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Characterizing the Effect of USDA Report Announcements in the Winter Wheat Futures Market Using Realized Volatility

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Abstract: The United States Department of Agriculture provides information about fundamental supply and demand conditions for major agricultural commodities. We consider whether USDA's crop reports facilitate price consensus in the winter wheat futures market by testing the hypothesis that uncertainty, as measured by realized price volatility, is reduced following the release of USDA reports. This hypothesis was originally developed in studies using implied volatility and found significant decreases. We instead calculate realized daily and intraday volatility using transaction level data from Kansas City Board of Trade futures contracts. Dates on which USDA reports are released are compared to the ten days around the report. Exploiting the full granularity of data, intraminute volatilities are computed to test whether there are distributional differences between report and non-report days. All results suggest that realized volatility does not decrease following USDA wheat report releases but instead increases. Regression analysis shows this result is robust to the inclusion of a limited but relevant set of controls.

Key words: Price Volatility, Wheat, USDA Report, Announcement Effect, Realized Volatility, Tick Data

Introduction

The price of a futures contract represents a point estimate forecast of the value of a commodity at a specified time of delivery. Information about future supply and demand conditions affects this estimate and there is a significant literature analyzing how such information influences the futures price. United States Department of Agriculture (USDA) crop reports are a major source of public information for agricultural commodity markets to which all traders have unrestricted access. These reports are closely watched by futures market participants for benchmark estimates of fundamental supply and demand conditions. Most studies have found significant "announcement effects" from these USDA reports; that is, public information about the underlying value of the commodity changes the point estimate represented by the futures price.

Uncertainty about prevailing supply and demand conditions at the time of delivery means that there exists a distribution of price forecasts around the point estimate provided by the futures price. The futures price alone as a point estimate gives no indication of the degree of uncertainty in the market, but the prospect of uncertainty affects futures prices and futures price variability (Williams, 2001, p. 794). Greater price variability implies more risk for individuals and firms whose profits depend on the commodity price. Price uncertainty matters because individuals and firms make production and consumption decisions based on expected outcomes, outcome uncertainty, and their preferences for risk (Moschini and Hennessy, 2001).

Since public information is non-rival and non-excludable, the provision of public information in commodity markets may function as a public good with social benefits if it can resolve uncertainty about price expectations. If public information equilibrates knowledge of fundamental market conditions, it will narrow the distribution of market participants' forecasts and reduce futures price variability. We test whether public information contained in USDA reports facilitates such consensus in agricultural futures markets by measuring price variability before and after the release of these reports.

A large literature dating at least to Miller (1979) has investigated USDA report announcement effects on futures prices. Recent findings conclude that the release of these reports significantly shifts the point estimate of a commodity's value represented by the futures price. For example, Isengildina-Massa et al. (2008a) and Adjemian (2012) both find that the absolute magnitude of close-to-open corn, soybean, and wheat futures returns are significantly greater on days when USDA reports are released. Lehecka, Wang, and Garcia (2014) measure the duration of this USDA announcement effect comparing the absolute magnitude of returns from minute to minute using transaction level data for corn futures. They find that returns are larger after announcements only in the first fifteen minutes of trading.

These studies confirm the announcement effect, but do not address how these reports influence the variability of futures prices. In part, this gap is driven by limited information in standard open-high-low-close daily futures price data. Since computing a standard deviation or variance requires at least two observations, calculating the variability of daily price returns requires at least three days of data. A larger number of days is required to accurately estimate the standard deviation of returns with any accuracy. If the effect of the report release on variability is at all short-lived, daily price data will not provide adequate granularity necessary to measure such an effect.

One alternative approach is to recover an estimate of the standard deviation of returns from options prices. Such implied volatility estimates are commonly available at daily frequency. Two previous studies focus on implied volatility as a measure of price uncertainty in the context of USDA report releases. McNew and Espinosa (1994) consider whether USDA crop production reports reduce implied volatility. They find that the implied standard deviation of corn and soybean futures price returns is significantly reduced on the day of a report release. In a very similar study, Isengildina-Massa, Irwin, Good, and Gomez (2008b) show a statistically significant reduction in implied volatility on days when the World Agricultural Supply and Demand Estimates (WASDE) are released by the USDA.

We consider a second alternative using transaction level futures price data to calculate the volatility of returns at higher than daily intervals. Such realized volatility (RV) estimators have not, to our knowledge, been used to address uncertainty and public information provision in commodity futures markets. Using RV, we seek to corroborate the finding that USDA reports generate price consensus similar to how Lehecka, Wang, and Garcia (2014) confirmed the USDA announcement effect using transaction level data. We consider a set of USDA reports including the WASDE to see if public information reduces price uncertainty as measured by RV.

We estimate RV using intraday data on Hard Red Winter (HRW) wheat futures prices from the Kansas City Board of Trade (KCBT). The volatility measure is "realized" because it is a near instantaneous measure of the spread of prices at that time based on actual transactions, providing a different estimate of uncertainty than implied volatility which relies on interpolation of volatility from a model based on only daily observations. Over the period of 2008 to 2012, different intervals of time and transactions compare the dynamics of price volatility on 75 days reports are announced to a 5 day window before and after the report's release. Based on Lehecka, Wang, and Garcia (2014)'s results, the effect of the reports on the distribution of prices is likely short lived, thus motivating the analysis over shorter time windows.

We measure RV over an entire trading day, over the first fifteen minutes of trading, and inside single minutes of trading. We compare RV on report and non-report days, essentially using non-report days as a control. Tabular analysis finds that report days are actually significantly more volatile than non-report days. Our minute-by-minute results show that at no point during the trading day is the RV measure of uncertainty reduced on report days. For much of the trading day, report days appear similar to non-report days. We use regression analysis to checks if this result is robust to a specific set of theoretical controls for price limits, calendar fixed effects, contract volume, and the magnitude of the overall price reaction to the report.

Our takeaway result is that USDA public information provision does not reduce futures price RV. This is in contrast to similar analysis conducted using implied volatility. The obvious implication is that there is a difference between what implied and RV are measuring. Given the technical differences between the two metrics, it may be that RV is not a market-wide aggregate estimate of forward-looking price uncertainty (as in commonly assumed of implied volatility). Instead, RV may measure "interpretation uncertainty": the degree to which the market must process new information that potentially conflicting with previous perceptions of market participants. Furthermore, the speed at which increased RV disappears, less than 10 minutes, attests to the efficiency of the wheat futures market.

Institutional Background

The USDA provides reports on current and expected supply and demand conditions for agricultural commodities. Specific reports relevant to the wheat market include the Crop Production, Grain Stocks, Prospective Planting, Acreage Reports, and the World Agricultural Supply and Demand Estimates (WASDE). The first four reports are provided by the National Agricultural Statistics Service (NASS) while the World Agricultural Outlook Board publishes the last. Lehecka, Wang, and Garcia (2014) study the same set of reports in the context of the corn futures market. All these reports contain similar data for wheat, making them by extension relevant to wheat futures.

Relevant Reports, Preparation, and Release

The WASDE is a spreadsheet of production and consumption data for numerous crops grown in the United States and other major crop producing countries. As a result, it is closely watched by grain markets. There are several basic components to the "balance sheet" nature of each WASDE report. Imports, existing stocks, and production forecasts are used to estimate existing supply, while the demand side is measured by exports, domestic use, and year-end stockpiles (Vogel and Bange, 1999, p. 9).

WASDE reports are produced by the collaboration of numerous USDA departments in what is called the Interagency Commodity Estimates Committee (ICEC). The ICEC is composed of analysts from the Economic Research Service, the Foreign Agricultural Service, the Agricultural Marketing Service, and the Farm Service Agency. These analysts employ NASS data, foreign estimates, forecasting models, weather predictions, and satellite imagery to determine their estimates (Vogel and Bange, 1999, p. 4).

The crop production report contains two basic elements, acres to be harvested and expected yields per acre. These data for each new crop of each grain in the U.S. are collected from NASS's surveys of farmers. The crop production and WASDE reports are released simultaneously between the 9th and 12th day of every month. The grain stocks report includes the amount of grain held on site at farms or off site, state by state, for corn, wheat, and soybeans. NASS gathers these numbers from quarterly surveys and publishes the figures in mid January and at the end of March, June and September.

