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Yao Yang and Andrew McKenzie

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Yao Yang and Andrew McKenzie[*]

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[*] Yao Yang is a post-doctoral research fellow and Andrew McKenzie is a professor in the Department of Applied Economics and Agribusiness at the University of Arkansas, Fayetteville.

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Abstract

This paper investigates the information value of USDA crop reports in terms of their impacts on rational agents' expectations of future realized price volatility. While it is well known that uncertainty – proxied by options market implied volatility – is reduced in the wake of USDA reports, this is the first study to examine if information contained in USDA reports update rational volatility expectations. We use a Hamilton-type approach to reveal that August crop reports are "newsworthy" – at least in some years – in refining rational agents' volatility expectations through harvest-time. However, results also show that corn options markets are slow to adjust to this news with both ex-post information about realized volatility and crop report news contributing to agents' volatility expectations for several days following the report release date, highlighting potential inefficiencies in options market volatility forecasts.

Key words: Hamilton-type approach, options implied volatility, new crop futures, volatility expectations, USDA crop reports

Introduction

Price volatility is a core factor influencing trading strategies, risk management, and financial instrument pricing. Especially in options markets, volatility plays a central role in determining the fair value for an option, or any derivative instrument with option features. Option pricing depends on the forward-looking volatility that will be experienced in the future, over the remaining lifetime of an option. Therefore, the market's forecasts of future price volatility are vital for derivatives trading.

Rational agents use new information to reevaluate their market expectations for future price volatility. As the primary source of public information in agriculture, the U.S. Department of Agriculture (USDA) provides a series of reports on crop production, livestock inventories, and other statistics necessary for decision-making by both buyers and sellers in agricultural commodity markets. An extensive literature in agricultural economics research has investigated the informational value of USDA crop production forecasts by the impacts on the mean and variance of cash and futures prices (e.g., Orazem and Falk 1989; Garcia et al. 1997; Good and Irwin 2006; McKenzie 2008; Karali, Irwin, Isengildina-Massa 2020). McKenzie (2008) points out, "the release of public information may play a role in coordinating the beliefs of market agents, even if the public announcement contains no valuable information concerning market fundamentals in itself." Our paper extends McKezine's (2008) work to investigate whether relative information about crop production forecasts can adjust agents' market expectations for future price volatility.

In options pricing, the release of USDA reports can affect the dynamics of option-based implied volatility (e.g., McNew and Espinosa 1994; Isengildina et al. 2008; Adjemian et al. 2018; Cao and Robe 2022). McNew and Espinosa (1994) observed reduced implied volatility in corn and soybean options after the release of USDA crop production forecasts. Isengildina-Massa et al. (2008) find a substantial drop in implied volatility (by 1.1. percentage points for corn and 1.5 percentage points for soybeans) after the release of WASDE and crop production reports within the growth cycle of corn and soybeans over the 1985-2002 period. Cao and Robe (2022) extend these findings to demonstrate that corn and soybean IVs not only drop immediately following the report release but remain low for up to five days after the USDA report releases. Our paper contributes to the literature on the informational value of USDA reports in option market reactions by investigating their impacts on rational volatility expectations of future realized volatility.

Our method uses Hamilton's (1992) methodology whose model uses various informational sources beyond futures prices to estimate the market expectation for agricultural commodity prices during the Great Depression. The major advantage of the Hamilton-type approach is to allow researchers to test the concepts of market efficiency hypothesis (MEH) and informational content of USDA reports by analyzing the relationship between each concerning rational agents' expectations. In addition, we can use the Hamilton-type approach to include a variety of informational sources beyond implied volatility in the volatility forecasting regression to estimate agents' volatility expectations. McKenzie (2008) uses the Hamilton-type approach to investigate the efficiency of corn futures prices to incorporate the informational content of USDA crop forecasts and points out the advantage of the Hamilton-type approach in detail, "the approach does not impose any a priori form of EMH rationality assumptions on futures prices but rather examines future price behavior around the release of USDA reports, using estimates of rational agents' price expectations as a benchmark."

Given the influence of USDA corn production forecasts on harvest-period corn futures prices (Arnade, Hoffman, and Effland 2021), we focus on USDA crop forecasts and final production values for corn and its major substitute, soybean, along with at-the-money implied volatility derived from the new crop (December) corn futures prices over the 1995-2022 period. Our results confirm the informational value of USDA crop reports in terms of rational agents' volatility expectations. Our results underscore the significance of incorporating USDA production forecasts in volatility forecasting when no available supply information in the market. Before the report release, IV estimates were biased and inefficient in forecasting realized volatility. Crop report news provides more significant contributions for rational agents to refine their volatility expectations for at-harvest corn, with fewer impacts on the deviation from true volatility expectations. Moreover, our historical analysis supports the information value since rational volatility expectations have a better performance in reducing overestimation or underestimation of IV expectations, especially for market anomalies, such as in 2007 and 2008.

Theoretical Model for Volatility Expectations and Production Forecasts

This section explains the modeling framework to infer agents' rational volatility expectations for at-harvest corn. We build a linear regression for forecasting realized volatility (RV) based on options IV,[1]

[1] For brevity, we ignore the period τ when symbolizing price volatility in the following equations throughout the theoretical section.

(1) $RV_T = \delta_0 + \delta_1 IV_{T-\tau} + u_T$.
where δ_0 is a constant, u_T represents the zero-mean error, and τ is the forecasting period. Therefore, a naïve expectation for future price volatility can be written with fitted values,
(2) $\tilde{\sigma}_T^e = \tilde{\delta}_0 + \tilde{\delta}_1 V_{T-\tau}$.
The rational expectation differed from equation (2) by considering information in addition to implied volatility of option prices that was useful for forecasting future price fluctuation. The omitted information that econometricians cannot directly observe from the option market at current, T-τ, for future volatility can be written as,
(3) $\alpha_{T-\tau} \equiv \sigma_T^e - \tilde{\sigma}_T^e$.
Moreover, the rational expectation can also be affected by errors made by agents in forecasting future price volatility at expiration date T. We defined the true errors as,
(4) $a_T \equiv \sigma_T - \sigma_T^e$.
Therefore, the forecasting regression error u_T in equation (3) can be decomposed into these two sorts of error terms,
(5) $u_T = \alpha_{T-\tau} + a_T$.
Under the assumption of rational expectations, all three errors (i.e., u_T, $\alpha_{T-\tau}$, and a_T) are assumed to be white noise, indicating that market is efficient and all relevant information has been used for volatility forecasting. In other words, information available at time $T{-}\tau$ should be uncorrelated with agents' errors in forecasting volatility. The variance of regression error is,
(6) $E[u_T^2] = \sigma_\alpha^2 + \sigma_a^2$,
Where $\sigma_\alpha^2 \equiv E[\alpha_{T-\tau}^2]$ is the variance of unobserved information term and $\sigma_a^2 \equiv E[a_T^2]$ the is variance of agents' true forecasting errors. The covariance between $\alpha_{T-\tau}$ and a_T (i.e., $cov(\alpha_{T-\tau}, a_T)$) equals to zero under the assumption of market efficiency.

Information from production forecasts
Price movements result from the supply-demand relationship. The United States Department of Agriculture (USDA) reports constitutes important public fundamental information for supply and demand on agricultural commodities. Specifically, price movements should only respond to the unanticipated component of new information in efficient markets. "New" or "surprise" component of the crop reports by calculating the difference in agents' production forecasts $q_{j,T-\tau}^{PF}$ and USDA forecasts $q_{j,T-\tau}^{UF}$ for commodity j. Furthermore, if it is assumed that private forecasts provide the market with unbiased estimates of USDA forecasts, and that USDA forecasts are log-normally distributed, then the unanticipated component of USDA reports, denoted by $\upsilon_{j,T-\tau}$, can be observed directly,
(7) $\upsilon_{j,T-\tau} = \left|q_{j,T-\tau}^{UF} - q_{j,T-\tau}^{PF}\right| - \tilde{\kappa}_j$,

where j = c (corn) and s (soybean). The term $\upsilon_{j,T-\tau}$ is assumed to be white noise and reflects unanticipated information contained in USDA crop reports that is potentially useful in determining final crop production levels and only becomes available to agents at time $T{-}\tau$.

How can the "news" component of USDA crop reports ($\upsilon_{j,T-\tau}$) influence the rational volatility expectations? The correlation between the regression error term (u_T) and crop reports "news" term ($\upsilon_{j,T-\tau}$) must be attributed to $\alpha_{T-\tau}$, the unobserved component of u_T. This is because these two terms represent information known by agents at $T{-}\tau$, and thus may be viewed as shared information about the co-movement of price volatility and production forecasts at harvest time. Hence, $\upsilon_{j,T-\tau}$ can be also written as a projection on $\alpha_{T-\tau}$,

(8) $\upsilon_{j,T-\tau} = \varphi_j^{\alpha} \alpha_{T-\tau} + \varepsilon_{j,T-\tau}$,

where $\varepsilon_{j,T-\tau}$ denotes USDA information about future production changes that is uncorrelated with corn volatility expectations at time $T-\tau$ (i.e., $cov(\varepsilon_{j,T-\tau}, \alpha_{T-\tau}) = 0$). We also assume that the covariance between the unobserved error (α_T) and "news" term ($\upsilon_{j,T-\tau}$) is zero. The covariance between u_T and $\upsilon_{j,T-\tau}$ is,

(9) $E[u_T \upsilon_{j,T-\tau}] = E\left[(\alpha_{T-\tau} + a_T)\left(\varphi_j^{\alpha} \alpha_{T-\tau} + \varepsilon_{j,T-\tau}\right)\right] = \varphi_j^{\alpha} \sigma_{\alpha}^2$.

