Market Uncertainty and Sentiment around USDA Announcements

An N.Q. Cao, Institute for Food and Resource Economics, University of Bonn, Germany
Michel A. Robe, College of ACES, University of Illinois at Urbana-Champaign, USA

Selected Paper prepared for presentation at the 2020 Agricultural & Applied Economics Association Annual Meeting, Kansas City, MO
July 26-28, 2020

Market Uncertainty and Sentiment around USDA Announcements

An N.Q. Cao, Institute for Food and Resource Economics, University of Bonn, Germany

Michel A. Robe, College of ACES, University of Illinois at Urbana-Champaign, USA[1]

Abstract

We examine empirically the impact of scheduled USDA information releases on uncertainty and sentiment in grains and oilseeds markets. We document that, for up to five trading days after the release of a scheduled USDA report (WASDE, stocks, prospective plantings, and acreage), agricultural option-implied (forward-looking) volatilities are significantly lower than they were a week before the release. These reports' uncertainty-resolution power is similar in magnitude in the corn, soybeans, and wheat markets. In the case of WASDE, the implied volatility drops more when there had been greater disagreement among market experts in the run-up to a report. For corn and beans (but not wheat), the implied volatility drop following a WASDE or a grain stock report is smaller when the USDA information surprises the market. Except for wheat, we find little evidence that the tightness of grain inventories prior to a USDA report affects the market's reaction. Finally, we show that contemporaneous changes in broad financial-market sentiment and macroeconomic uncertainty (jointly captured by the VIX event-day return) affects the extent to which agricultural markets respond to the USDA report.

---

[1] **Cao**: an.cao@ilr.uni-bonn.de. **Robe**: mrobe@illinois.edu. We are grateful to Scott Irwin, Thomas Heckelei and Todd Hubbs for helpful discussions. This paper was partly supported by a NIFA grant. Robe also gratefully acknowledges the financial support received in his capacity as The Clearing Corporation Foundation Professor in Derivatives Trading at the University of Illinois. While this paper was being written, Robe served as a part-time consulting senior economist at the U.S. Commodities Futures Trading Commission (CFTC); no CFTC resources or confidential information were used for this project. The views expressed in this article are those of the authors only and may not be attributed to the CFTC, the Commissioners, or other staff at those agencies. Errors and omissions, if any, are the sole responsibility of the authors.

1. Introduction

A large literature in agricultural economics shows that periodic USDA reports often move grains and oilseed prices substantially. The fact that agricultural markets react significantly to USDA announcements supports the notion that they bring valuable information to the market and help resolve disagreements among traders regarding demand and supply fundamentals.

Most of the extant literature investigates what happens to price levels on USDA event days (Adjemian 2012; Karali et al. 2019; Ying, Chen and Dorfman 2019) or documents how fast the USDA news is impounded into prices (Adjemian and Irwin 2018; Lehecka, Wang and Garcia 2014). As McNew and Espinosa (1994), A. McKenzie, Thomsen and Phelan (2007), and Isengildina-Massa et al. (2008) note, however, one cannot capture the full impact of the USDA reports without also analyzing how they affect market uncertainty and sentiment. Measuring that effect, and investigating for the first time what drives its magnitude, is the present paper's goal.

Accountants and financial economists have long used changes in option-implied volatilities (IVol) to study the impact of scheduled news releases on forward-looking market uncertainty (Ederington and Lee 1993; Patell and Wolfson 1979). In agricultural economics, likewise, McNew and Espinosa (1994) and Isengildina-Massa et al. (2008) utilize near-dated option-implied return volatilities for the same purpose. We extend this prior work along three key dimensions.

First, financial and agricultural markets have evolved massively over the course of the past two decades. Changes that could materially impact the manner or the extent of market reaction to USDA news include the growth (and, later, the dominance) of electronic and high-frequency trading (Haynes et al. 2017; Haynes and Roberts 2015); the demise of the futures trading pits (Gousgounis and Onur 2018); and, the influx of private forecasting services (Karali et al. 2019; A. M. McKenzie 2008) The datasets in the two extant studies, however, date back almost two decades or more—to a time before any of those developments took place. The present paper is the first to investigate IVol responses to USDA news in the years since.

Intuitively, if "the timing, although not the content, of scheduled announcements is known *a priori*," then the IVols should already, pre-release, "impound the anticipated impact of important releases on price volatility and (should) decline post-release as this uncertainty is resolved" (Ederington and Lee 1996, p. 513). Using an event-study methodology and data for four different types of USDA announcements (*vs*. one in prior studies)[2] in 2009-2019, we document that IVols in the corn, soybeans, and soft red winter (SRW) wheat markets decrease, on average, by two hundred basis points or more (equivalent to approximately one tenth of their respective pre-event levels) on the event day. Furthermore, we show that the IVol decrease remains statistically significant for at least four trading days, and sometimes for over a week, after the event. These results alone, in line with the finding of Karali et al. (2019) regarding the behavior of commodity futures returns following USDA crop reports, indicate that—as a group—these periodic USDA reports are highly payoff-relevant to market participants.

Second, our analysis innovates by recognizing that USDA reports are not released in a vacuum. In particular, we examine whether the sign or magnitude of the *post*-release IVol change depends on agricultural market experts' opinions in the runup to a release.

Ahead of all major USDA announcements, companies like Bloomberg and Reuters have for a number of years conducted and published surveys of market analysts' expectations regarding the upcoming reports. Those news agencies typically release the details of those surveys released in the week before the announcement. Armed with this information, we provide empirical evidence

[2] McNew and Espinosa (1994) investigate crop production reports; Isengildina-Massa et al. (2008), WASDE reports. In contrast, we consider WASDE, grain stocks, prospective plantings, and acreage reports.

that (i) the gap between the expert "consensus" forecast and the actual USDA figure (i.e., how big the market surprise is on the event day) as well as (ii) the dispersion of individual expert forecasts around that consensus (which captures disagreements among experts and, as such, can be seen as a proxy for pre-existing commodity-specific uncertainty) both affect the magnitude of the IVol responses to scheduled USDA announcements.[3]

Looking first at surprises, we find that the effects are most significant for the inventories-related news that are contained in WASDE or grain stock reports. *Ceteris paribus*, any grain stock surprise—whether "bad" (when the USDA numbers are lower than the market experts expected) or "good" (when they USDA numbers are higher than foreseen)—pushes forward-looking market uncertainty upward. The same is true in the case of a "bad" WASDE surprise (i.e., when the USDA announces higher forecasted stock levels than the Bloomberg consensus had foreseen): the worse the surprise, the more forward-looking volatility increases (good WASDE surprises, in contrast, leave IVols statistically unaffected). These results suggest that, when the market is caught flat footed by the USDA, forward-looking volatility goes up—all the more so when the news is bad.[4]

---

[3] Two other recent studies of USDA-announcement also study the roles of market expectations and uncertainty prior to the report releases. Karali et al. (2019) use a DCC MGARCH-X model to investigate the role of report surprises on the means and variances of historical commodity return, while Fernandez-Perez et al. (2019) examine the effect of both forecast surprise and dispersion on bid-ask spreads (as a proxy for asymmetric information) around USDA announcements. Both of those studies assume that price or bid-ask spread changes after USDA announcements can be solely attributed to the informational value of the reports.

[4] These effects are statistically significant for corn and soybeans but not for wheat, which suggests that the wheat market may be less dependent on US information—perhaps because its production is more geographically diversified worldwide. In the same vein, Janzen and Adjemian (2017) document that wheat's price discovery mechanism has become less US-centric in recent years.

Looking next at whether analysts are not necessarily clueless as a group but rather disagree a lot about an upcoming USDA report, we find that the USDA news settles the market—but only in the case of a WASDE report (we find statistically insignificant effects for Grain Stocks, Prospective Plantings, and Acreage reports). Precisely we find that, the bigger the analyst dispersion was before the WASDE, the bigger the IVol drop after its release. This evidence is consistent with the notion that, when experts were "confused" as a group, WASDE releases reset expectations and clarify the path forward.

We look, finally, at the importance of the prevailing market sentiment. For each report, we rate the pre-existing analyst consensus as "pessimistic" (*resp*. "optimistic") when the pre-report median expert forecast predicts a decrease (*resp*. an increase) in the forecasted USDA variable compared to an objective past reference point. We find, in the case of Grain Stock reports (but not other USDA reports), a significant negative association between the analysts' pessimism prior to the report and the IVol drop on the announcement day. Since we already control for fundamentals-related news (i.e., USDA surprises) and uncertainty (i.e., analyst dispersion) when running this analysis, the fact that we find a statistically significant correlation (between experts' sentiment and the IVol change) suggests that, when the market experts have been feeling pessimistic about the actual inventory situation, the calming effect of the USDA information will be more impactful.

Our third main contribution is to show the importance—when assessing the impact of USDA news on agricultural market uncertainty and sentiment—of also controlling for concomitant (i.e., event-day) changes in broad financial market uncertainty and sentiment. Bekaert, Hoerova and Lo Duca (2013) show that the VIX index (i.e., the Standard and Poor 500 equity-index option-implied volatility) captures both heightened uncertainty about global macroeconomic conditions and risk aversion among investors. Intuitively, the same should be true in agricultural markets. In particular, insofar as risk aversion permeates all asset markets, risk aversion levels in commodity markets should move at least partly in sync with equity-market risk aversion. Likewise, insofar as the demand for physical commodities reflects the strength of the global economy, uncertainty about the latter should percolate into agricultural markets.

Consistent with this intuition, Adjemian et al. (2016) show that increases in grain and oilseed IVols are driven to a non-trivial extent by increases in the VIX index. The question we ask here is whether a similar pattern can be seen on USDA announcement days and, thus, whether controlling for the VIX helps to tease out the respective impacts of global *vs*. commodity-specific market uncertainty and sentiment.

We find that the extent of the IVol change on USDA announcement days is statistically significantly *negatively* related to the VIX change on that day. That is, while prior research shows that agricultural market sentiment and uncertainty generally echo the same variables in equity markets, that pattern is partly discarded on days when USDA announcements take place. *Ceteris paribus*, if the VIX increases on the event day, then the IVol drops more that day—and *vice-versa*.

The remainder of this paper is organized as follows. Section 2 presents recent findings in the literature about market reactions to announcements—both in equity markets and agricultural commodity market—which, in Section 3, motivates our hypotheses. The paper proceeds with data description (Section 4), empirical tests of the hypotheses (Section 5), and concluding remarks and discussions of possible extensions (Section 6).

