Market Uncertainty and Sentiment around USDA Announcements

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Abstract

We provide comprehensive evidence that USDA reports substantially impact uncertainty and sentiment in agricultural markets. For up to five trading days after a scheduled release (WASDE, GS—Grain Stocks, Prospective Plantings, Acreage), option-implied volatilities (IVols) are significantly lower than a week earlier. On average, the reports' uncertainty resolution power is similar in magnitude for corn, soybeans, and wheat. The benefit of the USDA information is greater when there is more disagreement among market analysts in the run-up to a report (WASDE). It is smaller when the USDA news surprise the market—typically when the surprise is price-bullish (WASDE and GS) but also when the surprise is bearish (GS). While commodity IVols are often positively related to financial-market sentiment and to macroeconomic uncertainty (jointly captured by the VIX index), this co-movement breaks down on USDA report days—with the VIX and commodity IVols moving in opposite directions. Finally, in the case of the critical GS reports, the market-calming effect of USDA news is larger when analysts had been pessimistic about stock levels—that is, expert sentiment matters.

1. Introduction

A large literature shows that periodic USDA reports often move grain and oilseed prices substantially. The fact that agricultural markets react significantly to scheduled USDA announcements supports the notion that the latter contain valuable news and help resolve disagreements among market participants regarding demand and supply fundamentals.

Most of the extant literature investigates what happens to commodity price levels on USDA event days (e.g., Adjemian 2012; Karali *et al*. 2019; Ying, Chen and Dorfman 2019) or shows how fast the USDA information is impounded into those prices (e.g., Lehecka, Wang, and Garcia 2014; Adjemian and Irwin 2018). As McNew and Espinosa (1994), 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.

Documenting that effect, and exploring for the first time its duration and its determinants, is our objective in this paper. Because changes in uncertainty and sentiment map directly into the cost of options-based hedging strategies (see, e.g., Goyal and Adjemian 2020), our results have important implications not only for policy makers and academics, but also for the significant fraction of Corn Belt farmers who use options on futures to alter the exposure of a substantial part of their crop income to commodity price risk (Prager *et al*. 2020).

In equity and bond markets, accountants and financial economists have long used changes in option-implied return volatilities ("IVol") to study the impact of news on forward-looking market uncertainty (Patell and Wolfson 1979; Ederington and Lee 1993). In agricultural markets, two papers by McNew and Espinosa (1994) and Isengildina-Massa *et al*. (2008) use near-dated options-on-futures implied volatilities for the same purpose.[2] We extend that prior work along several key dimensions.

First, agricultural markets have evolved massively over the course of the past two decades. Quantitatively, the open interest in corn, soybean, and wheat options and futures is many times what it was 15 years ago (Robe and Roberts 2019). Qualitatively, 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 and Roberts 2015; Haynes *et al*. 2017); the demise of the futures trading pits (Gousgounis and Onur 2018); and, the influx of ever more sophisticated private forecasting services (McKenzie, 2008; Karali *et al*. 2019). Our first contribution is to complement earlier articles, which use data going back two decades or more (*i.e.*, predating any of those developments took place), by investigating IVol responses to scheduled USDA news releases in more modern times.

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 in 2009-2019,[3] we document that IVols in the U.S. corn, soybeans, and soft red winter (SRW) wheat markets fall significantly on the event day—by 2 to 2.7 percent on average depending on the commodity. For USDA reports that market observers generally view

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[2] In contrast to those studies and our paper, articles that look at market volatility around USDA events focus on realized volatility (captured by the variance equation in GARCH-type models or by the realized sample volatility) rather than forward-looking volatility. An exception is Adjemian *et al*. (2018), who value a missing 2013 WASDE report due to a U.S. government shutdown. Fortenbery and Sumner (1993) is the first study of option prices around scheduled USDA events. See Ying, Chen and Dorfman (2019) for a thorough review of the literature on USDA announcements.

[3] We consider WASDE, Grain Stocks, Prospective Plantings, and Acreage reports. In contrast, McNew and Espinosa (1994) focus on crop production reports only; Isengildina-Massa et al. (2008) focus on WASDE reports.

as the most important (which make up half of our sample of 151 events), the IVol is even larger—3.2 (wheat), 3.6 (soybeans) or 5.7 (corn) percent on average. Furthermore, the IVol decline remains statistically significant for at least four trading days, and sometimes for more than a week, after the event day. These results complement the finding of Karali *et al*. (2019) regarding the magnitude of commodity futures returns on USDA crop report days: they indicate that, as a group, scheduled USDA reports remain highly payoff-relevant to market participants.

Second, our analysis of commodity IVols innovates by recognizing that USDA reports are not released in a vacuum. Namely, we examine whether the sign or magnitude of the *post*-release IVol change depends on agricultural market experts' opinions in the run-up 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. We argue theoretically and, armed with Bloomberg survey information, provide empirical evidence 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 market experts and, as such, can be seen as a proxy for pre-existing commodity-specific uncertainty) and also (iii) analyst "sentiment" all affect the magnitude of the commodity IVol responses to scheduled USDA announcements.[4]

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[4] Two recent studies of USDA announcement also consider the possible roles of analyst expectations and uncertainty. Karali *et al*. (2019) use a DCC MGARCH-X model to investigate the role of report surprises on price levels and on the realized variance of agricultural commodity returns. We examine instead the link between prior expert opinions market expectations of *future* volatility. We look not only at whether expert forecasts were close to the actual release, but also at the extent to which analysts disagreed and at their sentiment (pessimistic or optimistic) prior to the news release. Further afield, Fernandez-Perez *et al*. (2019) examine the link between consensus forecast error and analyst dispersion on futures bid-ask spreads (which acts as a proxy for asymmetric information). Both of those recent studies posit that the price or bid-ask spread changes after USDA announcements can be solely attributed to the reports'

Looking first at surprises, we document that their effects are most significant in the case of inventories-related news contained in WASDE or Grain Stocks (GS) reports. With GS reports, any surprise—whether "bullish" for prices (when USDA figures come in lower than analysts expected) or "bearish" (when they are higher than foreseen)—pushes IVols upward (*ceteris paribus*). In the case of WASDE, the same is true only when the surprise is bullish (i.e., when the USDA announces lower future stock levels than the Bloomberg consensus had foreseen)—and, the more bullish the WASDE surprise is for prices, the more the forward-looking volatility increases.[5] In short, while IVols generally decrease after a USDA report, the decrease is muted (in some cases, so much so that the forward-looking volatility actually goes up) when the market is caught flat footed by the USDA—all the more so when the news is bullish for prices.[6]

Next, we look at analyst dispersion, i.e., the extent to which market experts disagree about an upcoming report. We find that, the bigger the dispersion of analyst opinions before the WASDE, the more the IVol decreases after the WASDE. This evidence is consistent with the intuition that, when experts are "confused" as a group, the WASDE release "settles the market"—resetting participants' expectations and clarifying the path forward.

Finally, we tease out how the *pre*-event market sentiment influences the market's reaction to USDA reports. For each report, we rate the prevailing analyst consensus as "pessimistic" (*resp*. "optimistic") when the median *pre*-report expert forecast predicts a decrease (*resp*. an increase) in

informational value, whereas we also control for (i) changes in macroeconomic uncertainty and financial market sentiment around USDA events and (ii) physical market conditions in the runup to the event.

[5] Bearish WASDE surprises, in contrast, do not statistically significantly modify the typical commodity IVol response to a scheduled announcement.

[6] The surprise effect is statistically significant for corn and soybeans but not for wheat, which suggests that the wheat market may be less dependent on U.S. 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.

the forecasted USDA variable compared to an objective past reference point. We find, in the case of Grain Stocks reports (but not other USDA reports), a significant negative association between the analyst 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, this result suggests that, when market experts have been feeling pessimistic about the actual level of grain inventories, the calming effect of the USDA information is more impactful. This finding is a novel contribution to a large literature showing the importance of inventories to commodity price dynamics – see, e.g., Bobenrieth *et al*. (2021).

Our third 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 essence, 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. In the same vein, given that the demand for physical commodities reflects the strength of the economy, uncertainty about the latter should percolate into agricultural markets.

Consistent with this intuition, Adjemian *et al*. (2017) show that, in the long run, changes in grains and livestock IVols are driven to a significant extent on a day-to-day basis by changes of the VIX index in the same direction. The question we ask here is whether a similar pattern is seen on USDA announcement days—and, thus, if controlling for the VIX helps separate the respective impacts of global *vs*. commodity-specific market uncertainty and sentiment. Surprisingly, we find that 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 commodity market sentiment and uncertainty generally move in the same direction as the VIX, we show that this overall pattern is reversed 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 paper proceeds as follows. Section 2 extends Ederington and Lee's (1996) theoretical model of market reactions to scheduled announcements, and draws on other literature, to derive testable hypotheses. Sections 3 describes the data. Section 4 discusses our empirical methodology. Section 5 presents our empirical findings. Section 6 concludes and discussions possible extensions.

2. Theory and Hypothesis Development

In this Section, we extend the Ederington and Lee (1996, EL96 for short) model to guide the study of how USDA reports should affect forward-looking market uncertainty and sentiment.

2.1. Predicted IVol Change before and after a scheduled USDA announcement

As noted in the Introduction, EL96 show theoretically that the expectation of future return volatility embedded in the price of a given option (IVol) should, *ceteris paribus*, first rise in the days leading to a scheduled news release and then fall in the latter's aftermath. In what follows, we adapt their model to predict IVol patterns when using constant-maturity options.

In the EL96 model, the implied variance (IMV) on day t is the average of the daily expected variances over the remaining life of a given option, starting from day t+1. Option traders form expectations using all information available up to day t. Thus, the IMV change on the scheduled report day, say T, is the sum of two changes:

(i) removing the expected realized variance on the event day T from the set of days (until the option's expiration) that was used to calculate the IMV on day T-1 (because day T is now the current day and thus no longer "expected");

(ii) revising the expectation of volatility (or variance) of all the option's remaining days to expiration, starting on day T+1.

Regarding the second term (ii) above, EL96 argue that, depending on whether the realized day-T volatility is higher or lower than had been expected at T-1, market participants will revise upward or downward their expectations of what future realized volatility will be until the option's expiration. However, "rational expectations imply that (...) upward and downward revisions are equally likely and the mean revision across many such scheduled announcements should be approximately zero" (EL96, p.517). We will return to this component in Section 2.2; for now, we can focus on the first term.