Although crop reports can bring valuable information for agents to adjust their trading strategies at the current time, their forecasts might also provide noisy signals for harvest-time production in the future. Isengeldina-Massa, Irwin and Good (2006) showed that there is a systematic tendency for the USDA to "smooth" crop forecast revisions, which implies that forecasts are biased. In other words, USDA production forecasts might be biased and inefficient estimates for final production of a marketing year. If the forecast discrepancy between USDA production forecasts and final value can be explained by other explanatory variables in the information set $\mathbf{x_{T-n}}$, then its impacts on volatility forecasting regression might be weakened. Rational agents could use additional information beyond that contained in USDA crop reports to make a better forecast for forecasting final production, this can be modeled by,

(10) $\left|q_{j,T} - q_{j,T-\tau}^{UF}\right| = \tilde{b}_j \mathbf{x}_{\mathrm{T}-\tau} + \upsilon_{j,T}$,

where $q_{j,T}$ and $q_{j,T-\tau}^{UF}$ is final production and USDA production forecast announced at date $T-\tau$ for commodity j, respectively. Similarly, the correlation between u_T and $\upsilon_{j,T}$ must be due to forecast errors a_T. The production forecast errors $\upsilon_{j,T}$ can be projected on a_T,

(11) $\upsilon_{j,T} = \varphi_j^{a} a_T + e_{j,T}$,

where $e_{j,t}$ represents unanticipated forecast errors of final production in corn and soybean markets that are uncorrelated with price volatility at harvest (i.e., $cov(e_{j,T}, a_T) = 0$). The covariance between u_T and $\upsilon_{j,T}$ is then given by,

(12) $E[u_T \upsilon_{j,T}] = E\left[(\alpha_{T-\tau} + a_T)\left(\varphi_j^{a} a_T + e_{j,T}\right)\right] = \varphi_j^{a} \sigma_a^2$.

In summary, production forecasts are expected to influence the volatility forecasting regression in two aspects: (i) the "new" component of crop production reports, that is the valuable information of crop reports moves market prices;(ii) forecast errors that reports made by themselves. Rational agents should take production forecasts into account if production information has an important impact on the forecasting regression. The importance of USDA reports on volatility expectations can be observed by parameters in variance equations (8) and (11), implying the correlation between forecast regression errors u_T and crop report news $\boldsymbol{\upsilon}_{\mathbf{T-\tau}}$, and the correlation between u_T and production forecast errors $\boldsymbol{\upsilon}_{\mathbf{T}}$, respectively.

Inference about rational volatility expectations

We follow Hamilton (1992) and McKenzie (2008) to create a system consisting of an option-based volatility forecasting regression, USDA production forecasts, and final production for corn and its major substitute, soybean,

(13) $RV_T = \tilde{\delta}_0 + \tilde{\delta}_1 IV_{T-\tau} + u_T$,

(14) $\left|q_{j,T-\tau}^{UF} - q_{j,T-\tau}^{PF}\right| = \tilde{\kappa}_j + \upsilon_{j,T-\tau}$,

(15) $\left|q_{j,T} - q_{j,T-\tau}^{UF}\right| = \tilde{b}_j \mathbf{x}_{T-\tau} + \upsilon_{j,T}$,

where j =c (corn) and s (soybean). Then, from equations (8), (11) and (14), the covariance matrix can be written as,

$$(16)\quad \mathbf{\Omega} \equiv E\begin{bmatrix} u_T \\ \boldsymbol{\upsilon}_{\mathbf{T-\tau}} \\ \boldsymbol{\upsilon}_{\mathbf{T}} \end{bmatrix}\begin{bmatrix} u_\iota & \boldsymbol{\upsilon}_{\boldsymbol{\iota-\tau}} & \boldsymbol{\upsilon}_{\boldsymbol{\iota}} \end{bmatrix}$$

$$= \begin{cases} \begin{bmatrix} (\sigma_a^2 + \sigma_\alpha^2) & \sigma_\alpha^2(\boldsymbol{\varphi}^{\boldsymbol{\alpha}})' & \sigma_a^2(\boldsymbol{\varphi}^{\boldsymbol{a}})' \\ \sigma_\alpha^2(\boldsymbol{\varphi}^{\boldsymbol{\alpha}}) & \sigma_\alpha^2(\boldsymbol{\varphi}^{\boldsymbol{\alpha}})(\boldsymbol{\varphi}^{\boldsymbol{\alpha}})' + \mathbf{\Sigma} & \mathbf{0} \\ \sigma_a^2(\boldsymbol{\varphi}^{\boldsymbol{a}}) & \mathbf{0} & \sigma_a^2(\boldsymbol{\varphi}^{\boldsymbol{a}})(\boldsymbol{\varphi}^{\boldsymbol{a}})' + \mathbf{S} \end{bmatrix} & \text{if } T = \iota \\ \mathbf{0} & \text{if } T \neq \iota \end{cases}$$

where $\boldsymbol{\varphi}^{\boldsymbol{\alpha}}$, $\boldsymbol{\varphi}^{\boldsymbol{a}}$, $\boldsymbol{\upsilon}_{\mathbf{T-\tau}} \equiv \begin{bmatrix} \upsilon_{c,T-\tau} \\ \upsilon_{s,T-\tau} \end{bmatrix}$ and $\boldsymbol{\upsilon}_{\mathbf{T}} \equiv \begin{bmatrix} \upsilon_{c,T} \\ \upsilon_{s,T} \end{bmatrix}$ are 2×1 vectors. $\mathbf{\Sigma} \equiv E[\boldsymbol{\varepsilon}_{\mathbf{T-\tau}}\boldsymbol{\varepsilon}'_{\mathbf{T-\tau}}]$ and $\mathbf{S} \equiv E[\mathbf{e_T}\mathbf{e}'_{\mathbf{T}}]$ are 2×2 matrices while $\boldsymbol{\varepsilon}_{\mathbf{T-\tau}}$ and $\mathbf{e_T}$ are 2×1 vectors defined in equation (9) and (12), respectively.

Equations (13)-(15) describe a stochastic, dynamic multiple-equation model along with three sets of restrictions. The first set of restrictions asserts that a constant term is the only explanatory variable in equation (16). The second set of restrictions assumes that crop report "news" should be uncorrelated with agents' production forecast errors. This restriction is characterized by forcing the 2×2 block of covariance matrix $\mathbf{\Omega}$ corresponding to the covariance between $\boldsymbol{\upsilon}_{\mathbf{T}}$ and $\boldsymbol{\upsilon}_{\mathbf{T-\tau}}$ to be zero. The third one is a restriction for identifying the individual elements of the covariance matrix $\mathbf{\Omega}$. Hamilton (1992) points out not all of the variance parameters in (16) are estimable without the aid of further identifying restrictions. It is possible to estimate the sum $\sigma_a^2 + \sigma_\alpha^2$ and the products $\sigma_\alpha^2(\boldsymbol{\varphi}^{\boldsymbol{\alpha}})$ and $\sigma_a^2(\boldsymbol{\varphi}^{\boldsymbol{a}})$, but not the individual elements, σ_a^2, σ_α^2, $\boldsymbol{\varphi}^{\boldsymbol{\alpha}}$and $\boldsymbol{\varphi}^{\boldsymbol{a}}$. He imposes the restriction $\boldsymbol{\varphi}^{\boldsymbol{\alpha}}= \boldsymbol{\varphi}^{\boldsymbol{a}}= \boldsymbol{\varphi}$ to achieving identification. After applying this restriction to equations (9) and (12), we can observe the relationship between σ_a^2 and σ_α^2 as follows,

$$(17)\quad \frac{E[u_T \upsilon'_{j,T}]}{E[u_T \upsilon'_{j,T-\tau}]} = \sigma_a^2/\sigma_\alpha^2,$$

where j = c and s. Equation (17) implies the vector of covariances between u_T and $\boldsymbol{\upsilon}'_{\mathbf{T}}$ is proportional to that of covariances between u_T and $\boldsymbol{\upsilon}'_{\mathbf{T-\tau}}$. More specifically, a large covariance between forecasting regression errors (u_T) and rational agents' error in forecasting the j^{th} commodity production level ($\upsilon_{j,T}$), indicates that much of the production forecast error was unanticipated at time $T-\tau$ (i.e., σ_a^2 is large). Alternatively, a large covariance between u_T and $\upsilon_{j,T-\tau}$ implies much of market surprises could be anticipated at $T-\tau$ (i.e., σ_α^2 is large).

We can further obtain inferences about agents' rational volatility expectations. Given that data follows a multivariate Gaussian normal distribution, the statistically optimal inference about agents' rational expectation of corn volatility is shown as,

(18) $\widehat{RV}_T^e = \left[\tilde{\delta}_0 + \tilde{\delta}_1 IV_{T-\tau}\right] + \left[\frac{\varphi'\mathbf{S}^{-1}\varphi + \sigma_a^{-2}}{\boldsymbol{\Delta}}\right]\left[RV_t - \tilde{\delta}_0 - \tilde{\delta}_1 IV_{T-\tau}\right]$

$$+ [\frac{\varphi'\boldsymbol{\Sigma}^{-1}}{\boldsymbol{\Delta}}]\begin{bmatrix} \left|q_{c,T-\tau}^{UF} - q_{c,T-\tau}^{PF}\right| - \tilde{\kappa}_c \\ \left|q_{s,T-\tau}^{UF} - q_{s,T-\tau}^{PF}\right| - \tilde{\kappa}_s \end{bmatrix} - [\frac{\varphi'\mathbf{S}^{-1}}{\boldsymbol{\Delta}}]\begin{bmatrix} \left|q_{c,t} - q_{c,T-\tau}^{UF}\right| - \tilde{b}_c\mathbf{x}_{T-\tau} \\ \left|q_{s,t} - q_{s,T-\tau}^{UF}\right| - \tilde{b}_s\mathbf{x}_{T-\tau} \end{bmatrix},$$

where $\boldsymbol{\Delta} \equiv \varphi'\mathbf{S}^{-1}\varphi + \sigma_a^{-2} + \varphi'\boldsymbol{\Sigma}^{-1}\varphi + \sigma_a^{-2}$.[2]

Overall, the inference about rational volatility expectation depends on estimates from a system of equations (13)‒(15). It is of interest to point out two extreme cases: (i) $\sigma_\alpha^2 = 0$, where agents had no better information that contained in the option-based volatility forecasting regression; (ii) $\sigma_a^2 = 0$, where rational agents perfectly anticipated price movements at harvest. When $\sigma_\alpha^2 = 0$, the predication in equation (18) would reduce to $\tilde{\delta}_0 + \tilde{\delta}_1 IV_{T-\tau}$, indicating that agents cannot use the informational content of crop reports to re-evaluate their expectations for future price volatility and option-based volatility estimates would perfectly uncover agents' ex-ante volatility expectations. On the other hand, when $\sigma_a^2 = 0$, the prediction in (18) should be same to the ex-post price volatility, indicating the agents can perfectly forecast corn price volatility at harvest.