The annual prospective planting report contains information on how many acres of the major crops are projected to be planted at the beginning of each season in March. The report is produced from an annual survey of farmers and is always published at the end of March. Similarly, the acreage report is also an annual update of actual grains planted in the United States on a state-by-state basis. NASS uses random sampling phone and in person surveys to give concrete numbers as to what was actually planted at the end of June (Vogel and Bange, 1999, p. 4).

Beginning May of 1994, all the reports in question were released at 8:30 am Eastern Time on the date of release. More recently, the entire group of reports release time again changed to 12 pm ET in January of 2013. We study the period between 2008 and 2012, so our estimates are unaffected by this change.

The USDA commits to the equal access and integrity of its data and report publications. For this reason, each report is prepared in a lock up session where the document of interest is compiled from analyzing and comparing data sources. During these sessions, only a few people are authorized to be in the windowless, guarded room to prevent to early release of information.

USDA reports are released both in person and online. The USDA website and its separate archive site hosted by Cornell University receive large amounts of traffic. For the year 2013, the USDA had almost 2 million downloads of their reports and around 150,000 hits per month. The Cornell archive also received 58,000 hits per month. Currently, there are close to 15,000 subscribers to the WASDE report.[1]

It is important to understand how such a report could be useful to a futures market, like the KCBT's HRW wheat. They each contain projections or actual numbers about how much wheat is being grown, harvested, exported, and stockpiled. None of this information explicitly tells the wheat futures market what the price of wheat should be, but it does provide clear information about the current and projected relative scarcity of wheat in the U.S. based on expected use, exports, and carry out or year-ending stocks.

Wheat contract holders or any others interested in wheat production data must then interpret the information contained in USDA reports as to how it reflects on the value of the wheat, the underlying commodity of their contract. While knowing if USDA reports change traders' perception of the fundamental value of their contracts is ideal, this is naturally unobservable. This analysis instead seeks to capture possible changes in traders' beliefs in wheat market fundamentals by measuring changes in price variability.

Kansas City Board of Trade Details

For the sample period consider, KCBT's HRW wheat contract traded exclusively on CME group's Globex platform. As with all agricultural commodities, HRW wheat saw immense price volatility during the 2007 and 2008 period, which drew increased scrutiny from regulators and traders, leading to changes in trading rules.

Price move limits have always been a feature of commodity markets and during the majority of the sample period KCBT's price move limit for HRW wheat was 60 cents. However there is an escalator system in effect. If any of the 5 nearest contract prices settled at the 60 cent day limit,

[1]Preliminary numbers provided by Office of the Chief Economist via personal correspondence.

the next day's limit would increase 50% or to 90 cents total. If again the market closes at the limit move of 90 cents it will increase 50% again to 135 cents. The limit move is capped at 135 cents. On each trading day following the increase, the price limit drops by the 50% it had increased by if the limit is not hit again, until the limit is again only 60 cents. [2]

HRW Wheat Futures Market Time Line

Figure 1 helps visualize and compare average trading report and non-report days at KCBT with reference points to important times, such as USDA report releases. The daily trading sessions are Monday through Friday, while the night sessions are Sunday through Thursday. All times are in Central Time (CT). Figure 1 not only shows the daily KCBT market time line but compares the average transaction volume per minute for report and non-report days over the 5 year sample period. There are only a small number of transactions per minute in the overnight session, so it is not considered in this analysis.

There is daily side-by-side trading, meaning both electronic and open outcry, from 9:30 am to 1:15 pm. An overnight electronic session runs from 6 pm to 6 am, until it was expanded on July 1st, 2009 by an hour and 15 minutes. From that point on the night session ran from 6 pm to 7:15 am.[3]

As figure 1 shows, there is on average more transactions on report days than on non-report days for every minute there is activity. In both cases, there is a significantly greater amount of transactions during the day trading session than the overnight session. Compared to the higher number of transactions, still many more transactions happen at the beginning and end of the 9:30 to 1:15 period for both types of days, giving them a distinctive "U" shape. For this reason, our analysis focuses solely on the day trading session of each date the market is open.

As indicated in figure 1, on days that WASDE and other USDA reports are released, it is at 7:30 CT. This gives market participants two hours to read and interpret these reports prior to trading on the information. On average much more trading activity takes place on report days than non-report days. This also helps to motivate the analysis of this piece of research, as one would anticipate that the dispersion of prices is connected with the number of transactions taking place.

Data

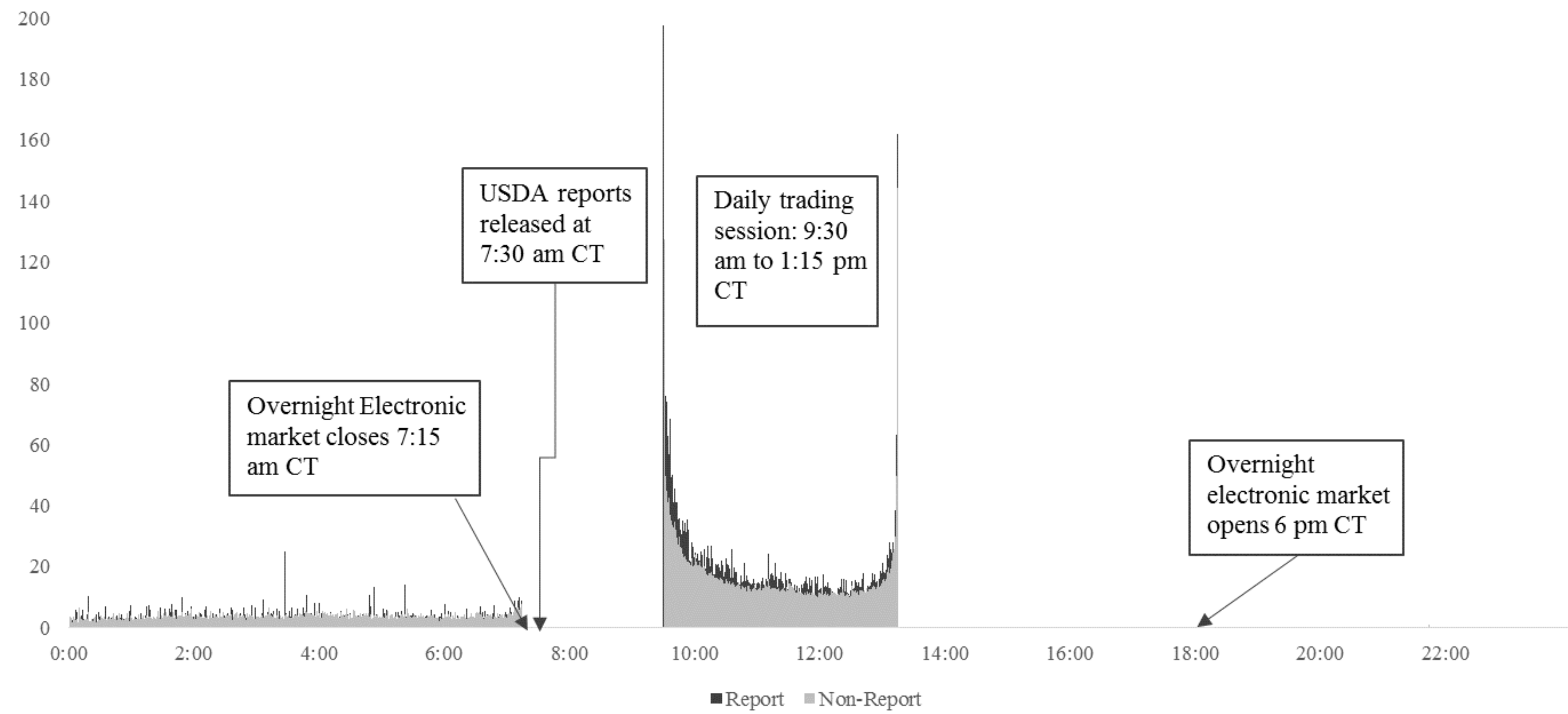
We collect the dates on which USDA reports are released from the USDA archive website hosted by the Albert R. Mann Library of Cornell University. In all, there are 75 unique report dates from the beginning of 2008 and the end of 2012. There are fifteen unique report dates per calendar year, twelve from WASDE releases, and three for the acreage, prospective planting, and grain stocks.