2. Motivation and Hypothesis Development

The impact of scheduled USDA announcements in agricultural futures market has been discussed extensively in prior literature. As noted in the Introduction, most of the extant literature focuses on the respective effects of different kinds of USDA reports on agricultural futures market returns. Comparatively few studies look at changes in market volatility in the aftermath of any of those reports, and—with the exceptions of McNew and Espinosa (1994) and Isengildina-Massa et al. (2008)— they all focus on realized volatility (as captured by the variance equation in GARCH-type models or the sampled realized volatility) as opposed to forward-looking volatility.[5]

Realized variances, however, are a backward-looking measure of grains and oilseed futures price volatility. By contrast, the USDA's WASDE, Prospective Plantings, and Acreage reports all provide forward-looking information about future demand-supply balances. In the same vein, even though the USDA's Grain Stock reports focus on the amounts *already* in storage, the latter reflect physical market participant decisions that are based on their expectations regarding *future* demand-supply balances. For this reason, it is essential to investigate how the USDA reports affect forward-looking market uncertainty and sentiment.

2.1. Average IVol Change on the day of—and the days after—a USDA announcement

As discussed in the introduction, commodity IVols should generally rise in the days leading to a scheduled government report' release, and they should fall in its aftermath. There is no reason to believe that the IVol drop should be a one-day affair. To the contrary, given that USDA reports convey exceptional amounts of information to agricultural market participants (Adjemian 2012) one expects that a given report's impact on commodity IVols should last for several days. Our first testable hypothesis is thus quite straightforward:

Hypothesis 1: Commodity IVols drop on the announcement day. This decrease persists for several business days. Prior to the report release, IVols go up.

---

[5] For example, Janzen and Bunek (2017) look at the intraday realized volatility in the wheat market following USDA announcements. See Ying, Chen and Dorfman (2019) for a thorough recent review of the literature on USDA announcements.

2.2. Pre-existing Commodity Market Beliefs and IVol Response to USDA News

Unlike their counterparts in finance and accounting, only a small number of agricultural economics studies control for market participants' expectations, uncertainty, or sentiment prior to a USDA releases. Two recent exceptions—(Karali et al. 2019) and (Fernandez-Perez et al. 2019)—focus on the event-day responses of either prices or intraday bid-ask spreads, not of volatility.

To the best of our knowledge, the present paper is the first to ask whether commodity IVol responses to a scheduled USDA announcement depend on (i) the extent to which market experts are surprised by the new information; (ii) those experts' *pre*-release pessimism about the upcoming release and the level of disagreement among them (a proxy for commodity-market uncertainty); and (iii) the tightness of physical inventories (a driver of commodity price volatility).

Hypothesis 2: The magnitude of the IVol change depends on market participants' pre-release expectations, uncertainty, and sentiment.

Traditionally, the announcement-day "surprise" is seen as capturing the new information brought to the market by corporate or government reports, relative to pre-announcement market expectations (Balduzzi, Elton and Green 1998; Ederington and Lee 1996). As such, one might expect that the uncertainty resolution of the USDA release is smaller (and, hence, the IVol drops less), the bigger the gap is between the *pre*-release market consensus and the USDA information. Indeed, one could even imagine that the IVol would increase in case of a huge event-day surprise.

An interesting question is whether the effect of a USDA surprise is asymmetrical or not. In favor of asymmetry is the intuition that, when the surprise is "bad" for price volatility (in that the stocks, acreage, plantings, etc. are lower than the market had expected and the physical market conditions are effectively tighter than foreseen), one might expect that forward-looking volatility would increase. By the same token, if the surprise is a "good" one, then commodity IVol would fall. An alternative intuition, however, suggests that the response should instead be symmetrical: that is if the market always becomes unsettled when surprised, and that in that case the bigger the surprise (whether good or bad), the higher the *post*-event IVol.

Intuitively, the magnitude of the IVol change after a scheduled USDA report should also depend on the level of commodity-market-specific uncertainty before that announcement. First, the IVol drop should be bigger, the greater was the pre-USDA uncertainty among market experts (proxied by the dispersion of their forecasts). Second, the market's reaction to the news release (i.e., the IVol change) may also depend on the extent to which the market was stressed *pre*-event, as proxied by a measure of grain inventories' tightness two weeks prior to a USDA announcement.

2.3. Global Macroeconomic Environment and Commodity IVol Response on Event Day

Hypothesis 2, insofar as it considers the relevance of analysts' forecast dispersion, looks at the possibility that pre-existing commodity-market uncertainty could impact the IVol response. Our last hypothesis considers the possibility that changes in the macroeconomic environment on the event day may also matter for the behavior of commodity IVols that day.

In contrast to an approach often taken in finance and accounting, no USDA announcement study to date controls for concomitant changes in the macroeconomic and financial environment. As a matter of empirical fact, however, commodity-market IVols are impacted by the VIX.[6] The

---

[6] See Robe and Wallen (2016) in the crude oil space; Covindassamy, Robe, and Wallen (2017) in the softs space; and Isengildina-Massa et al. (2016) in the livestock, and grains spaces.

IVol change on the event day should likewise reflect the VIX change that day, too. *Ceteris paribus*, if the VIX increases, then commodity IVols should go up and *vice-versa*. Thus, on USDA event days, (a) if the VIX return is positive, then the commodity IVols should drop less in reaction to the USDA information release than if the VIX had been unchanged whereas (b) in turn, on days when the VIX return is negative, the IVol *post*-release drop should be even larger than usual.

Hypothesis 3: The IVol response to the USDA news depends on the VIX return on the event day, i.e., on concomitant changes in broad financial market uncertainty and sentiment.

3. Data

We examine four groups of USDA announcements, including WASDE reports, Grain Stock (GS) reports, Prospective Plantings (PP) reports, and Acreage (AR) reports. Those are the most relevant reports about the supply of global grain and oilseed markets. Crucially for a key component of our analysis, these government reports have since 2009 been accompanied by a continuous record of corresponding analyst surveys conducted and published by Bloomberg.

These four sets of reports are released on 15 different USDA announcement days per year (except in 2013 and 2018, when there were only 14 announcement days in each year due to U.S. government shutdowns). From September 2009 to October 2019, there are 120 WASDE reports, 41 GS reports (of which 10 overlap with the January WASDE), 10 PP reports, and 10 AR reports; all the PP and AR reports overlap with the second and the third GS reports of the year. Altogether, we collect a sample of 151 USDA announcement days and the corresponding Bloomberg surveys for 181 reports in total. The characteristics of the reports, including their frequency and timing, and key information surveyed by Bloomberg, are summarized in Table 1.

Starting from September 2009, Bloomberg conducts analyst surveys prior to each of these reports. Results of the surveys are released at varying times on Bloomberg News, typically one week before USDA release. Since the exact timing of the result release is not documented in the survey dataset, we recover it by tracing back each release on Bloomberg News manually so as to define the event window for our analysis.

Our Bloomberg survey dataset contains not only the "consensus" analyst forecasts (which we compute as the mean or median forecasts), but also a full list of all the forecasters who participated in each survey and their individual forecasts. On average, a typical survey summarizes the opinions of about 20 commodity analysts regarding an upcoming USDA announcement. This information allows us to assess the distribution of analyst forecasts and to compute the dispersion around the consensus value.

As we are interested in forward-looking volatility, we use the constant 90-day IVol for CBOT corn, soybean, and soft red winter wheat futures. To match this maturity choice in the variable we use to test Hypothesis 3 (the VIX), we likewise use the CBOE's constant 90-day VIX index. All market series, such as daily IVol, prices and VIX, as well as USDA announcements and analyst surveys, are retrieved from Bloomberg.[7]

4. Methodology

In this section, we describe the testing strategies for our hypotheses and the construction of the variables needed for that purpose. With Hypothesis 1, we focus on statistical hypothesis

---

[7] A Bloomberg document authored by Cui (2012) details that company's methodology for extracting forward-looking volatility estimates from at-the-money option prices at the daily market close. Ederington and Guan (2002) and Yu, Lui, and Wang (2010) discuss some of the advantages of relying on Bloomberg implied-volatility estimates.

testing with the IVol sample around USDA announcement and extend the approach used in earlier studies. We examine Hypothesis 2 and Hypothesis 3 using multivariate regressions.

4.1. Testing Hypothesis 1: Commodity IVols drop on the day of announcement

1. Event-day testing. As the first step, we compare the mean and median IVol on day $t0$ against day $t-1$. Following Isengildina-Massa et al. (2008), we use both the parametric paired sample t-test and the non-parametric Wilcoxon signed rank test to account for the non-normality of the distribution of implied volatility changes. Denoting $Ivol_t$ and $Ivol_{t-1}$ respectively as the IVol levels on the day of announcement (t) and the day before ($t-1$), the common null-hypothesis of these two tests is $H_0 : Ivol_t = Ivol_{t-1}$ against $H_1 : Ivol_t < Ivol_{t-1}$.[8]

2. Event-window extension. Moving beyond the event-day IVol change, we seek a broader picture of how option-implied volatilities behave for several days on either side of the event. Our approach is to perform multiple comparisons of (i) IVol changes within the event window from (ii) a pre-event-window reference. By doing so, we can learn about the timing of any jump or drop in the commodity IVol, as well as how persistent these changes are.

A conventional extension of t-test and Wilcoxon test for more than two samples comparison is the parametric one-way ANOVA test to compare group means, and the non-parametric Kruskal-Wallis test to compare group medians, respectively. However, they only test

---

[8] The difference between the two tests is that the one-sided t-test assumes that $\Delta Ivol_t$ follows a normal distribution with mean zero and unknown variance under the null-hypothesis, while the Wilcoxon signed rank test only assumes that $Ivol_t - Ivol_{t-1}$ is drawn from a continuous distribution that has zero median and is symmetric around this median under the null. For a detailed description of these two tests, see Isengildina-Massa et al. (2008).

the null that all group means/medians are equal, *i.e*., $H_0 : \Delta Ivol_{t-5} = \Delta Ivol_{t-4} = ... = \Delta Ivol_{t+5}$, against the alternative that *at least* one group has statistically significantly different mean/median. Without further analysis, it is not possible to know whether each group mean/median is different from one another. Therefore, we perform multiple comparison procedure using the Turkey-Kramer method based on the result of one-way ANOVA and Kruskal-Wallis test.[9]

3. *Event window and pre-event-window preferences.* To capture possible differences between the *pre*- and *post*-event patterns of IVol changes, we consider a window of 5 days before and 5 days after the USDA announcement days. A natural baseline reference to assess in-the-window IVol changes is some "normal" period before the event window. However, since the timing of Bloomberg surveys varies in the period 1-7 days before USDA announcements, there are some overlaps between post-Bloomberg surveys and pre-USDA announcements with different time lengths. Therefore, to avoid these overlaps which may not serve well as a normal baseline, we choose the 5-day average before the Bloomberg surveys are released as the reference for normal daily Ivol, denoted $\overline{Ivol}$. Figure 1 illustrates this point.

