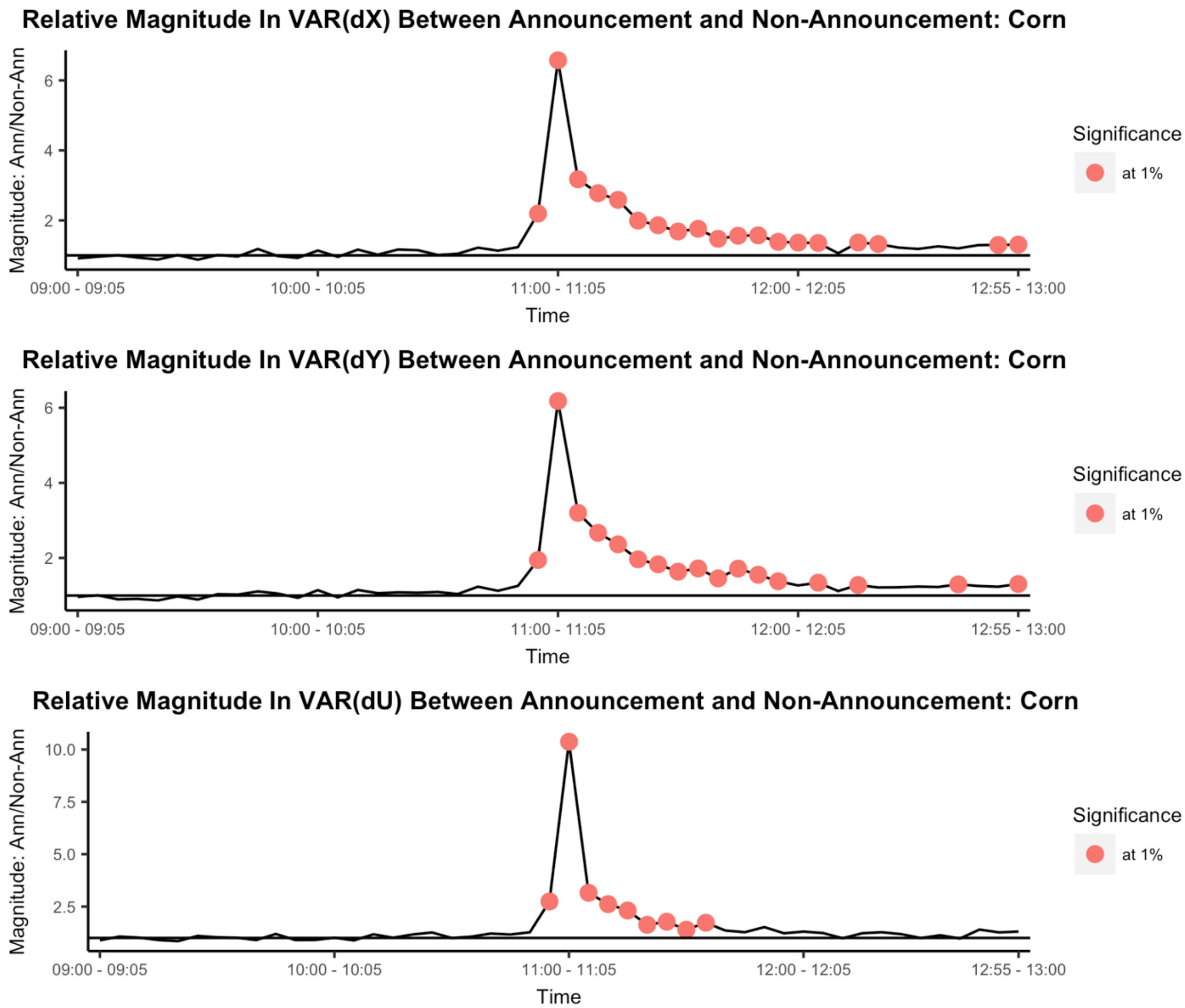

Figure 9: Relative Magnitude Between Martingale Decomposition Estimation of Corn Variance Terms on Announcement Days and Non-Announcement Days

Note: Plots represent the ratios of noise volatility measures in announcement and non-announcement days for every 5-minute interval from 09:00 to 13:00. Announcement day measure is the average across announcement days for the specific time-interval. Non-announcement days measure is the average across the 10 days (5 days pre/after announcement) estimation for the specific time-interval. The black horizontal line corresponds to number 1 and shows when the average estimation on announcement days equals the average estimation on non-announcement days. The red dots indicate measures that on announcement days are significantly different from the estimation on non-announcement days according to both the t test and Wilcoxon test at 1% level.