Only the report dates are collected, not the informational content of the reports. The WASDE report contains domestic new wheat crop survey data from NASS during the growing season of each year. The first report to contain the initial information is in May and the USDA updates it each month through August, with the numbers finalized in October.

[2] KCBT price move limit was traditionally 30 cents. It changed to 60 effective February 12th, 2008 early in the sample period following low trading due to the binding limit. This change is accounted for.

[3] While the daily electronic market still closed at 1:15, a ten minute "clean up" period was also added in July of 2009 which takes place in the open pits to finish any transactions that traders had not finalized. Given the sporadic nature of this post market session, transactions in this period are not considered.

Figure 1: Daily Trading Time Line of Kansas City Board of Trade with Average Number of Transactions per minute on Report and Non-Report Days



The KCBT website prior to its merger with CME provides the transaction price data for the KCBT HRW futures contract. Only a five year period of 2008 to 2012 is used where this data set contains the most reliably collected information from the CME Globex platform. The Quandl website facilitates the supplemental daily price data for the KCBT HRW wheat futures contract covering the same sample period, 2008 to 2012. These data are useful because the daily open and closing prices are not the same as the first and last transaction of each day. By using the settle price from the previous, we can determine if the price move limit is reached during a given trading day.

Our final dataset contains only transactions for the nearby contract, rolled from maturity to the next on the first trading day of the contract delivery month. Each contract is the nearby for approximately 60 to 90 days. Only the day trading session is considered. The day session uses side-by-side trading with both electronically-matched and traditional pit, or open outcry, trades.

We take the natural log of transaction and daily price data to reduce the weight of outliers and deal with likely heteroskedasticity. In the transaction level dataset, we have a wealth of data. To further reduce potential noise in the price series, we consider sampling a subset of the transactions/ticks or sampling transactions over some time interval. For this study, we use two sampling methods, literature-standard five minute returns and tick-by-tick returns for three different RV calculations.

After selecting a sampling scheme, the series is differenced to calculate period-to-period returns from which RV estimates can be made. The analysis uses an 11-day event window. With five days before and after each report plus the 75 announcement days themselves the event window contains 825 days total.[4]

Table 1 displays summary statics for daily RV estimates for two different sampling methods. The first, 5 minute calendar time sampling we use only for calculating daily RV estimates. The second is the unsampled transaction flow returns or tick by tick returns we use for both the minute RV and first fifteen minutes of each day. Noticeably, the minimum is always 0 on a day due to the fact that price limits during the most volatile period of early 2008 prevented any trading from taking place for several days.

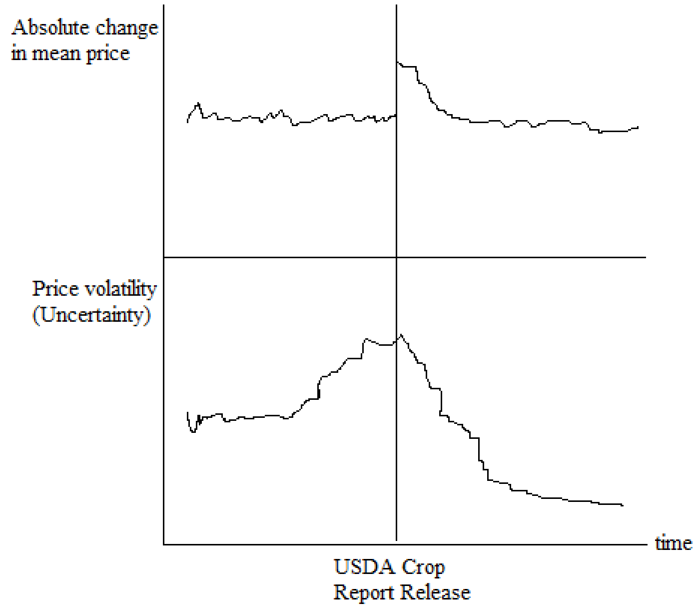
Table 1: Summary Statics of Daily RV Estimates

$Variable_{sampling}$	N	Mean	Std Dev	Minimum	Maximum
SD_{5min}	825	0.002471	0.001013	0	0.009124
SD_{15tick}	825	0.000649	0.000486	0	0.005698
SD_{tick}	825	0.000548	0.000446	0	0.005257

Table 1 displays the summary statistics for daily RV estimates in the first row then the first 15 minute and minute RV in the next two rows. The two RV estimates based on tick by tick returns are similar and significantly smaller than the daily RV based on 5 minute returns. This results conforms to the understanding that as the sampling frequency increases returns shrink because less time elapses between transactions. With less time between transactions there is fewer large price moves. Hence, the tick by tick sampling RV are smaller on averages.

[4]Report release date windows frequently overlap resulting in truncated intervals. To deal with this, days that are overlapped are counted twice, providing an observation for each event window. Thus there is in fact 825 observations.

Figure 2: Announcement Effect of Unanticipated Information in USDA Reports (Source: McNew and Espinosa (1994))



Hypothesis and Previous Work

Our hypothesis is similar to McNew and Espinosa (1994) and Isengildina-Massa et al. (2008b). They seek to ask how public information provided by USDA affects market uncertainty about futures prices. They measure uncertainty using implied volatility, the standard deviation of returns derived from the Black-Scholes option pricing model. They expect the absolute change in conditional mean to jump and as well as uncertainty to reduce after the release of unanticipated public information. Consistent with the concept of market efficiency, if the information is expected, then one should see no change in the moments of prices (McNew and Espinosa, 1994, p. 480).

They posit that if traders are uncertain whether the report will change their beliefs about the fundamental value of a good, one should see an increase in volatility up until the time of the information release. Following the publication, the news should help to resolve uncertainty about fundamentals resulting in a quick and measurable decrease in the range of prices. Figure 2 intuitively describes the path of volatility and mean price changes over time and is a reproduction of their graph. The top panel illustrates the jump in the point estimate change covered in numerous studies. The change in volatility is depicted in lower panel and is the reaction of interest in our study.

As Falk and Orazem (1985) states, since the market only reacts if there is surprise or unexpected information in the USDA reports, this theory is still consistent with an efficient market. This theory is a direct extension of Fama (1970) to agricultural markets. Even if regular trends persist in the markets, like the rising and falling of volatility shown in the lower panel of figure 2, McKenzie, Thomsen, and Phelan (2007) points out these are technical features of the underlying option. Furthermore, market participants around the time of USDA reports are unable to gain any systematic profit from the reaction again preserving market efficiency.

McNew and Espinosa and Isengildina-Massa et al. (2008b) do not find a significant increase in volatility leading up to the USDA release of crop production reports. But they do find a statistically significant decrease in implied volatility on the day immediately after publication, with some residual decline in later days. The later breaks out the results by month showing that particular reports drive the results. Overall, they find support for their hypothesis that USDA crop reports reduce uncertainty about market fundamentals. Both studies argue this is a clear sign of the economic value of USDA crop reports.

Differences of Opinions

More recently, difference-of-opinion models (Banerjee, 2011; Banerjee and Kremer, 2010; Banerjee, Kaniel, and Kremer, 2009) have been used to explain how the market reacts to information. While private information is subject only to opinions of the agent who holds it, public information is subject to interpretation by the market as a whole. Those interpretations can differ greatly despite the open source nature of the information. In particular, Banerjee and Kremer (2010) argue market participants may "agree to disagree" on the interpretation of public information (p. 1270). Studying trade volume, their work shows after a rigorous theoretical model development, difference of opinion can explain clustering and autocorrelation of volume which is consistent with other empirical work (p. 1294). Banerjee and Kremer suggest the difference of opinion framework is superior to asymmetric information models they consider at describing behavior in markets.

Fishe, Janzen, and Smith (2014) shows theoretically that equilibrium prices differ in a difference of opinion model compared to one with rational expectations. They explain the implications the difference of opinion idea has on prices, stating: "traders do not believe that prices fully incorporate the available information about fundamentals. Rather, they trust their own information signals when choosing positions" (Fishe, Janzen, and Smith, 2014, p. 543). While much of the analysis of information focuses on the differences between public and private, the scant difference of opinion literature shows a new light of interpretation of public information and its influence on agricultural market uncertainty.

