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RESEARCH ARTICLE

Market uncertainty and sentiment around USDA announcements

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Abstract

We investigate forward-looking commodity price volatility expectations (proxied by option-implied volatilities or IVols) around scheduled US Department of Agriculture (USDA) reports. We show that corn and soybean IVols are significantly lower for several trading days after a report. The IVol response to a release depends on agricultural market experts' disagreement and sentiment before the USDA report, and on the extent to which the USDA information surprises the market. Whereas commodity IVols are generally positively related to financial-market sentiment and macroeconomic uncertainty (jointly captured by the volatility index [VIX]), this comovement breaks down on report days—with the VIX and commodity IVols moving in opposite directions.

KEYWORDS

commodities, dispersion, forward-looking volatility, market sentiment, scheduled news, surprise

JEL CLASSIFICATION

Q11, G14, G13, G41, Q13

1 | INTRODUCTION

A vast literature in finance documents that equity and bond markets react to many US macroeconomic announcements—see, for example, Kurov et al. (2019). In the commodity space, similarly, prior work shows that agricultural markets react significantly to scheduled US Department of Agriculture (USDA) announcements. The latter fact supports the notion that USDA reports contain valuable news and help resolve disagreements among market participants regarding demand and supply fundamentals.

Most of the literature investigates what happens to commodity price levels on USDA event days (e.g., Adjemian, 2012; Karali, Isengildina-Massa, et al., 2019; Ying et al., 2019) or shows how fast the USDA information is impounded into those prices (e.g., Adjemian & Irwin, 2018; Lehecka et al., 2014). As McNew and Espinosa (1994), McKenzie et al. (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 are our objectives in this paper. We focus on corn and soybeans, because they are the two main US agricultural commodities and also because

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their growing areas and crop (and, thus, news) cycles broadly overlap. Since changes in uncertainty and sentiment map directly into the cost of options-based strategies (Goyal & Adjemian, 2021), our results have important implications not only for policy makers and academics, but also for commodity speculators and 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, financial economists and accountants have long used changes in option-implied return volatilities (“IVols”) to study the impact of news on forward-looking market uncertainty (Ederington & Lee, 1993; Patell & Wolfson, 1979). 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.¹ We extend that prior work along several dimensions.

First, agricultural markets have evolved massively over the course of the past two decades. Quantitatively, the open interests in corn and soybean options and futures are many times what they were 15 years ago (Robe & Roberts, 2019). Qualitatively, changes that could materially impact the manner or the extent of market reactions to USDA news include the growth (and, later, the dominance) of electronic and high-frequency trading (Haynes & Roberts, 2015; Haynes et al., 2017), the demise of the futures trading pits (Gousgounis & Onur, 2018), and the influx of ever more sophisticated private forecasting services (Karali, Irwin, et al., 2019; McKenzie, 2008). Our first contribution is to complement the early literature, which uses data from two decades ago or more (i.e., predating any of those developments), by investigating agricultural 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, prerelease, “impound the anticipated impact of important releases on price volatility and (should) decline postrelease as this uncertainty is resolved” (Ederington & Lee, 1996, p. 513). Using an event-study methodology and data for four different types of USDA announcements in 2009–2019,² we find that the commodity IVols fall significantly on the USDA event day—by 2% (soybean) to 2.7% (corn) on average in our 2009–2019 sample period. While these decreases are smaller in magnitude than those documented by Ederington and Lee (1996) in interest rate markets, they are similar to the IVol drops found for corn and soybeans two decades ago by Isengildina-Massa et al. (2008), using data from 1985 to 2002.³

For USDA reports that market observers generally view as the most important (which make up half of our sample of 151 events), we show that the average IVol drop is almost twice as large—3.6% (soybeans) or 5.7% (corn). Furthermore, the IVol remains significantly lower for at least four trading days, and sometimes more than a week, after the event day. These results complement the finding of Adjemian (2012) and Karali, Irwin et al. (2019) regarding the magnitude of commodity *futures* returns on USDA crop report days: They indicate that, as a group, scheduled USDA reports in recent years remain highly payoff-relevant to agricultural market participants.

Second, our analysis of commodity IVols innovates by recognizing that USDA reports are not released in a vacuum. Precisely, we use regression analyses to establish that the sign and the magnitude of the postrelease IVol change depend on agricultural market experts’ opinions in the runup to a release.

Ahead of all major USDA announcements, companies like Bloomberg and Reuters have for over a decade conducted and published surveys of market analysts’ expectations regarding the upcoming reports. Those news organizations typically release the details of their surveys in the week before the USDA announcement. We argue theoretically and, armed with Bloomberg survey information, provide empirical evidence that the magnitude of the grain and oilseed IVol responses to scheduled USDA announcements is significantly impacted by (i) the gap between the prerelease expert “consensus” forecast and the actual USDA figure (i.e., how big the market surprise is on the event day), (ii) the dispersion of individual expert forecasts around that

¹In 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 generalized autoregressive conditional heteroskedasticity (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 World Agricultural Supply and Demand Estimates (WASDE) report due to a US government shutdown. Fortenbery and Sumner (1993) is the first study of option prices around scheduled USDA events. See Ying et al. (2019) for a thorough review of the literature on USDA announcements.

²We consider the monthly WASDE, quarterly Grain Stocks (GS), annual Prospective Plantings (PP), and annual Acreage (AR) reports. McNew and Espinosa (1994) look at crop production (CP) reports only; Isengildina-Massa et al. (2008) focus on WASDE reports.

³Precisely, Isengildina-Massa et al. (2008) find that the average magnitude of the IVol decline equals about 3% of the annualized IVol level on the day before the report release for corn, and 4% for soybeans. As documented in EL96 and in this paper, the IVol on the day before the event is higher than average.

consensus (which captures disagreements among market experts and, as such, can be seen as a proxy for pre-existing commodity-specific uncertainty), and (iii) the prerelease expert “sentiment.”⁴

Looking first at surprises, we document that their effects are significant mostly in the case of inventories-related news contained in the monthly WASDE (prospective) and quarterly (realized) GS reports. With the GS reports, any surprise—whether “bullish” for prices (when USDA figures come in lower than analysts expected) or “bearish” (when the USDA figures are higher than analyst forecasts)—pushes IVols upward significantly (*ceteris paribus*). In the case of the WASDE reports, the same is true only when the surprise is price-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 Practically speaking, while commodity IVols generally decrease after a USDA report, the decrease is muted (so much so that the forward-looking volatility could actually go up) when the market is caught flat-footed by the USDA—all the more so when the news is bullish for prices.

Next, we look at analyst dispersion, that is, the extent to which market experts disagree about an upcoming report. Intuitively one would expect that, when experts are “confused” as a group, the USDA news would “settle the market”—resetting participants’ expectations and clarifying the path forward. Indeed, for the corn WASDE, the bigger the dispersion of *pre*-event analyst opinions, the more the IVol drops after the USDA release. The results for other corn reports and for soybeans are statistically insignificant, however, which suggests that dispersion matters less than surprises in agricultural markets.

Finally, we tease out how the *pre*-event expert 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 prereport expert forecast predicts a decrease (resp., an increase) in the forecasted USDA variable compared with an objective past reference point. We find, in the case of GS reports (but not other USDA reports), a significant negative association between the analyst pessimism before 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 the analysis, this result indicates that, when experts had been pessimistic about the actual level of grain inventories, the release of the GS information by the USDA has a stronger market-calming effect. This finding is a novel contribution to a large literature showing the importance of inventories to commodity price dynamics—see, for example, 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 et al. (2013) show that the volatility index (VIX; i.e., the Standard and Poor 500 equity-index option-implied volatility) captures jointly the uncertainty about global macroeconomic conditions and the risk aversion among investors. Intuitively, the same should be true in agricultural markets. In essence, insofar as risk aversion affects all asset classes, 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 also 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 versus 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. Section 3 describes the data.

⁴Two recent studies of USDA announcement also consider the possible roles of analyst expectations and uncertainty. Karali, Irwin 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) before 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’ 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.

⁵Price-bearish WASDE surprises, in contrast, do not statistically significantly modify the typical commodity IVol response to a scheduled announcement.

Section 4 discusses our empirical methodology. Section 5 presents our empirical findings. Section 6 concludes and discusses possible extensions.

2 | THEORY AND HYPOTHESIS DEVELOPMENT

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

2.1 | Predicted IVol change before and after a scheduled USDA announcement

As noted in Section 1, EL96 shows 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 a given 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), EL96 argues 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.

For the first term (i), 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.⁶ Thus, if the maturity date of the option (whose price EL96 used 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 (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.