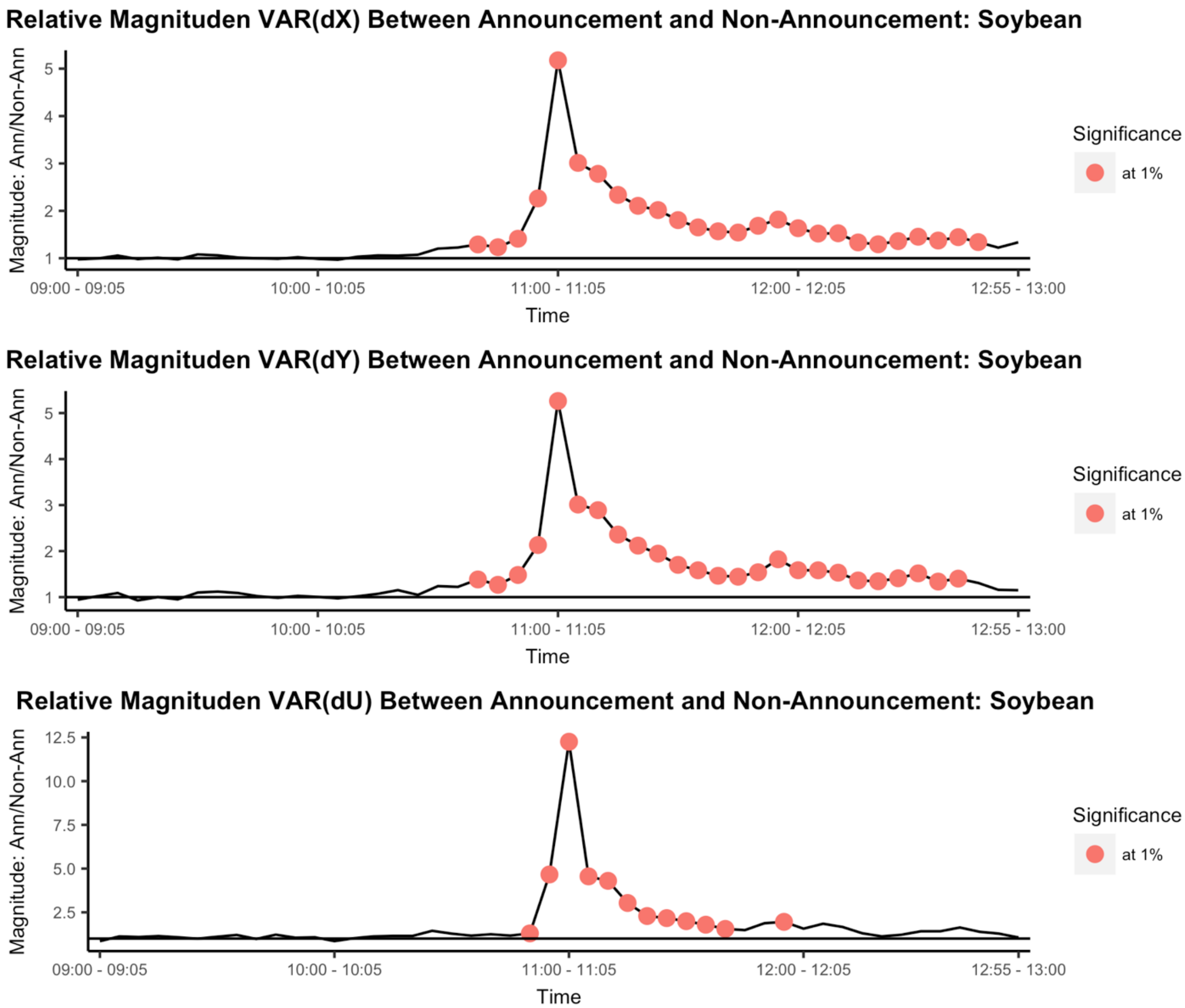

Figure 10: Relative Magnitude Between Martingale Decomposition Estimation of Soybean Variance Terms on Announcement Days and Non-Announcement Days

Note: Plots represent the ratios of noise volatility measures in announcement and non-announcement days for every 5-minute interval from 09:00 to 13:00. Announcement day measure is the average across announcement days for the specific time-interval. Non-announcement days measure is the average across the 10 days (5 days pre/after announcement) estimation for the specific time-interval. The black horizontal line corresponds to number 1 and shows when the average estimation on announcement days equals the average estimation on non-announcement days. The red dots indicate measures that on announcement days are significantly different from the estimation on non-announcement days according to both the t test and Wilcoxon test at 1% level.