Turning to the first term (i) above, the core assumption of the EL96 model is that, if there is a *scheduled* announcement on day T, then on day T-1 market participants should expect that asset returns will be more volatile than average on day T. The intuition is that prices should move a lot to react to the new information, an assumption that is indubitably borne out in the commodity space.[7] Thus, if the maturity date of the option whose price EL96 use to extract volatility expectations is fixed, then going from T-1 to T means removing a higher-than-normal volatility day from the expectation set in the first term (i), which makes the resulting (unconditional) average IMV fall on day T. The same mechanics drive an increase in the IMV in the runup to the event day.

[7] For example, Janzen and Bunek (2017) show that intraday realized volatility shoots up right after the USDA reports.

Unlike EL96, we rely for our empirical analysis on constant-maturity (90-day synthetic) options rather than on nearby options (whose time-to-maturity, as in EL96, would instead decrease over time). With constant-maturity options, it is straightforward to show analytically that (keeping the other assumptions of the EL96 model unchanged) the IVol does not increase as the event day approaches but that it still drops in the aftermath the scheduled news release (*ceteris paribus*).[8]

In the EL96 model and in our variant thereof, there is no theoretical reason why the *post*-event IVol decrease should be a one-day affair. First, note that USDA news are incorporated into prices promptly (Adjemian and Irwin, 2018), so the realized volatility increase on which EL96 focus is limited to the event day *T*. Second, insofar as the USDA reports convey large amounts of information to agricultural market participants (Adjemian, 2012), one can show that a given report's impact on part (i) of the IMV in the EL96 model should last for several days—until either new, non-USDA information is released or until a new USDA event day is included in the average (i). Our first testable hypothesis is thus straightforward:

Hypothesis 1: On average, commodity IVols fall on scheduled USDA report days. This decrease remains statistically significant for several business days and is greater for major USDA reports. There is no IVol increase in the run-up to a USDA report.

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

As noted in the Introduction, the present paper is the first to ask whether agricultural IVols' responses to scheduled USDA announcements depend on the extent to which market participants

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[8] One exception is when the 90th day added is also an event day, in which case the IVol should be unaffected by the news release on average. There are very few such cases in our sample. While the low number of such observations makes it difficult to control for this *caveat*, including those few observations in the sample should bias against our finding an IVol drop on USDA days.

(i) are surprised by the information and, before the event, (ii) disagreed about the upcoming release (a proxy for commodity-market uncertainty), and (iii) were pessimistic (a proxy for sentiment).

2.2.1. Market Consensus and USDA Surprise

The "analyst surprise" is the deviation of the information in the scheduled announcement from *pre*-event market expectations. By definition, it is the unanticipated shock that leads market participants to revise their expectations *post*-event. In financial markets, the surprise captures the unexpected information brought to the market by corporate or government reports (e.g., Balduzzi, Elton, and Green, 2001).

As noted in Section 2.1 above, the surprise is zero *on average* in the EL-96 model, and so part (ii) of the IMV change on the event day T is zero. One can readily extend the EL96 model to account for the fact that, in agricultural markets, one can sign the surprise insofar as (a) one has data about market expectations regarding the upcoming USDA news *and* (b) lower-than expected inventories or tighter-than-expected supply/demand balances should boost realized price volatility.

There is a long line of research showing theoretically and empirically that commodity prices are more volatile during a scarcity phase than amid conditions of plenty—see, e.g., Geman and Smith (2013) and references cited therein. In the same vein, the theory of storage (Kaldor 1939; Working 1948) states that high levels of commodity inventories help smooth out the impact of demand and/or supply shocks on commodity prices and therefore smooth out price volatility.[9] Defining *bullish surprises* as "tighter commodity supply and/or inventories or higher demand than expected, which should boost prices and volatility," and *bearish surprises* as the opposite, it is

[9] See Baur and Dimpfl (2018) for a recent summary of that literature.

straightforward to extend the EL96 model to derive the following prediction for the event-day IVol change conditional on the surprise:

Hypothesis 2: The IVol response to the USDA news depends on market participants' *pre*-release expectations. In case of a "bearish" surprise, the IVol should drop more on the event day than it would absent a surprise (i.e., if the market's prior expectations had been met by the content of the announcement). In case of a "bullish" surprise, the IVol should drop less (and could even increase) *post*-release than it does on average.[10]

2.2.2. Forecast Dispersion

Section 2.2.1 above focuses on the surprises relative to the pre-event consensus forecast. Intuitively, the magnitude of the IVol change after a scheduled USDA report should also depend on the level of disagreement between commodity market participants *before* that announcement. Studies in the equity space document a positive relationship between analysts' forecast dispersion and stock price volatility around firms' earnings announcements. A possible explanation is that forecast dispersion among analysts represents idiosyncratic risk: given that analysts are experts at their forecasted subjects, a high level of dispersion likely reflects uncertainty regarding the subject (Johnson 2004; Dubinsky *et al.* 2019).[11] If this view is shared by those who predicts future price

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[10] Hypothesis 2 predicts that the effect of a USDA surprise is asymmetrical: if the surprise is "bullish" for future prices and volatility (in that the stocks, acreage, prospective plantings, etc. are lower than the market had expected and the physical market conditions are effectively tighter than foreseen) then forward-looking volatility should increase—and, by the same token, if the surprise is a "bearish" one then commodity IVol should fall. An alternative intuition, which is outside the scope of the EL96 model, is that the IVol response is instead symmetrical: that is, if the market always becomes unsettled whenever it is surprised then, the bigger the surprise, the smaller the IVol drop (or, in extreme cases, the commodity IVol could even increase after any surprise).

[11] Another view brought by the difference-of-opinion school of thought (e.g., Diether, Malloy and Scherbina 2002), posits that forecast dispersion is a result of diverging opinions among market participants, which brings about mispricing once short-sale constraints arise on the market. In the case of commodity futures markets, however, this argument seems moot since there are no short sales constraints.

volatility, then we should also expect that the *pre*-event volatility expectation for the event day T of the IMV in the EL96 model is larger when analyst forecasts are more highly dispersed, causing the IVol to drop more after the USDA event day T is removed from the averaging set—component (i) in Section 2.1 above—once the announcement has taken place. Therefore, we have:

Hypothesis 3: *Ceteris paribus*, the IVol decrease after a USDA information release is inversely related to the pre-release dispersion of analyst forecasts.[12]

2.2.3. Commodity-specific Market Sentiment

The EL96 model is predicated upon the Rational Expectation Hypothesis, so that a change in volatility expectations can only be explained by the arrival of new fundamental information. In contrast, the behavioral economics literature suggests that changes in "market sentiment" can also cause a volatility reaction and that sentiment's effect on market volatility may be asymmetrical: in a seminal paper, Barberis, Shleifer and Vishny (1998) develop a theory where "representativeness bias" causes investor to project the most recent news into their future expectation. As such, a negative piece of news would be likely to be followed by other negative news, which would indicate that more uncertainty ought to be expected for the future (and *vice versa*).

Instrumenting commodity-specific sentiment by the degree of analyst optimism/pessimism about the upcoming announced information, we hypothesize that if market analysts are pessimistic before the USDA announcement day T about the supply/stock situation, then market participants

[12] In the same vein, if the magnitude of the IVol change after a scheduled USDA report depends on the level of commodity-market-specific uncertainty before that announcement, then not only should the IVol drop be bigger the greater was the pre-USDA uncertainty among market experts (proxied by the dispersion of their forecasts, Hypothesis 3) but 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 prior to the USDA announcement.

should expect higher volatility on day T (compared to what it would be in the EL96 model), causing the IVol to drop more after day T is removed from the averaging set on the announcement day (i.e., from component (i) in the EL96 model, see Section 2.1 above). Therefore, we have:

Hypothesis 4: After controlling for analyst surprise and dispersion, the magnitude of the IVol change depends on *pre*-release commodity-market analyst sentiment.

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

Hypotheses 3 and 4 look respectively at the possibility that pre-announcement commodity-market uncertainty and sentiment could impact the IVol response to the USDA news. In this Sub-Section, we turn to the possibility that changes in the macro-economic environment on the event day T itself may also matter for the behavior of commodity IVols on that day.

In contrast to an approach often taken in finance and accounting, no published study of scheduled USDA events' impact on IVols controls for concomitant changes in the macroeconomic and financial environment. As a matter of empirical fact, though, commodity IVols are in general impacted by the VIX: c*eteris paribus*, if the VIX increases, then IVols go up and *vice-versa*.[13] Therefore, on USDA event days, (I) when the VIX return is positive, the commodity IVols should drop less in reaction to the USDA information release than if the VIX had been unchanged whereas (II) when the VIX return is negative, the IVol *post*-release drop should be even larger than usual.

On the one hand, the IVol change on USDA event days could simply echo the VIX changes on those days—just as they do on regular (non-event) days. This is the perspective taken by Goyal

[13] See Robe and Wallen (2016) in the crude oil space; Covindassamy, Robe, and Wallen (2017) in the softs space; and Adjemian *et al*. (2017) in the livestock and grains spaces.

and Adjemian (2020) in a recent working paper on the cost of missing the 2019 WASDE. On the other hand, it is plausible that the commodity IVols respond to VIX innovations differently on scheduled announcement days than they do on other days. The EL96 model is mum on both of those two possibilities—so the matter of which is verified is in practice is an empirical question:

Hypothesis 5: 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 scheduled USDA announcements: WASDE, Grain Stocks (GS), Prospective Plantings (PP), and Acreage (AR) reports. Those are the most relevant reports published by the USDA about the supply of global grain and oilseed markets. Crucially for a key component of our analysis, these government reports have since fall 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 2019, 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 are released simultaneously with a GS report. 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 in September 2009, Bloomberg has conducted 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 detailed information about the forecasters who participated in each survey and all of their individual forecasts. 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 of the forecast.[14]

Since 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, we likewise use the CBOE's constant 90-day VIX index ("VIX") in order to test Hypothesis 3. All market series, such as the daily VIX, commodity IVols and futures prices—which we use to compute a proxy of *pre*-event market tightness as in Bruno, Büyükşahin, and Robe (2017)—as well as data on USDA announcements and analyst surveys, are retrieved from Bloomberg.[15]

[14] The Bloomberg database is missing some information regarding the forecasts of individual analyst ahead of the June 2010 wheat Acreage report (AR). We exclude the latter from the wheat regressions that require this piece of data.

[15] 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 technical advantages of relying on Bloomberg implied-volatility estimates. One major advantage, in the opinion of the present paper's authors, is that it makes the analyses easily reproducible.

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 testing with the IVol sample around USDA announcements and extend the approach used in earlier studies. We examine Hypotheses 2 to 5 using multivariate regressions.