Difference of opinion in general can show that conflicting interpretations of information can lead to a larger range of prices or higher volatility, a phenomena unexplained by the simple price reaction to new information shown in figure 2. The majority of existing analysis of USDA reports in agricultural commodity markets relies on the market efficiency concepts of Falk and Orazem (1985) and Fama (1970), to describe the interpretation of information. Difference of opinion may better explain the behavior in market prices, especially at high frequencies.

Realized Volatility: Theory and Methodology

Generally speaking, volatility refers to the variability of prices measured using standard deviation or variance. It is of interest in all markets because it indicates the level of risk involved in that investment. Furthermore, price volatility indicates uncertainty as to the fundamental value of the asset traded. The more volatile a market is, the more risky and the less participants actually know about what their commodity is worth. But what do high frequency data gain the practitioner? In brief, the higher granularity of data provides analysts with a more frequent and potentially more accurate measure of price volatility. For practical reasons this is useful because margin calls are more frequent and transactions costs are positive during more volatile periods in the market.

RV's primary benefit is as a near instantaneous measure of risk or volatility. While RV is still a historical measure of volatility, history becomes relative the more frequently one observes prices. For volatility calculated from daily observations their is a lag meaning enough days of data must be observed before volatility can be retrospectively estimated. With high frequency data, there are more observations inside a smaller window of time and volatility can be calculated over those shorter time windows. Thus, volatilities are computed for separate days or even particular parts of the day.

With more frequent measure of price dispersion, this study can look at the hypotheses suggested by McNew and Espinosa (1994) and Isengildina-Massa et al. (2008b) in a manner they were unable to. By investigating how USDA reports effect uncertainty over intraday time horizons, this study can provide concrete real-time evidence to whether information about fundamentals tightens the distribution of prices thereby creating futures price consensus.

Underlying Generation of High Frequency Data

As the period of time in which we observe prices gets narrower, the data generating process of those prices changes. The fundamental price represents the genuine relative scarcity of goods, the equilibrium interaction of supply and demand that produces prices in a market. This is what we generally think of when we speak of prices. However, this is never observable because of frictions are always present in the market that obscure the fundamental price. At more granular prices, these distortions are more prominent. Called market microstructure effects, they are institutional factors or artifacts of the trading process which result from behavior of market participants and technical limitations of the formal market. This means that in high frequency time series prices, one sees less of the fundamental price and more noise of the trading process.

The high frequency data literature provides a simple structure for understanding the microstructure noise component of the price. Equation 1 shows the basic theory of prices with microstructure noise, a price for a particular time or interval t (e.g. Bandi and Russell, 2008; McAleer and Medeiros, 2008).

$$\tilde{p}_t = p_t^* \vartheta_t \tag{1}$$

In this equation $\tilde{p}_t$ is the price of a transaction at that particular time. But it is composed of the true or fundamental price p_t^* which contains the information important to economic decision makers and is obscured by the microstructure effects, ϑ_t. Neither the microstructure noise or true price are observed - only the transaction price $\tilde{p}_t$. Logging this equation, which is typical of timeseries analysis, makes the fundamental price and noise term additively separable as shown in equation 2.

$$\underbrace{ln(\tilde{p}_t)}_{p_t} = \underbrace{ln(p_t^*)}_{m_t} + \underbrace{ln(\vartheta_t)}_{s_t} \tag{2}$$

Combining this equation with some of the basic concepts of market microstructure theory helps to explain the issue of the microstucture noise term on prices (e.g. Hasbrouck, 2007). Relying on the notation and work of Janzen, Smith, and Carter (2014) and the underlying theory of Hasbrouck (1993), We can describe the properties of the equilibrium or fundamental price as part of a semi-martingale random walk process using the underscore notation from equation 2:

$$m_t = m_{t-1} + w_t \tag{3}$$

In equation 3, the fundamental price at time t is m_t and is a product of the last time period's fundamental price, m_{t-1}, plus a random incremental shift, w_t. The term represents the change in fundamental value brought on by changes in underlying supply and demand factors. Such changes could be learned by new information, like a USDA report. Taking the first difference of the observed price p_t to get returns produces equation 4.

$$\Delta p_t = p_t - p_{t-1} \tag{4}$$

It is merely the current period t's price with the preceding period's price subtracted. Conveniently, the individual terms that compose p_t from equation 2 can be substituted into the equation as such:

$$\Delta p_t = m_t + s_t - m_{t-1} - s_{t-1} \tag{5}$$

5 shows the observed return, Δp_t, is comprised of the current period t's true price and noise term with the same parts from the preceding period, $t - 1$, subtracted. Using the parts from rearranging and plugging in Equation 3 into 5, a more informative equation is formed. Change in fundamental price is then equal to w_t and the change in the microstructure effects can be collected into the delta notation.

$$\Delta p_t = w_t + \Delta s_t \tag{6}$$

Thus, equation 6 shows that logged returns, the basic term used in this and most high frequency analysis, are always composed to two parts: the change in the equilibrium value, w_t, and a shift in the microstructure noise term. With this basic equation, the disruptive properties of microstructure noise on price dispersion can now be better illustrated. As shown in equation 7, taking a measure of the spread of prices like variance produces two terms:

$$Var(\Delta p_t) = Var(w_t) + Var(\Delta s_t) = \sigma_w^2 + \sigma_s^2 \tag{7}$$

As the equation displays, the variance of prices is equal to the spread of both the fundamental value and the microstructure effects. As a result, any volatility measure of high frequency data will necessarily be influenced by microstructure noise. This relationship only holds if changes in the fundamental value and mircrostructure noise are independent. They are by assumption because w_t as described in 3 is random and uncorrelated. Notice the presence of both terms makes any volatility measure larger than if it only contained the equilibrium price.

Microstructure noise can be caused by various institutional influences on the trading process known as irregular pricing, price discreteness, nonsynchronous pricing, and the ask-bid bounce (Zhou, 1996; Andersen and Bollerslev, 1997). As shown in equation 7, the problem with microstructure effects is that when returns are taken any volatility calculation then contains the noise term, σ_s, which obscures the underlying price variability. The statistical consequences of the bid-ask bounce is first-order negative autocorrelation of returns which produces an upward bias in volatility measures (Bai, Russell, and Tiao, 2001; Bandi and Russell, 2005; de Pooter, Martens, and van Dijk, 2008). Also, higher order autocorrelations can result from the return clustering that results from price nonsynchronicity and discreteness (Bandi and Russell, 2005, 2008).

Microstructure noise matters because it makes up more of the observed volatility the smaller the window of observation. This means $\frac{\sigma_s}{\sigma_w+\sigma_s} \to 0$, or the noise to signal ratio goes to zero as the length of time between prices increases. But these effects pose a problem only when this analysis focuses on the impact of situation and outlook information on the fundamental value of wheat returns. While this is important, it is not the only concern.

In order to measure and evaluate uncertainty and risk and by extension information's influence on volatility, one expects the behavior of the market, reflected in the microstructure noise, to be equally influenced by USDA reports. In this case, the inability to separate the noise from the fundamental value is less problematic because changes or lack thereof in the noise component is equally indicative of the information effects. Realistically, previous studies which employ implied volatility contain the same microstructure affects of the market and did not correct for it. While these affects are a concern, they do not undermine the nature of the analysis.

Realized Volatility

There is no agreed upon method of calculating RV. The finance literature typically employs a variant of the sum of squared returns, but we use the traditional standard deviation because the sum of squared returns measures are not comparable for different numbers of observations.[5] Since our study seeks to exploit these data at the highest frequency, tick to tick returns results in different number of returns for every unit of observation. This makes the sum of squared returns measure of RV unusable.

Equation 8 shows the basic formula for this standard deviation where r_i represents an observed return over a given interval of time or transactions, and is equivalent to Δp_t from equation 6. The sampling method determines i, and $\bar{r}_t$ represents the average return for that same period t. n_t is the number of observations for period t.

$$s_t = \sqrt{\sum_{i=1}^{n_t} \frac{(r_i - \bar{r}_t)^2}{n_t - 1}} \tag{8}$$

In order to calculate RV, we must choose i or the sampling frequency and t or the window of time over which RV is calculated. In an effort to balance the loss of accuracy and microstructure effects, nearly all empirical work with high frequency data employs some sampling scheme. Sampling seeks to reduce the influence of market microstructure effects. Sampling picks out certain

[5] Where possible results were also computed using square root of the sum of squared returns. Results were identical.

observations from the transaction-level data based on a rule. This sampling mitigates the disruptive effects of the microstructure noise, reducing the upward bias of volatility measurements. All future references to "sampling" refer to the process of drawing prices in a regular manner from the transaction-level data.