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.⁷

In the EL96 model and in our variant thereof, there is no theoretical reason why the postevent IVol decrease should be a 1-day affair. First, note that USDA news is incorporated into prices promptly (Adjemian & 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

⁶For example, Janzen and Bunek (2017) show that the realized volatility of intraday winter wheat futures prices shoots up right after the USDA reports.

⁷One 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.

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 runup to a USDA report.*

2.2 | Pre-existing commodity-market beliefs and IVol response to USDA news

As noted in Section 1, the present paper is the first to ask whether agricultural IVols' responses to scheduled USDA announcements depend on the extents to which market participants are surprised by the information and to which, before the event, experts disagreed about the upcoming release (a proxy for commodity-market uncertainty) and were pessimistic (a proxy for commodity-market 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. It is the unanticipated shock that leads market participants to revise their expectations postevent. For equities, the surprise captures the unexpected information brought to the market by corporate or government reports (e.g., Balduzzi et al., 2001).

As noted in Section 2.1, the surprise is zero *on average* in the EL96 model, and so part (ii) of the IMV change on the event day T is zero. Equity, bond, and forex markets, however, tend to react asymmetrically to “good” versus “bad” news. For example, Braun et al. (1995) find significant predictive asymmetry in both the market-wide and the firm-specific components of volatility for various stock portfolios. In a real-time analysis of US dollar spot exchange rates, Andersen et al. (2003) report larger surprise-induced conditional-mean jumps when the surprise is bad, compared with the good surprise case. In the same vein, Beber and Brandt (2010) investigate the respective effects of good versus bad macroeconomic news in the US 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.

There is no reason to believe that commodity markets are any different. One can readily extend the EL96 model to account for the fact that 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, for example, 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.⁸ Defining *price-bullish surprises* as “tighter commodity supply and/or inventories or higher demand than expected, which should boost prices and volatility,” and *price-bearish surprises* as the opposite, one can 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' prerelease 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) postrelease than it does on average.*⁹

⁸See Baur and Dimpfl (2018) for a recent summary of that literature.

⁹Hypothesis 2 predicts that the effect of a USDA surprise is asymmetrical. 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 is, the smaller the IVol drop should be (or, in extreme cases, the commodity IVol could even increase after any surprise).

2.2.2 | Forecast dispersion

Intuitively, the magnitude of the IVol change after a scheduled USDA report should 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 (Dubinsky et al., 2019; Johnson, 2004).¹⁰ If this view is shared by those who predict future price 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—once the announcement has taken place. Therefore, we have:

Hypothesis 3 – *Ceteris paribus, the IVol change after a USDA information release is inversely related to the prerelease dispersion of analyst forecasts.*

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 et al. (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 is likely to be followed by other negative news, which could imply that more uncertainty ought to be expected for the future (and vice versa).

Proxying 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 should expect higher volatility on day T (compared with 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). Therefore, we have:

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

2.3 | Global macroeconomic environment and commodity IVol response on event day

Hypotheses 3 and 4 look, respectively, at the possibilities that the preannouncement commodity-market uncertainty and sentiment could impact the IVol response to the USDA news. In this subsection, we turn to the possibility that changes in the macroeconomic environment on the event day T itself may also matter for the commodity IVol behavior that day.

Recent empirical work finds that, for a wide range of commodities, IVols are impacted by the VIX: When the VIX increases, IVols go up—and vice versa.¹¹ To tease out the impact of scheduled USDA events on corn and soybean IVols, one should therefore control for concomitant changes in the macroeconomic and financial environments:

Hypothesis 5 – *The IVol response to the USDA news depends on the VIX return on the event day, that is, on concomitant changes in broad financial-market uncertainty and sentiment.*

¹⁰Another view brought by the difference-of-opinion school of thought (e.g., Diether et al., 2002), posits that forecast dispersion is a result of diverging opinions among market participants, which brings about mispricing once short-sale constraints arise in the market. In the case of commodity futures markets, however, this argument seems moot since there are no short-sales constraints.

¹¹See Robe and Wallen (2016) in the crude oil space. See Covindassamy et al. (2017) in the softs space. And see Adjemian et al. (2017) and Goyal and Adjemian (2021) in the livestock and grains spaces.

3 | DATA

We examine four groups of scheduled USDA announcements: monthly WASDE, quarterly GS, and annual PP and AR reports. Those are the main reports published by the USDA about the global grain and oilseed markets.

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 per year due to US 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. Altogether, we collect a sample of 151 USDA announcement days and the corresponding Bloomberg surveys for 181 reports in total. Table 1 synthesizes the characteristics of the reports, including their coverage, frequency and timing, and key information surveyed by Bloomberg.

Since September 2009, Bloomberg has conducted analyst surveys before each of these reports. Results of the surveys are released at varying times on Bloomberg News, typically 1 week before USDA release. The exact timing of the result release is not documented in the survey data set, so we recover it by tracing back each release on Bloomberg News manually to define the event window for our analysis.

Our Bloomberg survey data set contains detailed information about the forecasters who participated in each survey. 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 both a “consensus” value (which we set as the median analyst forecasts) and the dispersion of individual analyst forecasts around the consensus.

A few of the USDA reports overlap. Specifically, the PP (March) and AR (June) reports are released together with the second and third GS reports, respectively. As well, the January WASDE and GS reports are released simultaneously. The latter overlap might seem problematic, in that both reports contain information on GS. However, the nature of the information in the two reports is different: The January GS report provides information on what *actual* stocks *were* as of December 1 of the previous year, whereas the January WASDE *estimates* what *future* stocks *should be* at the end of the current marketing year.¹²

Since we are interested in forward-looking volatility, we use the constant 90-day IVol for CBOT corn and soybean. To match this maturity choice, we likewise use the CBOE's constant 90-day “VIX” to test Hypothesis 3. All market series, such as the daily VIX, commodity IVols, and futures prices, as well as data on USDA announcements and analyst surveys, are retrieved from Bloomberg.¹³

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. We examine Hypotheses 2–5 using multivariate regressions.

4.1 | Testing Hypothesis 1: Commodity IVols decrease on the announcement day

1. *Event-day testing.* As a first step, we compare the mean and median IVols on the event day T against the corresponding values on day $T - 1$. Following Isengildina-Massa et al. (2008), we use both a parametric paired sample t test and a nonparametric Wilcoxon signed-rank test to account for the nonnormality of the distribution of IVol changes.

¹²In addition to the WASDE, PP, AR, and GS reports, the USDA also releases NASS CP reports simultaneously with the WASDE. The NASS CP and the WASDE methodologies to produce CP estimates are different—see Good and Irwin (2011). Still, the WASDE future stock projections reflect, in part, information about potential crop size (Isengildina-Massa et al., 2021). For this reason, our empirical analysis (precisely, the part dealing with the impact of analyst surprise, dispersion, and sentiment on commodity IVol responses to USDA announcements) focuses on the WASDE reports.

¹³A 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 et al. (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.

TABLE 1 USDA reports overview

	WASDE	Grain stocks (GS)	Prospective plantings (PP)	Acreage (AR)
Frequency	Monthly	Quarterly	Yearly	Yearly
Timing	Second week of the month	Second week of January and the end of first-third quarters	End of March	End of June
Overlap	First GS (January)	First WASDE; PP; AR	Second GS (March)	Third GS (June)
Information surveyed by Bloomberg	Projected US ending stock of the ongoing marketing year	US ending stock estimates as of Dec. 1, Mar. 1, Jun. 1, and Sep. 1	US farmers' planting intention for upcoming crop season	Survey-based estimate of US planted area for current crop season
Baseline for forecast "Pessimism"	WASDE of the previous month	GS of previous year's same quarter	AR of the previous year	PP of the current year

Note: Table 1 describes the 151 USDA reports that we collect for our sample, from September 2009 to October 2019. On some dates, the USDA releases more than one report: the third row in the table (labeled "Overlaps") explains which of the WASDE, GS, PP, and AR reports overlap. For part of the empirical analysis (see Table 5), we include information regarding expert opinions before the USDA news release. The information regarding analyst opinions comes from periodic Bloomberg surveys of market experts. The last row of Table 1 indicates the baselines that we use to characterize, for each type of report, whether the analyst consensus about upcoming USDA news is optimistic or pessimistic (as defined in Appendix A).
 Abbreviations: USDA, US Department of Agriculture; WASDE, World Agricultural Supply and Demand Estimates.