4.1. Testing Hypothesis 1: Commodity IVols Decrease on the Announcement Day

1. Event-day testing. As the first step, we compare the mean and median IVols on the event day *T* 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 the IVol levels on days *T* and *T-1* respectively as $Ivol_T$ and $Ivol_{T-1}$, the common null-hypothesis of these two tests is:[16]

$$H_0: Ivol_T = Ivol_{T-1} \qquad \text{against} \qquad H_1: Ivol_T < Ivol_{T-1}$$

2. Event-window extension. Moving beyond the event-day IVol change, we seek a broader picture of how option-implied volatilities behave for five 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.

[16] The difference between the two tests is that the one-sided t-test assumes that $\Delta Ivol_t$ (i.e., $Ivol_t - Ivol_{t-1}$) follows a normal distribution with mean zero and unknown variance under the null-hypothesis, while the Wilcoxon signed rank test only assumes that $\Delta Ivol_t$ 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).

A conventional extension of the 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 the null that all group means/medians are equal, *i.e*., H_0: $\Delta Ivol_{T-5} = \Delta Ivol_{T-4} = \ldots = \Delta Ivol_{T+5}$, 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.[17]

3. *Event-window and* pre-*event-window preferences.* To capture possible differences between the *pre*- and *post*-event IVol change patterns, we consider a window of 5 days before and 5 days after the USDA announcement days. A natural baseline reference to assess within-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 that may not serve well as a normal baseline, we choose the 5-day average before a given Bloomberg survey is released as the reference for "normal" daily IVol, denoted $\overline{Ivol}$. Figure 1 illustrates this point.

[17] 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 is no larger than the specified α (Hochberg and Tamhane 1987). The Turkey-Kramer procedure is designed to circumvent this issue 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.

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

$$\Delta Ivol_{T+i} = \ln\left(Ivol_{T+i} / \overline{Ivol}\right), \text{ where } i = -5, -4, \ldots 5$$

We first apply one-way ANOVA and Kruskal-Wallis test to see if there is at least one day in the event window when the mean/median $\Delta Ivol_{T+i}$ differs significantly from the others. If the test fails to reject the null, then no further action is needed. Otherwise, we feed the resulting estimated mean (or median) and standard errors into the Turkey-Kramer procedure to compare all possible pairs of $\Delta Ivol_{T+i}$ and $\Delta Ivol_{T+j}$.

4.2. Testing Hypotheses 2 to 5: Determinants of the IVol Drop

We regress the event-day commodity IVol change on a set of Bloomberg-survey-related variables (see Hypotheses 2 to 4 in Section 2.2), on the VIX return (our proxy for the event-day change in macroeconomic uncertainty and financial market sentiment—see Hypothesis 5 in Section 2.3), and on a number of control variables. Due to the overlap in the four different reports' respective release schedules, we consider the impact of the four reports on commodity IVols simultaneously. The regression equation is:

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

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

Our variables of interest include:

1. Surprise, $S_{i\tau}$. Traditionally, the 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 the market's expectations prior to a USDA announcement. For 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 ("consensus") forecast value $F_{i\tau}$ in the corresponding Bloomberg survey:

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

2. Dispersion $D_{i\tau}$. 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}. Due to the small size of the grain and oilseed markets compared to equity 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 drop 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.[18] 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".[19] To keep things simple, we use a set of dummy variables that 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 report; Appendix 1 provides additional details.

5. $Control_\tau$. We also introduce a vector of control variables including day-of-the-week dummies, seasonal dummies, a term structure slope-based measure of the (*pre*-event) tightness of the physical market, as well as lagged values of daily commodity futures returns, commodity IVol, and VIX, returns. Standard tests suggest that two lags should be included for each of these lagged-variable groups, denoted as *L2(.)*. Thus:

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

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

a. *Seasonality ($Seasonal_\tau$).* Every year, IVols in the U.S. corn, soybean, and SRW wheat markets all start increasing around April till June, which coincides broadly with the planting phase in the USA (see Appendix 2 for a visual illustration). To capture this

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[18] This approach is related 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.

[19] 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.

seasonal pattern, we use dummies corresponding to the main development phases of the US crop cycle: planting (April through June), pollination (July and August), and harvesting (September through November). The baseline season is the period when the land lays fallow (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 which specific day of the week τ the release takes place, by including four day dummies (Tuesday to Friday).

c. *Shape of the commodity futures term structure ($Slope^-$).* As a proxy for options and futures traders' views regarding the tightness of the physical market for a commodity before a USDA event, we follow Büyükşahin, Bruno, and Robe (2017) and use the slope of the term structure of futures prices (precisely, we use the slope nearby slope measured on the nearest Tuesday prior to the USDA announcement day.[20]

4.3. Is the impact of surprise asymmetric for bullish **vs.** *bearish surprises?*

The theoretical derivation of Hypothesis 2 reflects an empirical fact well known from the finance literature: equity, bond, and forex markets tend to 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-wide and the firm-specific components of volatility for various stock portfolios. Beber and Brandt (2010) investigate the respective effects of good *vs*. bad

[20] Ng and Pirrong (1994) provide empirical evidence that commodity markets are much more volatile when in backwardation than when in contango. Pirrong (2011) provides a theoretical explanation of this pattern. Accordingly, we truncate our *Slope* variable at 0 and denote the resulting variable $Slope^-$. In doing so, we hypothesize that the prevailing state of inventories is only relevant when the market is tight, *i.e.,* when the slope is negative. Our results are robust to using instead the original, non-truncated *Slope* variable. The robustness of our findings to using *Slope* or $Slope^-$ likely reflects the reality that, in our sample period, the slope is positive, stable, and small in magnitude much of the time—whereas negative values appear less frequently and, when they do, are much larger in absolute terms.

macroeconomic news in the U.S. treasury bond market: they find that bond returns react more strongly to bad news than to good news during expansions, and *vice-versa* during recessions. In a real-time analysis of U.S. dollar spot exchange rates, Andersen *et al*. (2003) report larger surprise-induced conditional-mean jumps when the surprise is bad, compared to the good surprise case.

As discussed in Section 2.2.1, in order to investigate this conjecture within the context of agricultural IVols, we split the report surprises into price- (and volatility-) “bullish” and “bearish” surprises. A bullish surprise $S_{i\tau}^{-}$ occurs if the USDA announces lower stocks (WASDE, GS) or acreage levels (PP, AR) than had been forecasted by market analysts (hence the negative superscript in our notation); a bearish surprise $S_{i\tau}^{+}$ represents the opposite situation. The regression equation then becomes:

$$\Delta Ivol_{\tau} = \beta_0 + \sum \beta_i^{-} S_{i\tau}^{-} + \sum \beta_i^{+} S_{i\tau}^{+} + \sum \delta_i D_{i\tau} + \varphi \Delta VIX_{\tau} + \sum \gamma_i Pessimism_{i\tau} + \eta Control_{\tau} + \varepsilon_{\tau}, \tag{2}$$

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^{+}, we can answer the question of whether there is asymmetry in the reaction 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 summary statistics for our main variables of interest, including the IVol and VIX levels and returns (on announcement days and all sample days), futures term structure slope, analyst surprise and dispersion, and the forecast change (FC)—i.e., the difference between the median Bloomberg forecast and the corresponding reference point that we use to determine our sentiment ("pessimism") variables, as discussed in Section 4.2.4. Table 2 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 a clear pattern on the announcement day: both the median and the mean of $\Delta Ivol_{\tau}$ are negative in all markets. Negative IVol returns make up more than two-thirds of the whole sample for each commodity and, across all 151 USDA event days, IVols fall by 2 to 2.7 percent on average depending on the commodity. For the subset of more than 80 USDA reports that market observers generally view as the most important,[21] the proportion of negative IVol returns jumps to more than four fifths, and the median IVol drop ranges from 2.2 (wheat) to 3.6 (beans) and up to 5.7 (corn) percent on average.

For the majority of reports and of commodities, the magnitude of the surprise tends to be small, (less than 1.5 percent of the forecast median) and it varies a lot over time. Most of the time, the surprise is bearish for prices and volatility (exceptions include the GS, PP and AR reports for soybeans, for which surprises tend to be bullish). Consistently across markets, the dispersion of expert forecasts is widest for WASDE reports (more than 10 percent of the average forecast for

[21] As in Adjemian & Irwin (2018), those "big events" include a subset of the WASDE reports as well as all the Grain Stocks, Prospective Plantings, and Acreage reports.

beans, and 7 percent for corn), followed by forecasts for GS reports. PP and AR forecasts exhibit the least dispersion. Similar to surprises (in that the latter are mostly price-bearish), forecast changes appear to be 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.

The futures term structure slope is mostly positive in our sample, with most of the episodes of backwardation concentrated in 2010 (wheat) and 2011-2012 (corn, soybeans). Both the mean and median ΔVIX_{τ} are negative in our sample, but they very close to zero. Finally, it is worth noting that quite a few variables in our models will have zero value for most of the sample, which suggests a need for heteroskedasticity-robust estimation.

5.2. Hypothesis 1: IVols decrease on average following a scheduled USDA announcement

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 IVol drop on the day of announcement.

In the next step, one-way ANOVA and Kruskal-Wallis tests (last two columns) also show that, for all commodities, there is at least one day in the 11-day even window when $\Delta Ivol$ (*vs*. the 5-day average before the Bloomberg survey) is significantly different from the other days.[22] We therefore perform the multiple comparison procedure described in Section 4.1.

[22] For corn, the statistical significance holds for all tests and for all events – small and big. For soybeans and wheat, statistical significance is strongest for the subset of 87 USDA reports that market observers rank as most important.

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, commodity IVols are higher than "normal" on days leading up to the announcement but, as predicted by Hypothesis 1, the increase is never statistically significant.[23]
- In sharp contrast to that *pre*-event behavior, commodity IVols fall significantly on the event day and they remain statistically significant lower for at least four trading days thereafter. Figures 2a to 2c show that, for all commodities, the 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 yields similar results.[24]

In short, our empirical evidence supports Hypothesis 1. Our above results extend to the past decade findings based on older data, in Isengildina-Massa *et al*. (2008) and McNew and Espinosa (1994), that IVol drops significantly on the day of a USDA report release. Moreover, we further extend those earlier finding by showing that commodity IVols trend upward (though not statistically significantly) for several days before the USDA announcement, before dropping significantly on the event day and remaining significantly below "normal" level for approximately one week.

[23] The corn IVol gradually increases for four days before the announcement and reaches its highest pre-event level on the day before the event day. For wheat, the increase appears to start earlier, but then the IVol stabilizes until the event day. The soybean IVol does not exhibit any visible change from the "normal" level prior to the event day. Using t-tests and Wilcoxon signed-rank tests, we find that the commodity IVols are not statistically significantly different the day before and the day after the Bloomberg survey release, i.e., the pre-USDA-event IVols do not respond to the Bloomberg surveys.

