USDA Forecasts Of Crop Ending Stocks: How Well Have They Performed?

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Disciplines
Agricultural and Resource Economics | Economic History | Growth and Development | Macroeconomics | Meteorology

Comments
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Keywords: Ending stocks, fixed-event forecasts, forecast efficiency.

JEL: C11, C23, Q11

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Supplementary material: Online Appendix

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Introduction
The U.S. Department of Agriculture (USDA) provides forecasts of supply and demand for major agricultural commodities in its monthly World Agricultural Supply and Demand Estimates (WASDE) reports. These forecasts include various balance sheet components for each crop, such as beginning stocks, imports, production, domestic use, exports, and ending stocks. It can be argued that the public provision of this information is valuable for market participants and enhances the overall functioning of agricultural markets. The WASDE forecasts not only provide the commodity’s fundamental conditions for the private sector to make decisions, but also constitute an important basis for relevant government policies (Allen 1994). Researchers have found that farmers, agribusinesses, government agencies and other market participants place substantial value on WASDE forecasts, and adjust their market behavior accordingly (e.g., Bauer and Orazem 1994; Garcia et al. 1997; Isengildina-Massa et al. 2008a, 2008b; Adjemian 2012).

Ending stocks measure the carryover of a commodity which enters the supply side of the market in the following marketing year. They are a measure of the scarcity of the crop just before the next crop harvest, and they play an important role in the decision-making process for agricultural producers, processors, and policymakers. For producers and processors, the ending stocks provide information on the relative strengths of crop supplies versus demands. This information influences the prices they face and the production decisions they make. Ending stocks or the stocks-to-use ratio (the ratio of ending stocks to the overall usage of the crop during the marketing year) are often used as a major indicator for price forecasting. For example, Irwin and Good (2016) re-examined the connection between stocks and prices for use in price forecasting. Over the past few years, producer groups have raised some concerns about USDA’s ending stocks estimates, especially for soybeans (for example, see Anderson (2016)). Overestimates of ending stocks could lead to lower prices for producers as the market anticipates
ample supplies, whereas underestimates of stocks could lead to higher prices. For the three crops contained in this study (corn, soybeans, and wheat), the last ten years have included sizable shifts in demand and ending stock levels. Corn and soybean demand has risen with the development of biofuels. Chinese demand for soybeans has increased dramatically. Global wheat trade has experienced significant shifts.

Policymakers also examine ending stock levels as they explore, propose, and negotiate agricultural policy. For example, during the “food vs. fuel” debate surrounding the high crop prices in 2010-2012, two bills were introduced in the U.S. Congress to adjust the Renewable Fuels Standard based on the projected levels of corn ending stocks (112th Congress, 2011-2012, H.R. 3097 and S. 3428). Thus, consistent, accurate forecasts of crop ending stocks are crucial to agriculture.

There are two major sources of crop ending stock forecasts: the U.S. Department of Agriculture and private analysts. The USDA produces ending stock forecasts to provide summary agricultural data to all participants in the agricultural markets. Private analysts produce ending stock forecasts to assist their clients in their agricultural business opportunities. In both cases, the provision of consistent, accurate forecasts is critical as the forecasts summarize the current and expected market situations and outline the uncertainties faced by market participants and policymakers. For both entities, the forecasts begin over a year before the final estimates are determined. The first few forecasts include both supply and demand uncertainty as the crops are still growing. Later forecasts reflect mainly demand uncertainty, as production estimates are derived from the crop harvests.

Within USDA, two entities monitor crop ending stocks. The World Agricultural Outlook Board (WAOB) is the entity that produces the ending stock forecasts reported in the WASDE reports and it is their forecasts that we are investigating. The National Agricultural Statistics Service (NASS) surveys crop producers and crop storage facilities to determine the final ending stock values and does not provide ending stock forecasts. However, the quarterly crop stock
reports published by NASS provide guidance to the WAOB as they create the ending stock forecasts.