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 is¹⁴

$$H_0 : Ivol_T \geq Ivol_{T-1} \quad \text{against} \quad H_1 : Ivol_T < Ivol_{T-1}.$$

2. *Event-window extension.* Moving beyond the event-day IVol change, we seek a broader picture of how IVols behave for 5 days on either side of the event. Our approach is to perform multiple comparisons of the IVol changes within the event window from a *pre-event-window* reference. By doing so, we can learn about the timing of any change in the commodity IVol, as well as how persistent these changes are.

Extensions of the t test and Wilcoxon test that allow comparisons of more than two samples include the parametric one-way analysis of variance (ANOVA) test to compare group means, and the nonparametric Kruskal–Wallis test to compare group medians. However, they only test the null that all group means/medians are equal, that is, $H_0 : \Delta Ivol_{T-5} = \Delta Ivol_{T-4} = \dots = \Delta Ivol_{T+5}$, against the alternative that *at least* one group has statistically a significantly different mean or median. Without further analysis, it is not possible to know whether each group's mean or median differs from the others. Therefore, we perform multiple-comparison procedures using the Turkey–Kramer method based on the result of one-way ANOVA and Kruskal–Wallis tests.¹⁵

3. *Event-window and pre-event-window reference.* To capture possible differences between the pre- and postevent IVol change patterns, we consider a window of 5 days before and 5 days after the USDA announcement day. A natural baseline reference to assess within-window IVol changes would be the period just before that 11-day window around the event. One complication is that, because the timing of the Bloomberg analyst surveys varies from 1 to 7 days before a USDA announcement, there can be an overlap between the *post-Bloomberg* and the *pre-USDA* periods. To avoid such overlaps, we choose as the reference (i.e., baseline) IVol the 5-day average IVol before the Bloomberg survey is released, denoted \overline{Ivol} . Figure 1 illustrates the timeline and the overlap.

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

$$\Delta Ivol_{T+i} = \ln(Ivol_{T+i}/\overline{Ivol}), \quad \text{where } i = -5, -4, \dots, 5. \quad (1)$$

We first apply one-way ANOVA and Kruskal–Wallis tests to see if there is at least 1 day in the event window when the mean or 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 2–5: Determinants of the IVol drop

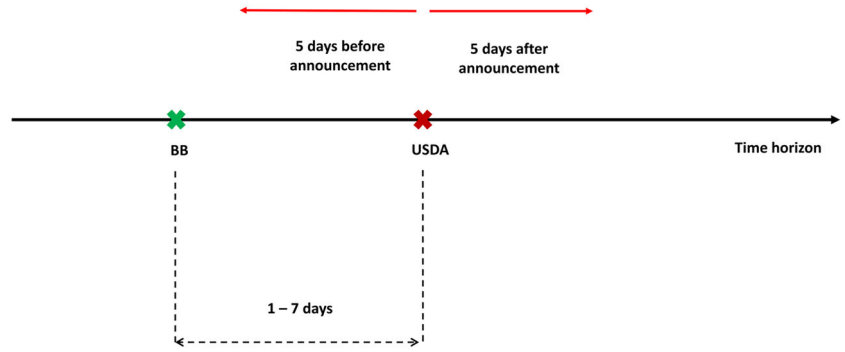
We regress the event-day commodity IVol change on a set of Bloomberg-survey-related variables (see Hypotheses 2–4 in Section 2.2), on the VIX return (our proxy for the event-day change in macroeconomic uncertainty and financial-market sentiment—see Hypothesis 5 in Section 2.3), and on additional control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

The information of interest in PP and AR reports is similar in nature (acreage expected to be or actually planted in the current year). Effectively, the AR report is an updated version of the PP report released earlier that year. Thus, we treat the PP and AR reports as a single type of report, which we call “Planted Area” (denoted PA). This approach has two advantages: It cuts the number of right-hand side variables, and thus increases the number of degrees of freedom;

¹⁴The 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 0 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 0 median and is symmetric around this median under the null. For a detailed description of these two tests, see Isengildina-Massa et al. (2008).

¹⁵An 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 & 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, for example, Stoline (1981) for a review of multiple-comparison methods, including the Turkey–Kramer procedure.

FIGURE 1 Timing of Bloomberg analyst surveys and scheduled Department of Agriculture (USDA) announcements



and it helps reduce multicollinearities among the surprise, dispersion, and sentiment variables related to those two annual reports, a problem that stems from their low frequency and the large proportion of observations for these variables that simultaneously have a null value.

Formally, we estimate the following relationship:

$$\Delta Ivol_i = \beta_0 + \sum_j \beta_j S_{i,j} + \sum_j \delta_j D_{i,j} + \sum_j \gamma_j Sentiment_{i,j} + \varphi \Delta VIX_i + \eta Control_i + \varepsilon_i, \tag{2}$$

where $i = 1, 2, \dots, 151$ denotes the i th event day in our 11-year sample, $j = \{WASDE, GS, PA\}$ denotes the type of report, and the Δ operator denotes daily close-to-close returns (log difference) on the event day T from the previous day $T - 1$.

Our variables of interest include:

1. *Surprise*, $S_{i,j}$. As in Couleau et al. (2020), we use the median Bloomberg analyst forecast as a proxy for the consensus market expectations before a USDA announcement. For report j , on the i th event in our sample, we define the “report surprise” as the percentage difference (approximated as a log difference) between the USDA’s announced value $A_{i,j}$ and the median forecast value $F_{i,j}$ in the corresponding survey:

$$S_{i,j} = \ln(A_{i,j}/F_{i,j}). \tag{3}$$

As discussed in Section 2.2.1, we split the surprises into “bullish” versus “bearish” surprises. A price-bullish surprise $S_{i,j}^-$ occurs if the USDA announces lower stocks (WASDE and GS) or acreage levels (PP and AR) than had been forecasted by the market consensus (hence the negative superscript in our notation); a price-bearish surprise $S_{i,j}^+$ captures the opposite situation.

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

The regression Equation (2) thus becomes:

$$\Delta Ivol_i = \beta_0 + \sum_j \beta_j^- S_{i,j}^- + \sum_j \beta_j^+ S_{i,j}^+ + \sum_j \delta_j D_{i,j} + \sum_j \gamma_j Sentiment_{i,j} + \varphi \Delta VIX_i + \eta Control_i + \varepsilon_i. \tag{5}$$

By comparing the signs and magnitudes of β_j^- and β_j^+ , we can test whether there is an asymmetry in the reaction of grain and oilseed volatility expectations to USDA surprises.

2. *Dispersion* $D_{i,j}$. For each forecasted piece of information, we follow prior work—see, for example, Fernandez-Perez et al. (2019) and references cited therein—and calculate dispersion as the ratio of the interquartile range (IQR) to the mean forecast:

$$D_{i,j} = IQR_{i,j}/\mu_{i,j}. \tag{6}$$

This approach avoids issues related to outliers, unlike the alternative methodology of using the standard deviation of analyst forecasts as a dependent variable.

3. *VIX changes*, ΔVIX_i . Grain and oilseed markets are much smaller than equity markets, so we treat the VIX as an exogenous variable for the purposes of this study.

4. *Expert Sentiment* $_{i,j}$. Having controlled for forecasters' expectation (through the surprise), pre-existing commodity-market uncertainty (through dispersion), and global market uncertainty and sentiment (through the VIX), we can test whether the IVol drop on the event day is related to other nonfundamental factors, that is, to commodity-market "sentiment." We take the "pessimism" of forecasters about an upcoming report as a form of prior market sentiment.¹⁶ We rate a consensus forecast as "pessimistic" when the median predicts a decrease in the forecasted indicator from a reference point. When it predicts an increase, we rate it as "optimistic."¹⁷ To keep things simple, we set *Sentiment* $_{i,j}$ equal to 1 if the median of the analyst forecast for report *j* released on the *i*th event day in our sample is pessimistic, and 0 otherwise. The last row of Table 1 lists the reference point used to rate the sentiment for each type of report; Appendix A provides additional details.

5. *Control* $_i$. Regression Equation (5) specifies a vector of control variables including day-of-the-week dummies, seasonal dummies, as well as a set of lagged daily returns:

- a. *Seasonality*: Every year, IVols in the US corn and soybean markets generally start increasing from April to June, which coincides broadly with the US planting phase (see Appendix B for a visual illustration). To capture this seasonal pattern, we use dummies corresponding to the main development phases of the US crop cycle: planting (April–June), pollination (July and August), and harvest (September–November). The baseline season is the period when the land lays fallow (i.e., December to the following March).
- b. *Day-of-the-week*: We control for the possibility that the IVol reaction to a USDA announcement might differ depending on which specific day of the week the release takes place, by including four weekday dummies (Tuesday–Friday).
- c. *Lagged returns*: For each commodity, we include 1-day lagged returns (using closing prices 2 days and 1 day before the *i*th event day) for the nearby commodity futures, the 90-day commodity IVols, and the VIX.