Components of rational volatility expectations

It is natural to raise a question how IV and production forecasts contribute to the rational volatility expectation. As shown in equation (18), the rational expectation $\widehat{RV}_T^e$ consists of four terms. The first term $\tilde{\delta}_0 + \tilde{\delta}_1 IV_{T-\tau}$ is the agent prediction for price volatility by only using the implied volatility in option markets. The three remaining terms represent the other components contributing to the rational volatility expectations but cannot be directly observed at T-τ. The second term $\left[(\varphi'\mathbf{S}^{-1}\varphi + \sigma_a^{-2})/\boldsymbol{\Delta}\right][RV_T - \tilde{\delta}_0 - \tilde{\delta}_1 IV_{T-\tau}]$ is the weight on ex-post price volatility of harvest corns from $t-\tau$ to the expectation of corn futures. The larger the variance of agents' forecast error (σ_a^2) is, the less weight is placed on ex-post price volatility. The third term $[\varphi'\boldsymbol{\Sigma}^{-1}/\boldsymbol{\Delta}]\begin{bmatrix} \left|q_{c,T-\tau}^{UF} - q_{c,T-\tau}^{PF}\right| - \tilde{\kappa}_c \\ \left|q_{s,T-\tau}^{UF} - q_{s,T-\tau}^{PF}\right| - \tilde{\kappa}_s \end{bmatrix}$ is the weight on crop report "news" for corn and its substitute, soybean. When holding φ constant, the weight on new components of USDA reports decreases as its variance $\boldsymbol{\Sigma}$ increases. Conversely, the greater the influence of shared information on the co-movement between harvest-time price and production (φ), the greater the weight that should be placed on USDA crop reports. The fourth term $-[\varphi'\mathbf{S}^{-1}/\boldsymbol{\Delta}]\begin{bmatrix} \left|q_{c,t} - q_{c,T-\tau}^{UF}\right| - \tilde{b}_c\mathbf{x}_{T-\tau} \\ \left|q_{s,t} - q_{s,T-\tau}^{UF}\right| - \tilde{b}_s\mathbf{x}_{T-\tau} \end{bmatrix}$, is the weight to be placed on crop production forecast errors. Although this term is uncorrelated with $\alpha_{T-\tau}$, it is correlated with price volatility as the maturity of contracts is approaching, which is in turn used to uncover an inference about $\alpha_{T-\tau}$. It may appear anomalous to include terms $\widehat{RV}_T^e$ in which contain information available only after the time when forecasts were made. This information, however, allows the econometrician to make ex-post inferences about the ex-ante value of $\alpha_{T-\tau}$. In other words, this weight generates another sort of information–the larger the correlation between rational agents' production forecast errors and option-based corn volatility

[2] We follow the Hamilton's (1992) approach to infer the rational volatility expectation. More details on the Hamilton's approach can be found in the Appendix C of his paper.

regression forecast errors (i.e., **S** is larger), the less value should be attributed to production forecasts in predicting price volatility.

Data and Model Specifications

In this section, we explain data sources and the empirical framework to investigate the impacts of USDA crop reports on volatility expectations for corn. We use two sorts of data over the 1995-2022 period: (i) production forecasts and final value of corn soybeans from the USDA crop reports and (ii) historical implied volatility derived from at-the-money call and put option of the December corn futures contracts. We then delve into the model specifications by using a likelihood-ratio test to evaluate our model against the alternative models with fewer restrictions.

Market surprises and forecast errors of USDA crop production reports

As noticed in our theoretical model, production forecasts affect the inferences about rational volatility expectations in two perspectives. One is known as the "news" component of crop reports reflecting unanticipated information contained in the USDA reports beyond private analysts' forecasts. The absolute surprises are shown in figures 1 and 2 for corn and soybean over the 1995-2022 period, respectively.[3] More specifically, we focus on August, September, October, and November, which are within the growth cycle of corn and soybeans. Market surprises in August are found to be the most volatile associated with the highest average, 1.92% for corn and 2.22% for soybean, indicating that the August report is most likely to bring new information to both corn and soybean markets. This finding is consistent with empirical evidence from previous research (e.g., Karali et al. 2019; Isengildina-Massa 2021).

Another impact comes from the production forecast errors. Various factors can influence the accuracy and efficiency of production forecasts, such as forecasting methodologies and extreme weather events. For example, smoothing is a well-known issue in production forecast revisions for corn and soybean due to a conservative bias in farm operators' assessment (e.g., Isengildina-Massa, Irwin, and Good 2006; Xie, Isengildina-Mass, and Sharp 2016). Also, extreme weather events or climatic anomalies have detrimental effects on regional crop production, further influence the basis or futures returns of agricultural commodities (e.g., Makkonen et al. 2021; MacSkevas, Brown, and Thompson 2022). Production forecast errors are measured by absolute difference between true price volatility and volatility expectation.[4] Figure 3 displays the absolute changes in production forecast errors caused by corn reports released across years. The August and September reports have larger forecast errors than the November and December. Specifically, the August report has the largest average over the sample period, and its production errors can be up to 9.66 percentage points. As shown in figure 4, the soybean reports also have the largest average errors in August. The errors from the August report are more volatile than in later months. It is not surprising to observe relatively large errors in August because of the limited data available to make predictions at the early stage of the ongoing harvest year.

In summary, the August report can be considered the most "newsworthy" to affect market expectations for either corn or its major substitute, soybean. Therefore, we focus on the impacts

[3] The growth cycle is from August to November for corn and soybean. We focus on these months and compare the changes in market surprises among these months.

[4] USDA finalizes the corn and soybean production in January of each marketing year. Therefore, we use data in January reports as the final value of annual production.

of production forecasts released in August and analyze the changes in price volatility around the August report.

Implied and realized volatility of new crop futures around the August report
We use historical IV derived from at-the-money (ATM) options for Chicago Board of Trade (CBOT) corn and soybeans futures contracts. Our IV data are obtained from Bloomberg covering the period from 1995 to 2022.[5] CBOT corn contracts are delivered in March, May, July, September, and December, while soybean contracts can be delivered January, March, May, July, August, September, and November. The delivery months for crop futures indicate the source of supply at a particular time. Therefore, we investigate the impacts of the August report on December corn and November soybean contracts, whose price dynamics capture changes in anticipated supply of newly harvested crops (CBOT 2023).

To capture whether USDA production forecasts are helpful to improve market expectations, we estimate rational volatility expectations in the pre-report periods when no information for crop production is available in the markets. We label the three days before as -1, -2, and -3. The "true" price volatility, known as realized volatility (RV), is calculated by the historical price series from day *n* prior to the August release to the expiration of at-harvest corn futures. We compute the RVs as the standard deviation of daily returns of underlying corn futures contracts.[6] In option markets, traders use implied volatility as a forward-looking measure for future price fluctuations. Implied volatility is a forecast for realized volatility calculated within the same interval. We take the average of Bloomberg IVs of call and put options in the pre-report periods of August report, *t*.[7]

Table 1 reports summary statistics of implied and realized volatility in the pre-report periods. The average level of RVs before the release is 23.6 percentage points, which is 1.1 percentage points lower than that of IV in the pre-release periods. The prominent drops in price volatility are found in historical IVs since USDA information is valuable for markets to resolve the uncertainty (e.g., Isengildina-Massa et al. 2008). Our IV data is consistent with previous findings, and figure 5 displays a decline in average IV after the release.

Besides the visualization of a decline in IVs on the release days, we further investigate the statistical significance of the changes in IVs on pre-release days with the release day.[8] Table 2 presents a summary of Z and Wilcoxon signed-ranked test statistics, respectively. The Z tests examine the proportion of the release day when its implied volatility decreases relative to pre-report trading days. The Z statistics indicate a significant decrease in IV the report (i.e., p-values are below 0.05). For example, implied volatility in corn on release days of the August report is

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[5] Bloomberg Listed Implied Volatility Engine (LIVE) provides ATM implied volatility of individual listed option based on the canonical Black-Scholes formula. The time to maturity of options is at least 20 trading days out from a selected date to the 1st listed expiry. LIVE uses linear interpolation and flat extrapolation with no smoothing attempted that historical IV data for non-equity is calculated from a weight average of the volatilities of the two call (put) options closest to the ATM strike.
[6] $r_k = [\ln(p_k) - \ln(p_{k-1})] \times 100$, where p_k is the futures prices of December corn futures on day *k*.
[7] For example, IV_{t-1} refers to the implied volatility from one day before the USDA August report to the expiration date of December corn futures. For brevity, we simplify the subscription without adding expiration date.
[8] We follow Isengildina-Massa et al. (2008) to conduct the Z and Wilcoxon tests. The detail of the two tests is explained in their paper.

lower than that on one day before the release 71% of the time by an average of 1.04 percentage points, with a statistical significance level at 0.02. In addition, the Wilcoxon tests support the finding of significant changes in IV before the release, by examining implied volatility differences between the release day and other trading days. The pre-release test statistics range from 67.50 to 83.00 associated with the statistical significance at 0.01 or below, indicating the significant difference in mean implied volatility on the release day and any of three trading days before it.

Overall, we find a significant decrease in IV of at-harvest corn futures from the pre-report days to the release day of the August report. This empirical finding implies that the corn market has assimilated the information from the August reports to adjust its expectations for future price fluctuations at harvest. More importantly, the adjustment in market expectations is more likely to happen on the pre-release days since IVs are relatively stable after the release.