These methods are separated into two basic categories: calendar time and transaction time. Alternatively they can be titled clock time and tick time. The practical goal of either sampling method is to produce a time series with consistently spaced observations, making it able to produce consistent volatility estimates (e.g. Wasserfallen and Zimmermann, 1985; Hansen and Lunde, 2006; Russell and Engle, 2010). Two sampling schemes are used in this study: every five minutes and the full tick-by-tick transaction series.

When considering calendar time sampling, irregular pricing and price discreteness make it rare that transactions fall at identical points in each minute. Interpolation methods must be employed to manufacture the desired equidistantly spaced time series. We employ the most common type of interpolation method when using calendar time sampling called the previous tick method. It takes the first observed price of each interval as the sampled transaction for that interval. For sampling intervals missing observations, the previous observation, or "previous tick," is used to fill in (Wasserfallen and Zimmermann, 1985; Hansen and Lunde, 2006). For greater detail on common sampling methods see the relevant discussions in Andersen and Bollerslev (1997) and Hansen and Lunde (2006).

In order to grapple with the complexities of sampling high frequency data, research has developed methods of finding the optimal number of observations and manner to sample them. The influence of microstructure distortions can be mitigated by reducing the frequency of the data. Nevertheless, the practitioner must balance the trade-off between bias caused by these microstructure effects and sampling error, reduced accuracy, or power of volatility estimation due to using less data (Bandi and Russell, 2008, 2005; de Pooter, Martens, and van Dijk, 2008; Andersen et al., 2000). For this reason the literature standard 5 minute return calendar sampling method is used for the daily RV measures. However, in order to drill down to a shorter time scale more frequent sampling is used. Hence we accept greater microstructure distortions in our data in order to capture the minute by minute impacts of reports on RV.

Daily Realized Volatility Analysis

We turn to the work of McNew and Espinosa (1994) to compare the daily volatility of the event window around USDA reports in the wheat market. Table 2 presents the average daily RV measure of each day across months and years of the event window.

We normalize numbers by the volatility of the day before a report release. This helps to remove seasonal or time fixed effects that might be present and invalidate testing (McNew and Espinosa, 1994, p. 484). For that reason, the day before the report or day -1 is not reported because its average is 1 by construction. The literature standard of 5 minute calendar time returns are used to calculate RV. In this case, daily standard deviations are used to make the analysis more comparable to previous work with implied volatility. Each day then has 75 observations.

The first striking element of table 2 is that the first day the wheat market trades on the new USDA information is much larger than any other day on average in the report window. Furthermore, every day on average is above one. This means that every day in the event window is on

Table 2: Average Daily Wheat RV Relative to Day Before Release Using 5 Minute Returns

t	-5	-4	-3	-2	0	+1	+2	+3	+4	+5
$\sigma_t \backslash \sigma_{-1}$	1.108	1.154	1.139	1.062	1.398	1.141	1.161	1.139	1.160	1.116

average more volatile than the day before a USDA report is released. Extending the analysis of table 2, Kruskal-Wallis non-parametric difference-in-distribution tests compare RV of all the observations of each day in the event window to one another. This test assesses whether there are locational differences in the distribution of volatility. These tests are performed on RV on a given day relative to Day -1, the day before the report. The p-values of the test between each day of the event window are reported in table 3. The null hypothesis is RV is the same on each day of the event window. Stated formally - $H_0 : \sigma_i = \sigma_j$. The alternative is stated at the top of the table. The table is symmetric so the top right numbers are not displayed.

Table 3: Probability Values for Kruskal-Wallis Test Statistic on Daily Wheat RV using 5 Minute Returns

	H$_a$: $\sigma_i \neq \sigma_j$									
j	-5	-4	-3	-2	-1	0	+1	+2	+3	+4
i										
-4	0.613									
-3	0.821	0.762								
-2	0.497	0.187	0.476							
-1	0.069	0.034	0.363	0.879						
0	0.003	0.007	0.005	0.000	0.000					
+1	0.505	0.842	0.645	0.204	0.071	0.008				
+2	0.480	0.818	0.637	0.158	0.006	0.016	0.985			
+3	0.994	0.478	0.960	0.430	0.762	0.002	0.469	0.443		
+4	0.632	0.878	0.794	0.248	0.363	0.009	0.842	0.848	0.651	
+5	0.972	0.628	0.869	0.384	0.069	0.003	0.634	0.514	0.847	0.689

The results show that the first day where the KCBT trades on USDA report information, Day 0, has statistically different price volatility than nearly every other day in the event window at the 99% level. This is except for Day +1, for which the difference is only significant at the 95% level, showing there may be some residual volatility impact on that day following the report. The averages of daily RV suggests that the day before the report is also different than all other days in the event window. These results only provide marginal significance for that hypothesis. No other pattern stands out in the table suggesting limited difference between volatility on most days.

What stands out is that the results are in direct contrast to the findings of McNew and Espinosa (1994) and Isengildina-Massa et al. (2008b). Both of those works find that USDA reports reduce futures market uncertainty as measured by implied volatility at the daily level. These basic results suggests that USDA reports instead increase market uncertainty as measured by the primary statistic, RV, challenging the hypothesis that USDA reports reduce uncertainty and facilitate price consensus.

Table 3 presents the results of a two-tailed test, not the one tailed tests performed by McNew and Espinosa (1994). This is because, as suggested by the averages of table 2, the volatility is actually greater on report days then non-report. This means the directional tests would return no results, because on average reports have more rather than less volatility relative to other days. Nor do the volatility measures lend themselves to the pre-report gradual increase in volatility that their hypothesis suggests. Instead the tests of table 3 show a possible lull before the report release.

While table 3 gives no directional tests, it is a fact that Day 0 is significantly larger than all other report days. The day before the report release, Day -1, is moderately smaller compared to sporadic days. As a two tailed test, the null hypothesis rejection region is split in half make the results even more robust than one tailed tests.

Intraminute Realized Volatility

Because our initial results suggest that uncertainty, as measured by RV, actually increases following USDA report releases, we move to intraday analysis to further characterize the price adjust process to new information. An alternative explanation for higher volatility is that there is an initial adjustment period or shock which increases uncertainty following a report release, something possibly driven by different and conflicting interpretation of the USDA data. Following the resolution of these difference of opinion possibly uncertainty reduces later in the day. This can only be identified by looking at RV over intervals inside the trading day.

To better assess this possible change in RV, we disaggregate non-report days into the 5 days before the report, the pre-report days, and the five days after, the post-report days. By doing so, we can then compare days in two dimensions. First, compare across days to see how the distribution of RV changes from the days leading up to and following the report date is self.

This comparison across days is similar to previous studies comparing implied volatility across days, but this analysis adds an additional dimension by comparing RV of particular trading minutes inside of a day. This allows the original hypothesis to be tested with a closer observation of the reaction but also allows for potentially identifying results consistent with the alternative hypothesis suggested.

In order to take full advantage of the new time scale added, the full transaction-by-transaction sample exploits its greater number of observations. The higher frequency of the data provides at times over 200 transactions in a single minute.

Microstructure noise is likely prominent in the standard deviations of returns measured inside of each minute of each day. It is therefore difficult to measure variability of fundamental price volatility. As a result, at this level of frequency we cannot test any hypothesis about the fundamental value of wheat. Nevertheless, we posit that distortions like microstructure noise are interesting in themselves because they reflect trading behavior in the wheat market.

Hence, detecting changes in the RV due to shifts in the fundamental value, the microstructure noise component, or both is equally demonstrative of the impact of USDA reports on trading in the market as well as uncertainty.