For each day within the event window, we calculate the percentage change in IVol as

$$\Delta Ivol_{t+i} = \ln\left(Ivol_{t+i} / \overline{Ivol} \right),$$

[9] An important motivation for using multiple comparisons (rather than simultaneously applying t-tests to every pair of samples) is that the rate of type-I error will be inflated in proportion to the number of pairs of groups being compared simultaneously. Consequently, we can no longer be sure that the probability of incorrectly rejecting the null hypothesis is no larger than the specified α Hochberg and Tamhane (1987). The Turkey-Kramer procedure is designed to circumvent this problem by using a studentized range distribution, and adjust the p-values of the pairwise test-statistics accordingly (see, e.g. Stoline (1981) for a review of multiple comparison methods, including the Turkey-Kramer procedure).

where $i = -5, -4, \ldots 5$. One-way ANOVA and Kruskal-Wallis test are first applied to test whether there is at least one day in the event window when the mean/median $\Delta Ivol_{t+i}$ is different from the others. If the test fails to reject the null, no further action is needed. Otherwise, the resulting estimated mean/median and standard errors are fed into the Turkey-Kramer procedure to compare all pairs of $\Delta Ivol_{t+i}$ and $\Delta Ivol_{t+j}$.

4.2. Testing Hypotheses 2 and 3: Analyst forecasts and the VIX matter for the drop in IVol

We regress the event-day IVol change on a set of Bloomberg-survey-related variables, the VIX (which acts as a proxy for macroeconomics uncertainty and financial market sentiment), and a number of potentially relevant market factors. Due to the overlap in the four different reports' respective release schedules, we consider the impact of the four reports on IVols simultaneously. The regression equation is:

$$(1)\ \Delta Ivol_{\tau} = \beta_0 + \sum \beta_i S_{i\tau} + \sum \delta_i D_{i\tau} + \varphi \Delta VIX_{\tau} + \sum \gamma_i Pessimism_{i\tau} + \eta Control_{\tau} + \varepsilon_{\tau} ,$$

with $i = \{WASDE, GS, PP, AR\}$ and $\tau = 1, 2, \ldots, 151$

Our variables of interest include:

1. Surprise, $S_{i\tau}$. Traditionally, surprise is considered a measure of the new information brought to the market by the reports, relative to pre-announcement market expectations (Balduzzi, Elton and Green 1998; Ederington and Lee 1996). For the purposes of this analysis, we assume that the median Bloomberg analyst forecast is representative of market expectations prior to a USDA announcement. For each report i, on reporting day τ, we define the report surprise as the percentage difference (approximated as a log difference) between the USDA's announced value $A_{i\tau}$ and the median forecast value $F_{i\tau}$ in the corresponding Bloomberg survey:

$$S_{i\tau} = \ln\left(A_{i\tau} / F_{i\tau}\right).$$

2. Dispersion $D_{i\tau}$. The interpretation of forecast dispersion is still theoretically debated. Johnson (2004) and Dubinsky et al. (2019), in financial market contexts, establish that dispersion is a proxy for idiosyncratic risk in firms' earning. They argue that, because financial analysts (the forecasters) are supposed to be experts on the forecasted subjects, a high level of dispersion will likely reflect uncertainty regarding the firm's earning. Diether, Malloy and Scherbina (2002), however, postulate that forecast dispersion is a result of differences in (forecasters') opinion, which will lead to mispricing once short-sale constrains arise on the market. In the present paper, we posit that forecast dispersion captures both potential commodity-level uncertainty (risk) and sentiment (unexplained by fundamentals). To avoid the issue of outliers, we do not use the standard deviation of analyst forecasts as a dependent variable. Rather, for each forecasted bit of information, we follow prior work (see, e.g., Fernandez-Perez et al. (2019) and references therein) and calculate dispersion as the ratio of the interquartile range (IQR) to the mean forecast

$$D_{i\tau} = IQR_{i\tau} / \mu_{i\tau}.$$

3. VIX changes, ΔVIX_{τ}. Adjemian et al. (2016) show that implied volatility in agricultural markets is driven in part by the VIX. As noted earlier, we adopt that paper's approach and use the VIX as a proxy for macroeconomic uncertainty as well investor risk aversion and sentiment, without decomposing these factors. Due to the small size of the grain and oilseed markets compared to the size of financial markets, we treat the VIX as an exogeneous variable for the purposes of this study. We measure the VIX change as the percentage change (log difference) of the constant 90-day VIX index on reporting day τ from the previous day

$$\Delta VIX_{\tau} = \ln\left(VIX_{\tau} / VIX_{date(\tau)-1}\right).$$

4. Forecasters' $Pessimism_{i\tau}$. Having controlled for forecasters' expectation (*i.e.*, the surprise), pre-existing commodity-market uncertainty (*i.e.*, dispersion) and global market uncertainty and sentiment (i.e., the VIX), it is possible to test if the IVol drops is related to other non-fundamental factors, namely commodity-market sentiment. We view the "pessimism" of forecasters about the upcoming report as a form of market sentiment. This approach is connected to the concept of *"forecast change"* pioneered by Amir and Ganzach (1998). In a corporate finance context, these authors show that the sign of the "forecast change" (defined as the difference between the analysts' earnings forecasts and the previous actual earning of a company) is a significant predictor of the over- or under-reaction in forecasts. Thus, if we find that the positive/negative tenor of the market experts' forecasts statistically significantly affects the extent of the USDA-induced IVol drop, then it would be a sign that market sentiment plays a role in how the market reacts to the announcement.

We rate a forecast as "pessimistic" when its median predicts a decrease in the forecasted indicator from a reference point. When it shows an increase, we rate it "optimistic".[10] To keep things simple, we only use a set of dummy variables which equal 1 if the median of the analyst forecast for report i on day τ is pessimistic, and 0 otherwise. The last row of Table 1 lists the reference point for each type of reports. Appendix 1 provides additional details.

5. $Control_{\tau}$. We also introduce a vector of control variables including day-of-the-week dummies, seasonal dummies, the "truncated" slope of commodity term structure, lagged daily returns, lagged

[10] It is important to note that forecast pessimism and forecast surprise need not have the same sign. For instance, the surprise can be "positive" when the USDA releases less bad information than what the analysts had predicted.

daily IVol changes, and lagged daily VIX changes. Standard tests suggest that two lags should be included for each of these lagged-variable groups, denoted as $L2(.)$. Specifically,

$$Control_{\tau} = \left[Seasonal_{\tau} \quad DoW_{\tau} \quad Slope_{\tau}^{-} \quad L2(\Delta VIX_{\tau}) \quad L2(\Delta ivol_{\tau}) \quad L2(R_{\tau}) \right],$$

where $R_{\tau} = \ln\left(P_{\tau} / P_{date(\tau)-1}\right)$ is the price return, $L2(\Delta VIX_{\tau}) = \left[\Delta VIX_{date(\tau)-1} \;\; \Delta VIX_{date(\tau)-2} \right]$, and so on. In particular:

a. *Seasonality:* $Seasonal_{\tau}$. Since our sample is not very long (just over ten years), monthly dummies would consume too many degrees of freedom. Fortunately, there is a clear pattern that IVols in the corn, soybean and wheat markets all start increasing around April till June, which coincides to the planting phase in North America. We therefore introduce seasonal dummies that characterize development phases of the crop cycle in this area. They include planting (i.e. April through June), pollination (i.e. July and August), harvesting (i.e. September through November). The baseline season is the none-cropping period (i.e. December through the following March).

b. *Day-of-the-Week effect,* DoW_{τ}**.** We control for the possibility that the IVol reaction to a USDA announcement might differ depending on the day of the week when the release takes place, by including four dummies (Tuesday to Friday).

c. *Truncated slope of commodity term structure:* $Slope^{-}$. To account for the tightness of inventory, we follow Bruno, Büyükşahin and Robe (2017) and compute the slope of the term structure of futures prices for each commodity. The slope is calculated for the nearest Tuesday prior to the USDA announcement day, and is truncated from above at zero, such that those positive values are set to zero[11].

4.3. Is the impact of surprise asymmetric for positive vs. *negative surprise?*

Part of our Hypothesis 2 reflects a fact well known from the finance literature: markets react asymmetrically to "good" *vs.* "bad" news. For example, using EGARCH models, Braun, Nelson and Sunier (1995) find significant predictive asymmetry in both the market and the firm-specific components of volatility across various stock portfolios. Beber and Brandt (2010) investigate the effect of good and bad macroeconomic news on the U.S. treasury bond market and document that bond returns react more strongly to bad news than to good news during expansions, and *vice-versa* during recessions. Using real-time analysis for U.S. dollar spot exchange rates, Andersen et al. (2003) report larger surprise-induced conditional mean jumps when it is a bad surprise, compared to the good surprise case.

In order to investigate this conjecture in the context of agricultural markets, we split the report surprises into "good" and "bad" surprise. "Bad" surprise $S_{i\tau}^{-}$ occurs when the USDA announces higher stock/acreage level than forecasted by the analysts, and a "good" surprise $S_{i\tau}^{+}$ represents the reverse. The regression equation then becomes:

(2)

$$\Delta Ivol_{\tau} = \beta_0 + \sum \beta_i^{-} S_{i\tau}^{-} + \sum \beta_i^{+} S_{i\tau}^{+} + \sum \delta_i D_{i\tau} + \varphi \Delta VIX_{\tau} + \sum \gamma_i Pessimism_{i\tau} + \eta Control_{\tau} + \varepsilon_{\tau} \ ,$$

[11] This truncation comes from the observation that, during our sample period, the slope is positive, stable, and small in magnitude for most of the time. In contrast, negative values appear at lower frequency, and with much larger magnitude. Hence, we hypothesize that the prevailing state of inventories is only relevant when the market is tight, *i.e.*, when the slope is negative.

where:

$$S_{i\tau}^{-}=\begin{cases}S_{i\tau}, if\ S_{i\tau}<0\\ 0, otherwise\end{cases} \quad ; \text{and} \quad S_{i\tau}^{+}=\begin{cases}S_{i\tau}, if\ S_{i\tau}>0\\ 0, otherwise\end{cases}$$

By comparing the signs and magnitudes of β_i^- and β_i^+, one can answer the question of whether there is asymmetry of grain and oilseed volatility expectations to USDA surprises.

5. Results

In this section, we first provide a summary of the data before presenting the empirical results of the three hypotheses.

5.1. First look at the data

Table 2 reports the summary statistics of our variables of interest, namely the IVol change on announcement days, the VIX change on announcement days, the USDA report surprises and dispersions, and the forecast change (FC)—i.e., the difference between the median Bloomberg forecast and the corresponding reference point which we use to determine our pessimism variables, as discussed in the previous Section. Table 1 provides information on the median, mean, standard deviation (SD), minimum and maximum values, as well as counts of the number of negative observations (in the last column).

There is an clear pattern on the announcement day: both the median and the mean of $\Delta Ivol_\tau$ are negative in all markets, and the numbers of negative observations account for more than two-thirds of the samples. In the most extreme cases, the IVol level increases by 20 percent (for corn and soybean) or drops by 23 percent (corn) on the announcement day. For the majority of reports and of commodities, the magnitude of the surprise tends to be small, i.e. less than 1.5 percent of the forecast median, and it varies a lot over time.