5 | RESULTS

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

5.1 | First look at the data

Table 2 reports summary statistics for our main variables of interest, including the levels and returns for the commodity IVol and the VIX, the analyst surprises and dispersions, and the percentage forecast changes (FCs)—precisely, the log difference between the median Bloomberg forecast and the corresponding reference point that we use to determine our sentiment variables (see Item 4 in Section 4.2). Table 2 provides values for medians, means, standard deviations (SD), minima, and maxima, as well as (in the last column) the counts of negative observations.

There is a clear pattern: The median and the mean of the daily IVol return are negative on the announcement day, for both corn and soybeans. USDA event days with negative IVol returns make up more than three-quarters of the whole sample for each commodity and, across all 151 USDA event days, the IVols fall by 2% (soybeans) to 2.7% (corn) on average.

¹⁶This 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 underreaction in forecasts. Thus, if we find that the pessimistic/optimistic 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.

¹⁷It is important to note that forecast pessimism and forecast surprise need not have the same sign. For instance, the surprise can be "price-bearish" when the USDA releases less "bad" information than what the analysts had predicted.

TABLE 2 Summary statistics

	Median	Mean	SD	Min.	Max.	No. Obs.	Obs. < 0
VIX	17.65	18.99	5.15	11.85	43.38	2567	N/A
VIX daily returns (USDA event days only)	-0.009	-0.003	0.047	-0.109	0.184	151	88
<i>A. Corn</i>							
IVol, daily	25.68	26.06	7.06	11.41	45.09	2567	N/A
IVol, all USDA event days ^a	25.41	25.80	6.73	11.73	43.34	151	N/A
IVol, big-event days ^b	23.84	25.13	7.03	11.73	43.34	82	N/A
Ivol daily returns, all days	-2.8e-4	-2.9e-4	0.03	-0.41	0.36	2567	1295
Ivol daily returns, all USDA event days	-0.027	-0.032	0.053	-0.231	0.198	151	119
Ivol daily returns, only big-event days	-0.057	-0.045	0.063	-0.231	0.199	82	69
WASDE surprise	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
Planted Area surprise	0.004	0.007	0.018	-0.017	0.055	20	8
WASDE dispersion	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
Planted Area dispersion	0.008	0.009	0.004	0.005	0.022	20	N/A
WASDE forecast change ^c	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
Planted Area forecast change	-0.001	-0.004	0.026	-0.067	0.043	20	10
<i>B. Soybean</i>							
IVol, daily	20.43	20.72	4.63	10.87	37.23	2567	N/A
IVol, all USDA event days ^a	19.98	20.35	4.40	11.05	31.95	151	N/A
IVol, big-event days ^b	19.84	20.03	4.44	11.36	31.95	82	N/A
Ivol daily returns, all days	-0.001	-4.2e-4	0.032	-0.301	0.258	2567	1337
Ivol daily returns, all USDA event days	-0.020	-0.022	0.045	-0.153	0.210	151	114
Ivol daily returns, only big-event days	-0.036	-0.032	0.048	-0.153	0.155	82	67
WASDE surprise	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
Planted Area surprise	-0.004	-0.008	0.021	-0.078	0.034	20	15
WASDE dispersion	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
Planted Area dispersion	0.011	0.011	0.006	0.005	0.025	20	N/A
WASDE forecast change ^c	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
Planted Area forecast change	0.009	0.009	0.022	-0.041	0.053	20	4

Note: Table 2 provides summary statistics for the main variables used in our analysis, including the event-day “surprise” relative to analysts’ consensus forecast before the event and the “dispersion” of those forecasts around the consensus. Panel A is for corn, and Panel B is for soybeans. The last three rows of each panel are the changes compared with the baselines used to capture analyst sentiments ahead of the forecast (see Table 1 and Appendix A). The sample runs from September 2009 to October 2019 and covers 151 USDA reports in that period.

Abbreviations: IVol, option-implied volatility; N/A, not applicable; SD, standard deviation; USDA, US Department of Agriculture; VIX, volatility index; WASDE, World Agricultural Supply and Demand Estimates.

^aComputed for all 151 Grain Stocks, Prospective Planting, Acreages, and WASDE announcement days in the sample.

^bCorn and soybean “Big-event” days include the WASDE reports in January, August, September, October, and November (not any other), as well as all Grain Stocks, Prospective Plantings, and Acreages report—see Adjemian and Irwin (2018).

^c“Forecast change” is the log difference between (a) the value forecasted by the analysts interviewed by Bloomberg for the upcoming USDA announcement and (b) the baseline value.

TABLE 3 Paired t test and Wilcoxon signed-rank test results

	IVol on USDA event day T versus day $T - 1$		11-Day event window around day T	
	Paired sample t test	Wilcoxon signed-rank test	One-way ANOVA test	Kruskal–Wallis test
<i>A. Corn</i>				
All USDA announcements	-6.39***	-7.24***	6.66***	83.38***
Big-event days	-5.89***	-6.05***	16.47***	187.03***
Small-event days	-3.51***	-3.58***	2.21***	16.62*
<i>B. Soybean</i>				
All USDA announcements	-5.13***	-6.17***	3.55***	58.68***
Big-event days	-5.60***	-5.27***	6.70***	102.81***
Small-event days	-1.41*	-3.03***	1.14	8.54

Note: The first two columns of Table 3 present the two-sample parametric (Student t) and nonparametric (Wilcoxon signed rang) test statistics for $H_0: Ivol_T \geq Ivol_{T-1}$. The two rightmost columns show the results of one-way analysis of variance (ANOVA) and Kruskal–Wallis tests for $H_0: \Delta Ivol_{T-5} = \Delta Ivol_{T-4} = \dots = \Delta Ivol_{T+5}$, with $\Delta Ivol_{T+i} = \ln(Ivol_{T+i}/Ivol_T)$. For the t tests, Table 3 reports left-sided t values; for the Wilcoxon tests, it reports the left-sided z values. For the one-way ANOVA and Kruskal–Wallis tests, the F - and χ^2 statistics are reported. For both commodities, we run each test for all USDA announcements together, and also separately for “big-event” days and “small-event” days (see Table 2 for the definition of “big” and “small” USDA events). A bold font indicates that an estimate is significant at least at 10% significance; the precise level of statistical significance is indicated by asterisks using *10%, **5%, and ***1%.

Abbreviations: IVol, option-implied volatility; USDA, US Department of Agriculture.

Not all USDA reports are equally important: Only a good half of the 151 USDA reports in our sample are considered by market observers to be “big events.”¹⁸ On “big” days, the proportion of event days with negative IVol returns jumps from three-quarters to almost six-sevenths, and the median IVol drop is almost twice as large, averaging 3.6% (soybeans) to 5.7% (corn).

The event-day market surprise is small on average (in absolute terms, less than 0.4% of the median forecast for corn and less than 1.1% for beans) but its standard deviation is very large. In the case of corn, surprises tend to be bearish for prices and volatility (with all three types of USDA reports), whereas they tend to be bullish for prices and volatility in the case of soybeans.

The *pre*-event median dispersion of expert forecasts is widest for WASDE reports (11.1% of the average forecast for soybeans, and 6.5% for corn), followed by forecasts of the quarterly GS reports. The annual PA forecasts exhibit the least dispersion. These patterns hold for both corn and beans.

Turning to expert sentiment ahead of USDA reports, the analyst forecasts are mostly optimistic (the only exception is the corn PA analyst forecasts), that is, analysts tend to anticipate higher levels of GS or planted areas compared with the (previous) reference point. The FC is largest on average in the case of the quarterly GS reports, for both commodities. The magnitude of the change, however, is generally small.

Finally, both the mean and median of the VIX returns are small on USDA event days, although the returns' standard deviation is large in the sample.

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 for one-sided t test and Wilcoxon signed-rank test. For both the corn and the soybean markets, the null can be rejected with a high level of confidence, that is, there is a statistically significant commodity IVol drop on the USDA announcement day.

¹⁸Adjemian and Irwin (2018) list the “big events” for corn and soybeans as the WASDE reports released in January, August, September, October, and November, as well as all the GS, PP, and AR reports.

In the last two columns of Table 3, one-way ANOVA and Kruskal–Wallis tests show that, for both commodities, there are at least 2 days in the 11-day event window whose $\Delta IVol$ values (where the log difference Δ is computed by reference to the 5-day average IVol value before the latest *pre*-event Bloomberg survey of agricultural market analysts) are significantly different from each other.¹⁹ We therefore perform the multiple-comparison procedure described in Section 4.1.