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

Hypotheses 2 to 4:* Pre-*event Market Expert Forecasts Influence the IVol Response

Table 5 summarizes our estimations 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 commodity IVols to drop on USDA scheduled announcement days, consistent with the tests of Hypothesis 1 (even if, in the soybean equation, the intercept is not statistically significant).

The effect of analyst surprise and dispersion vary across markets and reports, in terms of signs and magnitudes. Different reports have different impacts on different markets. In particular:

The role of report surprises. In Equation (1), we do not differentiate between bearish and bullish surprises. In this empirical setting, the regressions coefficients show that the IVol change tends to be inversely related to the report surprise, but only the WASDE surprise coefficients in the models for corn and soybean are statistically significant. *Ceteris paribus,* if the USDA announced stock projection comes in one percent higher than the median Bloomberg forecast, then the result is a 0.24 *(resp. 0.1)* percent drop in IVol of corn *(resp. soybean)* on announcement day. One way to interpret this relationship is that the more price-bearish the news that the USDA report brings to the market, the more it helps calm the market, resulting in a bigger IVol decrease. Still, the lack of statistical significance of a potentially important variable points to the need for differentiating between bullish and bearish surprises, a topic to which we return in Section 5.3.

The role of forecast dispersion. As with surprises, most of the coefficients for our dispersion variables are negative. This result highlights the uncertainty-resolution effect of USDA reports in times of much uncertainty or disagreement. That is, the more dispersion there was 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 and resolve uncertainty. Consequently, conditioning on disagreement among analysts, the implied volatility should drop more following the USDA report release. Indeed, we find that a one-percent increase in WASDE forecast dispersion around the mean forecast significantly contributes to 0.15 percent *(resp. 0.25)* percent decrease in IVol for corn *(resp. wheat), ceteris paribus*.[25] This finding complements the argument of Karali *et al*. (2019), that USDA reports are valuable even in the presence of private forecasts.

The role of forecast pessimism. Using the same reasoning as with dispersion, we expect the forecast pessimism coefficients to be negative if the figures released by the USDA effectively act as the new market consensus. When market experts are pessimistic about quantities, the market is 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. The two highly significantly coefficients, GS for corn and AR for soybean, support this view. *Ceteris paribus*, the corn IVol drops 5.5 percent more when the majority of forecasters had been pessimistic about the upcoming corn GS report, compared to when they are optimistic or neutral. It is 8 percent for soybean IVol when the AR forecast are pessimistic. One interpretation of this finding is that, having controlled for new fundamental-related information (proxied by surprises) and for uncertainty (proxied by dispersion), a statistically significant effect of the pessimism variable is evidence that market sentiment (not just market fundamentals) plays a role in the behavior of commodity IVols around USDA announcements.

The role of inventory conditions. In general, we do not find a significant relationship between market tightness prior to the USDA event and the IVol drop on the announcement day, except for

[25] No significant effect of PP and Acreage forecast dispersion is found. GS dispersion has an unexpectedly positive sign (statistically significant), meaning it reduces the resolution effect of the report(s).

wheat. Since our variable is truncated from above at zero, the positive coefficient for the wheat slope indicates that, *ceteris paribus,* a one-percent decrease in the wheat cost of carry (net of interest rates) 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.

5.3: Is the Impact of the USDA Surprise Asymmetric (for bullish **vs.** *bearish surprises)*

The estimation results of Equation (2) are shown in Table 6. It is apparent that the effect of report surprises on IVol change becomes more significant when we separate bullish (negative value) from bearish (positive value) surprises. While many bullish surprise coefficients are significantly different from zero, it is less so for bearish surprises. *Ceteris paribus*, bullish WASDE surprises drive up corn and soybean IVols significantly on the announcement day, while the impact of bearish surprises is less significant. The same holds for Acreage surprises in the wheat market.

A second aspect of the asymmetry is the sign of the coefficients. Hypothesis 2 predicts that bullish news should drive IVols up whereas bearish news should bring IVols down. Given the way in which we compute the surprises, bearish surprises are positive and bullish surprises are negative. Empirical support for Hypothesis 2 therefore requires that, in Equation (2), the coefficients of surprises be negative for both bearish and bullish surprises. However, this is not the case for GS reports, as the coefficients of bearish GS surprises are consistently positive for all markets—and statistically highly significant for corn and soybeans. This finding implies that *any* GS surprise, whether bearish or bullish for prices, drives IVols upward. Moreover, the marginal increases are of very similar magnitudes, which explains why the GS coefficient was insignificant in the pooled regression.

Differentiating between bullish and bearish surprises does not affect our main results. while While the effect of GS dispersion on corn IVol changes becomes insignificant in Equation (2), WASDE dispersion remains a significant contributor to corn and soybean IVol decreases. GS forecast pessimism now significantly impacts IVol decreases now only for corn but also for beans. The coefficient of Pessimistic AR remains robust. In general, this result is more consistent with the theory that we discussed previously. Finally, we note that the regression coefficients for the VIX return and the slope of the futures term structures are qualitatively similar in Tables 5 and 6: we turn to this question next.

5.4. Hypothesis 5: Macroeconomic Uncertainty and Financial Market Sentiment.

We obtain *negative* coefficients for all three markets. *Ceteris paribus*, a one-percent VIX increase on the announcement day is associated with an around 0.1 percent *drop* in IVol. This finding contradicts our Hypothesis 5, which states that (like any other day) if the VIX goes up on a USDA announcement day, then commodity IVols should go up that day, too. The fact that IVols move opposite from the VIX on scheduled USDA event days thus contradicts our prediction in Hypothesis 5, as well as the empirical relationship documented on a daily basis by Adjemian *et al*. (2017) and Goyal and Adjemian (2020) that VIX and commodity IVols are positively correlated.

This surprising finding lends additional support for the role of the USDA information as the "new consensus." Assuming that commodity IVol changes are generally positively driven by VIX changes, then on those few days when the USDA announcements take place, the USDA news helps mitigate the VIX spillover. Put differently, the influence of financial market uncertainty and sentiment is reduced in agricultural markets on USDA event days. In order to verify this conjecture, we run an additional, daily analysis of IVol changes on VIX changes for our entire sample period.[26] For each commodity, we run the following regression across all 2,567 days in our sample:

$$(3) \qquad \Delta IVol_t = \beta_0 + \beta_1 \Delta VIX_t + \beta_2 D_{USDA} + \beta_3 \Delta VIX_t * D_{USDA,t} + \beta_4 \Delta IVol_{t-1} + \varepsilon_t,$$

in which $\Delta IVol_t$ is the daily log-difference of IVol, ΔVIX_t is the daily log-difference of VIX, and $D_{USDA,t}$ is a dummy variable set equal to 1 when day t is a USDA announcement day. Our main purpose in using Equation (3) is to see whether the relation between $\Delta IVol_t$ and ΔVIX_t is significantly different on USDA announcement days and other days. Analogously to Goyal and Adjemian (2020), we first use simple OLS to estimate equation (3). Since the error terms of our OLS estimation exhibit autocorrelation for the three commodities according to the Durbin-Watson test, we also estimate equation (3) with standard GARCH (*i.e.*, sGARCH) and exponential GARCH (*i.e.*, eGARCH). For the sGARCH and eGARCH models, our diagnostic tests indicate that a GARCH(1,1) with ARMA(1,1) is sufficient for corn, while soybeans and wheat require a GARCH(1,1) with ARMA(3,1).

The estimation results are reported in Table 7. Our results show that, consistent with earlier studies, the coefficients of ΔVIX_t (i.e. β_1) are significantly positive for corn.[27] Likewise, β_2 is consistently negative and highly significant for all commodities and specifications, which strengthens our earlier finding that USDA reports significantly reduce commodity IVols. However, the effects of the VIX change on the IVol returns are all reversed on USDA announcement days,

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[26] We run the regression analysis in first differences to ensure that all series are stationary.

[27] The VIX regression coefficients are statistically insignificant for soybeans and wheat. This lack of significance likely reflects the two facts that, (i) among all the determinants of agricultural IVols, macroeconomic uncertainty and financial market sentiment matter the most during periods of elevated financial stress as shown in the historical decomposition of Adjemian *et al.* (2017) and (ii) with the exception of August 2011, there is no major VIX spike after 2009.

with β_3 being negative across all commodities and specifications—with statistically significant coefficients for corn (all models) and soybeans (eGARCH model). Moreover, in all cases, the absolute size of β_3 is much larger than that of β_1, leading to a negative *net* effect of the VIX change on the IVol change on USDA announcement days. This result indicates that, while in general commodity IVols are positively affected the changes in macroeconomic conditions (instrumented by the VIX), this relationship does not hold on USDA announcement days. This result further supports our interpretation that, when there is more macroeconomic uncertainty yet commodity-specific consensus-making information is available through the USDA reports, grain and oilseed market participants rely more on the information in the reports (i.e., they give it more weight). This result also points to the need for more theoretical work on the matter.

5.5. Discussion: Correlation or causality?

Since OLS coefficients only tell us about the correlation of variables, it is reasonable to ask whether Bloomberg analyst surveys truly influences the IVol change on USDA announcement days, or whether the correlation might be spurious. Balduzzi, Elton and Green (1998) suggest 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 from the results (see Appendix 3 for details) that Bloomberg analyst forecasts are informationally valuable to market participants. Importantly, the median forecasts appear to provide unbiased predictions of the corresponding USDA announced information. Together with the generally small size of the surprises, this result indicates that, in the specific case of Bloomberg forecast, we do not have the problem with measurement errors in supply expectations—as tentatively raised by Karali, Irwin, and Isengildina-Massa (2019).

6. Conclusion

We provide novel evidence on 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, Grain Stocks, Prospective Plantings, and Acreage), forward-looking volatilities (IVols) are significantly lower in agricultural markets than they had been a week before the release. The USDA reports' uncertainty-resolution power is substantial and similar in magnitude for the corn, soybeans, and wheat markets.

We document for the first time that the benefit of the USDA information is greater when there is more disagreement among market experts in the run-up to a report (WASDE) and smaller when the USDA news surprises the market. Although commodity IVols are, in general, positively related to broad financial-market sentiment and macroeconomic uncertainty (jointly captured by the VIX index), we show that this co-movement surprisingly breaks down on USDA report days—with the VIX and commodity IVols moving in opposite directions on that day. Finally, in the case of the critical Grain Stocks reports, we show that the calming effect of USDA news is larger when market analysts had been pessimistic about stock levels: commodity expert sentiment also matters.