Unlike $\Delta Ivol_{\tau}$, most of the time the surprises are positive. Exceptions include the GS, PP and AR reports for soybeans, where surprise tends to be negative. Consistently across markets, expert forecasts for WASDE reports are most widely dispersed (more than 10 percent of the average forecast for soybeans and 7 percent for corn), followed by forecasts for GS reports. PP and AR forecasts exhibit less dispersion.

Similar to surprises, forecasted changes appears to be positive, or optimistic, in general. Exceptions are AR forecast changes for corn and wheat, and PP forecast changes for wheat. The forecast change of GS reports is largest on average for all commodities.

Interestingly, both sample mean and median ΔVIX_{τ} are negative, but they very close to zero. Finally, it is worth noticing that quite a few variables in our models will have zero value for most of the sample, which suggest a need for heteroskedasticity-robust estimation.

5.2. Hypothesis 1: There is a drop in IVol on the event day

In the first two columns of Table 3, we report the test-statistics and p-values for the one-sided t-test and Wilcoxon signed rank test. For all markets, H_0 can be rejected with a high level of confidence, meaning there is a statistically significant drop in Ivol on the day of announcement.

In the next step, one-way ANOVA test and Kruskal-Wallis tests (the last two columns) also indicate that there is at least on one day in the 11-day even window when $\Delta Ivol$ (from 5-day average before the Bloomberg survey) is significantly different from the other days. We therefore perform the multiple comparison procedure described in the methodology section.

The results based on one-way ANOVA are visualized in Figure 2a (corn), 2b (soybean) and 2c (SRW wheat), and the p-values of the test-statistics are reported in Table 4. The patterns of $\Delta Ivol_{t+i}$ before and after USDA announcement are clearly different.

- In general, IVol is significantly higher than "normal" on days before the announcement. Corn IVol gradually increases for four days before the announcement and reaches its highest pre-event level on the day $t-1$ For wheat, the increase appears to start earlier, but then the IVol remains unchanged. Soybean IVol, however, does not exhibit any substantial change from the "normal" level before the announcement.
- In sharp contrast to the pre-event behavior, commodity IVols fall significantly on the event day, and this drop persists for at least four more trading days after the day of the USDA announcements. Figures 2a to 2c show that, for all three commodities, IVol gradually reverts toward its "normal" level. This visual observation is confirmed by the one-sided t-test of $Ivol_{t+i}$ against $\overline{Ivol}$, as shown in the first column of table 4. The Kruskal-Wallis test provides similar results.[12]

In short, these results confirm Hypothesis 1. They are consistent with previous findings, by Isengildina-Massa et al. (2008) and McNew and Espinosa (1994), that IVol drops significantly on the days of USDA report release. Moreover, we extend these finding by showing that Ivol tends to gradually increase several days before the USDA announcement, then largely drop on the event day and remain significantly below "normal" level for approximately one week.

---

[12] Tables summarizing the Kruskal-Wallis test result are available by request.

5.3. Hypothesis 2: Pre-event market expert opinions matter for the drop in IVol

Table 5 presents the estimation result of equation (1). Heteroskedasticity-consistent standard errors with small-sample adjustment are reported. The intercepts are negative for all three markets, which confirms again the tendency of IVol to drop on announcement day, consistent with the conclusion of Hypothesis 1 (however, in the soybean equation, the intercept is not significant). The effect of surprise and dispersion seem to vary across markets and reports, both in signs and magnitudes. Different reports have different impacts on different markets. In particular:

The role of report surprises. The IVol change tends to be inversely correlated with the report surprise, with 8/12 surprise coefficients being negative. Among those, only the WASDE surprise coefficients in the models for corn and soybean are statistically significant. *Ceteris paribus (c.p)*, one percent higher in USDA announced stock projection than the median Bloomberg forecast will lead to 0.24 percent and 0.1 percent drop in IVol of corn and soybean on announcement day, respectively. One way to think about this relationship is that the more good news about supply that the USDA report brings to the market, the more it helps calm the market, resulting in an IVol decrease. In contrast, if the surprise is a bad news, then it has a deleterious impact on market expectations about future volatility, which is echoed by an increase in implied volatility. However, quite unexpectedly, this claim is not verified in the case of the GS surprise: the coefficients are positive but insignificant for both corn and wheat. Hence, it is probable that such a simple, linear relationship does not always hold. We examine this issue more closely in the next subsection.

The role of forecast dispersions. As with surprises, most of the coefficients are negative. This result highlights the uncertainty-resolution effect of USDA reports in the times of much uncertainty or disagreement, which is likely a driver of increasing tendency of IVol before the day of report release, as observed earlier. That is, the more dispersion there used to be among analysts (who often are also traders), the more uncertainty there was prior to the USDA report release. In this case, the information released in the report should become be the new consensus that resolves uncertainty. Consequently, conditioning on disagreement among analysts, the implied volatility should drop more following the USDA report release. This logic is in line with the claim of Karali et al. (2019), that the value of USDA reports exists even in the presence of private forecasts. In particular, a one-percent increase of WASDE forecast dispersion around the mean forecast significantly contributes to 0.15 percent and 0.25 percent decrease in IVol for corn and wheat, *c.p.* Here again, GS dispersion has unexpectedly positive sign, and even statistically significant, meaning it reduces the resolution effect of the report(s). No significant effect of PP and Acreage forecast dispersion is found.

The role of forecast pessimism. Using the same reasoning as with dispersions, we expect the forecast pessimism coefficients to be negative, provided that USDA reports acts as the consensus. When the overall forecast is pessimistic, the market become more uncertain before it is reassured again by the information from the USDA, ultimately leading to a larger drop on announcement day. This is indeed the case for most of the coefficients. However, having controlled for new fundamental-related information (proxied by surprises) and uncertainty (proxied by dispersion), we view a significant effect as sign that market sentiment, not just market fundamentals, plays a role in the behavior of IVol changes surrounding USDA announcements. The two highly significantly coefficients, GS for corn and AR for soybean, support this view. Corn IVol will drop 5.5 percent more when the majority of forecasters are pessimistic about the upcoming corn GS report, compared to when they are optimistic or neutral, *c.p*. It is 8 percent for soybean IVol when the AR forecast are pessimistic.

The role of inventory conditions. We do not find significant relationship between the tightness of inventory and IVol drop on announcement days, except for wheat. Since our variable is truncated from above at zero, the positive coefficient indicates that *c.p*, a one-percent decrease in the cost of carry predicts an IVol decrease of 2 percent on the upcoming USDA announcement day. Again, the resolution effect of the reports is amplified when a low-inventory situation is perceived.

5.4. Hypothesis 3: The role of broad market uncertainty and/or sentiment.

We obtain negatively significant coefficients for all three markets. Ceteris paribus, a one-percent increase in VIX on the announcement day is associated by around 0.1 percent drop in IVol. This finding contradicts our anticipation that, like any other day, if the VIX is going up on the USDA announcement day, then the commodity IVol should be going up, too. This surprising finding lends more support to the role of USDA information as the "new consensus." Assuming that the IVol change is positively driven by VIX change, on those days when the USDA announcements are in place, it helps mitigate the spillover. In that sense, the influence of broad market uncertainty and/or sentiment on USDA announcement days is reduced on event days.

5.5. Correlation or causality?

Since OLS coefficients only tell us the correlation of variables, it is reasonable to ask whether Bloomberg analyst surveys indeed impact the change of Ivol on USDA announcement day, or it is just a spurious correlation. Balduzzi, Elton and Green (1998) suggests regressing the value of each actually announced information on (i) the corresponding forecasted value; and (ii) the returns from forecast day to announcement day, in order to test the informational value of the forecasts to the markets. We follow this approach and conclude that Bloomberg analyst forecasts are informationally valuable to the market. Moreover, the median forecasts appear to be unbiased prediction for the corresponding USDA announced information. Together with the small size of surprises, this result indicates that with Bloomberg forecast, we do not have the problem with measurement errors in supply expectation – as raised by Karali, Irwin and Isengildina-Massa (2019). Details of this step is documented in Appendix II.

5.6. Is the impact of the USDA surprise asymmetric (for positive vs. negative surprise)

The estimation result of equation (2) is shown in table 6. It is apparent that the effect of report surprises on IVol change becomes more significant when we separate bad (negative) and good (positive) surprises. While many bad surprise coefficients are significantly different from zero, it is less so for good surprises. For instant, WASDE bad surprises substantially drive up corn and soybean IVol on the announcement day, while the impact of good surprises is subtle. The same holds for Acreage surprises in wheat market. Only for the soybean market, good PP news appear to outweigh bad news. A second aspect of the asymmetry is the sign of the coefficients. The claim that bad news drives IVol up and good news brings IVol down, when the relationship is inversely linear as found with equation (1), requires that in equation (2) the coefficients of surprises must be negative for both directions. However, this is not the case for GS report, when the coefficients of good surprise are consistently positive for all markets and even highly significant for corn and soybean. This finding implies that any surprise in GS reports, either good or bad, will drive IVol up. Moreover, the marginal increases are of very similar magnitudes, which explains why the GS coefficient was insignificant in the pooled regression. Altogether, this confirms our previous intuition that the relationship between surprise and IVol change is non-linear and asymmetric between bad and good news.

WASDE dispersions remains a significant source of corn and soybean IVol drop, while the influence of GS dispersion on corn market becomes negative (and insignificant) in this specification. Not only for corn, but pessimistic GS forecast significantly predicts IVol drop now also for soybean. The coefficient Pessimistic AR remains robust. In general, this result is more consistent with the theory that we discussed previously. Finally, we note that the results for VIX changes and slope of term structures are very similar to before.

6. Conclusion

We examine empirically, for the first time in almost two decades, the impact of scheduled USDA information releases on uncertainty and sentiment in grains and oilseeds markets. We document that, for up to five trading days after the release of a scheduled USDA report (WASDE, stocks, prospective plantings, and acreage), forward-looking volatilities (IVol) are significantly lower in agricultural markets than they had been a week before the release. The USDA reports' uncertainty-resolution power is similar in magnitude in the corn, soybeans, and wheat markets: approximately one-tenth of the prior IVol level.

In the case of the WASDE, the implied volatility drops more when there had been, prior to the report, greater disagreement among market experts. For corn and soybeans (but not wheat), the implied volatility drop following a WASDE or a Grain Stock report is smaller when the USDA information surprises the market. Except for wheat, we find little evidence that the tightness of grain inventories prior to a USDA report affects the market's reaction. Finally, we show that contemporaneous changes in broad financial-market sentiment and macroeconomic uncertainty (jointly captured by the VIX event-day return) affects the extent to which agricultural markets respond to the USDA report.

These results shed light on how USDA announcement help resolve uncertainty. Focusing on implied volatility, our study goes beyond the extant literature in at least three ways: (i) our analysis provides evidence on uncertainty and sentiment *prior* to the announcement, which offers a closer look into how these variables evolve; (ii) it teases out the respective impacts of global *vs*. commodity-specific market uncertainty and sentiment; and (iii) our sample extends the set of USDA reports over time and covers all four groups of USDA reports.