Specification tests and final model specification

We examine our model specification by comparing alternative models with fewer restrictions. Our empirical model builds on three sorts of restrictions. The first sort of restrictions (Type A) asserts that option-based IVs can only provide information for capturing the changes in RVs rather than crop report "news" or forecast errors. The second sort (Type B) forces the 2×2 block of (18) corresponding to the covariance between $\upsilon_{j,T}$ and $\upsilon_{j,t-n}$ to become zero. The third one (Type C) belongs to a practical restriction, known as "classical identification restriction", where $\boldsymbol{\varphi}^{\boldsymbol{\alpha}}= \boldsymbol{\varphi}^{\boldsymbol{a}}= \boldsymbol{\varphi}$ is imposed to identify the individual elements of covariance matrix $\boldsymbol{\Omega}$. When more than one commodity is included in the model, this classical restriction imposes an over-identifying assumption that can be tested against the data. It is necessary to explore whether the model can be better without some of these restrictions. Table 3 reports the results from likelihood ratio tests to compare our model specification against seven alternative models with fewer restrictions. The test results show we cannot reject the null hypothesis by any day in the pre-release period. For example, the likelihood-ratio test statistic and associated p-value for Day -1 (i.e., one day before the report release) indicate that our model specification is easily accepted against the most general model (χ^2_{10}= 2.81, p-value = 0.99).[9]

Empirical Results

We simultaneously estimate a system of mean equations (13)-(15), along with the covariance matrix (16) by using full-information maximum likelihood (FIML).[10] Model estimates are obtained for three days before the report release.

Volatility forecasts for realized volatility

Estimates of mean equations (13), (14), and (15) presented in table 4 correspond to Day -1, but results for other surrounding days are quantitatively similar.[11] Except for the constant term ($\tilde{\delta}_0$), parameters are statistically significant at the 0.01 level. Our interest in mean parameters is from the option-based corn volatility forecasting regression in equation (13). The coefficient on the

[9] The most general model refers to the model without any of three restrictions in table 3.
[10] Estimates were obtained by maximizing the unconcentrated log likelihood function.
[11] The estimates of mean equations for all selected days are presented in Appendix table A.1

IV parameter ($\tilde{\delta}_1$) is 0.87 and the constant ($\tilde{\delta}_0$) is 0.40.[12] We further investigate whether IV is unbiased and efficient for forecasting ex-post price volatility in the regression. We follow Canina and Figlewski's (1993) rationality test to jointly examine whether $\tilde{\delta}_0 = 0$ and $\tilde{\delta}_1 = 1$ by using the Wald test. The statistic of the joint Wald test (χ_2^2 = 6.38, p-value = 0.04) confirms that we can reject the null hypothesis (i.e., H_0: $\tilde{\delta}_0 = 0,\ \tilde{\delta}_1 = 1$), and thus IV is biased and inefficient for forecasting realized volatility on Day -1.[13] This finding implies that the IV for new crop futures is biased for volatility forecasting before the release, but the arrival of USDA information could help to adjust agent's volatility expectations.

Information value of production forecasts in volatility forecasting regression
The impact of the USDA report on volatility expectations stems from the correlation between price volatility and production forecasts. The correlation consists of two variance parameters, standard deviations and projection parameters, as detailed in equations (11) and (14). In table 5, we report the estimates of these parameters for trading days surrounding the release. The standard deviations for production forecast errors σ_a and crop news σ_α are statistically significant at the 0.01 level. More specifically, the standard deviation of the production forecast errors (σ_a) ranges from 5.57% to 6.26%, which is larger than that of crop report "news" (σ_α) from 2.64% to 2.99%. The larger discrepancy in production forecast errors compared to crop report news results from the timing of forecasts. Analysts' forecasts are collected several days before the release, while the production forecasts are made four months before new crop delivery, hence introducing more variability.

Moreover, projection coefficients φ_j capture the sensitivity of production forecasts in response to the price volatility of commodity j. A higher value of the projection coefficient indicates that production forecasts are more sensitive to changes in volatility expectations. Corn projection coefficients (φ_c) are all negative and statistically significant at the 0.01 level, ranging from -0.06% to -0.08%. In particular, it slightly increases on the release day of the August reports, indicating that the market expectations for corn price volatility could affect the market forecasts of corn production. Similarly, soybean projection coefficients (φ_s) are negative and statistically significant during the pre-report days, but no statistical significance exists on the trading day immediately after the USDA release. Notably, φ_s is consistently smaller than φ_c. These findings uncover the relationship between volatility forecasting and production forecasts. In periods lacking reliable fundamental information (before the report), volatility expectations for corn can inform production forecasts for both soybean and its own. However, once fundamental information becomes available (the trading day following the report), corn production forecasts correlate solely with its volatility expectations.

Potential contribution of various components in rational volatility expectations
How do production forecasts help to adjust agents' volatility expectations? We infer rational volatility expectations in equation (18), which consists of four components: IV regression, ex-

[12] Under the assumption of rational expectations and market efficiency, agents should make good use of all available information, and thus residuals of each equation should be white noise. The results from a battery of residual diagnostic tests at the bottom of table 4 indicate that mean equations are well specified. Error terms cannot be rejected by the null hypothesis of multivariate normal distribution at the 0.01 level, and there is no evidence of serial correlation.
[13] The joint Wald test statistics for all three pre-report days are shown at the bottom of Appendix table A.1.

post volatility, crop report news, and production forecast errors. Ex-post volatility, crop report news, and production forecast error contribute to an optimal ex-ante inference associated with weights. The component weights show the importance of each component in drawing an inference about agents' volatility expectation. Table 6 reports the weights of each component.

Under our model assumption, the corn market cannot have information for production forecasts in the pre-report periods. The weights for each component on pre-report expectations indicate that information would significantly influence volatility expectations if information contained in the August report is "magically" revealed in advance of the release date. It indicates, if agents can "magically" obtain the production forecast before its release, corn report news have largest impacts on the adjustment in rational volatility expectations. The negative sign of corn report news contributes to lower volatility expectations, indicating larger new information from the USDA report helps to resolve market uncertainty for future price movements in the corn market. Similarly, soybean report news also decreases the agents' expectations for future corn price volatility; however, their impacts are much smaller than those from corn markets. It is not surprising to observe a minor potential contribution of production forecast errors in either the corn or soybean market because production forecast error is ex-post information for agents who have made their volatility expectations in August.

Historical volatility expectations

We examine ex-ante volatility expectations estimated around the release for historical crop years to shed further light on two questions: (i) whether the USDA crop report contains valuable information; and (ii) whether changes in IV reflect this information in the post-report period. We report the hypothetical volatility expectations estimated conditionally for Day -1 and augmented by the August report "news", ex-post price volatility, and production forecast errors in table 7. The relative contribution of each component of rational volatility expectations is reported along with the actual price volatility. As shown in table 7, information contained from ex-post volatility would often have led to adjustments in agents' volatility expectations within the range of -1.80 to 4.93 percentage points on Day -1. The contribution of the August report news would adjust agents' expectations by the range of -1.47 to 0.72 percentage points, while the contribution of production forecast errors is relatively small, ranging from -0.20 to 0.45. The information contained in α_{t-n} (i.e., ex-post volatility, crop report news, and production forecast errors) is valuable to configure rational volatility expectations, and thus would more closely align expectations with realized price volatility. For example, in 2010, the option-based volatility forecasting regression predicted price volatility of corn harvest-time futures is 31.15 percentage points, an underestimation of realized volatility by approximately 4.80 percentage points. Contributions of ex-post volatility (1.00 percentage points), crop report news (0.43 percentage points), and production forecast errors (0.26 percentage points) realign volatility expectations upwards to 32.84 percentage points. However, the adjustment from the α_{t-n} is limited when IV forecasts suffer from anomalies. For example, the IV regression extremely underestimated the realized volatility by approximately 23.79 percentage points in 2008. Ex-post volatility and crop report news contribute to the upward adjustments by 4.93 and 0.35 percent points, respectively, to raise volatility expectations to 32.74 percentage points.

When report information is not available to agents before the release, in this case, the IV regression ($\tilde{\delta}_0 + \tilde{\delta}_1 IV_{T-(t-n)}(\omega)$) generally represents the best estimate of rational agents' expectations on Day -1. On the other hand, if the information is "magically" available, then rational agents incorporate production forecasts into volatility expectations. We compare these two cases to actual price volatility (i.e., RV) to explore the dynamics in volatility expectations over time. In tables 8, we illustrate the disparities between rational volatility and RV, alongside the discrepancies between implied volatility and RV on Day -1 and the release day. In the pre-report period, rational volatility expectations often better capture the dynamics in realized volatility since the differences between realized volatility and rational volatility expectations are relatively smaller than those between implied volatility. It indicates that incorporating the production forecasts can help to improve the IV forecasting for realized volatility in the pre-report period. The changes in IV and rational expectations are often higher than the actual volatility changes. IV includes a risk premium, representing the additional return that investors demand for taking on the risk of volatility. This premium can push IV above the level suggested by realized volatility (RV). Investors are willing to pay more for options when they expect higher volatility, as the potential for profit increases with larger price volatility. This demand for options in anticipation of higher volatility can inflate IV above RV. Moreover, as shown in figure 6, the largest discrepancies between inferred volatility and actual price volatility occurred in the years 1996, 1997, and 2019, indicating moments when the risk premium was particularly high. For example, in 1996, the change in IV regression was 2.26 percentage points, while the actual price volatility only increased by 0.26 percentage points. Similarly, the change in rational volatility reached a notable peak of -3.56 percentage points compared to an increase in actual price volatility of just 0.03 percentage points in 2019. These suggest that during these years, there may have been significant events or market conditions that led investors to expect, and therefore price in, much higher levels of volatility than what was realized.

Conclusions

Our paper contributes to the literature on the information value of USDA reports by investigating their impacts on market expectations for future price volatility in the U.S. corn market. We use a Hamilton-style approach to evaluate the impacts of crop production forecasts on rational agents' volatility expectations. Specifically, we study the price volatility of new crop futures contracts since price movements in newly harvested crops are more active in the ongoing production forecasts. Since the August forecast is generally considered the most important of the reports in the growth cycle of corn in a year, we focus on pre-report days of the August reports to investigate whether new information contained in USDA reports contribute to the changes in rational volatility expectations.

Our empirical results provide three major findings. Although IV derived from option prices are commonly used as market expectations for future prices, it might not be a good proxy for the market's best forecast of true price volatility since theoretical option pricing does little against the noisy forces of supply and demand in the market (Figlewski 1997). Our results reveal that IV is biased and inefficient in forecasting realized volatility over the three-day pre-report period. However, the USDA production reports provide valuable news for agents to re-evaluate their expectations for future price volatility. Market participants, who rely on IV estimates for volatility forecasting, need to consider the production information revealed in these reports to improve their volatility forecasting.