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 uncertainty and 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 and risk management 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.

Our findings suggest several venues for further research. First, most our empirical predictions are theoretically grounded based on an extension of the Ederington and Lee (1996) model of implied volatility around scheduled public announcements. While our empirical analysis provides strong support for most of those predictions, it also points to the need for more theoretical work to better understand (i) why analyst surprises regarding grain inventories boost (*ceteris paribus*) the market's *post*-USDA-report volatility expectations even when the surprise is bearish for prices and volatility and (ii) why the generally positive relationship between VIX returns and commodity IVols breaks down on USDA event days.

Second, our paper focuses on commodity IVols that can be used as forecasts of future realized volatility. Those IVols are computed using the most liquid, at-the-money, options. Options on agricultural commodities, however, are unique in that out-of-the-money call options are usually more expensive than puts (Norland, 2019). In other words, agricultural options exhibit positive skew. Given that the underlying returns in these markets generally do not exhibit positive skewness, the likely explanation is market structure: food buyers appear more willing to pay a premium for upside protection than farmers seem ready to pay for downside protection. A natural question is what happens to the volatility skew around USDA events. We leave this question for further research.

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Appendix 1. Reference for "Pessimism" in Forecasts

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

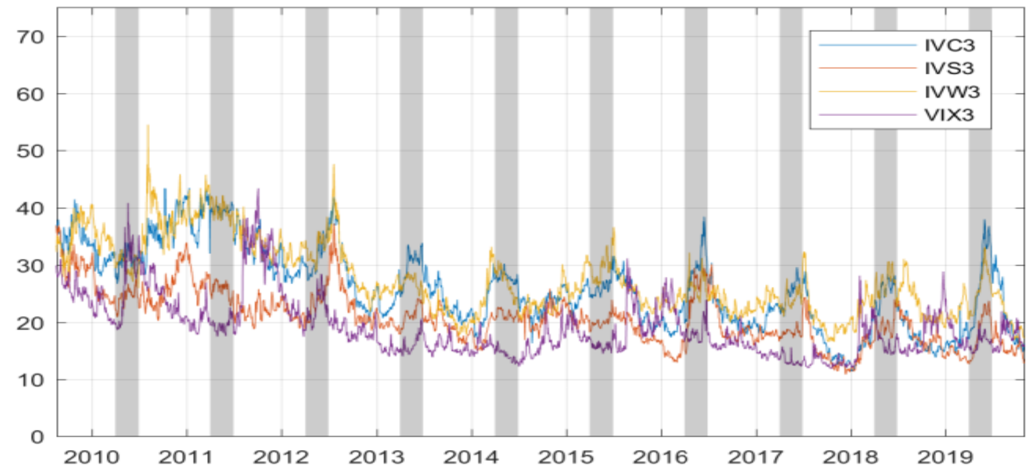
1. WASDE. The forecast we use is also the most frequently surveyed information—the projected U.S. ending stock of the current marketing year. Every month, the USDA update the projections in the WASDE in light of demand and supply developments. As the most suitable baseline for the forecast, we choose the actual value in previous month's report.

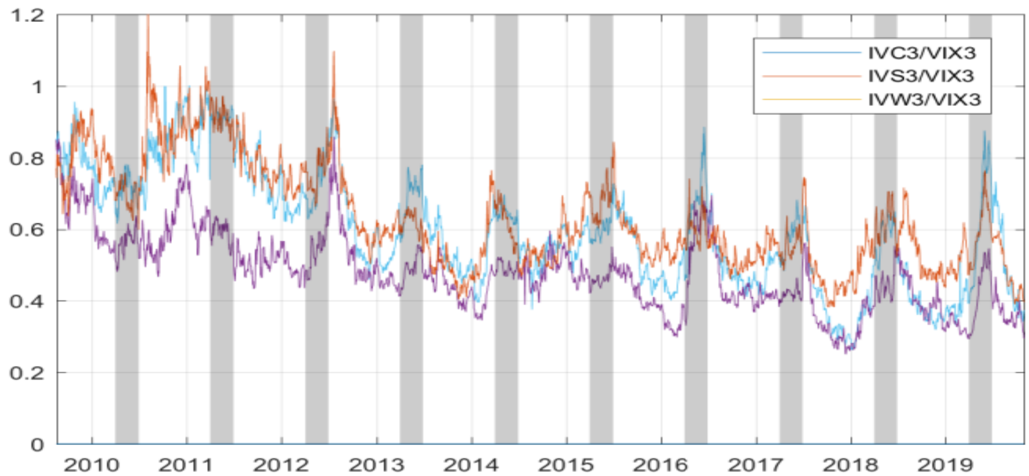
2. GS reports. The USDA estimates U.S. ending stocks as of the end of the previous quarter. Due to the seasonality of crop production and demand, grain and oilseed inventories also fluctuate seasonally. We therefore use the same period (*i.e*., quarter) of the previous year as the reference point. When forecasters predict a lower *(resp. higher)* stock level than at the same time in the prior year, we call them "pessimistic" *(resp. "optimistic")* about the inventory situation.[28]

3. PP and AR report. The Prospective Plantings and Acreage reports both provide information on the planting area of the current crop year. By construction, the AR report is the updated version of the PP report for the same crop year. For the AR report, we therefore proceed as for the WASDE reports, and use the earlier information (in the PP report) to determine if the estimates in the later report (AR) is lower ("pessimistic") or higher ("Optimistic"). For the PP report, we define "optimistic" or "pessimistic" analyst sentiment by comparing the current year's planting intentions (in the PP report) to the planted area in the previous year (in the prior year's AR report).

[28] A similar kind of terminology is often used in the media for a range of financial variables (inflation, GDP, etc.).

Appendix 2. Seasonality of Agricultural Option-implied Volatilities (IVol), 2009-2019





Note: The above figures plot the daily values of the 3-month VIX and of the forward-looking return volatilities that are embedded in the prices of (synthetic) constant-maturity 90-day at-the-money options on agricultural futures (corn, IVC3; soybean, ICS3; soft red winter wheat, IVW3) from August 2009 through September 2019. The top panel plots the actual values in percent. The bottom panel expresses the commodity IVols in terms of the contemporaneous VIX. The spring season is shaded to better highlight the seasonality of the commodity IVols (Source: Bloomberg).

Appendix 3. Informational Value of the Bloomberg-Survey Analyst Forecasts

Balduzzi, Elton and Green (1998) propose the regression equation (hereafter, the BEG equation):

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

where $A_{i\tau}$ and $F_{i\tau}$ are, respectively, the actual and the forecasted values of indicator i for the announcement day τ, 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 Stocks estimates (there are too few observations for the regression to make sense in the case of PP and AR reports). The original BEG regression is presented in the first two columns of Table A3.1 ("BEG1"); in the next two columns ("BEG2"), R_τ is replaced by $Rivol_\tau$ (*i.e.*, the log of the change in commodity implied volatility from the forecast day to the announcement day). Finally, the last two columns ("BEG3") include both R_τ and $Rivol_t$ in one regression.

Table A3.1: BEG regression results

	BEG1		BEG2		BEG3	
	WASDE	GS	WASDE	GS	WASDE	GS
A. Corn						
Intercept (α_0)	27.29	38.02	-8.67	43.69	10.66	50.58
	(31.47)	(43.91)	(35.42)	(56.46)	(33.08)	(44.31)
$F_{i\tau}$	0.99***	1.00***	1.00***	1.00***	0.99***	1.00***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
R_τ	-1856***	-2474***			-1694***	-2620***
	(361)	(522)			(374)	(526)
$Rivol_\tau$			-516***	109.	-284	386
			(190)	(347)	(183)	(278)
B. Soybeans						
Intercept (α_0)	5.25	11.13	-5.14	9.33	5.09	10.25
	(6.18)	(9.96)	(7.42)	(9.98)	(6.84)	(10.12)
$F_{i\tau}$	1.00***	0.99***	1.01***	0.99***	1.00***	0.99***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
R_τ	-787***	-168			-785***	-152
	(130)	(208)			(138)	(211)
$Rivol_\tau$			-103*	-71.58	-3.00	-63.80
			(58)	(95.64)	(55.03)	(96.85)
C. Wheat						
Intercept (α_0)	6.94	14.60	15.34	15.95	12.90	31.88
	(14.62)	(25.71)	(15.30)	(27.87)	(15.01)	(29.19)
$F_{i\tau}$	1.00***	1.00***	0.99***	1.00***	0.99***	0.99***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
R_τ	-209**	-205			-269**	-467
	(103)	(209)			(109)	(298)
$Rivol_\tau$			48.12	19.79	103	234
			(63.02)	(136)	(65.77)	(191)

Statistical significance code: *** *0.01* ** *0.05* * *0.10*

The regressions show that, for all three agricultural commodities and for 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 for the implied volatility change tends to become insignificant.

Table 1: USDA Reports Overview

	WASDE	Grain Stocks (GS)	Prospective Plantings (PP)	Acreage (AR)
Frequency	Monthly	Quarterly	Yearly	Yearly
Timing	2nd week of the month	End of Quarter	End of March	End of June
Overlap	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

Note: Table 1 describes the 151 USDA reports that we collect for our sample from September 2009 through October 2019. On some dates, the USDA releases more than one report: the third row in the table (labeled "Overlaps") shows which of the WASDE, GS, PP and AR reports overlap. For part of the empirical analysis (see Table 5 & 6), we include information regarding expert opinions prior to the USDA news release: consensus analyst forecast, analyst dispersion, and analyst sentiment. Our estimates of analyst opinions come from periodic Bloomberg surveys of market experts. The last row in Table 1 indicates the baseline that we use to characterize whether the analyst consensus about upcoming news is optimistic or pessimistic, as explained in Appendix 1.