Our findings offer both practical and policy implications for market participants and policy makers. First, they show that the USDA information has value and impacts market sentiment. Second, short-run hedging decisions and other derivatives-market positioning around USDA announcement could be improved by considering the IVol forecast-to-announcement patterns that we document, leading to more efficient pricing in the long run. Finally, public programs involving price volatility, such as crop insurance (Sherrick 2015) or USDA season-average price forecasts that incorporate forward-looking volatility (as advocated by Adjemian, Bruno and Robe (2020)) should also benefit from our conclusions.

References

Adjemian, M. K. (2012). Quantifying the WASDE Announcement Effect. *American Journal of Agricultural Economics*, *94*(1), 238–256. https://doi.org/10.1093/ajae/aar131

Adjemian, M. K., Bruno, V. G. and Robe, M. A. (2019). Incorporating Uncertainty Into USDA Commodity Price Forecasts. Advance online publication. https://doi.org/10.2139/ssrn.3414585

Adjemian, M. K., Bruno, V. G. and Robe, M. A. (2020). Incorporating Uncertainty into USDA Commodity Price Forecasts. *American Journal of Agricultural Economics*, *102*(2), 696–712. https://doi.org/10.1002/ajae.12075

Adjemian, M. K., Bruno, V. G., Robe, M. A. and Wallen, J. (2016). What Drives Volatility Expectations in Grain Markets?

Adjemian, M. K. and Irwin, S. H. (2018). usda Announcement Effects in Real-time. *American Journal of Agricultural Economics*, *100*(4), 1151–1171.

Amir, E. and Ganzach, Y. (1998). Overreaction and underreaction in analysts' forecasts. *Journal of Economic Behavior & Organization*, *37*(3), 333–347. https://doi.org/10.1016/S0167-2681(98)00092-4

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Vega, C. (2003). Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *American Economic Review*, *93*(1), 38–62. https://doi.org/10.1257/000282803321455151

Balduzzi, P., Elton, E. J. and Green, T. C. C. (1998). Economic News and the Yield Curve: Evidence from the U.S. Treasury Market. *SSRN Electronic Journal*. Advance online publication. https://doi.org/10.2139/ssrn.65030

Beber, A. and Brandt, M. W. (2010). When It Cannot Get Better or Worse: The Asymmetric Impact of Good and Bad News on Bond Returns in Expansions and Recessions *Review of Finance*, *14*(1), 119–155. https://doi.org/10.1093/rof/rfp006

Bekaert, G., Hoerova, M. and Lo Duca, M. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, *60*(7), 771–788. https://doi.org/10.1016/j.jmoneco.2013.06.003

Braun, P. A., Nelson, D. B. and Sunier, A. M. (1995). Good News, Bad News, Volatility, and Betas. *The Journal of Finance*, *50*(5), 1575–1603. https://doi.org/10.1111/j.1540-6261.1995.tb05189.x

Bruno, V. G., Büyükşahin, B. and Robe, M. A. (2017). The Financialization of Food? *American Journal of Agricultural Economics*, *99*(1), 243–264. https://doi.org/10.1093/ajae/aaw059

Covindassamy, G., Robe, M. A. and Wallen, J. (2017). Sugar with your Coffee? Fundamentals, Financials, and Softs Price Uncertainty. *Journal of Futures Markets*, *37*(8), 744–765. https://doi.org/10.1002/fut.21846

Cui, C. (2012). Commodity implied volatility surface. *Bloomberg OVDV Commodity Volatility Surface White Paper*.

Diether, K. B., Malloy, C. J. and Scherbina, A. (2002). Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance*, *57*(5), 2113–2141. https://doi.org/10.1111/0022-1082.00490

Dubinsky, A., Johannes, M., Kaeck, A. and Seeger, N. J. (2019). Option Pricing of Earnings Announcement Risks. *The Review of Financial Studies*, *32*(2), 646–687. https://doi.org/10.1093/rfs/hhy060

Ederington, L. H. and Guan, W. (2002). Measuring implied volatility: Is an average better? Which average? *Journal of Futures Markets*, *22*(9), 811–837. https://doi.org/10.1002/fut.10034

Ederington, L. H. and Lee, J. H. (1993). How Markets Process Information: News Releases and Volatility. *The Journal of Finance*, *48*(4), 1161–1191. https://doi.org/10.1111/j.1540-6261.1993.tb04750.x

Ederington, L. H. and Lee, J. H. (1996). The Creation and Resolution of Market Uncertainty: The Impact of Information Releases on Implied Volatility. *The Journal of Financial and Quantitative Analysis*, *31*(4), 513. https://doi.org/10.2307/2331358

Fernandez-Perez, A., Frijns, B., Indriawan, I. and Tourani-Rad, A. (2019). Surprise and dispersion: informational impact of USDA announcements. *Agricultural Economics*, *50*(1), 113–126. https://doi.org/10.1111/agec.12470

Gousgounis, E. and Onur, E. (2018). The effect of pit closure on futures trading. *Journal of Commodity Markets*, *10*, 69–90. https://doi.org/10.1016/j.jcomm.2017.11.002

Haynes, R., Raman, V., Robe, M. A. and Yadav, P. K. (2017). *Algorithmic Trading and Livestock Market Quality*. Paper presented at the 2017 NCCC-134 Conference in St Louis, MO. April. 2017.

Haynes, R. and Roberts, J. S. (2015). Automated trading in futures markets. *CFTC White Paper*.

Hochberg, Y. and Tamhane, A. C. (1987). *Multiple comparison procedures*: John Wiley & Sons, Inc.

Isengildina-Massa, O., Irwin, S. H., Good, D. L. and Gomez, J. K. (2008). Impact of WASDE reports on implied volatility in corn and soybean markets. *Agribusiness*, *24*(4), 473–490. https://doi.org/10.1002/agr.20174

Isengildina-Massa, O., Karali, B., Irwin, S. H., Cao, X., Adjemian, M. [M.] and Johansson, R. [R.] (2016). *The market impact of USDA crop and livestock reports in the big data era.*

Janzen, J. P. and Adjemian, M. K. (2017). Estimating the Location of World Wheat Price Discovery. *American Journal of Agricultural Economics*, *99*(5), 1188–1207. https://doi.org/10.1093/ajae/aax046

Janzen, J. P. and Bunek, G. (2017). Does Public Information Facilitate Price Consensus? Characterizing the Effect of USDA Crop Reports Using Realized Volatility.

Johnson, T. C. (2004). Forecast Dispersion and the Cross Section of Expected Returns. *The Journal of Finance*, *59*(5), 1957–1978. https://doi.org/10.1111/j.1540-6261.2004.00688.x

Karali, B., Irwin, S. H. and Isengildina-Massa, O. (2019). Supply Fundamentals and Grain Futures Price Movements. *American Journal of Agricultural Economics*, *44*(3), 362. https://doi.org/10.1002/ajae.12012

Karali, B., Isengildina-Massa, O., Irwin, S. H., Adjemian, M. K. and Johansson, R. [Robert] (2019). Are USDA reports still news to changing crop markets? *Food Policy*.

Lehecka, G. v., Wang, X. and Garcia, P. (2014). Gone in Ten Minutes: Intraday Evidence of Announcement Effects in the Electronic Corn Futures Market. *Applied Economic Perspectives and Policy*, *36*(3), 504–526. https://doi.org/10.1093/aepp/ppu010

McKenzie, A., Thomsen, M. and Phelan, J. (2007). How do you straddle hogs and pigs? Ask the Greeks! *Applied Financial Economics*, *17*(7), 511–520. https://doi.org/10.1080/09603100500428230

McKenzie, A. M. (2008). Pre-Harvest Price Expectations for Corn: The Information Content of USDA Reports and New Crop Futures. *American Journal of Agricultural Economics*, *90*(2), 351–366. https://doi.org/10.1111/j.1467-8276.2007.01117.x

McNew, K. P. and Espinosa, J. A. (1994). The informational content of USDA crop reports: Impacts on uncertainty and expectations in grain futures markets. *Journal of Futures Markets*, *14*(4), 475–492. https://doi.org/10.1002/fut.3990140408

Patell, J. M. and Wolfson, M. A. (1979). Anticipated information releases reflected in call option prices. *Journal of Accounting and Economics*, *1*(2), 117–140. https://doi.org/10.1016/0165-4101(79)90003-X

Robe, M. A. and Wallen, J. (2016). Fundamentals, Derivatives Market Information and Oil Price Volatility. *Journal of Futures Markets, 36*(4), 317–344. https://doi.org/10.1002/fut.21732

Sherrick, B. (2015). Understanding the Implied Volatility (IV) Factor in Crop Insurance. *Farmdoc Daily*, *5*.

Stoline, M. R. (1981). The status of multiple comparisons: simultaneous estimation of all pairwise comparisons in one-way ANOVA designs. *The American Statistician*, *35*(3), 134–141.

Ying, J., Chen, Y. and Dorfman, J. H. (2019). Flexible Tests for USDA Report Announcement Effects in Futures Markets. *American Journal of Agricultural Economics*, *94*(1), 238. https://doi.org/10.1093/ajae/aaz013

Yu, W. W., Lui, E. C.K. and Wang, J. W. (2010). The predictive power of the implied volatility of options traded OTC and on exchanges. *Journal of Banking & Finance*, *34*(1), 1–11. https://doi.org/10.1016/j.jbankfin.2009.06.017