Our results also show that crop report news provides more potential contributions for rational agents' volatility expectations than production forecast errors. It is not surprising to have lower weights on production forecast errors since the forecast errors are ex-post adjustments that market participants can hardly obtain accurate production forecasts in the early stage of the production process. In addition, we examine the volatility expectation inferences for historical crop years to capture the changes in actual contributions of each component over time. Our historical findings further support the information value of USDA production reports since three components of omitted information, ex-post volatility, crop report news, and production forecast errors, have a better performance in reducing overestimation or underestimation of IV regression forecasts in the pre-release period, especially when markets are anomalies.

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Table 1. Summary Statistics of Realized and Implied Volatility around the August Report

	t-n		
	-3	-2	-1
RV_{t-n}			
Mean	23.58	23.58	23.55
Std. Dev.	8.59	8.57	8.60
Min	13.84	13.82	13.62
Max	55.57	55.64	55.53
Skewness	2.07	2.08	2.06
Kurtosis	8.03	8.12	7.97
IV_{t-n}			
Mean	26.49	26.76	26.47
Std. Dev.	6.24	6.29	6.03
Min	18.59	18.72	18.94
Max	40.98	40.88	40.46
Skewness	0.75	0.72	0.69
Kurtosis	2.52	2.46	2.45

Notes: The sample period is from January 1995 to December 2022. IV_{t-n} represent option-based implied volatility of December corn futures contracts from day *n* before the release of the August report *t* to the expiration date of the December contract, where *n* =-3, -2, and -1. RV_{t-n} represents the realized volatility calculated by standard deviation of first-difference log prices from day *t-n* to the expiration of the December corn contract.

Table 2. Changes in IV Between Pre-Report Days and USDA Reports

	t-n		
	-3	-2	-1
Z	0.75	0.82	0.71
	[0.01]	[0.00]	[0.02]
Wilcoxon	75.00	67.50	83.00
	[0.00]	[0.00]	[0.01]

Notes: The table reports the statistics for a Z test and a paired t test to investigate whether the IVs are different before and after the USDA release. We choose IV on the same day after the release as a benchmark. The Z test is for the proportion of WASDE releases when IV declines relative to the trading days around the announcement. Its null hypothesis is that the proportion equals to 0.5, indicating there is indifference between increase and decreases. On the hand, the Wilcoxon test examines the difference between mean implied volatility on pre-report and release days. The null hypothesis of the Wilcoxon test is that the mean implied volatility on release days is equal to that of pre-report days. The p-values of each test are in brackets.

Table 3. Likelihood Ratio Tests of Model Specifications

Restrictions imposed			Log likelihood				Likelihood ratio test χ^2_{df}			
A	B	C	*k*	*t-n*			*df*	*t-n*		
				-3	-2	-1		-3	-2	-1
H_0: final model specification										
yes	yes	yes	16	-328.49	-328.09	-328.83				
H_1: alternative model specification										
no	no	no	26	-326.94	-326.57	-327.43	10	3.09	3.03	2.81
								[0.98]	[0.98]	[0.99]
no	no	yes	24	-326.98	-326.64	-327.48	8	3.00	2.91	2.70
								[0.93]	[0.94]	[0.95]
no	yes	no	22	-327.42	-327.05	-327.90	6	2.13	2.08	1.87
								[0.91]	[0.91]	[0.93]
yes	no	no	22	-327.95	-327.53	-328.28	6	1.08	1.13	1.10
								[0.98]	[0.98]	[0.98]
yes	no	yes	20	-327.99	-327.59	-328.34	4	0.99	1.00	0.99
								[0.91]	[0.91]	[0.91]
no	yes	yes	20	-327.45	-327.10	-327.94	4	2.07	1.98	1.78
								[0.72]	[0.74]	[0.78]
yes	yes	no	18	-328.46	-328.04	-328.79	2	0.06	0.10	0.08
								[0.97]	[0.95]	[0.96]

Notes: This table reports log-likelihood values and their corresponding likelihood ratio tests on pre-release days of the August report *t*, Day *t-n*. Type A asserts the option based IV can only explain the realized volatility in equation (13). Type B forces the 2 by 2 block of (16) corresponding to the covariance between $\boldsymbol{\upsilon}_{\mathbf{T-\tau}}$ and $\boldsymbol{\upsilon}'_{\mathbf{T}}$ to be zero. Type C is the Hamilton-type approach to identify the elements of covariance matrix $\boldsymbol{\Omega}$, where $\boldsymbol{\varphi}^{\alpha}= \boldsymbol{\varphi}^{a}= \boldsymbol{\varphi}$. *k* refers to the number of parameters estimated in each specification, *df* presents the degree of freedom for likelihood ratio tests. The p-values of χ^2_{df} are in the brackets.

Table 4. FIML Estimates of Mean Equation Parameters, Day -1

	(13)	(14)		(15)	
		c	*s*	*c*	*s*
Parameters					
$\tilde{\delta}_0$	0.40				
	(1.08)				
$\tilde{\delta}_1$	0.87*				
	(0.04)				
$\tilde{\kappa}_j^{\alpha}$		1.92*	2.22*		
		(0.04)	(0.05)		
$\tilde{\kappa}_j^{a}$				3.11*	4.55*
				(0.10)	(0.14)
Residual Diagnostics					
LM test	1.24	0.59	2.06	4.39	0.53
	[0.74]	[0.90]	[0.56]	[0.22]	[0.91]
Multivariate normality test					
$b_{1,5}$	10.81				
	[0.04]				
$b_{2,5}$	34.51				
	[0.88]				

Notes: The table reports the estimated results from five mean equations. commodity *j=c* for corn and *s* for soybean. Standard errors of parameters are in the parenthesis, while the p-values of test statistics are in the brackets. LM test denotes Breusch–Godfrey Lagrange multiplier test for serial autocorrelation, and maximal order of serial correlation to be tested is three. The null hypothesis of BG test is no autocorrelation. In addition, we use Marida's multivariate normality tests. $b_{1,5}$ represents the multivariate skewness test, while $b_{2,5}$ is for the kurtosis test in the dimension of 5. The null hypothesis of $b_{1,5}$ ($b_{2,5}$) is that the distribution has the appropriate level of skewness (kurtosis) expected under a multivariate normal distribution. The asterisks * indicate statistical significance at the 5% or lower level.

Table 5. FIML Estimates of Key Variance Parameters

		t-n	
Parameters	-3	-2	-1
σ_α^2	2.70*	2.99*	2.99*
	(0.70)	(0.64)	(0.55)
σ_a^2	5.81*	5.57*	5.80*
	(0.36)	(0.37)	(0.32)
φ_c	-0.06*	-0.06*	-0.07*
	(0.02)	(0.02)	(0.02)
φ_s	-0.04*	-0.04*	-0.04*
	(0.02)	(0.02)	(0.02)

Notes: The standard errors are in parentheses. σ_α^2 represents the variance of crop report "news", σ_a^2 is for the variance of production forecast error. φ_i refers to the projection coefficients of each commodity *i*, where *i* = *c* (corn) and *s* (soybean). The asterisks * indicate statistical significance at the 5% or lower level.

Table 6. Estimated Weights for Volatility Expectations

Components	-3	-2	-1
$RV_T - \tilde{\delta}_0 - \tilde{\delta}_1 IV_{T-(t-n)}$	0.18	0.22	0.21
$\left\|q^{UF}_{c,T-\tau} - q^{PF}_{c,T-\tau}\right\| - \tilde{\kappa}^{\alpha}_{c}$	-0.26	-0.33	-0.39
$\left\|q^{UF}_{s,T-\tau} - q^{PF}_{s,T-\tau}\right\| - \tilde{\kappa}^{\alpha}_{s}$	-0.09	-0.08	-0.08
$\left\|q_{c,T} - q^{UF}_{c,T-\tau}\right\| - \tilde{\kappa}^{a}_{c}$	0.05	0.06	0.07
$\left\|q_{s,T} - q^{UF}_{s,T-\tau}\right\| - \tilde{\kappa}^{a}_{s}$	0.01	0.01	0.01

Notes: The subscription *c* presents corn and *s* presents soybean.

Table 7. Components of Inferred Volatility Expectations about Corn Volatility, Day -1

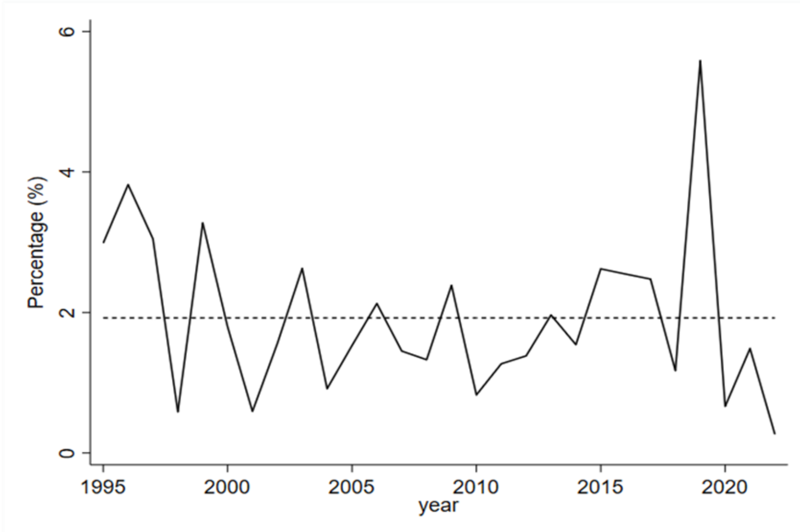
Year	Actual Price Volatility	IV Regression Forecast	Ex-Post RV	Crop Report News	Production Forecast Errors	Expected Price Volatility
1995	13.62	17.81	-0.87	-0.54	0.45	16.86
1996	17.65	23.51	-1.22	-0.75	0.23	21.78
1997	22.95	20.88	0.43	-0.39	-0.19	20.72
1998	17.89	16.96	0.19	0.66	-0.12	17.69
1999	19.13	23.41	-0.89	-0.42	-0.08	22.03
2000	16.62	18.95	-0.48	0.13	0.09	18.69
2001	17.25	20.15	-0.60	0.62	-0.08	20.08
2002	21.99	24.54	-0.53	0.12	-0.13	24.01
2003	25.98	18.27	1.60	-0.39	-0.05	19.43
2004	19.77	18.75	0.21	0.36	0.37	19.69
2005	16.72	22.54	-1.21	0.31	0.34	21.97
2006	33.18	22.02	2.32	-0.13	0.11	24.31
2007	27.70	26.09	0.33	0.27	-0.24	26.45
2008	55.53	31.74	4.93	0.35	-0.15	36.88
2009	36.75	35.78	0.20	-0.07	0.00	35.90
2010	35.95	31.15	1.00	0.43	0.26	32.84
2011	29.22	31.87	-0.55	0.11	0.04	31.47
2012	23.25	31.93	-1.80	0.09	-0.14	30.08
2013	24.99	22.08	0.60	-0.08	-0.17	22.43
2014	24.51	21.32	0.66	0.32	-0.13	22.16
2015	21.18	25.04	-0.80	-0.45	-0.22	23.57
2016	22.15	20.37	0.37	-0.29	-0.20	20.26
2017	15.30	18.89	-0.75	-0.36	-0.05	17.74
2018	17.22	17.77	-0.11	0.19	-0.18	17.66
2019	23.49	24.28	-0.17	-1.47	-0.12	22.52
2020	19.82	16.99	0.59	0.37	0.32	18.27
2021	19.96	28.30	-1.73	0.30	-0.07	26.80
2022	19.51	27.86	-1.73	0.72	0.11	26.96

Notes: The table reports the components of volatility expectations calculated one day prior to the release of the August crop report.