Table 2: Summary Statistics

	Median	Mean	StdDev	Min	Max	No. Obs	Obs < 0
VIX	17.65	18.99	5.15	11.85	43.38	2567	N/A
VIX change[1], average on all USDA event days	-0.009	-0.003	0.047	-0.109	0.184	151	88
Panel A: Corn							
IVol, daily	25.68	26.06	7.06	11.41	45.09	2567	N/A
IVol, average on USDA event days[2]	25.41	25.80	6.73	11.73	43.34	151	N/A
IVol, big-event days[3]	23.84	25.13	7.03	11.73	43.34	82	N/A
Ivol change, daily	-2.8e-4	-2.9e-4	0.03	-0.41	0.36	2567	1295
Ivol change, average on USDA event days	-0.027	-0.032	0.053	-0.231	0.198	151	119
Ivol change, average on big-event days	-0.057	-0.045	0.063	-0.231	0.199	82	69
Slope[4]	0.098	0.053	0.157	-0.821	0.097	151	20
WASDE surprise[5]	0.004	0.006	0.077	-0.242	0.326	121	52
Grain Stocks surprise	0.002	0.011	0.068	-0.165	0.196	41	20
Prospective Planting 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[6]	0.065	0.083	0.058	0.006	0.253	121	N/A
Grain Stocks dispersion	0.021	0.029	0.024	0.009	0.131	41	N/A
Prospective Planting 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 forecast change[7]	0.000	-0.005	0.169	-0.621	1.008	121	58
Grain Stocks forecast change	0.010	0.010	0.189	-0.558	0.376	41	15
Prospective Planting forecast change	0.012	0.002	0.030	-0.043	0.043	10	4
Acreage forecast change	-0.003	-0.011	0.022	-0.067	0.006	10	6

[1] "Changes" are computed as the log difference of the current value from the previous period's value, except for forecast changes as explained below.

[2] Averages on USDA event days are computed for all 151 Grain Stocks, Prospective Planting, Acreages and WASDE announcement days in our September 2009-October 2019 sample.

[3] "Big-event" days includes the WASDE reports in January, August, September, October, and November (not any other) and all Grain Stocks, Prospective Plantings, and Acreages report, as discussed in Adjemian & Irwin (2018).

[4] The slope of the term structure of future prices for each commodity is computed at the weekly frequency on Tuesday. We use the slope on the nearest Tuesday prior to the USDA announcement day, using the nearby and first-deferred contracts.

[5] "Analyst surprise" is defined as the log difference of the USDA announced value and the median Bloomberg analysts forecast.

[6] "Analyst dispersion" is defined as the interquartile range of the forecast distribution divided by mean forecast.

[7] "Forecast change" is the log difference of the current period's variable and from the reference point, forecasted by the analysts. See details in Appendix 1.

Table 2 *(cont.)*: Summary Statistics

	Median	Mean	StdDev	Min	Max	No. Obs	Obs < 0
Panel B: Soybeans							
IVol, daily	20.43	20.72	4.63	10.87	37.23	2567	N/A
IVol, average on USDA event days[1]	19.98	20.35	4.40	11.05	31.95	151	N/A
IVol, big-event days[2]	19.84	20.03	4.44	11.36	31.95	82	N/A
Ivol change,[3] daily	-0.001	-4.2e-4	0.032	-0.301	0.258	2567	1337
Ivol change, average on USDA event days	-0.020	-0.022	0.045	-0.153	0.210	151	114
Ivol change, average on big-event days	-0.036	-0.032	0.048	-0.153	0.155	82	67
Slope[4]	0.029	-0.038	0.190	-1.193	0.078	151	50
WASDE surprise[5]	0.000	0.000	0.101	-0.310	0.452	121	55
Grain Stocks surprise	-0.011	0.001	0.091	-0.346	0.265	41	26
Prospective Plantings 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[6]	0.111	0.125	0.076	0.011	0.401	121	N/A
Grain Stocks dispersion	0.036	0.047	0.030	0.012	0.118	41	N/A
Prospective Plantings 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 forecast change[7]	0.000	0.007	0.146	-0.357	0.747	121	60
Grain Stocks forecast change	0.077	0.093	0.298	-0.623	0.821	41	11
Prospective Plantings forecast change	0.013	0.008	0.031	-0.041	0.053	10	3
Acreage forecast change	0.008	0.010	0.008	0.000	0.022	10	1

[1] Averages on USDA event days are computed for all 151 Grain Stocks, Prospective Planting, Acreages and WASDE announcement days in our September 2009-October 2019 sample.

[2] "Big-event" days includes the WASDE reports in January, August, September, October, and November (not any other) and all Grain Stocks, Prospective Plantings, and Acreages report, as discussed in Adjemian & Irwin (2018).

[3] All "changes" are computed as the log difference of the current value from the previous period's value, except forecast changes as explained below.

[4]The slope of the term structure of future prices for each commodity is computed at the weekly frequency on Tuesday. We use the slope on the nearest Tuesday prior to the USDA announcement day, using the nearby and first-deferred contracts.

[5] "Analyst surprise" is defined as the log difference of the USDA announced value and the median Bloomberg analysts forecast.

[6] "Analyst dispersion" is defined as the interquartile range of the forecast distribution divided by mean forecast.

[7] "Forecast change" is the log difference of the current period's variable and from the reference point, forecasted by the analysts. See details in Appendix 1.

Table 2 *(cont.)*: Summary Statistics

	Median	Mean	StdDev	Min	Max	No. Obs	Obs < 0
Panel C: SRW Wheat							
IVol, daily	25.89	27.49	6.29	16.56	54.51	2567	N/A
IVol, average on USDA event days[1]	25.60	27.20	6.17	17.03	45.43	151	N/A
IVol, big-event days[2]	26.19	27.72	5.99	17.63	45.43	81	N/A
Ivol change,[3] daily	-8.8e-4	-2.5e-4	0.0318	-0.165	0.193	2567	1327
Ivol change, average on USDA event days	-0.026	-0.023	0.038	-0.130	0.126	151	119
Ivol change, average on big-event days	-0.022	-0.022	0.042	-0.119	0.126	81	66
Slope[4]	0.122	0.123	0.072	-0.013	0.380	151	2
WASDE surprise[5]	0.006	0.007	0.039	-0.139	0.138	121	45
Grain Stocks surprise	0.012	0.007	0.029	-0.074	0.055	41	16
Prospective Plantings 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	9	4
WASDE dispersion[6]	0.035	0.047	0.039	0.004	0.259	121	N/A
Grain Stocks dispersion	0.025	0.029	0.014	0.009	0.071	41	N/A
Prospective Plantings 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	9	N/A
WASDE forecast change[7]	0.000	-0.005	0.042	-0.217	0.103	121	41
Grain Stocks forecast change	0.039	0.029	0.146	-0.189	0.343	41	16
Prospective Plantings forecast change	-0.013	-0.025	0.056	-0.111	0.053	10	6
Acreage forecast change	-0.001	-0.002	0.010	-0.023	0.010	9	5

[1] Averages on USDA event days are computed for all 151 Grain Stocks, Prospective Planting, Acreages and WASDE announcement days in our September 2009-October 2019 sample.

[2] "Big-event" days includes the WASDE reports in January, August, September, October, and November (not any other) and all Grain Stocks, Prospective Plantings, and Acreages report, as discussed in Adjemian & Irwin (2018).

[3] All "changes" are computed as the log difference of the current value from the previous period's value, except forecast changes as explained below.

[4]The slope of the term structure of future prices for each commodity is computed at the weekly frequency on Tuesday. We use the slope on the nearest Tuesday prior to the USDA announcement day, using the nearby and first-deferred contracts.

[5] "Analyst surprise" is defined as the log difference of the USDA announced value and the median Bloomberg analysts forecast.

[6] "Analyst dispersion" is defined as the interquartile range of the forecast distribution divided by mean forecast.

[7] "Forecast change" is the log difference of the current period's variable and from the reference point, forecasted by the analysts. See details in Appendix 1.

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
Panel A. Corn				
All USDA announcements	**-6.39*****	**-7.24*****	**6.66*****	**83.38*****
	(<0.00)	**(<0.00)**	**(<0.00)**	**(<0.00)**
Big-event days	**-5.89*****	**-6.05*****	**16.47*****	**187.03*****
	(<0.00)	**(<0.00)**	**(<0.00)**	**(<0.00)**
Small-event days	**-3.51*****	**-3.58*****	**2.21*****	**16.62***
	(<0.00)	**(<0.00)**	**(0.02)**	**(0.06)**
Panel B. Soybeans				
All USDA announcements	**-5.13*****	**-6.17*****	**3.55*****	**58.68*****
	(<0.00)	**(<0.00)**	**(<0.00)**	**(<0.00)**
Big-event days	**-5.60*****	**-5.27*****	**6.70*****	**102.81*****
	(<0.00)	**(<0.00)**	**(<0.00)**	**(<0.00)**
Small-event days	**-1.41***	**3.30*****	1.14	8.54
	(0.08)	**(<0.00)**	(0.32)	(0.58)
Panel C. SRW Wheat				
All USDA announcements	**-6.86*****	**-7.05*****	**4.00*****	**62.58*****
	(<0.00)	**(<0.00)**	**(<0.00)**	**(<0.00)**
Big-event days	**-4.45*****	**-4.62*****	**4.29*****	**54.80*****
	(<0.00)	**(<0.00)**	**(<0.00)**	**(<0.00)**
Small-event days	**-5.55*****	**-5.40*****	0.8	**17.70***
	(<0.00)	**(<0.00)**	(0.63)	**(0.06)**

Note: The first two columns present the two-sample parametric (t-test) and nonparametric test statistics 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. P-values of the test-statistics are reported in the brackets. For each commodity, we run the tests for all USDA announcement days as well as for "big-event" days and "small-event" days separately.

Significant code: ****0.01* ***0.05* **0.10*

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

A. 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.

Significant code: *** *0.01* ** *0.05* * *0.10*

Table 4 (cont.): p-value matrix of ANOVA-based multiple comparison tests among days in the window event and paired t-test to average 5 days before

B. Soybeans	$\overline{ivol}$	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$	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

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.

Significant code: *** *0.01* ** *0.05* * *0.10*

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

C. 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

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.