Appendix 1. Reference for pessimism forecasts

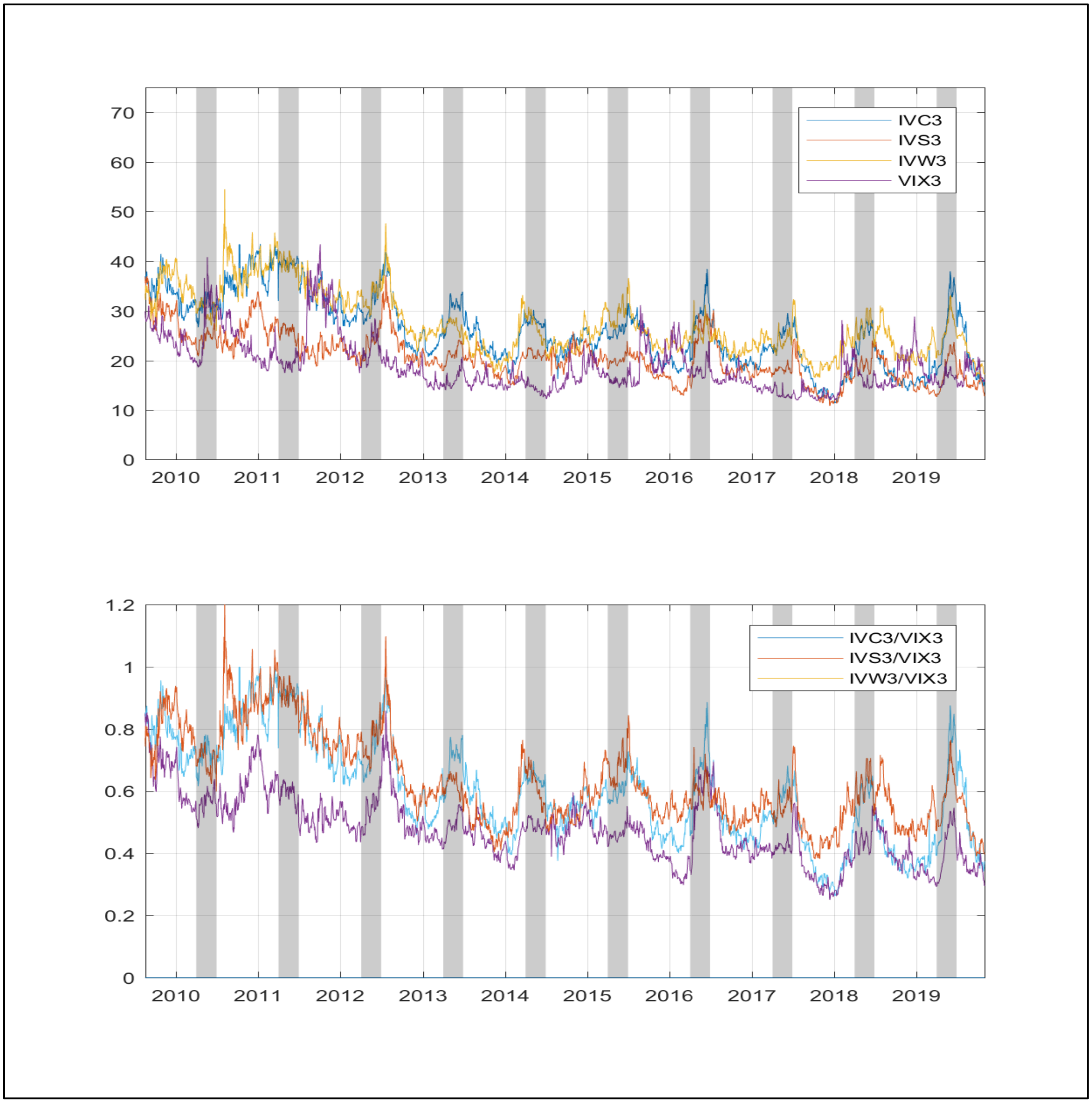
Based on the nature of the forecasted information in each report, we define their reference point as follows:

WASDE. the forecast we are using is also the most frequently surveyed information – the projected U.S. ending stock of current year. Every month, USDA will update this projection in WASDE according to the development of demand and supply. Hence, the most suitable baseline for the forecast is the actual value in previous month's report.

GS reports. U.S. ending stock as of the end of previous quarter is forecasted. Due to the seasonality in crop production and demand, stock level of grains and oilseeds also fluctuates seasonally. We therefore use the same period (i.e. quarter) of the previous year as the reference. When forecasters predict a lower stock level than the same time in previous year, they are pessimistic about inventory situation, and *vice versa.* In fact, the same comparison is often discussed on the media for a range of stock variables such as inflation, GDP, etc.

PP and AR report share the same information of interest which is the planting area of the current crop year. By construction, AR report is the updated version of PP report for the same crop year. This is similar to the case of WASDE report, in which the earlier information (in PP report) can be used to determine if the prediction of the later (in AR report) is more negative, i.e. pessimistic, or not. On the other hand, it would be logical to compare the planting intention (in PP report) to the planted area in previous year, which is released in the previous year's AR report.

Appendix 2. Seasonality of IVol



Appendix 3. Informational Value of Bloomberg-Survey Analyst Forecasts

Specifically, the regression equation (hereafter, BEG equation) is:

$$(1) \qquad A_{i\tau} = \alpha_0 + \alpha_1 F_{i\tau} + \alpha_2 R_\tau + \varepsilon_{i\tau} \ ,$$

where $A_{i\tau}$ and $F_{i\tau}$ are the actual and the forecasted values of indicator i for announcement day τ, respectively, and R_τ is the cumulative market return from the day Bloomberg releases the survey result to the announcement day. Several hypotheses can be tested with this regression:

- If α_1 is significantly different from zero, then the forecast contains information;
- If α_0 is not significantly different from zero and α_1 is not significantly different from 1, then the forecast is unbiased;

If α_2 is significantly different from zero, then market expectations have been revised between the forecast day and the announcement day. In this case, new information arrives in the market after the forecast.

Table A3.1 reports the result of three different versions of the BEG equation; for each version, we run a regression for the monthly WASDE ending stock forecasts and one for the quarterly Grain Stock estimates. The original BEG regression is presented in the first two columns, in the next two columns, R_τ is replaced by $\Delta Ivol_\tau$ - the log of the change in implied volatility from the forecast day to the announcement day. Finally, the last two columns include both R_τ and $\Delta Ivol_\tau$ in one regression. There are too few AR and PP observations for the regression.

Table A3.1: BEG regression results

	BEG1		BEG2		BEG3	
	WASDE	GS	WASDE	GS	WASDE	GS
(a) Corn						
Intercept (α_0)	27.29 (31.47)	38.02 (43.91)	-8.67 (35.42)	43.69 (56.46)	10.66 (33.08)	50.58 (44.31)
F_{it}	**0.99 (0.02)**	**1.00 (0.01)**	**1.00 (0.02)**	**1.00 (0.01)**	**0.99 (0.02)**	**1.00 (0.01)**
R_τ	**-1856.50 (361.42)**	**-2474.00 (522.37)**			**-1694.20 (374.65)**	**-2620.50 (526.74)**
$\Delta Ivol_\tau$			**-516.56 (190.35)**	109.63 (347.59)	-284.21 (183.60)	386.72 (278.30)
(b) Soybean						
Intercept (α_0)	5.25 (6.18)	11.13 (9.96)	-5.14 (7.42)	9.33 (9.98)	5.09 (6.84)	10.25 (10.12)
F_{it}	**1.00 (0.01)**	**0.99 (0.01)**	**1.01 (0.02)**	**0.99 (0.01)**	**1.00 (0.01)**	**0.99 (0.01)**
R_τ	**-787.92 (130.67)**	-168.14 (208.62)			**-785.49 (138.62)**	-152.64 (211.50)
$\Delta Ivol_\tau$			**-103.42 (58.61)**	-71.58 (95.64)	-3.00 (55.03)	-63.80 (96.85)
(c) Wheat						
Intercept (α_0)	6.94 (14.62)	14.60 (25.71)	15.34 (15.30)	15.95 (27.87)	12.90 (15.01)	31.88 (29.19)
F_{it}	**1.00 (0.02)**	**1.00 (0.02)**	**0.99 (0.02)**	**1.00 (0.02)**	**0.99 (0.02)**	**0.99 (0.02)**
R_τ	**-209.25 (103.58)**	-205.48 (209.82)			**-269.25 (109.70)**	-467.25 (298.71)
$\Delta Ivol_\tau$			48.12 (63.02)	19.79 (136.34)	103.97 (65.77)	234.62 (191.76)

The regressions show that, for all commodities and both WASDE and GS, there is informational content in the forecasts. Moreover, the forecast is unbiased. When including both returns and implied volatility change in the same regression (BEG3), the coefficient of implied volatility change tends to become insignificant.

Table 1: USDA Reports—An Overview

	WASDE	Grain Stocks (GS)	Prospective Planting (PP)	Acreage (AR)
Frequency	Monthly	Quarterly	Yearly	Yearly
Timing	2nd week of the month	End of Quarter	End of March	End of June
Overlaps	1st GS	1st WASDE; PP; AR	2nd GS	3rd GS
Information surveyed by Bloomberg	Projected U.S. ending stock of the on-going marketing year	U.S. Ending stock estimates as of 1st Dec, 1st Mar, 1st Jun and 1st Sep	U.S. farmers' planting intention for upcoming crop season	Survey-based estimate of U.S. planted area for current crop season
Baseline for forecast pessimism	WASDE of previous month	GS of previous year's same quarter	AR of previous year	PP of current year

Table 2: Summary Statistics

	Median	Mean	SD	Min	Max	No. Obs	Obs < 0
ΔVIX_{τ}	-0.009	-0.003	0.047	-0.109	0.184	151	88
(a) Corn							
$\Delta Ivol_{\tau}$	-0.027	-0.032	0.053	-0.231	0.198	151	119
Slope	0.098	0.053	0.157	-0.821	0.097	151	20
WASDE Suprise	0.004	0.006	0.077	-0.242	0.326	121	52
GS Surprise	0.002	0.011	0.068	-0.165	0.196	41	20
PP Surprise	0.000	0.003	0.017	-0.017	0.039	10	5
Acreage Surprise	0.010	0.011	0.019	-0.016	0.055	10	3
WASDE Dispersion	0.065	0.083	0.058	0.006	0.253	121	N/A
GS Dispersion	0.021	0.029	0.024	0.009	0.131	41	N/A
PP Dispersion	0.009	0.010	0.002	0.007	0.013	10	N/A
Acreage Dispersion	*0.007*	*0.009*	*0.005*	*0.005*	*0.022*	10	N/A
WASDE FC	*0.000*	*-0.005*	*0.169*	*-0.621*	*1.008*	121	*58*
GS FC	*0.010*	*0.010*	*0.189*	*-0.558*	*0.376*	41	*15*
PP FC	*0.012*	*0.002*	*0.030*	*-0.043*	*0.043*	10	*4*
Acreage FC	*-0.003*	*-0.011*	*0.022*	*-0.067*	*0.006*	10	*6*
(b) Soybean							
$\Delta Ivol_{\tau}$	-0.020	-0.022	0.045	-0.153	0.210	151	114
Slope	0.029	-0.038	0.190	-1.193	0.078	151	50
WASDE Suprise	0.000	0.000	0.101	-0.310	0.452	121	55
GS Surprise	-0.011	0.001	0.091	-0.346	0.265	41	26
PP Surprise	*-0.013*	*-0.009*	*0.011*	*-0.022*	*0.014*	10	*8*
Acreage Surprise	*-0.002*	*-0.006*	*0.029*	*-0.078*	*0.034*	10	*7*
WASDE Dispersion	*0.111*	*0.125*	*0.076*	*0.011*	*0.401*	121	N/A
GS Dispersion	*0.036*	*0.047*	*0.030*	*0.012*	*0.118*	41	N/A
PP Dispersion	*0.013*	*0.014*	*0.005*	*0.006*	*0.023*	10	N/A
Acreage Dispersion	*0.007*	*0.009*	*0.006*	*0.005*	*0.025*	10	N/A
WASDE FC	*0.000*	*0.007*	*0.146*	*-0.357*	*0.747*	121	*60*
GS FC	*0.077*	*0.093*	*0.298*	*-0.623*	*0.821*	41	*11*
PP FC	*0.013*	*0.008*	*0.031*	*-0.041*	*0.053*	10	*3*
Acreage FC	*0.008*	*0.010*	*0.008*	*0.000*	*0.022*	10	*1*
(c) Soft red winter wheat							
$\Delta Ivol_{\tau}$	-0.026	-0.023	0.038	-0.130	0.126	151	119
Slope	0.122	0.123	0.072	-0.013	0.380	151	2
WASDE Suprise	0.006	0.007	0.039	-0.139	0.138	121	45
GS Surprise	0.012	0.007	0.029	-0.074	0.055	41	16
PP Surprise	*0.001*	*-0.005*	*0.019*	*-0.038*	*0.018*	10	*5*
Acreage Surprise	*0.007*	*0.005*	*0.010*	*-0.008*	*0.018*	10	*4*
WASDE Dispersion	*0.035*	*0.047*	*0.039*	*0.004*	*0.259*	121	N/A
GS Dispersion	*0.025*	*0.029*	*0.014*	*0.009*	*0.071*	41	N/A
PP Dispersion	*0.013*	*0.012*	*0.004*	*0.007*	*0.019*	10	N/A
Acreage Dispersion	*0.007*	*0.009*	*0.003*	*0.005*	*0.014*	10	N/A
WASDE FC	*0.000*	*-0.005*	*0.042*	*-0.217*	*0.103*	121	*41*
GS FC	*0.039*	*0.029*	*0.146*	*-0.189*	*0.343*	41	*16*
PP FC	*-0.013*	*-0.025*	*0.056*	*-0.111*	*0.053*	10	*6*
Acreage FC	*-0.001*	*-0.002*	*0.010*	*-0.023*	*0.010*	10	*5*