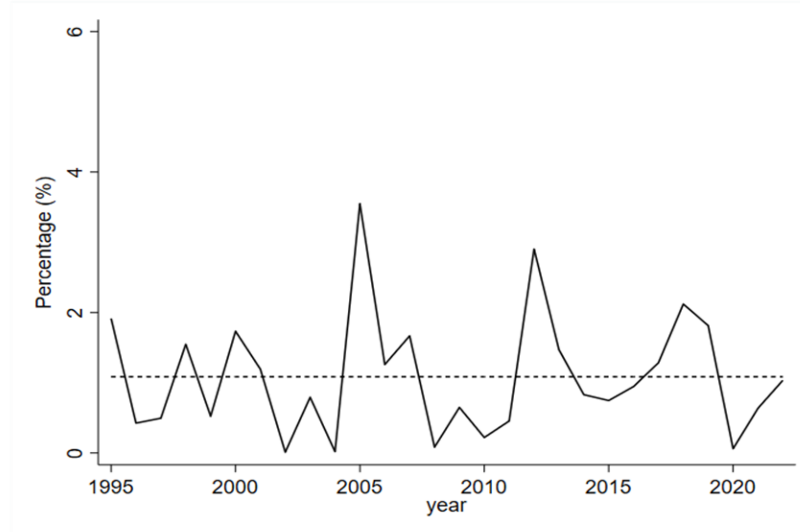
Table 8. Changes in Price Volatility between Day -1 and Day 1

Year	Rational Volatility	IV Regression	Actual Price Volatility
1995	1.24	0.09	0.07
1996	2.82	2.26	0.07
1997	4.03	4.51	0.00
1998	-0.85	-2.18	0.09
1999	0.82	-0.21	-0.20
2000	-0.54	-2.00	0.04
2001	0.42	-0.71	0.02
2002	1.15	0.32	-0.07
2003	1.02	0.78	0.00
2004	0.25	-0.67	-0.03
2005	-0.09	-1.49	0.02
2006	-1.80	-2.75	0.16
2007	-1.47	-2.83	-0.25
2008	-1.48	-1.10	0.32
2009	-1.87	-3.31	0.21
2010	0.26	-0.18	0.21
2011	0.11	-1.10	0.17
2012	-1.06	-3.10	0.07
2013	0.55	-0.22	0.04
2014	-0.78	-1.83	0.06
2015	-0.61	-2.23	-0.68
2016	1.07	0.38	0.12
2017	-0.49	-2.27	0.03
2018	-0.04	-1.38	0.07
2019	-3.56	-6.22	0.13
2020	0.26	-0.65	0.11
2021	0.27	-1.18	0.04
2022	1.13	0.04	-0.05

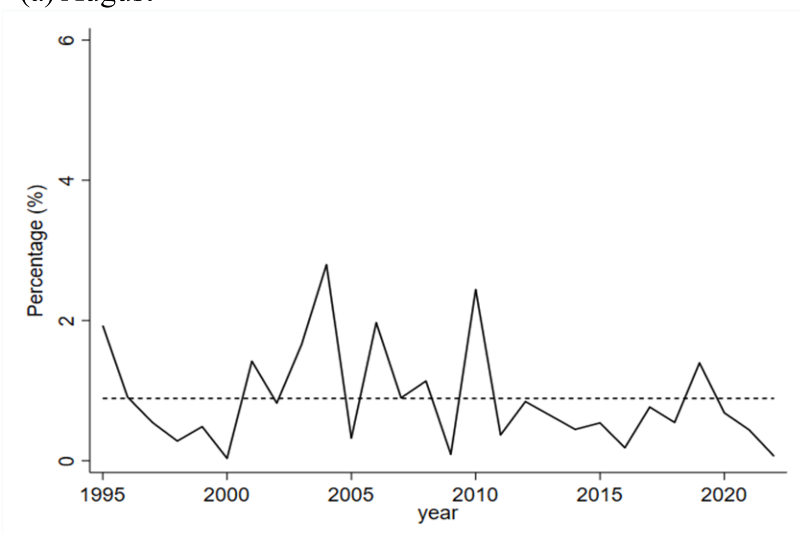
Notes: The table reports the changes in expected volatility, option based IV, and actual price volatility between one day prior and the day immediately after the release of the August report. The unit is percentage points.



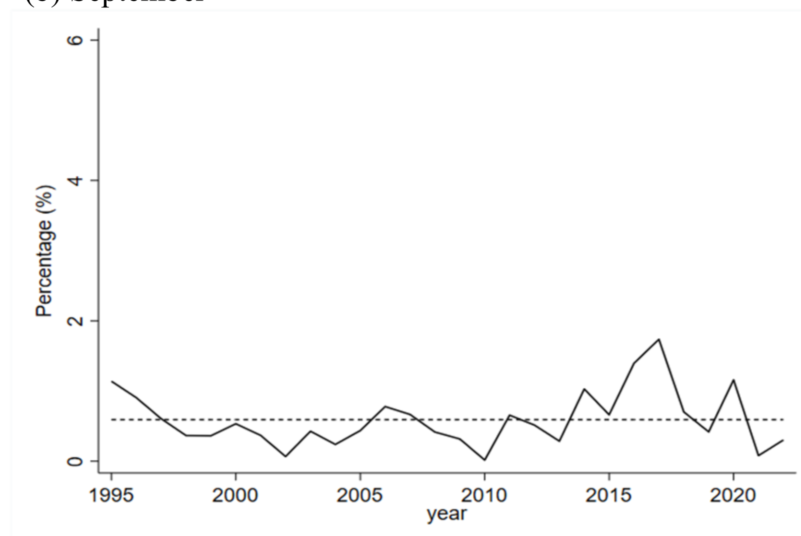
(a) August



(b) September



(c) October

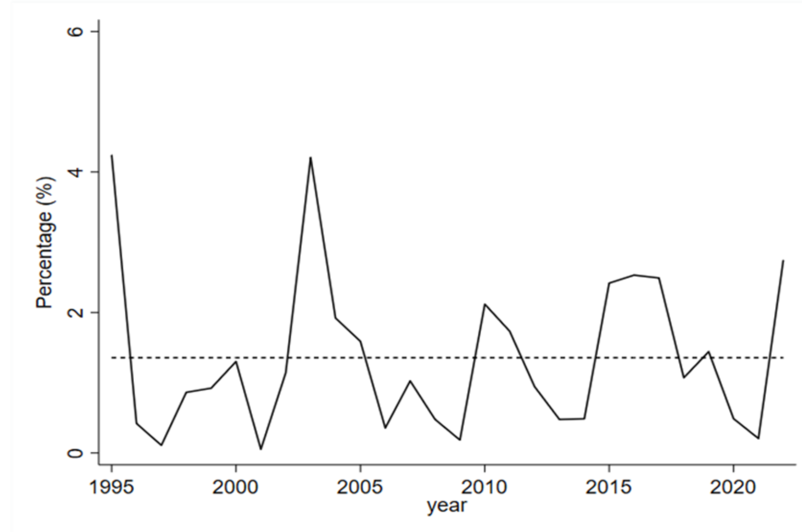


(d) November

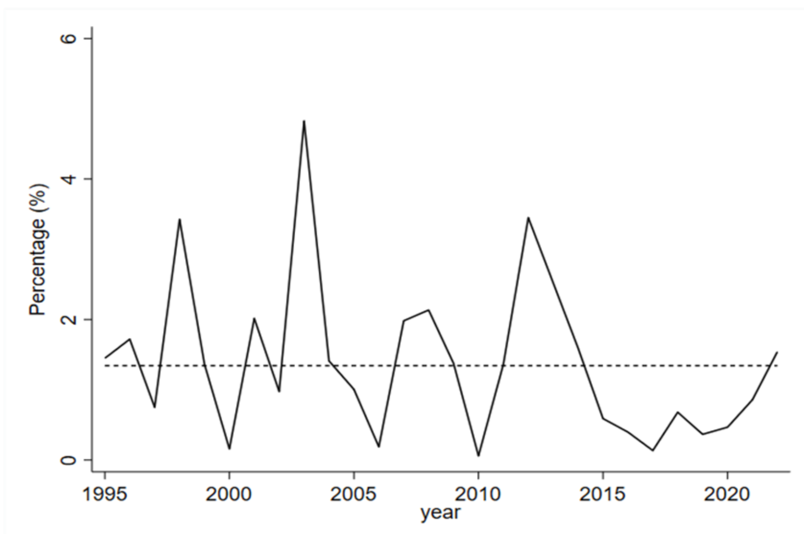
Figure 1. Absolute Market Surprises in Corn Production Report, 1995-2022

Notes: The solid line represents the absolute magnitude of market surprises for corn production in each month of the growth cycle of corn. The dash line is a reference for the average of the absolute market surprise over the whole sample period from 1995 to 2022.