Significant code: ****0.01* ***0.05* **0.10*

Table 5: Forecast surprise, Analyst Dispersion, Expert Sentiment, and Commodity IVol Changes on Scheduled USDA Announcement Days

	Corn	**Soybeans**	**Wheat**
Intercept (β_0)	**-0.038***	-0.027	**-0.022****
	(0.020)	(0.022)	**(0.011)**
WASDE Surprise	**-0.238****	**-0.104***	0.081
	(0.098)	**(0.061)**	(0.082)
Grain Stocks Surprise	0.140	-0.013	0.129
	(0.212)	(0.075)	(0.287)
Prospective Planting Surprise	-2.139	0.816	-0.810
	(1.896)	(1.158)	(0.775)
Acreage Surprise	-0.984	0.024	-0.909
	(1.153)	(0.544)	(2.366)
WASDE Dispersion	**-0.153***	-0.029	**-0.219*****
	(0.082)	(0.061)	**(0.087)**
Grain Stocks Dispersion	**0.578****	0.335	-0.019
	(0.253)	(0.223)	(0.310)
Prospective Planting Dispersion	1.221	-0.957	0.350
	(6.647)	(1.629)	(1.381)
Acreage Dispersion	-2.745	-1.197	-0.158
	(3.923)	(2.028)	(2.248)
Pessimistic WASDE forecast	0.007	0.008	0.000
	(0.009)	(0.009)	(0.008)
Pessimistic Grain Stocks forecast	**-0.055****	-0.016	-0.016
	(0.024)	(0.018)	(0.018)
Pessimistic Prospective Planting forecast	-0.046	-0.002	-0.034
	(0.092)	(0.029)	(0.023)
Pessimistic Acreage forecast	0.021	**-0.080*****	0.002
	(0.037)	**(0.018)**	(0.044)
VIX change	**-0.118***	-0.125	**-0.097***
	(0.069)	(0.076)	**(0.052)**
Truncated slope	-0.019	0.013	**2.072*****
	(0.019)	(0.018)	**(0.794)**
OLS Adjusted R-squared	*0.192*	*0.0689*	*-0.0495*
Heteroskedasticity-consistent Wald-statistics	***108.08******	***557******	***41.18*****

Notes: Table 5 provides OLS estimates of the impact of forecast surprises, analyst dispersion, and analyst pessimism on IVol changes on the day of scheduled USDA announcements.

- Heteroskedasticity-consistent standard errors are reported in brackets.
- The sample period covers all WASDE, Grain Stocks, Prospective Planting, and Acreage reports from September 2009 to October 2019. Corn and Soybean models have 151 announcement-day observations. Wheat analyst survey data not available for the June 2010 Acreage report. We therefore exclude this observation from the wheat sample, leading to 150 observations.
- For each commodity, other control variables include two daily lags of nearest-to-maturity future returns, two daily lags of the VIX return (log-difference), two daily lags of the IVol return, seasonal dummies, and day-of-the-week dummies.
- Statistical significance code: *** *0.01* ***0.05* **0.10*

Table 6: Bearish *vs*. Bullish Surprises and IVol Changes on USDA Announcement Days

	Corn	**Soybeans**	**Wheat**
Intercept (β_0)	**-0.052*****	-0.023	**-0.023****
	(0.018)	(0.022)	**(0.012)**
Bearish WASDE Surprise	-0.084	0.091	-0.089
	(0.120)	(0.078)	(0.134)
Bullish WASDE Surprise	**-0.418***	**-0.307****	-0.058
	(0.247)	**(0.127)**	(0.158)
Bearish Grain Stocks Surprise	**0.744****	**0.316*****	0.506
	(0.373)	**(0.104)**	(0.667)
Bullish Grain Stocks Surprise	**-0.703***	**-0.274*****	-0.402
	(0.392)	**(0.088)**	(0.628)
Bearish Prospective Planting Surprise	-1.323	**-3.571****	-1.172
	(2.861)	**(1.484)**	(1.477)
Bullish Prospective Planting Surprise	-4.615	2.125	-0.631
	(3.227)	(1.364)	(1.190)
Bearish Acreage Surprise	-2.142	-0.413	2.584
	(2.080)	(1.150)	(3.724)
Bullish Acreage Surprise	-0.205	0.921	**-12.327***
	(2.357)	(0.964)	**(6.869)**
WASDE Dispersion	**-0.183****	-0.113	**-0.201***
	(0.075)	(0.072)	**(0.105)**
Grain Stocks Dispersion	-0.343	0.139	-0.431
	(0.497)	(0.253)	(0.444)
Prospective Planting Dispersion	-0.013	0.896	0.526
	(8.742)	(1.716)	(2.160)
Acreage Dispersion	1.247	1.428	-5.079
	(6.152)	(3.122)	(4.367)
Pessimistic WASDE forecast	0.009	0.006	0.000
	(0.008)	(0.009)	(0.008)
Pessimistic Grain Stocks forecast	**-0.065*****	**-0.043*****	-0.012
	(0.024)	**(0.016)**	(0.018)
Pessimistic Prospective Planting forecast	-0.049	-0.019	-0.032
	(0.070)	(0.027)	(0.027)
Pessimistic Acreage forecast	0.007	**-0.079*****	-0.017
	(0.046)	**(0.018)**	(0.042)
VIX change	**-0.131***	-0.111	**-0.097***
	(0.072)	(0.077)	**(0.053)**
Truncated slope	-0.011	-0.005	**1.965****
	(0.019)	(0.019)	**(0.879)**
Adjusted R-squared	*0.235*	*0.144*	*-0.041*
Heteroskedasticity-consistent Wald-statistics	***293.27******	***1380******	***51.40******

Notes: Table 6 OLS estimates of the asymmetric effect of forecast surprises on IVol change on the day of USDA announcements. Whereas Table 5 makes no difference between price-bullish and price-bearish surprises, Table 6 does. See the footnote to Table 5 for details on the sample period, variables, and notations.

Table 7: General effect *vs*. USDA Event-day Impact of VIX changes on IVol Changes

	Corn			Soybeans			Wheat		
	OLS	sGARCH	eGARCH	OLS	sGARCH	eGARCH	OLS	sGARCH	eGARCH
Intercept	**0.002*****	**0.002*****	**0.002*****	0.001	0.000	**0.001*****	**0.001***	**0.001****	**0.001*****
	(0.001)	**(0.001)**	**(0.000)**	(0.001)	(0.001)	**(0.000)**	**(0.001)**	**(0.000)**	**(0.000)**
VIX	**0.032****	**0.043*****	**0.047*****	0.003	0.011	0.013	-0.006	-0.004	-0.005
	(0.014)	**(0.013)**	**(0.006)**	(0.014)	(0.015)	(0.009)	(0.014)	(0.012)	(0.012)
USDA announcement	**-0.034*****	**-0.033*****	**-0.032*****	**-0.023*****	**-0.023*****	**-0.022*****	**-0.024*****	**-0.028*****	**-0.027*****
	(0.004)	**(0.004)**	**(0.003)**	**(0.004)**	**(0.003)**	**(0.003)**	**(0.003)**	**(0.003)**	**(0.004)**
VIX*USDA announcement	**-0.152***	**-0.159****	**-0.166*****	-0.094	-0.053	**-0.057*****	-0.059	-0.051	-0.059
	(0.088)	**(0.079)**	**(0.021)**	(0.072)	(0.079)	**(0.010)**	(0.051)	(0.054)	(0.055)
Lagged daily Ivol log-difference	-0.045	**-0.814*****	**-0.767*****	0.032	**0.844*****	**0.860*****	0.004	**0.926*****	**0.933*****
	(0.057)	**(0.204)**	**(0.017)**	(0.038)	**(0.072)**	**(0.043)**	(0.028)	**(0.043)**	**(0.017)**
Model statistics									
AIC	-10153	-4.1388	-4.2140	-10339	-4.1420	-4.1585	-10484	-4.2139	-4.2140
BIC	-10118	-4.1114	-4.1798	-10304	-4.1101	-4.1243	-10449	-4.1820	-4.1798
LM tests[1]	**17.375*****	0.4641	0.5078	**11.316*****	3.203	3.860	**15.577*****	2.8289	3.340

Notes: Table 7 provides estimates of the daily impact of VIX changes on commodity IVol changes on USDA *vs*. non-USDA days.

- Heteroskedasticity-consistent standard errors are reported in brackets.
- Daily models cover the period from August 17, 2009 to October 31, 2019.
- For both eGARCH and sGARCH models, we estimate a GARCH(1,1) with ARMA(1,1) for corn, and GARCH(1,1) with ARMA(3,1) for both soybean and wheat based on our diagnostic tests.
- Wald test statistics is reported for OLS models, weighted ARCH LM test statistics is reported for GARCH models at lag 7
- Significant code: *** 0.01 **0.05 *0.10

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

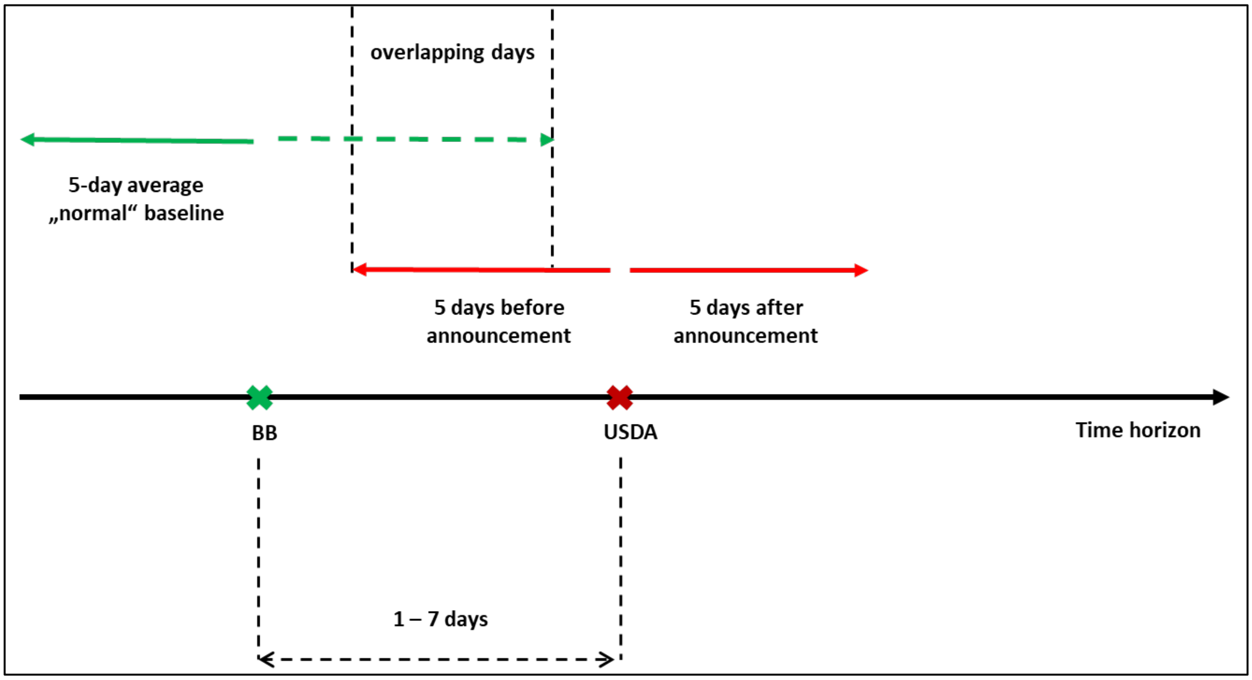
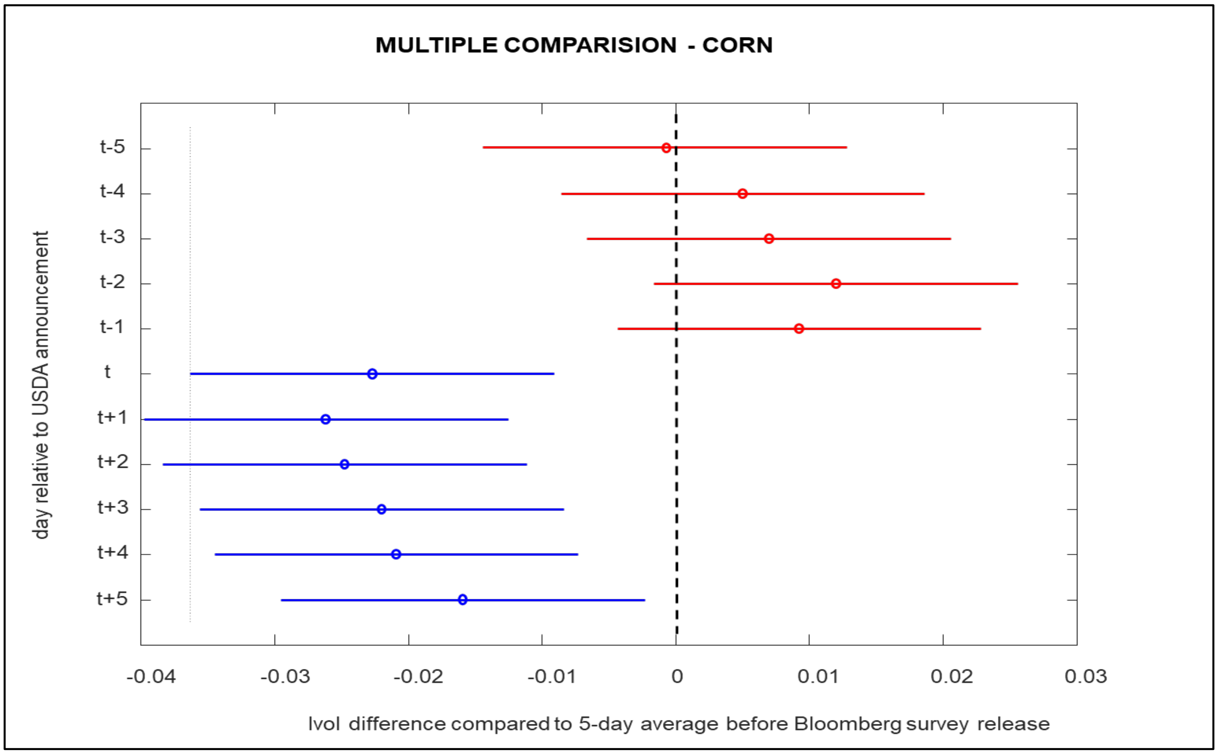