Table 3: Paired t-test and Wilcoxon Signed Rank Test Results

	IVol on Day t *vs*. day t-1		11-day event window	
	Paired sample t-test	**Wilcoxon signed rank test**	**one-way ANOVA test**	**Kruskal-Wallis test**
(a) Corn				
Test statistic	-6.3922	-7.2404	6.6604	83.3760
p-value	<0.000	<0.000	<0.000	<0.000
(b) Soybean				
Test statistic	-5.1295	-6.1703	3.5520	58.6808
p-value	<0.000	<0.000	0.0001	<0.000
(c) Wheat				
Test statistic	-6.8606	-7.0509	6.1572	122.3106
p-value	<0.000	<0.000	<0.000	<0.000

Note: The first two columns present the two-sample parametric (t-test) and nonparametric test results for $H_0 : Ivol_t = Ivol_{t-1}$. The last two columns show the results of one-way ANOVA and Kruskal-Wallis tests for $H_0 : \Delta Ivol_{t-5} = \Delta Ivol_{t-4} = ... = \Delta Ivol_{t+5}$, with $\Delta Ivol_{t+i} = \ln\left(Ivol_{t+i} / \overline{Ivol} \right)$. For the t-test, left-sided t- and p-values are reported; for the Wilcoxon test, left-sided z- and p-values are reported; for one-way ANOVA and Kruskal-Wallis test statistics it is F and chi-square distributions, respectively.

Table 4a: p-value matrix of ANOVA-based multiple comparison tests among days in the window event and paired t-test to average 5 days before—Corn

	$\overline{ivol}$	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
$t-5$	0.616										
$t-4$	**0.049**	1.000									
$t-3$	0.**018**	0.998	1.000								
$t-2$	**0.002**	0.916	0.999	1.000							
$t-1$	**0.032**	0.984	1.000	1.000	1.000						
t	**0.000**	0.255	**0.042**	**0.019**	**0.002**	**0.007**					
$t+1$	**0.000**	**0.095**	**0.010**	**0.004**	**0.000**	**0.001**	1.000				
$t+2$	**0.001**	0.146	**0.019**	**0.008**	**0.001**	**0.003**	1.000	1.000			
$t+3$	**0.006**	0.302	**0.054**	**0.026**	**0.003**	**0.010**	1.000	1.000	1.000		
$t+4$	**0.007**	0.382	**0.078**	**0.039**	**0.005**	**0.016**	1.000	1.000	1.000	1.000	
$t+5$	**0.059**	0.789	0.318	0.196	**0.039**	**0.101**	0.999	0.981	0.994	1.000	1.000

Note: For each element of the matrix, p_{ij} reports the p-value for $H_0 : \Delta Ivol_{t+i} \neq \Delta Ivol_{t+j}$, with $i, j = -5, -4, ..., 5$ and $i \neq j$. The first column reports the p-value for one-sided t-test of each $Ivol_{t+i}$ against the 5-day average before Bloomberg survey, i.e. $\overline{ivol}$. For the days before USDA announcement (i.e. from $t-5$ though $t-1$), the null hypothesis is that the implied volatility on that day is larger than $\overline{ivol}$, indicating an increase in implied volatility. In contrast, the null for the days after USDA announcement (i.e. from $t+1$ to $t+5$) is that the mean implied volatility on that day is smaller than $\overline{ivol}$, indicating a drop in implied volatility following the report release.

Table 4b: p-value matrix of ANOVA-based multiple comparison tests among days in the window event and paired t-test to average 5 days before, soybean

	$\overline{ivol}$	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
$t-5$	0.541										
$t-4$	0.606	1.000									
$t-3$	0.510	1.000	1.000								
$t-2$	0.144	1.000	1.000	1.000							
$t-1$	**0.073**	1.000	1.000	1.000	1.000						
t	**0.000**	0.199	0.254	0.181	**0.040**	0.297					
$t+1$	**0.000**	**0.084**	0.114	**0.074**	**0.013**	0.138	1.000				
$t+2$	**0.002**	0.188	0.241	0.170	**0.037**	0.282	1.000	1.000			
$t+3$	**0.020**	0.532	0.614	0.502	0.179	0.667	1.000	0.999	1.000		
$t+4$	**0.065**	0.909	0.944	0.894	0.565	0.961	0.986	0.917	0.983	1.000	
$t+5$	0.334	1.000	1.000	1.000	0.989	1.000	0.538	0.307	0.523	0.877	0.999

Table 4c: p-value matrix of ANOVA-based multiple comparison tests among days in the window event and paired t-test to average 5 days before, wheat

	$\overline{ivol}$	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
$t-5$	**0.019**										
$t-4$	**0.006**	1.000									
$t-3$	**0.068**	1.000	1.000								
$t-2$	**0.059**	1.000	1.000	1.000							
$t-1$	0.186	1.000	1.000	1.000	1.000						
t	**0.000**	**0.004**	**0.001**	**0.007**	**0.002**	**0.012**					
$t+1$	**0.002**	**0.004**	**0.001**	**0.007**	**0.002**	**0.012**	1.000				
$t+2$	**0.015**	**0.036**	**0.013**	**0.059**	**0.024**	**0.093**	1.000	1.000			
$t+3$	**0.031**	**0.066**	**0.026**	0.104	**0.046**	0.155	0.999	0.999	1.000		
$t+4$	**0.065**	0.168	**0.078**	0.243	0.124	0.332	0.983	0.984	1.000	1.000	
$t+5$	0.146	0.492	0.299	0.611	0.407	0.719	0.808	0.810	0.990	0.998	1.000

Table 5: Ivol Change *vs*. Forecast Surprise, Dispersion, and Expert Pessimism

	CORN		**SOYBEAN**		**WHEAT**	
	Coeff	Std err	Coeff	Std error	Coeff	Std error
Intercept (β_0)	**-0.038***	**0.020**	-0.027	0.022	**-0.022****	**0.011**
WASDE Suprise	**-0.238****	**0.098**	**-0.104***	**0.061**	-0.081	0.082
GS Surprise	0.140	0.212	-0.013	0.075	0.129	0.287
PP Surprise	-2.139	1.896	0.816	1.158	-0.810	0.775
Acreage Surprise	-0.984	1.153	0.024	0.544	-0.909	2.366
WASDE Dispersion	**-0.153***	**0.082**	-0.029	0.061	**-0.219*****	**0.087**
GS Dispersion	**0.578****	**0.253**	0.335	0.223	-0.019	0.310
PP Dispersion	1.221	6.647	-0.957	1.629	0.350	1.381
Acreage Dispersion	-2.745	3.923	-1.197	2.028	-0.158	2.248
Pessimistic WASDE forecast	0.007	0.009	0.008	0.009	0.000	0.008
Pessimistic GS forecast	**-0.055****	**0.024**	-0.016	0.018	-0.016	0.018
Pessimistic PP forecast	-0.046	0.092	-0.002	0.029	-0.034	0.023
Pessimistic Acreage forecast	0.021	0.037	**-0.080*****	**0.018**	0.002	0.044
ΔVIX_{τ}	**-0.118***	**0.069**	**-0.125***	**0.076**	**-0.097***	**0.052**
$Slope^{-}$	-0.019	0.019	0.013	0.018	**2.072*****	**0.794**
OLS Adjusted R-squared	*0.192*		*0.0689*		*-0.0495*	
p-value of heteroskedasticity-consistent Wald-statistics						

Significance code: **** 0.01* *** 0.05* ** 0.1*

Table 6: Asymmetric Effect of a USDA Surprise

	CORN		SOYBEAN		WHEAT	
	Coeff	Std error	Coeff	Std error	Coeff	Std error
Intercept (β_0)	**-0.052*** **	**0.018**	-0.023	0.022	**-0.023** **	**0.012**
Good WASDE Suprise	-0.084	0.120	0.091	0.078	-0.089	0.134
Bad WASDE Suprise	**-0.418***	**0.247**	**-0.307** **	**0.127**	-0.058	0.158
Good GS Surprise	**0.744** **	**0.373**	**0.316*** **	**0.104**	0.506	0.667
Bad GS Surprise	**-0.703***	**0.392**	**-0.274*** **	**0.088**	-0.402	0.628
Good PP Surprise	-1.323	2.861	**-3.571** **	**1.484**	-1.172	1.477
Bad PP Surprise	-4.615	3.227	2.125	1.364	-0.631	1.190
Good Acreage Surprise	-2.142	2.080	-0.413	1.150	2.584	3.724
Bad Acreage Surprise	-0.205	2.357	0.921	0.964	**-12.327***	**6.869**
WASDE Dispersion	**-0.183** **	**0.075**	-0.113	0.072	**-0.201***	**0.105**
GS Dispersion	-0.343	0.497	0.139	0.253	-0.431	0.444
PP Dispersion	-0.013	8.742	0.896	1.716	0.526	2.160
Acreage Dispersion	1.247	6.152	1.428	3.122	-5.079	4.367
Pessimistic WASDE forecast	0.009	0.008	0.006	0.009	0.000	0.008
Pessimistic GS forecast	**-0.065*** **	**0.024**	**-0.043*** **	**0.016**	-0.012	0.018
Pessimistic PP forecast	-0.049	0.070	-0.019	0.027	-0.032	0.027
Pessimistic Acreage forecast	0.007	0.046	**-0.079*** **	**0.018**	-0.017	0.042
ΔVIX_τ	**-0.131***	**0.072**	-0.111	0.077	**-0.097***	**0.053**
$Slope^-$	-0.011	0.019	-0.005	0.019	**1.965** **	**0.879**
Adjusted R-squared	*0.235*		*0.144*		*-0.041*	
p-value of heteroskedasticity-consistent Wald-statistics						