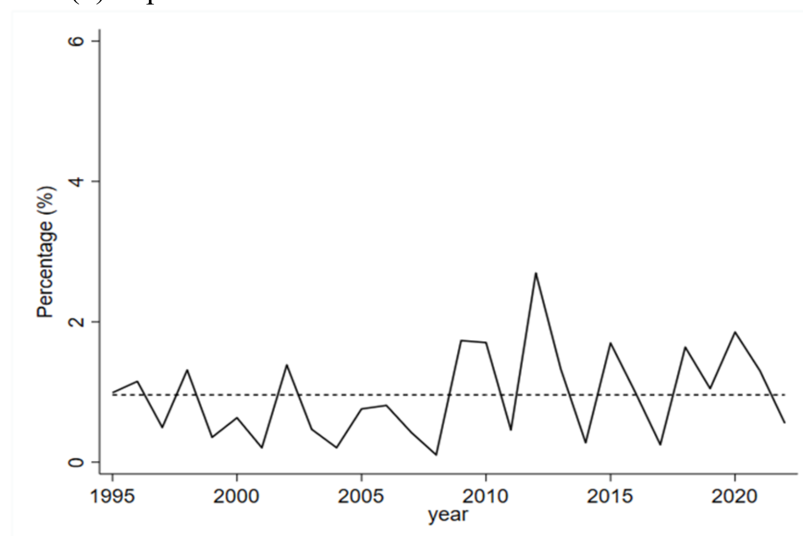
(a) August



(b) September



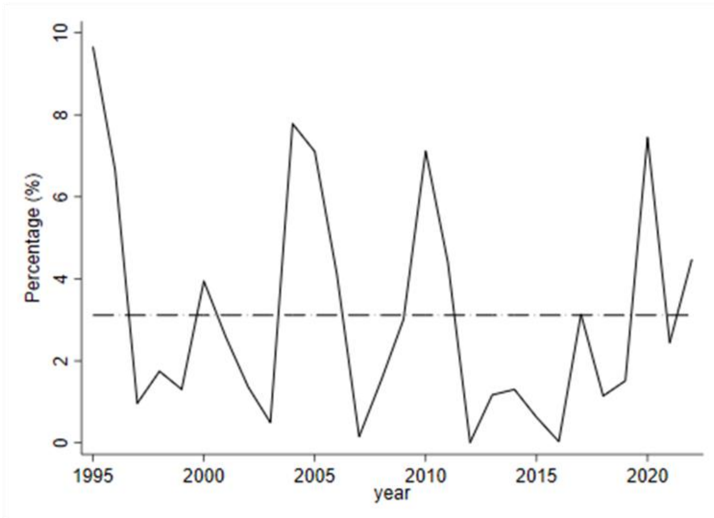
(c) October



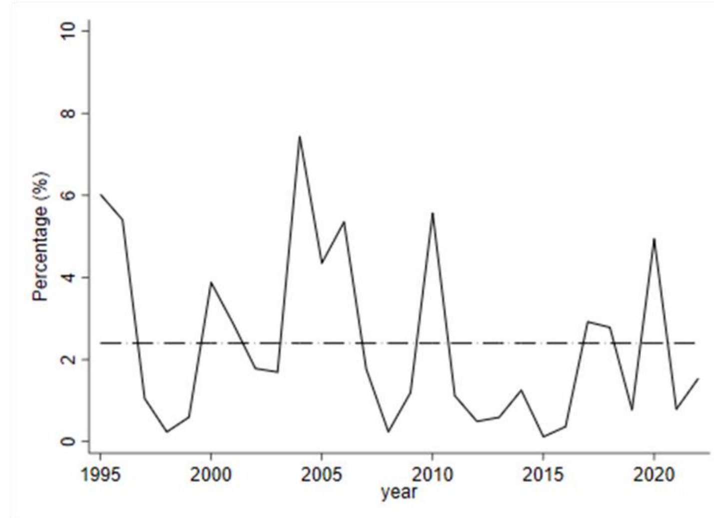
(d) November

Figure 2. Absolute Market Surprises in Soybean Production Report, 1995-2022

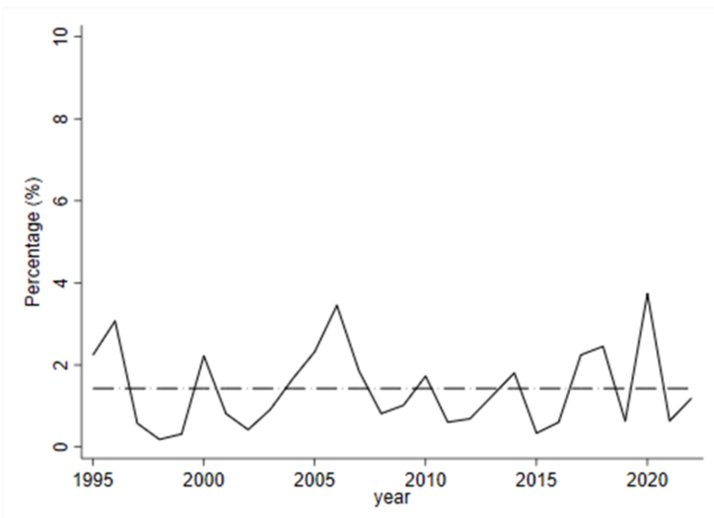
Notes: The solid line represents the absolute size of market surprises for soybean production in each month of the growth cycle of soybean. The dash line is a reference for the average of the absolute market surprise over the whole sample period from 1995 to 2022.



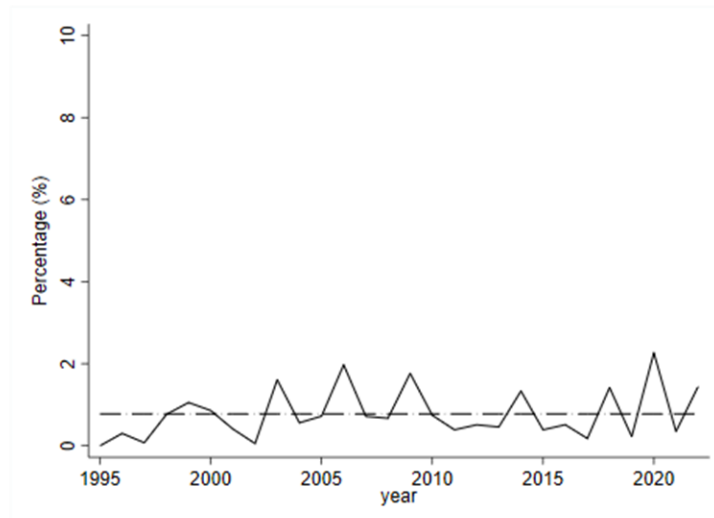
(a) August



(b) September



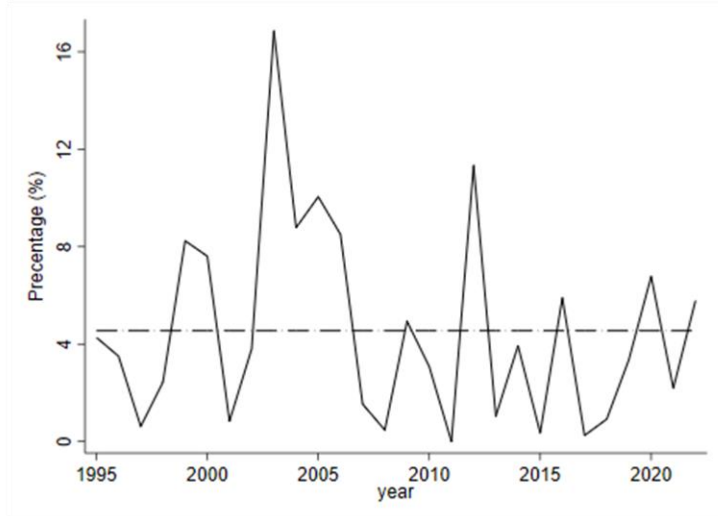
(c) October



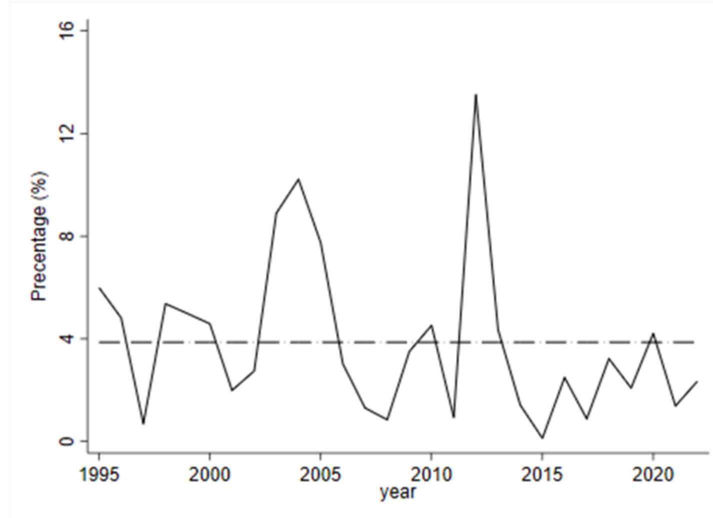
(d) November

Figure 3. Absolute Production Forecast Errors in Corn Markets, 1995-2022

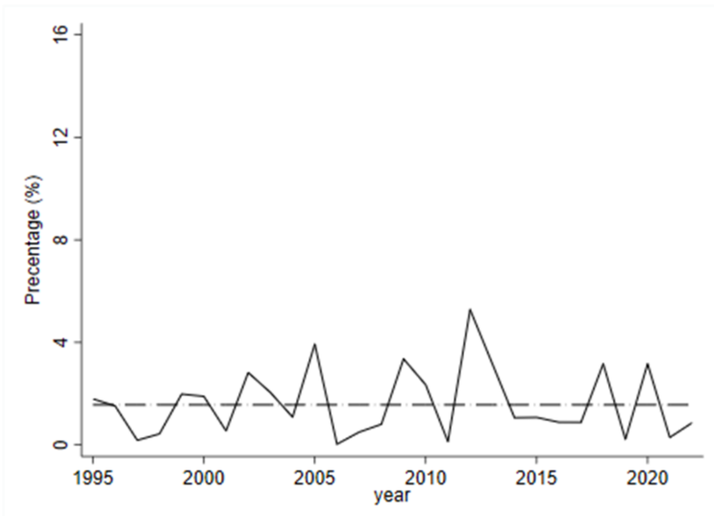
Notes: The solid line represents the absolute magnitude of production forecast errors in corn markets, while the dash line refers to the average of the absolute forecast errors over the sample period from 1995 to 2022.