Table 4 shows the average RV per minute for the first 30 minutes of the day trading session on report, pre-report, and post-report days. A longer period of the opening trading day is shown to consider the possibility of a longer more gradual adjustment in volatility through time. The

Table 4: Intraminute RV on Pre, Post, and Report Days

t	ARV_r	ARV_{pr}	ARV_{po}	Rep-Pre	Rep-Post	Pre-Post	$KW_{Rep/Pre}$	$KW_{Rep/Post}$	$KW_{Pre/Post}$
9:30	0.0011	0.0008	0.0009	0.0003	0.0002	-0.0001	15.1526***	7.2318**	4.9313**
9:31	0.0008	0.0005	0.0005	0.0003	0.0002	0.0000	10.7153***	5.2044**	2.3345
9:32	0.0007	0.0005	0.0005	0.0002	0.0002	0.0000	3.6153	2.6616	0.1126
9:33	0.0006	0.0005	0.0005	0.0002	0.0001	0.0000	4.5700*	3.5602*	0.1349
9:34	0.0008	0.0005	0.0005	0.0003	0.0003	0.0000	7.7528**	6.7996**	0.0352
9:35	0.0006	0.0005	0.0005	0.0001	0.0000	-0.0001	6.3544**	2.1214	2.5924
9:36	0.0006	0.0005	0.0005	0.0001	0.0001	0.0000	1.4420	1.1763	0.0098
9:37	0.0006	0.0005	0.0005	0.0001	0.0000	-0.0001	6.4947**	3.9934*	0.4867
9:38	0.0005	0.0005	0.0005	0.0001	0.0000	0.0000	0.0040	0.0238	0.1875
9:39	0.0006	0.0005	0.0006	0.0002	0.0000	-0.0001	0.7613	0.1966	0.6585
9:40	0.0008	0.0005	0.0005	0.0003	0.0002	-0.0001	0.5347	0.0476	0.7974
9:41	0.0006	0.0005	0.0006	0.0001	0.0000	-0.0001	0.0178	0.0305	0.3025
9:42	0.0008	0.0004	0.0006	0.0003	0.0002	-0.0002	2.4979	0.8396	1.1629
9:43	0.0007	0.0005	0.0006	0.0002	0.0001	-0.0001	0.0412	0.5703	3.1325
9:44	0.0008	0.0005	0.0006	0.0003	0.0002	-0.0001	0.3353	0.0440	0.3622
9:45	0.0007	0.0005	0.0006	0.0002	0.0002	-0.0001	2.8102	3.0206	0.0786
9:46	0.0008	0.0005	0.0005	0.0003	0.0002	-0.0001	5.3881**	4.8854*	0.0035
9:47	0.0007	0.0005	0.0005	0.0002	0.0002	-0.0001	1.4123	1.0724	0.0109
9:48	0.0008	0.0004	0.0005	0.0004	0.0003	-0.0001	15.9685***	9.9339**	1.9277
9:49	0.0006	0.0005	0.0005	0.0002	0.0002	0.0000	5.5055**	4.2133*	0.2293
9:50	0.0007	0.0005	0.0005	0.0002	0.0002	0.0000	13.148***	7.2682**	2.4289
9:51	0.0006	0.0004	0.0005	0.0002	0.0001	-0.0001	1.4053	0.3799	0.8916
9:52	0.0007	0.0005	0.0005	0.0002	0.0002	0.0000	0.1987	0.3117	0.1436
9:53	0.0007	0.0005	0.0005	0.0002	0.0002	0.0000	2.0913	2.9996	0.2718
9:54	0.0007	0.0005	0.0005	0.0002	0.0002	0.0000	2.0322	2.0783	0.0369
9:55	0.0007	0.0005	0.0006	0.0003	0.0002	-0.0001	4.2273*	1.8924	1.3121
9:56	0.0007	0.0004	0.0006	0.0003	0.0002	-0.0001	2.0651	1.8519	0.0154
9:57	0.0006	0.0004	0.0005	0.0002	0.0001	-0.0001	2.6192	0.6934	1.7197
9:58	0.0005	0.0004	0.0005	0.0001	0.0001	-0.0001	1.3684	0.5607	0.4431
9:59	0.0006	0.0005	0.0005	0.0002	0.0002	0.0000	1.0588	1.3473	0.0522

Notes: A single (*) denotes statistical significance at the 10%, a double asterisk (**) indicates significance at the 5%, and a triple asterisk (***) means statistical significants at the 1% level.

first column presents the per minute averages for days on which reports are released. There are typically 70 report days for each minute. The second column reports the same for the five days before the report release of the event window for which there are always at least 330 days. The third displays is then the average minute by minute volatility for the 5 days following a report.

The next three columns then present the differences between average volatility on report and pre-report days, report and post-report, and finally pre-report and post-report days. The final three columns then display the Kruskal-Wallis non-parameteric tests statistics with significance levels for the comparison of the three types of days to one another.

The Rep-Pre difference column shows RV on average is larger on the day USDA wheat information is released than on the five previous trading days. Shown in the $KW_{Rep/Pre}$ column, the test statistic is significant at least at the 95% level for about the first 7 minutes, very similar to Lehecka, Wang, and Garcia (2014)'s pooled results. What is more interesting is that following this there is no major trend of difference in RV between pre-report days and the report date. This means that following the initial jump in volatility, it returns to the same level as the previous days if not occasionally higher. While not shown here for brevity, this same finding plays out through the entire trading day.

In the second difference column, Rep-Post, average RV is again larger on report days than on the days following a USDA publication, however, the difference is not as large. The second KW column, $KW_{Rep/Post}$, provides a significant difference at the 95% level in the distribution of minute-by-minute RV estimates for only the first 5 minutes. Thus, in minutes of the days following the release of reports RV is smaller over all on the post report days but not significantly so. This is partially consistent with implied volatility results in that volatility is not significantly different on post report days than report days.

The result of higher RV on report days could mask a gradual lagged reduction in the volatility over the few days following the report. This would in some ways confirm the initial hypothesis just over a more generous interval of time. However, it rules out entirely that in later minutes in the day volatility is significantly reduced. In order to consider a longer more gradual reduction in uncertainty we can compare the change from the days before the report to the days after. Hence, this comparison could capture an overall reduction in the magnitude of volatility following the report day's increase. The Pre-Post column presents such results.

The majority of minutes of the post-report days have a slightly higher average volatility than the days prior, as evidenced by the negative sign. This finding is not unanimous, since on some days pre-report days are slightly larger. Nevertheless, as the Kruskal-Wallis test, in column $KW_{Pre/Post}$, the spread of RV minutes of pre and post report days is not enough to suggest the distribution of observed RV for each minute is different.

These results are interesting in that they provide strong evidence that the release of USDA information does not reduce uncertainty in the wheat futures market either in the immediate day following the release or over the 5 days following its release. Considering all the tests, it is clear that on the day of the reports' release locational difference exist in the RV for the first 10 minutes roughly from all other days in the event window. While little statistical significance results in any other minute or day comparison, RV in magnitude is still larger on average on the report day than any other day. More interestingly, average RV on the days following the report is still slightly larger than the days prior. These results present contradictory evidence to previous studies on USDA's impact on uncertainty in agricultural futures markets. Though one cannot conclude that USDA reports directly lead to increased volatility.

Regression Analysis

Having found that RV is greater following the release of USDA reports, we use regression analysis to consider whether other factors may explain observed changes in RV. This analysis does not seek to establish causality but rather check if the results are robust to the consideration of other technical factors that theory suggests influence RV.

The primary control we introduce is the change in the fundamental value of wheat. Recall the fundamental value of futures is unobservable. But with the arrival of relevant USDA data, one would expect a shift in market participants' grasp of the fundamental value of their contracts. In its simplest form, one can think of changes in the fundamental value of wheat brought on by USDA information as a change in price. Thus we use the move in the level of prices over a given interval of time as a proxy for the change in the fundamental value of wheat.

Controlling for the move in prices is important for to two reasons. First, not all USDA reports are created equal. Some reports contain more information than others e.g. the January report. While some report days have a greater price impact than others, e.g. the September or October report. Secondly, the absolute size of the overall price move affects RV. It is a mathematical necessity that as the price move gets larger over a given range the RV over that same range will be larger as well. This is due to the fact that as the movement of prices is larger, the range of prices is larger for a calculation of volatility thus increasing the magnitude of the measure.