Significance code: **** 0.01* *** 0.05* ** 0.1*

Figure 1. Timing of Bloomberg Analyst Surveys and Scheduled USDA Announcements

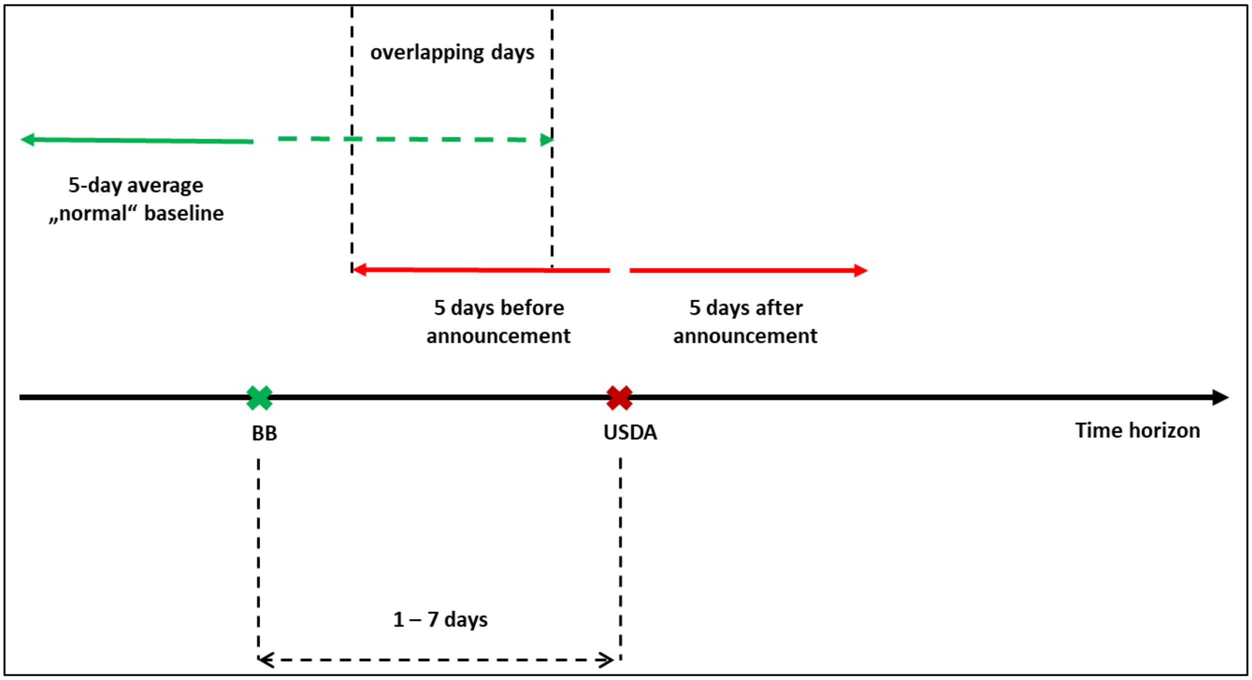
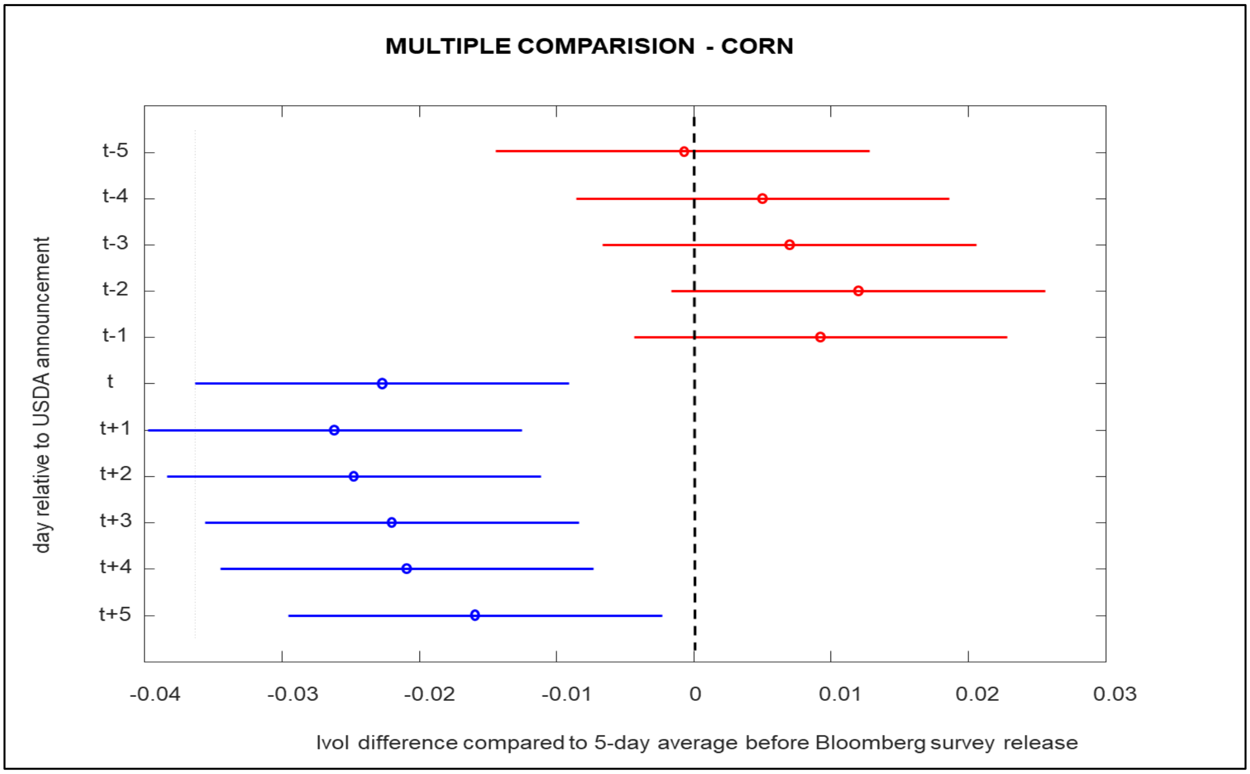


Fig. 2a: Daily IVol Change *(vs. 5-day average IVol prior to latest Bloomberg survey)*—Corn.



Note: The dots in Figures 2a (corn), 2b (soybean) and 2c (soft red winter wheat) show the mean estimates of the difference $\Delta Ivol_{t+i}$ between (a) the 90-day option-implied volatility at the market close on day *t+i* (i=-5,…,5) and (b) the 5-day-average Ivol prior to the most recent *pre*-event Bloomberg survey. For each day, the lines represent estimated 95-percent confidence intervals. If the confidence intervals of two groups overlap each other, then the difference between them are not statistically significant. The group of 5 days before a USDA announcement are in red; the announcement day t and the 5 next days appear in blue.

Fig. 2b: Daily IVol Change *(vs. 5-day average IVol prior to latest Bloomberg survey)*—Beans

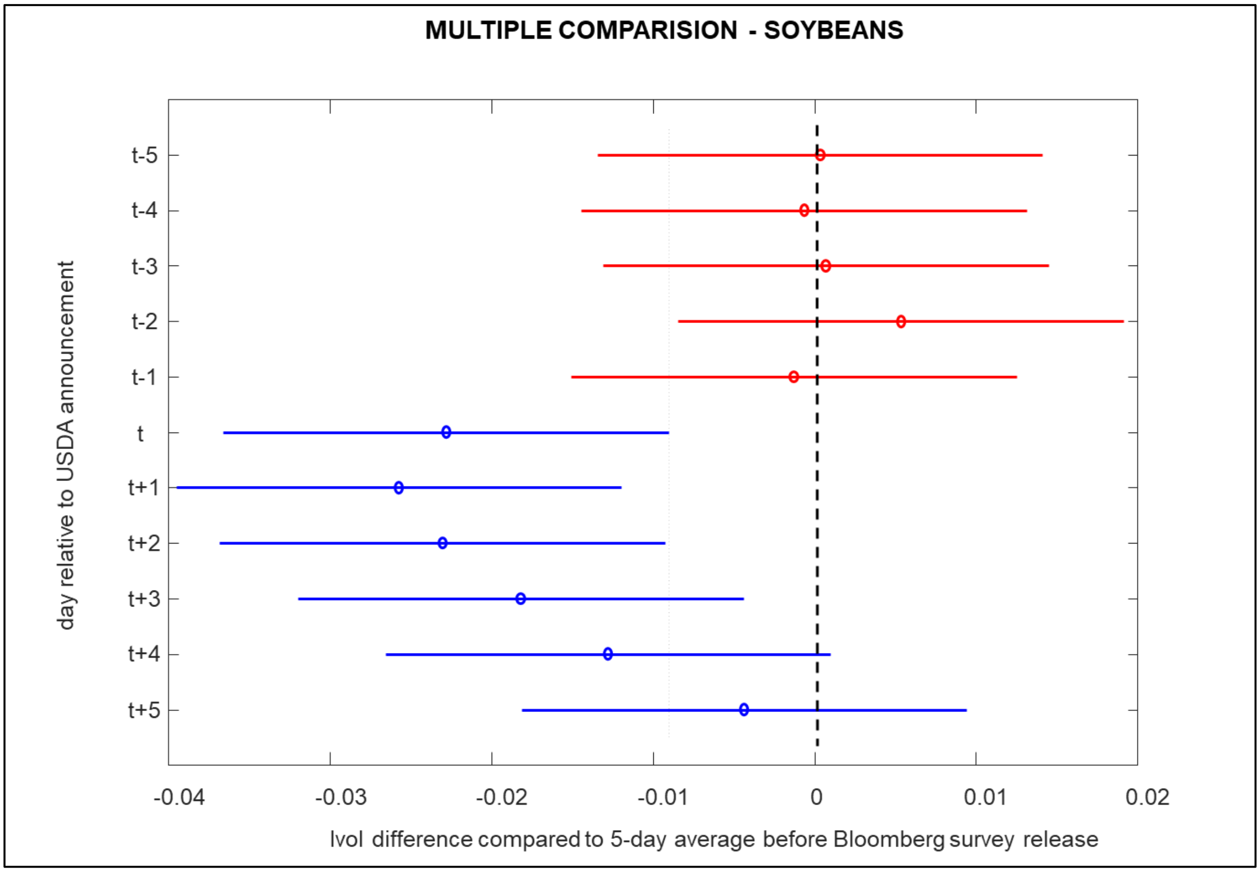


Fig. 2c: Daily IVol Change *(vs. 5-day average IVol prior to latest Bloomberg survey)*—Wheat