The results of these multiple-comparison tests are visualized in Figure 2a (corn) and 2b (soybeans). Table 4 reports the p values of the test statistics. For both commodities, the patterns of the log IVol differences between (a) each of the 11 days around the USDA announcement and (b) the 5-day average or “normal” IVol before the Bloomberg survey are clearly dissimilar:

- In general, corn and soybean IVols are higher than “normal” on the 5 days leading up to the announcement but, as predicted by Hypothesis 1, the increase is never statistically significant.²⁰
- In sharp contrast to that *pre*-event behavior, commodity IVols fall significantly on the USDA event day and they remain statistically significantly lower than “normal” for at least four trading days thereafter. Figure 2a,b shows that, for both commodities, the IVol gradually reverts toward its “normal” level. This visual observation is confirmed by the one-sided t test, as shown in the first column of Table 4.²¹

In short, the empirical evidence supports Hypothesis 1. Our above results extend to the past decade early findings in Isengildina-Massa et al. (2008) and McNew and Espinosa (1994), that IVols drop significantly on the day of a USDA report release. More importantly, we extend those previous findings by showing that commodity IVols trend upward (though not statistically significant) for several days before the USDA announcement, before dropping significantly on the event day and remaining significantly below “normal” for approximately 1 week.

5.3 | Hypotheses 2–4: Pre-event expert forecasters' influence on the IVol response

Equation (5) could be estimated by Ordinary Least Squares (OLS) for each commodity separately, since the residuals are not serially correlated across announcement days.²² However, because we find significant cross-equation residual correlations, Seemingly Unrelated Regressions (SUR)—as proposed by Zellner (1962)—are more efficient.²³ We therefore focus on the results obtained with the SUR method.²⁴

Table 5 summarizes our estimations of Equation (5) jointly for corn and soybean markets using the SUR estimator. Heteroskedasticity-consistent standard errors are reported in brackets. To compare the predictive importance of the explanatory variables, we also report standardized regression coefficients.

Our result shows that the effects of market surprise and analyst dispersion vary across markets and across reports, in terms of signs as well as magnitudes.

5.3.1 | The role of report surprises

Given how we compute surprises, price-bearish surprises are positive while bullish surprises are negative. Hence, a negative coefficient for bearish surprises ($\beta_j^+ < 0$) indicates an IVol decrease, whereas a positive value

¹⁹For corn, the statistical significance holds for all tests and for all events—small and big. For soybeans, the statistical significance is strongest for the subset of 87 USDA reports that market observers rank as “most important”—see Adjemian and Irwin (2018).

²⁰The corn IVol gradually increases for 4 days before the announcement and reaches its highest *pre*-event level on the day before the USDA event day. The soybean IVol does not exhibit any visible change from the “normal” level before the event day. None of those increases, however, is statistically significant.

²¹The Kruskal–Wallis tests yield similar results. Tables summarizing the KW test result are available by request.

²²Breusch–Godfrey statistics for serial correlation tests, using a maximum of 30 lags, are 22.239 and 37.398 for corn and soybeans OLS residuals, respectively. With these test statistics, we cannot reject the null hypothesis of no serial correlation of any order up to 30 across event days for both commodities.

²³The cross-equation (i.e., between corn and soybeans) residual correlation is 0.353. The Breusch–Pagan test statistic is 18.867, which strongly rejects the diagonality (i.e., null-covariance) of the corn and soybean IVol residual variance–covariance matrix.

²⁴OLS results are available upon request.

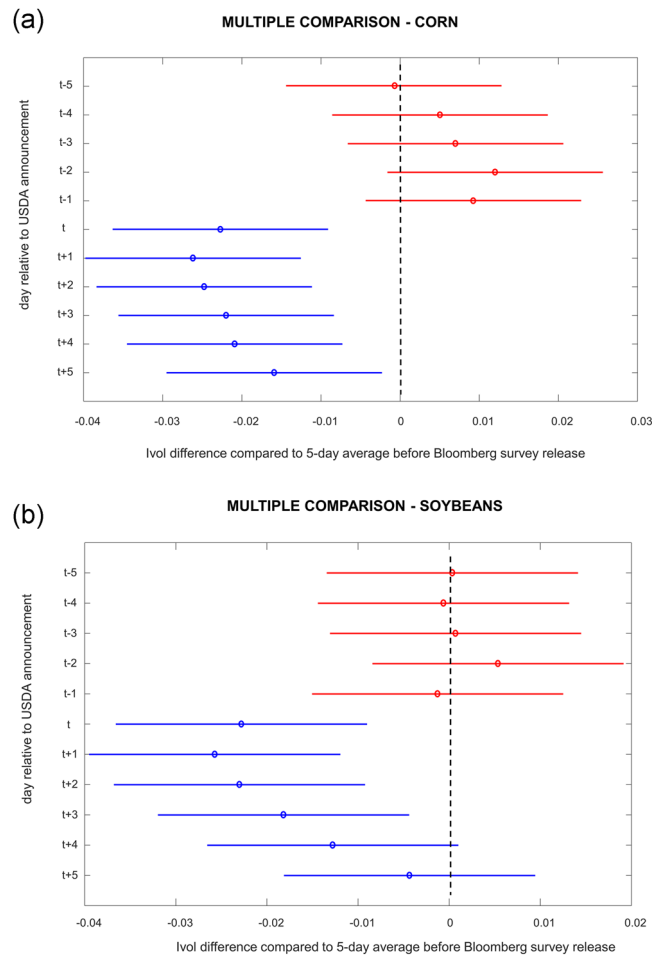


FIGURE 2 Daily IVol change (vs. 5-day average IVol before the latest Bloomberg survey). (a) Corn and (b) soybeans. *Note:* The circles in Figure 2a (corn) and 2b (soybeans) show the mean estimates of $\Delta IVol_{T+i}$ ($i = -5, -4, \dots, +5$) for 5 days before and 5 days after 151 US Department of Agriculture (USDA) scheduled announcement days (day T) from September 2009 to October 2019. For each day, we compute log differences between (a) the 90-day commodity option-implied volatility (IVol) at the market close on day $T + i$ and (b) the average IVol for the 5 days before the most recent *pre-event* Bloomberg survey (which typically takes place five to seven days before the USDA event day). For each day, the colored bars represent the estimated 95% confidence intervals. If the confidence intervals of 2 days overlap each other, then the difference between IVols on those 2 days is not statistically significant. Likewise, if a colored bar crosses the zero dashed line, then the IVol on that day is not statistically significantly different from the average IVol in the 5 days before the Bloomberg survey. Test results (bars) for each of the 5 days before a USDA announcement are plotted in red; the bars for the announcement day T and for the next five trading days appear in blue. *Sources:* USDA, Bloomberg and authors' computations

of β_j^+ indicates an IVol increase. The opposite holds for a bullish surprise β_j^- . Hypothesis 2 therefore implies that β_j^+ and β_j^- should *both* be negative.

Table 5 shows that, for both corn and soybeans, the bullish-surprise coefficients (β_j^-) are indeed statistically significantly negative for both WASDE and GS announcements.²⁵ In other words, a lower-than-predicted level of commodity inventories (whether actual in a GS report, or projected in a WASDE) brings about a smaller-than-average IVol drop (or even an outright IVol increase) postannouncement. Precisely, if the USDA corn (*resp.*, soybean) stock projection in a WASDE comes in 1% under the median Bloomberg forecast, then the result is *ceteris paribus* a

²⁵For corn, bullish PA report surprises are not statistically significant. The effect of bullish soybean PA surprises is negative and significant—an unexpected result. Bearish PA surprises have statistically insignificant impacts on the event-day IVol return, for both commodities.