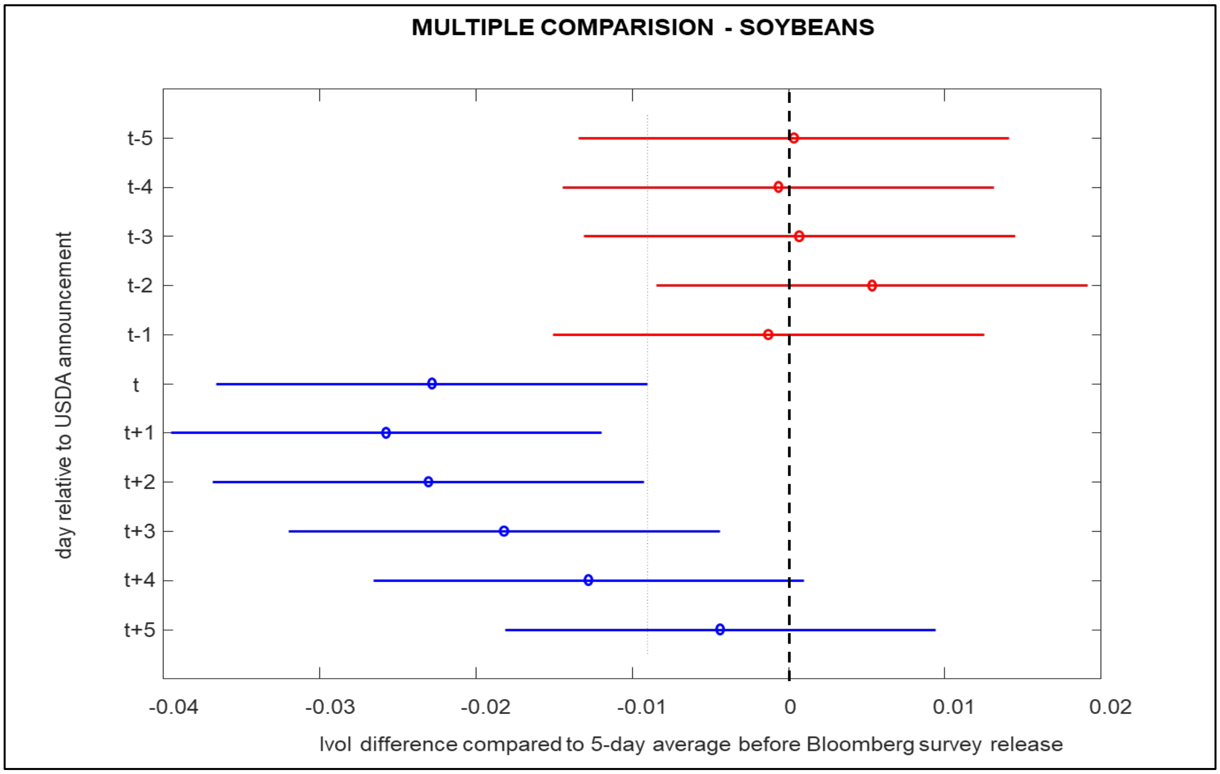
Fig. 2a: Daily IVol Change (*vs*. 5-day average IVol prior to latest Bloomberg survey) – Corn



Note: The circles in Figures 2a (corn) show the mean estimates of $\Delta IVol_{T+i}$ (i=-5, -4, …, +5) for 5 days before and after 151 USDA scheduled announcement days (T) in 2009-2019. For each day, we compute log differences between (a) the 90-day commodity 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 (typically five to seven days before the event day). 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 five days before a USDA announcement are in red; the announcement day T and the next five trading days appear in blue.

Sources: USDA, Bloomberg and authors' computations.

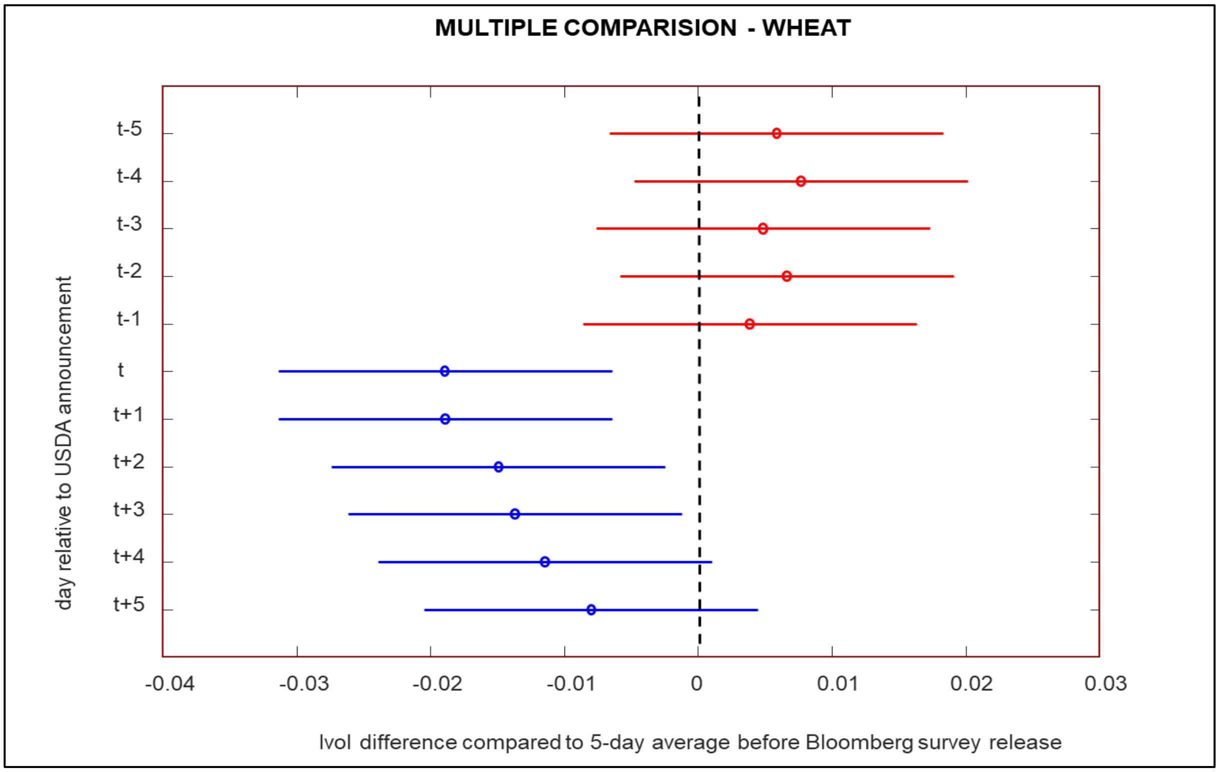
Fig. 2b: Daily IVol Change (*vs*. 5-day average IVol prior to latest Bloomberg survey) – Beans



<u>*Note*</u>: The circles in Figure 2b (soybeans) show the mean estimates of $\Delta IVol_{T+i}$ (i=-5, -4, …, +5) for 5 days before and after 151 USDA scheduled announcement days (T) in 2009-2019. For each day, we compute log differences between (a) the 90-day commodity 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 (typically five to seven days before the event day). 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 five days before a USDA announcement are in red; the announcement day T and the next five trading days appear in blue.

Sources: USDA, Bloomberg and authors' computations.

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



Note: The circles in Figure 2c (soft red winter wheat) show the mean estimates of $\Delta IVol_{T+i}$ (i=-5, -4, …, +5) for 5 days before and after 151 USDA scheduled announcement days (T) in 2009-2019. For each day, we compute log differences between (a) the 90-day commodity 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 (typically five to seven days before the event day). 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 five days before a USDA announcement are in red; the announcement day T and the next five trading days appear in blue.

Sources: USDA, Bloomberg and authors' computations.