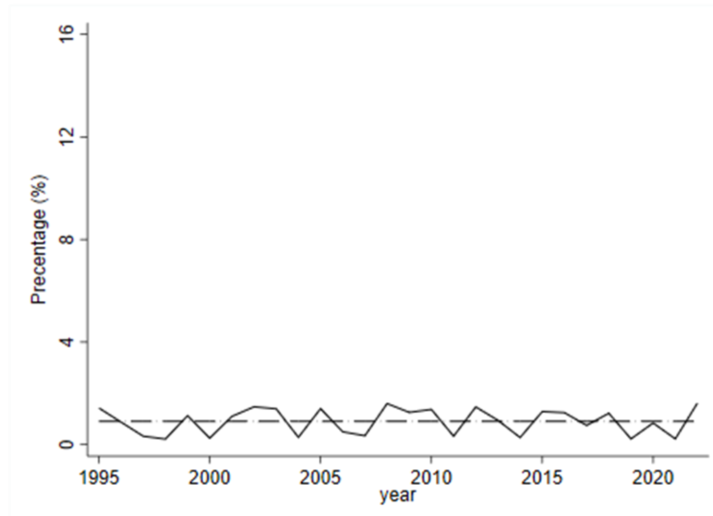
(a) August



(b) September



(c) October



(d) November

Figure 4. Absolute Production Forecast Errors in Soybean Markets, 1995-2022

Notes: The solid line represents the absolute magnitude of production forecast errors in soybean markets; while the dash line refers to the average of the absolute forecast errors over the sample period from 1995 to 2022.

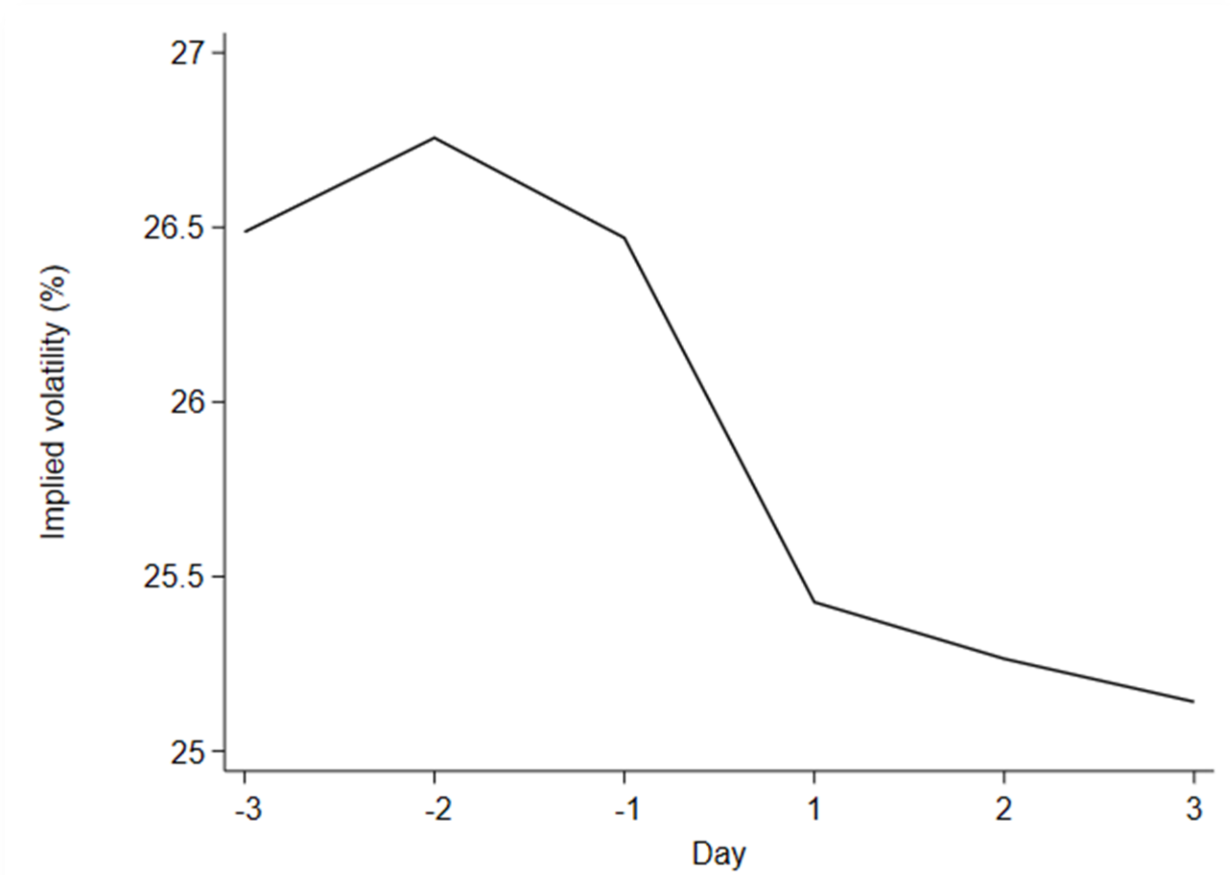


Figure 5. Implied Volatility Around the August Report
Notes: The solid line represents the implied volatility of corn options. The x axis refers to the day relative to the release date of the Augst report. For example, Day -3 represents three trading days before the release of the August report.

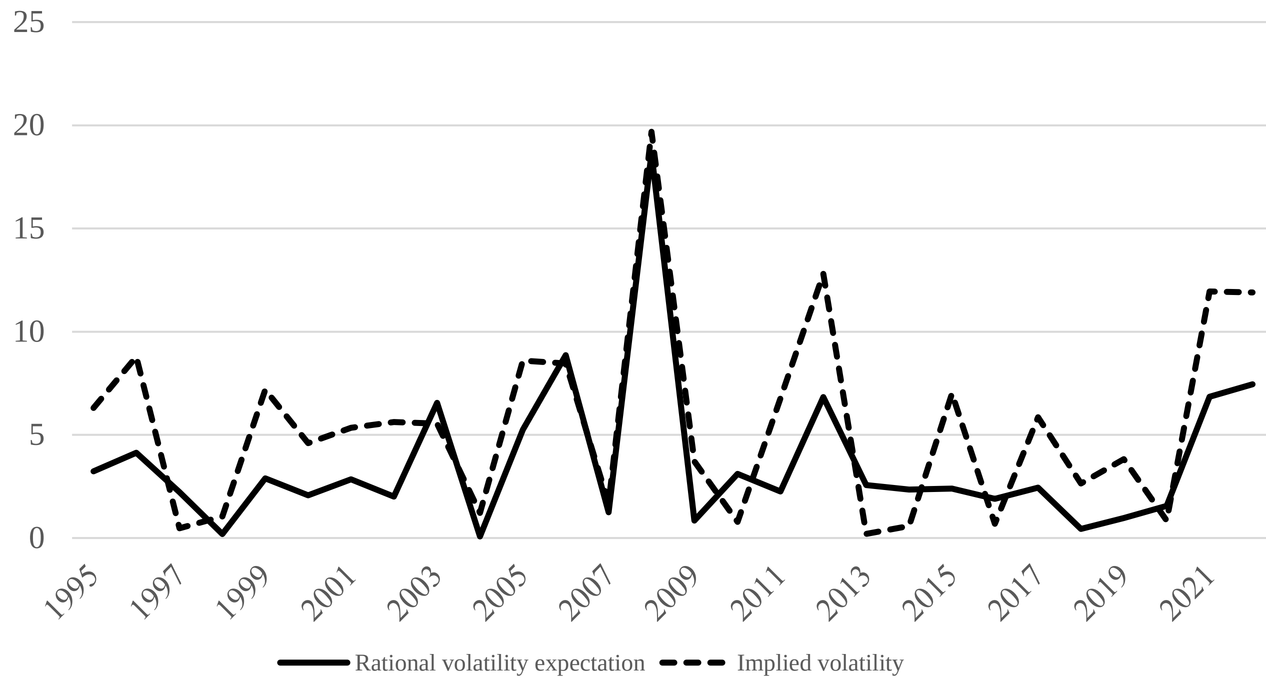


Figure 6. Difference between Actual Price Volatility and Volatility Forecasts on Day -1
Notes: The solid and dashed lines represent the difference in realized volatility and rational volatility expectation, and difference in RV and IV, respectively. We take the absolute value of the differences to display the magnitude of the difference on Day -1.

Appendix Table

Table A 1. FIML Estimates of Mean Equation on Trading Days Around the Release

		t-n	
	-3	-2	-1
Parameters			
$\tilde{\delta}_0$	0.74	0.29	0.40figure
	(1.04)	(1.03)	(1.08)
$\tilde{\delta}_1$	0.86*	0.87*	0.87*
	(0.04)	(0.04)	(0.04)
$\tilde{\kappa}_c^{\alpha}$	1.92*	1.92*	1.92*
	(0.04)	(1.04)	(2.04)
$\tilde{\kappa}_s^{\alpha}$	2.22*	2.22*	2.22*
	(0.05)	(1.05)	(2.05)
$\tilde{\kappa}_c^{a}$	3.11*	3.11*	3.11*
	(0.10)	(1.10)	(2.10)
$\tilde{\kappa}_s^{a}$	4.55*	4.55*	4.55*
	(0.14)	(1.14)	(2.14)
Wald test: $H_0: \tilde{\delta}_0 = 0,\ \tilde{\delta}_1 = 1$			
χ_2^2	6.18	7.66	6.38
	[0.05]	[0.02]	[0.04]

Notes: The table reports the estimates of mean equations for pre-report days, Day *t-n*. We also test whether IV forecasts are unbiased and efficient in the volatility forecast regression by using Wald test. χ_2^2 represents chi-square statistics with 2 degrees of freedom. Standard errors are in the parenthesis, while p-values are in the brackets. The asterisks * indicate statistical significance at the 5% or lower level.