TABLE 4 IVols around USDA announcements—multiday comparison tests

	\overline{Ivol}	$T - 5$	$T - 4$	$T - 3$	$T - 2$	$T - 1$	T	$T + 1$	$T + 2$	$T + 3$	$T + 4$	$T + 5$
<i>Panel A: Corn</i>												
$T - 5$	0.62											
$T - 4$	0.05**	1.00										
$T - 3$	0.02**	1.00	1.00									
$T - 2$	<0.00***	0.92	1.00	1.00								
$T - 1$	0.03**	0.98	1.00	1.00	1.00							
T	<0.00***	0.26	0.04**	0.02**	<0.00***	0.01***						
$T + 1$	<0.00***	0.10*	0.01*	<0.00***	<0.00***	<0.00***	1.00					
$T + 2$	<0.00***	0.15	0.02**	0.01***	<0.00***	<0.00***	1.00	1.00				
$T + 3$	0.01***	0.30	0.05*	0.03**	<0.00***	0.01***	1.00	1.00	1.00			
$T + 4$	0.01***	0.38	0.08*	0.04**	0.01***	0.02**	1.00	1.00	1.00	1.00		
$T + 5$	0.06*	0.79	0.32	0.20	0.04**	0.10*	1.00	0.98	0.99	1.00	1.00	
<i>Panel B: Soybean</i>												
$T - 5$	0.54											
$T - 4$	0.61	1.00										
$T - 3$	0.51	1.00	1.00									
$T - 2$	0.14	1.00	1.00	1.00								
$T - 1$	0.07*	1.00	1.00	1.00	1.00							
T	<0.00***	0.20	0.25	0.18	0.04**	0.30						
$T + 1$	<0.00***	0.08*	0.11	0.07*	0.01**	0.14	1.00					
$T + 2$	<0.00***	0.19	0.24	0.17	0.04**	0.28	1.00	1.00				
$T + 3$	0.02**	0.53	0.61	0.50	0.18	0.67	1.00	1.00	1.00			
$T + 4$	0.07*	0.91	0.94	0.89	0.57	0.96	0.99	0.92	0.98	1.00		
$T + 5$	0.33	1.00	1.00	1.00	0.99	1.00	0.54	0.31	0.52	0.88	1.00	

Note: Table 4 shows the p value matrix of analysis of variance (ANOVA)-based multiple-comparison tests comparing (a) the option-implied volatility (IVol) values on the days in the event window (columns 2–12 covering days $T - 5$ to $T + 5$) and paired t tests (column 1) to (b) the average IVol value in the 5 days before the Bloomberg survey of grain and oilseed market analysts. Each cell in columns 2–12, denoted p_{ij} , reports the p value for $H_0 : \Delta Ivol_{T+i} = \Delta Ivol_{T+j}$, with $i, j = -5, -4, \dots, 5$ and $i \neq j$. In the first column, each cell reports the p value for a one-sided t test of each $Ivol_{T+i}$ against the average IVol on the five trading days before the Bloomberg survey, denoted \overline{Ivol} . For the days before the US Department of Agriculture (USDA) announcement day T (i.e., from $T - 5$ to $T + 5$), the null hypothesis is that the IVol on that day is larger than \overline{Ivol} , indicating an increase in commodity option-implied volatility. In contrast, the null for the days after USDA announcement (i.e., from $T + 1$ to $T + 5$) is that the mean IVol on that day is smaller than \overline{Ivol} , indicating a drop in implied volatility following the USDA report release. Panel A shows the result for corn; Panel B, for soybeans. A bold font indicates that an estimate is significant at least at 10% significance; the precise level of statistical significance is indicated by asterisks using *10%, **5%, and ***1%.

0.36% (resp., 0.26%) increase in the 90-day corn (resp., soybean) IVol on the USDA announcement day. For GS reports, the corresponding numbers are 0.61% and 0.28%.

In contrast, the estimated bearish-surprise coefficients β_j^+ do not appear to support the part of Hypothesis 2 predicting that IVols should drop more strongly following a bearish report surprise. First, we find that bearish WASDE and PA surprises have statistically insignificant impacts on the postevent IVol change. Put differently, apart from the IVol drop due to the removal of expected high volatility on the announcement day T (as discussed in Section 2.1), the market's corn and soybean volatility expectations (IVols) are not significantly revised further downward due to a higher-than-expected projected stock level or planted area. Second, bearish GS surprises are

TABLE 5 Forecast surprise, analyst dispersion, sentiment, and commodity IVol changes^a

	Corn		Soybean	
	Unstandardized	Standardized ^b	Unstandardized	Standardized ^b
Constant	-0.055*** (0.017)	-0.416 (0.301)	-0.037** (0.018)	-0.169 (0.345)
Bearish ^c WASDE Surprise	-0.081 (0.103)	-0.073 (0.084)	0.073 (0.068)	0.091 (0.091)
Bullish ^c WASDE Surprise	-0.363* (0.208)	-0.261*** (0.077)	-0.263** (0.112)	-0.336*** (0.090)
Bearish ^c Grain Stocks Surprise	0.711*** (0.296)	0.383*** (0.119)	0.266*** (0.100)	0.192* (0.109)
Bullish ^c Grain Stocks Surprise	-0.614* (0.318)	-0.221** (0.106)	-0.278*** (0.076)	-0.201** (0.093)
Bearish ^c Planted Area Surprise	-1.598 (1.662)	-0.189 (0.131)	-0.257 (0.942)	-0.018 (0.083)
Bullish ^c Planted Area Surprise	-1.267 (2.460)	-0.059 (0.105)	1.451** (0.617)	0.236* (0.108)
WASDE Dispersion	-0.158** (0.068)	-0.182* (0.101)	-0.070 (0.061)	-0.131 (0.117)
Grain Stocks Dispersion	-0.311 (0.450)	-0.104 (0.136)	0.280 (0.212)	0.164 (0.117)
Planted Area Dispersion	1.290 (5.310)	0.082 (0.177)	1.351 (1.467)	0.134 (0.134)
WASDE Sentiment	0.005 (0.006)	0.102 (0.167)	0.010 (0.007)	0.229 (0.169)
Grain Stocks Sentiment	-0.060*** (0.021)	-1.124*** (0.334)	-0.042** (0.016)	-0.938** (0.410)
Planted Area Sentiment	-0.018 (0.029)	-0.340 (0.440)	-0.018 (0.025)	-0.402 (0.549)
VIX returns	-0.135** (0.061)	-0.120* (0.074)	-0.088 (0.069)	-0.093 (0.078)
Observations	151		151	
R ²	0.359		0.283	
F statistic (<i>df</i> = 23; 127)	3.078***		2.196***	
Cross-equation residual correlation	0.353			
Breusch-Pagan test of diagonality	18.867***			

Note: Table 5 reports the Seemingly Unrelated Regression (SUR) estimation results for corn and soybeans. Heteroskedasticity-consistent standard errors are reported in brackets. The variables are described in Table 2. *Sample period*: September 2009–October 2019. A bold font indicates that an estimate is significant at least at 10% significance; the precise level of statistical significance is indicated by asterisks using *10%, **5%, and ***1%.

Abbreviations: IVol, option-implied volatility; USDA, US Department of Agriculture; VIX, volatility index; WASDE, World Agricultural Supply and Demand Estimates.

^aFor both commodities, the dependent variable is the IVol daily return on the USDA announcement day *T*.

^bThe standardized coefficients report the number of standard deviations change in the dependent variable associated with a one standard deviation change in the independent variables (except for dummy variables).

^cGiven the way in which we compute event-day surprises, price-bearish surprises are positive numbers and price-bullish surprises are negative numbers. Hence, a negative bearish surprise coefficient ($\beta_j^+ < 0$) indicates an IVol decrease, whereas a positive β_j^+ indicates an IVol increase (holding all other factors constant).

actually followed by a significant IVol *increase* in corn and soybean IVols. This finding implies that *any* GS surprise, whether bearish or bullish for prices, drives IVols upward (by similar amounts in both cases).

5.3.2 | The role of forecast dispersion

For most reports, we do not find statistically significant coefficients for analyst dispersion. The only exception is for the corn WASDE. Consistent with Hypothesis 3, we find that the *pre*-event WASDE forecast dispersion significantly predicts the postevent IVol change in the corn market. Insofar as more disagreement among analysts (who could be traders too) implies greater corn market uncertainty before the WASDE release, the negative corn WASDE dispersion coefficient implies that the information released in the report becomes the new market consensus and resolves that uncertainty. Quantitatively, we find that a 1% increase in WASDE forecast dispersion around the mean analyst forecast contributes to a statistically significant 0.16% decrease in the corn

IVol (other things held equal). This finding complements the conclusion of Karali, Isengildina-Massa et al. (2019), that USDA reports remain valuable even in the presence of private forecasts.

5.3.3 | The role of forecaster sentiment

As discussed in Section 2.2.3, we expect coefficients of our forecast sentiment dummies to be negative. This is indeed what we find for GS reports. *Ceteris paribus*, the corn (*resp.*, *soybean*) IVol drops an extra 6.0% (*resp.*, 4.2%) when a majority of forecasters are pessimistic (sentiment dummy = 1) about the corn (*resp.*, *soybean*) inventory level in an upcoming GS report, compared with when a majority are optimistic or neutral (sentiment dummy = 0). Both percentage drops are equivalent to about one standard deviation of the IVol change, either for corn and soybeans.