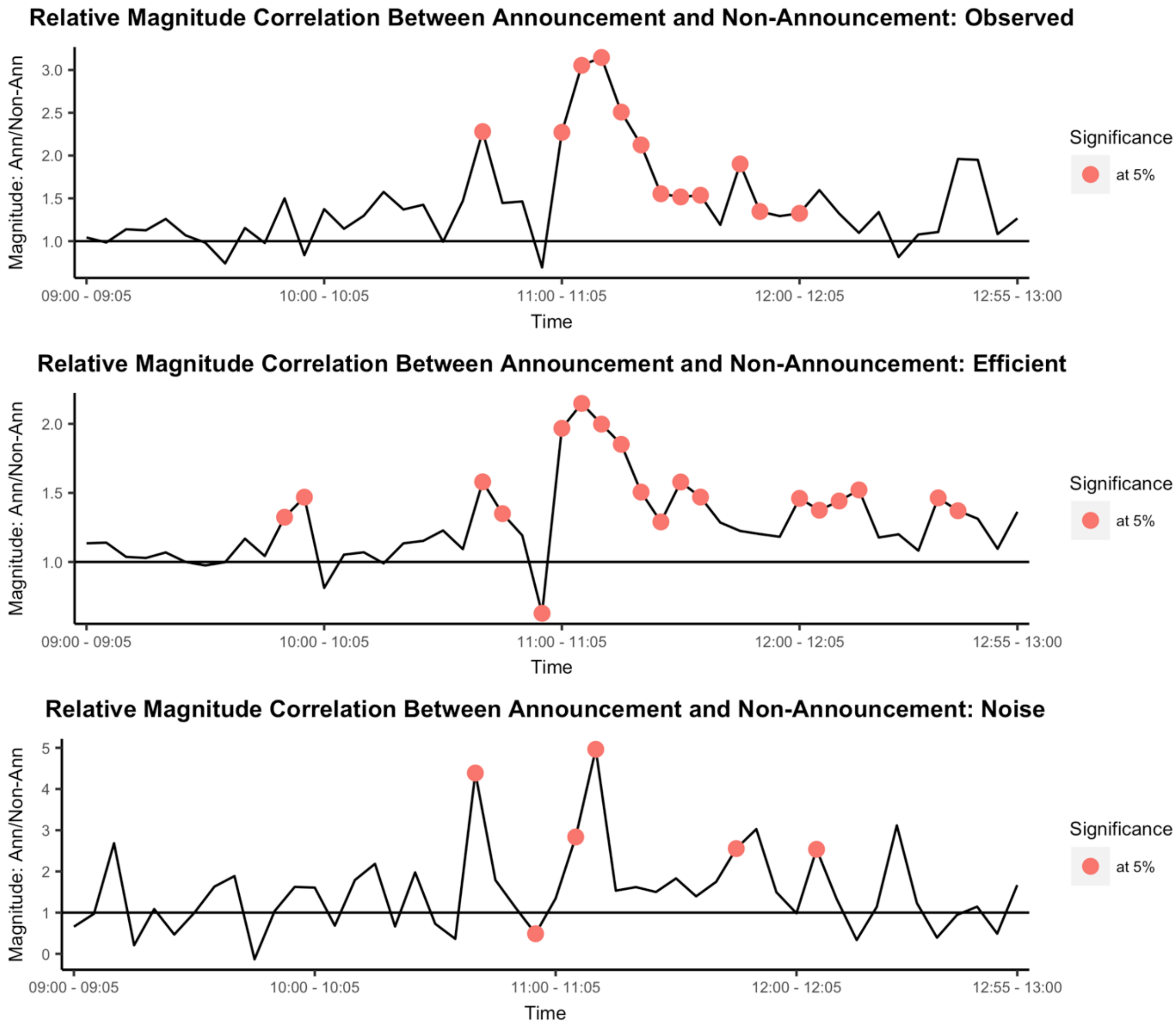

Figure 11: Relative Magnitude Between Martingale Decomposition Estimation of Correlation Terms on Announcement Days and Non-Announcement Days

Note: Plots represent the ratios of correlation measures in announcement and non-announcement days for every 5-minute interval from 09:00 to 13:00. Announcement day correlation measure is the average across announcement days for the specific time-interval. Non-announcement days correlation measure is the average across the 10 days (5 days pre/after announcement) estimation for the specific time-interval. The black horizontal line corresponds to number 1 and shows when the average estimation on announcement days equals the average estimation on non-announcement days. The red dots indicate correlation measures that on announcement days are significantly different from the estimation on non-announcement days according to both the t test and Wilcoxon test at 5% level.

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