In order to capture the magnitude of the shift itself the absolute price move is calculated to approximate the change in fundamental value. In addition to controlling for the absolute price move, controlling for the number of contracts traded in a day is also indicative of how active as well as volatile the market is. The daily measure of market volume controls for this. The full model is shown in equation 9.

(9)

$$\begin{aligned}\boldsymbol{RV}_{15,i} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{ReportDate}_i + \boldsymbol{\beta}_2 |\boldsymbol{PriceMove}|_{15,i} + \boldsymbol{\beta}_3 \boldsymbol{Volume}_i + \boldsymbol{\beta}_4 \boldsymbol{NegPM}_i \\ + \boldsymbol{\alpha}_1 (\boldsymbol{PM}_{15,i} \times \boldsymbol{RD}_i) + \boldsymbol{\beta}_5 \boldsymbol{Limit}_i + \boldsymbol{\beta}_6 \boldsymbol{Limit}_{i-1} + \boldsymbol{\gamma}_1 \boldsymbol{CropYear}_i + \boldsymbol{\varepsilon}_i\end{aligned}$$

In this equation $\boldsymbol{RV}_{15,i}$ is the dependent variable and represents the standard deviation of natural log transaction to transaction returns for the first 15 minutes of each day $i = 1...825$ for all the days of the event window 5 year sample. The period of observation is limited to the first 15 minutes since the previous analysis suggested a short-lived impact from USDA reports. The $\boldsymbol{\beta}_i$'s represent the estimated coefficients. $\boldsymbol{ReportDate}_i$ is the variable of interest which is merely an indicator variable which turns on for each of the 75 report dates, using non-report days as the contrast. $\boldsymbol{Volume}_i$ is the daily volume of contracts exchanged for each day i.

The previous sections have already established that RV is higher on report days, thus we expect this coefficient on that estimate to be positive. Conversely, the more contracts are traded the more liquid the market is. We expect this to then reduce volatility since market participants can more easily exchange contracts reducing frictions in the market and large price jumps.

To then see how the addition of the absolute price move influences the coefficient estimate of the report day indicator, we then add the price move variable to the equation. Basic theory predicts that the coefficient of the absolute price move should be positive since as the price change increases the size of the volatility estimate for that same time also increases. We predict the addition of the price move might mitigate some of the impact of report days on RV.

An indicator for when the price move is negative in direction is added in order to capture possible differences in the magnitude of the market reaction. In an efficient market, one would anticipate market reactions that drive prices down or up to be symmetrical because one does not contain more information than the other. Thus, we predict the coefficient on this to be economically and statistically insignificant. This variable is titled $\boldsymbol{NegPM}_i$.

Then interaction term between the Report Day indicator and the absolute price move variable is included to attempt to control for a conditional impact of USDA reports on wheat RV based on the level of the absolute price move. It is shown in 9 as $(\boldsymbol{PM}_{15,i} \times \boldsymbol{RD}_i)$. We expect this coefficient to be positive and significant. It is difficult to predict exactly how is will impact the magnitude of the price move variable and more so the report day dummy variable.

We also include an indicator variable that equals one when prices move up or down the 60 cent limit that KCBT places on trading. Controlling for these days is important because RV was restricted on several dates in early February 2008 where no trading took place because of the price move limit. Due of the limiting effect on prices by this rule, the next trading day might see additional correction or be exceptionally volatile. Thus an additional indicator is added to see if the day following a limit move day sees greater volatility. These variables are indicated by the $\boldsymbol{Limit}_i$ and $\boldsymbol{Limit}_{i-1}$ symbols respectively. We expect them to both be positive since if the limit is struck we expect prices to be very volatile on that day.

Finally, crop year indicators are included for the the 5 crop years covered in the sample. The new wheat crop begins in July then runs through June of the next year. As a result 2007-2008 is the first crop year. The most recent season of the sample, the 2012-2013 year, is used as the baseline so that the exceptionally volatile years of 2007 and 2008 are not used as the comparison. The matrix of crop year indicator is represented by $\boldsymbol{CropYear}_i$ for each day i.

To estimate this equation, Ordinary Least Squares is used with Newey-West standard errors to correct for autocorrelation and heteroskedasticity. The price move variable is calculated as the absolute change in log price over the 15 minute period following the opening of trading. Also, volume is reported in 1000's of contracts traded.

Table 5 presents the coefficient estimates and standard errors for the progressive addition of controls leading to equation 9. The results for the basic regression are consistent with the predictions. The coefficient on Report Date is positive and significant. It can be interpreted as report days being .000371 more volatile than non-report days. While the magnitude of this estimate seems minuscule, keep in mind that the average RV is about .00065 on all trading days. So a .000371 increase represents an increase of almost 60% in RV on average for report days compared to non-report days. Volume's coefficient is negative and significant but very small, indicating it does not have a large economic impact on RV.

Adding the price move variable produces results consistent with the predictions, shown in the second column. The coefficient estimate is also positive and significant at the 99% level with a much larger magnitude. This means that for a 1% increase in the absolute price change, there is a .0255 increase in the magnitude of RV. This confirms the theory that as the price move increase so does RV. The coefficient on report dates adjusts downward to .000283, a drop of only 15% in magnitude. This means that as expected some portion of volatility is driven by the overall change in price not just uncertainty, however the coefficient is still positive and significant. That implies that controlling for the size of the price move, a proxy for information arrival, reports days are still more volatile than non-report days.

Table 5: Report and Non-report Day Model with Controls

	Dependent Variable for OLS using Newey-West Std. Er.					
$Variable$	$RV_{First15}$	$RV_{First15}$	$RV_{First15}$	$RV_{First15}$	$RV_{First15}$	$RV_{First15}$
Intercept	0.000874***	0.000721***	0.000747***	0.000781***	0.000753***	0.000291***
	(0.000074)	(0.000065)	(0.000067)	(0.000063)	(0.000063)	(0.000074)
Report Date	0.000371***	0.000283***	0.000287***	0.000027	0.000018	-0.000044
	('0.000094)	(0.000078)	(0.000079)	(0.000116)	(0.000120)	(0.000121)
Volume	-0.000024***	-0.000025***	-0.000026***	-0.000024***	-0.000024***	-0.000005
	(0.000006)	(0.000005)	(0.000006)	(0.000006)	(0.000007)	(0.000007)
|Price Move|		0.025500***	0.025800***	0.018800***	0.018200***	0.011500***
		(0.004006)	(0.004014)	(0.003252)	(0.003786)	(0.002904)
Neg PM			-0.000049	-0.000056*	-0.000042	-0.000033
			(0.000030)	(0.000030)	(0.000027)	0.0000229
|Price Move| x Report Date				0.028600***	0.029900**	0.035400***
				(0.012900)	(0.012600)	(0.012700)
Limit					0.000033	-0.000114
					(0.000287)	(0.000306)
Lag Limit					0.000599**	0.000340
					(0.000317)	(0.000333)
Crop Years						Yes
R^2	0.0792	0.1644	0.1669	0.1867	0.222	0.3635

Notes: Standard Errors are shown in parentheses. A single (*) denotes statistical significance at the 10%, a double asterisk (**) indicates significance at the 5%, and a triple asterisk (***) means statistical significants at the 1% level.

The fourth column includes a interaction term between report days and the absolute price move. This is to capture a possible conditional effect that the magnitude of the price move on report days may differ from that on non-report days. As is turns out it is significant and positive.

The interpretation of the interaction term is more subtle. In order to get the conditional impact, we must sum the coefficient of the report day dummy variable with the multiple of the coefficient of the interaction term and the appropriate price move. This means for a one percentage increase in the price move variable, a .000027 + .028600(1) increase in volatility results. Interestingly, the inclusion of the interaction term wipes out both the magnitude and significance of the report day indicator, implying that most of the difference in RV on report and non-report days is driven by the magnitude of the price move. It also reduces the magnitude of the the price move variable itself by about 30%.

This conforms to the theory that we would expect larger moves in the fundamental value of wheat to have a large impact on volatility. Furthermore, this also suggests that there is little difference between RV on report and non-report days unless there is large change in the understanding of market fundamentals, proxied by the price move variable. Also, the indicator for the price move direction gains significance, suggesting that price moves do not have as symmetric an effect on RV as thought. It is very small and thus possibly economically insignificant but it could suggest that market participants are more uncertain about bearish news than bullish news.