The Efficient Market Hypothesis (EMH) states that fundamentals-related information should be incorporated into market expectations as soon as it becomes available to market participants. Hence, having controlled for new fundamental-related information (proxied by surprises) and for uncertainty (proxied by dispersion), IVol change on day T should not be significantly predicted by information available before that day. Given how we construct the sentiment variable (see Appendix A) and given the timing of the Bloomberg survey's release, the pessimistic/optimistic nature of the median analyst forecast is already known to market participants at the latest by day $T - 1$. Therefore, the implication of our finding a significant GS sentiment coefficient is that market sentiment (not just market fundamentals) plays a role in how commodity IVols react to USDA announcements.

5.4 | Hypothesis 5: Macroeconomic uncertainty and financial-market sentiment

For both corn and soybeans, the coefficient of the VIX return is *negative*. It is statistically significant for corn. All other things equal, a 1% VIX increase on the USDA event day is associated with a 0.14% *decrease* in corn IVol. As noted in the development of Hypothesis 5 (see Section 2.3), prior work documents empirically that daily VIX and commodity IVol returns are positively correlated.

One possible interpretation of our surprising VIX finding is that it lends additional support to the argument that the USDA information is the “new market consensus.” Given that commodity IVol changes are generally positively driven by VIX changes, it must be that, on those few days when the USDA announcements take place, the USDA news helps mitigate the VIX spillover.

To verify empirically our conjecture that the influence (on grain and oilseed IVols) of financial-market uncertainty and sentiment is reduced on USDA event days, we run an additional analysis of the relation between VIX and commodity IVol returns for *all* days in sample period.²⁶ For each commodity, we run the following regression across all 2567 days in our sample:

$$\Delta IVol_t = \beta_0 + \beta_1 \Delta VIX_t + \beta_2 D_{USDA,t} + \beta_3 \Delta VIX_t * D_{USDA,t} + \beta_4 \Delta IVol_{t-1} + \varepsilon_t, \quad (7)$$

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.

Analogously to Goyal and Adjemian (2021), we first use simple OLS to estimate Equation (7). To account for conditional heteroskedasticity, we also estimate (7) 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 require a $GARCH(1, 1)$ with $ARMA(3, 1)$.

Table 6 summarizes our regression results. As in earlier studies, we find that the coefficient of ΔVIX_t (β_1) is positive for both commodities.²⁷ Likewise, β_2 is consistently negative and highly significant for both commodities

²⁶We run the regressions in first differences to ensure that all series are stationary.

²⁷As in Table 5, the VIX regression coefficient is statistically significant for corn but not for soybeans. This lack of significance may reflect the conjunction of two facts. One, historical decompositions by Adjemian et al. (2017) show that, in contrast to other determinants of agricultural IVols, macroeconomic uncertainty and financial-market sentiment matter the most during periods of elevated financial stress. Two, with the exception of August 2011, there is no major VIX spike in our sample period (2009–2019).

TABLE 6 VIX impact on commodity IVols—regular days versus USDA event days

	Corn			Soybeans		
	OLS	sGARCH	eGARCH	OLS	sGARCH	eGARCH
Constant	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.000)	0.001 (0.001)	0.000 (0.001)	0.001*** (0.000)
VIX	0.032** (0.014)	0.043*** (0.013)	0.047*** (0.006)	0.003 (0.014)	0.011 (0.015)	0.013 (0.009)
USDA announcement	-0.034*** (0.004)	-0.033*** (0.004)	-0.032*** (0.003)	-0.023*** (0.004)	-0.023*** (0.003)	-0.022*** (0.003)
VIX*USDA announcement	-0.152* (0.088)	-0.159** (0.079)	-0.166*** (0.021)	-0.094 (0.072)	-0.053 (0.079)	-0.057*** (0.010)
Lagged daily IVol log-difference	-0.045 (0.057)	-0.814*** (0.204)	-0.767*** (0.017)	0.032 (0.038)	0.844*** (0.072)	0.860*** (0.043)
AIC	-10,153	-4.1388	-4.2140	-10,339	-4.1420	-4.1585
BIC	-10,118	-4.1114	-4.1798	-10,304	-4.1101	-4.1243
Wald/LM tests	17.375***	0.4641	0.5078	11.316***	3.203	3.860

Note: Table 6 provides estimates of the daily impact of VIX changes on commodity IVol changes on USDA vs. non-USDA days. 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 a $GARCH(1, 1)$ with $ARMA(3, 1)$ for soybean. The choices of the model are based on diagnostic tests as in Goyal and Adjemian (2021). For the regression coefficients, heteroskedasticity-consistent standard errors are reported in brackets. Wald test statistics are reported for the OLS models; weighted ARCH LM test statistics are reported for the GARCH models at lag 7. In all cases, a bold font indicates that an estimate is significant at least at 10% significance; the precise level of statistical significance is indicated by asterisks using *10%, **5%, and ***1%.

Abbreviations: AIC, Akaike's Information Criteria; ARMA, autoregressive moving average; BIC, Bayesian Information Criteria; eGARCH, exponential GARCH; GARCH, generalized autoregressive conditional heteroskedasticity; IVol, option-implied volatility; LM, Lagrange Multiplier; OLS, Ordinary Least Squares; sGARCH, standard GARCH; USDA, US Department of Agriculture; VIX, volatility index.

in all three specifications, which reinforces the conclusion that USDA reports reduce commodity IVols. However, the effect of the VIX return on the IVol return is reversed on USDA announcement days: β_3 is negative across all specifications for both corn and soybeans—with statistically significant values 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.

In sum, our results show that, while in general grain and oilseed IVol returns are positively related to changes in macroeconomic uncertainty and sentiment (jointly captured by the VIX), this relationship does not hold on USDA announcement days. This empirical finding points to the need for theoretical work to understand why the value placed by agricultural market participants on the commodity-specific (but consensus-making) information of the USDA reports seems to increase in the level of financial-market uncertainty.

5.5 | Discussion: Information value of Bloomberg surveys

As a final check of our results, we revisit the Bloomberg analyst surveys that precede a scheduled announcement. We ask two questions. One, do the surveys themselves contain new information—in which case, they might influence commodity returns or IVols before a USDA information release (which in turn would impact our measure of the IVol change on the announcement day). Second, is the median analyst survey a biased predictor of the USDA numbers—in which case, our measure of surprise could be affected?²⁸

To answer these questions, we adopt and adapt the approach proposed by Balduzzi, et al. (BEG, 2001) to study analyst forecasts of corporate earnings (see Appendix C for details). We regress the value of each USDA figure on (i) the median forecasted value in the Bloomberg survey and (ii) the IVol and price returns between the survey publication day and the USDA day.

²⁸Karali, Irwin et al. (2019) raise a measurement-error concern in the case of surveyed analysts' CP forecasts.

TABLE 7 BEG regressions

	BEG1		BEG2		BEG3	
	WASDE	GS	WASDE	GS	WASDE	GS
A. Corn						
Constant (α_0)	27.29 (31.47)	38.02 (43.91)	-8.67 (35.42)	43.69 (56.46)	10.66 (33.08)	50.58 (44.31)
$F_{t,j}$	0.99*** (0.02)	1.00*** (0.01)	1.00*** (0.02)	1.00*** (0.01)	0.99*** (0.02)	1.00*** (0.01)
R_t	-1856.50*** (361.82)	-2473.96*** (522.37)			-1694.21*** (374.65)	-2620.53*** (526.74)
ΔIvol_t			-516.56*** (190.35)	109.63 (347.59)	-284.21 (183.60)	386.72 (278.30)
Observations	120	41	120	41	120	41
R^2	0.96	1.00	0.96	1.00	0.96	1.00
F statistic ($H_0: \alpha_0 = 0; \alpha_1 = 1$)	0.51	0.55	0.04	0.53	0.94	1.23
B. Soybeans						
Constant (α_0)	5.25 (6.18)	11.13 (9.96)	-5.14 (7.42)	9.33 (9.98)	5.09 (6.84)	10.25 (10.12)
$F_{t,j}$	1.00*** (0.01)	0.99*** (0.01)	1.01*** (0.02)	0.99*** (0.01)	1.00*** (0.01)	0.99*** (0.01)
R_t	-787.92*** (130.67)	-168.14 (208.62)			-785.49*** (138.62)	-152.64 (211.51)
ΔIvol_t			-103.42* (58.61)	-71.58 (95.64)	-3.00 (55.03)	-63.80 (96.85)
Observations	120	41	120	41	120	41
R^2	0.98	1.00	0.97	1.00	0.98	1.00
F statistic ($H_0: \alpha_0 = 0; \alpha_1 = 1$)	0.69	3.19*	0.27	3.29**	0.49	3.23*

Note: Table 7 reports the result of three different versions of the Balduzzi, et al. (BEG, 2001) equation. For each version (BEG1, BEG2, and BEG3), we run a regression for the monthly WASDE ending stock forecasts and another regression for the quarterly Grain Stocks estimates. The original BEG regression is presented in the first two columns of Table 7 ("BEG1"); in the next two columns ("BEG2"), R_t is replaced by ΔIvol_t (i.e., returns of commodity IVol from the forecast day to the USDA announcement day T). The last two columns ("BEG3") include both R_t and ΔIvol_t in one regression. Finally, the last row of each panel shows the F statistic of the joint hypothesis test for $H_0: \alpha_0 = 0; \alpha_1 = 1$ —implying the analyst forecasts are unbiased. In all cases, a bold font indicates that an estimate is significant at least at 10% significance; the precise level of statistical significance is indicated by asterisks using *10%, **5%, and ***1%.