It is also interesting to note how time fixed effects impact the other estimates. First, one should notice that the statistical significance of the volume estimate is completely eliminated. While the price move is still significant its coefficient is reduced by nearly 50%. The report day indicator is still small and statistically insignificant. Interestingly, the interaction term gains in magnitude and remains significant, meaning that controlling for different volatilities in different crop cycles the conditional impact of a price move on a report day is greater. Lastly, the annual fixed effects renders the limit move and move direction insignificant.

Overall these result show the necessity of annual fixed effects but also evince that when a large shift in prices occurs, which we posit represents an arrival of more information valuable to the market, report days exhibit greater volatility than non-report days. Also, there does not seem to be a economically or statistically significant difference in negative or positive price moves which conforms with an efficient market.

Event Window Model

In our final model we break out the individual days of the event window. In this manner we can analyze the event window similarly to the tabular analysis in previous sections but with greater ability to control for confounding factors. This means that indicator variables are added for each day of the event window so individual coefficients can be estimated for them in addition to the report date.

Sticking to a simple framework, the new model with all the controls is displayed in equation 10. In this equation, the only new variable is $\boldsymbol{EVENT}_i$ which represents a matrix of dummy variables for 10 days of the event window excluding day - 1, the date before a USDA report. This way, all event window day estimate coefficients, represented by the matrix $\boldsymbol{\gamma}_1$ are calculated relative to the day before a report like the previous tabular analysis. Consistent with previous results, a positive coefficient is expected for each day of the event window with the largest and most significant for the report day. We expect similar signs and magnitudes for all other variables as in previous analysis.

$$(10) \quad \boldsymbol{RV}_{15,i} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\boldsymbol{Volume}_i + \boldsymbol{\beta}_2|\boldsymbol{PriceMove}|_{15,i} + \boldsymbol{\beta}_3\boldsymbol{Limit}_i + \boldsymbol{\beta}_4\boldsymbol{Limit}_{i-1} + \boldsymbol{\gamma}_1\boldsymbol{EVENT}_i + \boldsymbol{\gamma}_2\boldsymbol{CropYear}_i + \boldsymbol{\varepsilon}_i$$

Table 6 presents the incremental results for equation 10. The first column contains the simplest form of this regression using only the price move and volume controls but adding the even window matrix instead of merely the report day indicator. The estimated coefficients for this equation are mostly as predicted. The price move and volume coefficients barely change which is expected since all that has been done is parsing out the coefficient of the report day into its various parts. Most of the days in the event window are positive but only the report day and the day after the report are the largest. Days -2, -3, and -5 turn out to have negative but small and insignificant coefficients meaning that RV is slightly lower on those days relative to the day before a report.

The report date is still significant at the 99% and almost the same magnitude as previous regressions. It is deceptive to claim it is identical because table 6 present coefficients relative to the day before any report rather than merely report relative to non-report days. Hence, the coefficient does not have the same meaning. Interestingly, the day after a report is significant at 95% and positive showing a residual impact on RV the day following a USDA report release. The inclusion of the other controls has the same impact as in previous analysis and no major change is seen in event window estimates.

Like previous results, report days are more volatile on average than non-report days and there is no reduction in RV following a report's release. The regression does reveal that several days in the event window prior to day 0 are smaller than the day before the report but not significantly so. None of the days after the report release are on average smaller. This model confirms the previous results using the daily data.

Conclusion and Discussion

This work uses realized volatility of transaction-by-transaction Kansas City Board of Trade's Hard Red Winter wheat futures data to test the hypothesis that the release of United States Department of Agriculture crop reports reduce price uncertainty. McNew and Espinosa (1994) and Isengildina-Massa et al. (2008b) introduced this hypothesis using implied volatility from options pricing models. Both of these papers show strong evidence of reduced futures price volatility following the release of relevant USDA crop reports.

We suggest that the supply and demand information contained in USDA reports, especially the WASDE, could help equilibrate beliefs about the fundamental value of wheat contracts leading to price consensus observed by a measurable reduction in the intraday spread of prices following the information's release. The primary contribution is the use of a new tick data set of HRW wheat contracts from the KCBT website from which volatility can be calculated from observed prices.

Breaking the day into smaller intervals of time we estimate RV to identify if price consensus is reached by measuring the magnitude of RV throughout the day. The results of various tests reject this hypothesis and suggest that RV is higher following report releases. We use regression analysis to ensure that the increase in RV is not a result of mechanical process of calculating volatility,

Table 6: Event Window Model with Controls

Dependent Variable for OLS using Newey-West Std. Er.			
$Variable$	$RV_{First15}$	$RV_{First15}$	$RV_{First15}$
Intercept	0.000842***	0.000700***	0.000232**
	(0.000086)	(0.000080)	(0.000094)
Volume	-0.000026***	-0.000026***	-0.000007978
	(0.000006)	(0.000006)	(0.000007)
|Price Move|		0.025200***	0.020000***
		(0.004158)	(0.003905)
-5	0.000009	-0.000024	-0.000004084
	(0.000048)	(0.000049)	(0.0000450
-4	0.000056	0.000017	0.0000289
	(0.000050)	(0.000055)	(0.000049)
-3	-0.000011	-0.000065	-0.000035
	(0.000040)	(0.000044)	(0.000039)
-2	0.000000	-0.000019	-0.000009
	0.0000393	(0.000044)	(0.000042)
Report Date	0.000420***	0.000301***	0.00031***
	(0.000093)	(0.000078)	(0.000078)
+1	0.000170***	0.000105*	0.000127**
	(0.000061)	(0.000063)	(0.000059)
+2	0.000121	0.0000743	0.0000949
	(0.000084)	(0.000077)	(0.000073)
+3	0.000036	0.0000171	0.0000377
	(0.000066)	(0.000065)	(0.000059)
+4	0.000079	0.0000435	0.0000699
	(0.000055)	(0.000058)	(0.000054)
+5	0.000005	-0.000023	0.0000175
	(0.000050)	(0.000051)	(0.000047)
Limit		0.0000419	-0.000095
		(0.000305)	(0.000330)
Lag(Limit)		0.000567*	0.00031
		(0.000321)	(0.000335)
Crop Years		No	Yes
R^2	0.0917	0.208	0.3417

Notes: Standard Errors are shown in parentheses. A single (*) denotes statistical significance at the 10%, a double asterisk (**) indicates significance at the 5%, and a triple asterisk (***) means statistical significants at the 1% level.

institutional trading limits, or seasonality. After controlling for the size of the price move over the relevant range, there is no difference between report day and non-report day volatility.

The results are compelling because even if fundamental price variability can not be distinguished due to frictions in the market, the noise term is the result of behavior in the market. If the noise increases or changes then clearly behavior is changing in the market, likely as a result of the new information. Although we cannot parse whether the variation observed is due to fundamental value change, microstructure noise, or both, it is clear that we have identified a salient feature of observed wheat futures volatility - the variability of intraday wheat prices does not decrease following the release of USDA crop information.

The results provided by RV raise serious questions. Are realized and implied volatility actually measuring the same thing? What is RV capturing that is different than implied volatility? Some of the basic differences between Implied volatility and RV can easily be identified. The RV estimates provide a snapshot look in time at the tangled variability of fundamental value and microstructure noise. It provides a near instantaneous view of the distribution of prices. Implied volatility on the other hand is more forward looking, giving an expected variability of the underlying futures price over the life of an option for that future. Implied volatility is predictive given a set of parameters in contrast to the hardened snap shot nature of RV.

The difference in results suggests that RV is not a measure forward-looking, or anticipatory price uncertainty. Implied volatility may therefore be a better predictor of forthcoming price risk. RV could instead measure the spread of disparate expectations at the time of the report. This dispersion of expectations is the same in essence as the difference of opinion previously discuss.

It seems plausible that traders develop private heterogeneous beliefs about the underlying value of wheat prior to any USDA publication. The authoritative nature of the report may challenge traders expectations prompting them to agree to disagree on the interpretation of the data leading to an increase in the distribution of prices as they trade to profit on their disparate opinions. The data suggests that if this occurs the process happens quickly, but never reduced volatility. This analysis then seems to lend support to the difference of opinion explanation for market reactions, but ultimately attests to the effeciency of the wheat futures market.

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