Abbreviations: GS, Grain Stocks; IVol, option-implied volatility; USDA, US Department of Agriculture; WASDE, World Agricultural Supply and Demand Estimates.

We consider three versions of the BEG model. For each, we run a regression for the monthly WASDE ending stock forecasts and another for the quarterly GS estimates (there are too few observations for the BEG regression to make sense in the case of the annual PP and AR reports).

Table 7 summarizes the results. They suggest that the Bloomberg analyst forecasts are informationally valuable to market participants: The regression coefficient for the median forecast is significantly different from 0 in all specifications. Table 7 also suggests that the median forecast is an unbiased predictor of the USDA information: None of the intercepts is significantly different from 0, and the median forecast coefficients are not significantly different from 1.²⁹ Most importantly for our analysis, however, the BEG3 specifications in Table 7 show that the IVol return coefficients are not statistically significant after we control for the price returns. We conclude that market participants do not significantly revise their volatility expectations between the Bloomberg survey and the USDA announcement day, which assuages the concern of measurement errors.

6 | CONCLUSION

We provide novel evidence on the impact of scheduled USDA information releases on forward-looking volatilities (IVols) in agricultural markets. We document that, for up to five trading days after the release of a scheduled USDA report (WASDE, GS, PP, and AR), corn and soybean IVols are significantly lower than they had been a week before the release. The USDA reports' uncertainty-resolution power is substantial for both commodities.

The benefit of the USDA information in resolving market uncertainty is impacted by analyst disagreement and sentiment ahead of the report, and by the extent to which the market is surprised on the announcement day. Those three variables, however, do not have uniform impacts on the USDA reports' uncertainty resolution. Notably, for WASDE and GS reports, event-day surprises that are bullish for prices tend to boost commodity IVols. The effect of price-bearish surprises is more muted, except for GS reports. The impact of disagreement among market experts in the runup to a report is usually insignificant, except for the corn WASDE (with greater *pre*-USDA dispersion boosting the IVol drop on the event day).

Sentiment also matters—both commodity experts' sentiment ahead of the release and changes in broad financial-market sentiment on the event day. One, in the case of the GS reports, we document that the calming effect of USDA news is larger when market analysts had been pessimistic about stock levels. Two, while 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 comovement surprisingly breaks down on USDA report days—with the VIX and commodity IVols moving in opposite directions on that day.

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 volatility expectations. Second, short-run hedging and other derivatives-market positioning around USDA announcements 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 et al. (2020)—should also benefit from our conclusions.

Our findings suggest several venues for further research. First, most our empirical predictions are theoretically grounded in 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 when the surprise is bearish for prices and (ii) why the generally positive relationship between VIX returns and commodity IVols reverses on USDA event days.

Second, our paper focuses on commodity IVols that can be used as forecasts of future realized volatility (Egelkraut et al., 2007). The IVols on which we rely are derived from 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

²⁹In the case of soybean GS reports, the *F* statistic for the joint hypothesis that the intercept is equal to 0 and the median forecast coefficient is equal to 1 is rejected at 10% level of significance. However, the size of these coefficients is very close to 1: We cannot reject, using *t* tests, the hypothesis that the median forecast coefficients equal 1. We therefore conclude that, even if there is a bias in the case of analysts' soybean GS forecasts, it is very small.

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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DATA AVAILABILITY STATEMENT

All the data used for this study were obtained from Bloomberg. Restrictions apply to the availability of these data, which were used under license for this study. Data are available with the permission of Bloomberg.

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APPENDIX A: BASELINES FOR “PESSIMISM” IN FORECASTS

On the basis of the nature of the forecasted information in each report, we define their respective reference points as follows:

1. *WASDE*: The forecast we use is also the most frequently surveyed information—the projected US ending stock of the current marketing year. Every month, the USDA updates the projections in the WASDE in light of demand and supply developments. As a reference point or baseline, we therefore choose the actual value in the previous month's report.
2. *GS reports*: The USDA estimates US ending stocks as of the end of the previous quarter. Due to the seasonality of CP and demand, grain and oilseed inventories also fluctuate seasonally. We therefore use the same 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.
3. *PP and AR report*: The *PP* and the *AR* 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*) are 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).

APPENDIX B: SEASONALITY OF AGRICULTURAL IVols, 2009–2019

In this appendix, we plot the daily values of the 90-day 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) from August 2009 to September 2019. The top panel plots the actual implied-volatility values in percent. The bottom panel expresses the commodity 90-day IVols in terms of the contemporaneous 90-day VIX. The spring season is shaded to better highlight the seasonality of the commodity IVols (Figure B1).

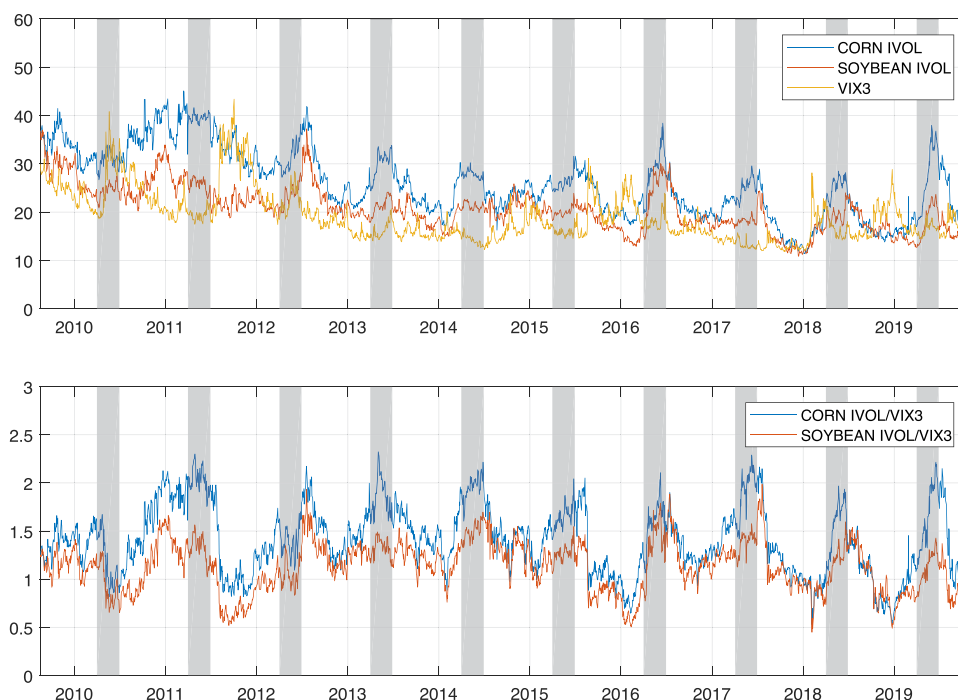


FIGURE B1 Seasonality of agricultural option-implied volatilities (IVols), 2009–2019

APPENDIX C: INFORMATIONAL VALUE OF THE BLOOMBERG-SURVEY ANALYST FORECASTS

Balduzzi, et al. (2001) propose the regression equation (hereafter, the BEG equation):

$$A_{i,j} = \alpha_0 + \alpha_1 \bar{F}_{i,j} + \alpha_2 R_i + \varepsilon_{i,j}, \quad (C1)$$

where $A_{i,j}$ and $\bar{F}_{i,j}$ are, respectively, the actual and the forecasted values of indicator j for the announcement day i , and R_i is the cumulative market return from the day when 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.