Many studies in agricultural forecasts have analyzed the accuracy and efficiency of USDA price and production forecasts (e.g., Irwin et al. 1994, 2014; Sanders and Manfredo 2002, 2003; Isengildina et al. 2004, 2006; Bailey and Brorsen 1998). In contrast, little attention has been paid to the ending stock forecasts. To the best of our knowledge, only Botto et al. (2006) and Isengildina-Massa et al. (2013) have included ending stock forecasts in their analyses. Botto et al. (2006) used a frequentist approach to investigate the accuracy of USDA ending stock forecasts and estimated the trends in the forecast accuracy over the marketing years 1980/81 through 2003/04. They find a significant downward trend in the variance of forecast errors when the forecast horizon shortens. They also find that almost all balance sheet categories are significant in explaining errors in ending stock forecasts. Isengildina-Massa et al. (2013) analyzed how WASDE forecast errors are affected by selected behavioral and macroeconomic factors over the marketing years 1987/88 through 2009/10. They found strong evidence of inefficiency for both types of factors for the ending stock forecasts.

USDA ending stock forecasts are fixed-event forecasts, because they are made for a specific target (ending stocks), but have different forecast horizons. In this case, the forecasts all target the crop stocks being held at the end of the marketing year. Previous research on fixed-event forecasts has often examined macroeconomic variables, such as the inflation rate, interest rate, and real and nominal GDP growth rates (e.g., Clements 1995, 1997; Romer and Romer 2000; Harvey et al. 2001; Clements et al. 2007). The models in the literature can be classified into two main categories, namely, those based on Nordhaus (1987) and the ones following Davies and Lahiri (1995, 1999).

The models based on Nordhaus (1987) focus on forecast revisions. Nordhaus introduced a weak efficiency test which only uses information on past forecasts, because the forecast history is always in the forecaster’s information set. The test consists of assessing whether changes in forecasts are affected by past forecast changes. Nordhaus applied the test to several
macroeconomic, energy consumption, and oil price forecasts. He found significant autocorrelations in the revisions of these forecasts. Isengildina et al. (2006) extended Nordhaus’ test and applied it to evaluate the USDA crop production forecasts.

Unlike the Nordhaus model, the framework advocated by Davies and Lahiri (1995, 1999) directly focuses on the forecast errors. They decompose the forecast errors into the sum of unforecastable shocks and the forecaster’s own idiosyncratic errors. Their framework provides a way to explain why forecasts made at a date closer to the target event tend to be more precise. Specifically, the fact that early forecasts typically have large mean squared errors can be explained by the stack of unforecastable shocks. As the forecasting horizon shortens, unforecastable shocks are gradually revealed, so that less uncertainty remains. This approach is in line with studies of fixed-event forecasts in other areas (e.g., see Egelkraut et al. (2003) for crop production forecasts).

Lahiri and Sheng (2008) sought to generalize the Nordhaus model and strengthen the power of the efficiency test. Their approach differs from Nordhaus in that current forecast errors are required to be uncorrelated with current forecast revisions, whereas Nordhaus requires the same for past revisions. They also discuss concerns about an assumption within the Nordhaus framework that forecasters include new information in a consistent manner for any given forecast horizon. As they point out, information flow is not consistent over time and forecasters may adjust their incorporation of new information, depending on the forecast horizon.

Based on the Davies and Lahiri framework, Clements et al. (2007) first analyzed forecast revisions by differencing the forecast errors. In this way, they avoided the possible problem that could arise in the original Davies and Lahiri model if the dependent variables are correlated with the errors. However, Clements et al. only investigated the relationship between non-adjacent forecast revisions, as endogeneity would occur if adjacent forecast revisions were used. Therefore, they did not consider the impact of the most recently updated information. In addition, they simplified the estimation by only considering the diagonal elements of the error covariance matrix, or restricting the idiosyncratic errors to be zero.
The purpose of the present study is to examine the efficiency of USDA ending stock forecasts, using an estimation framework based on the model proposed by Clements et al. (2007). We revisit the Nordhaus (1987) and Davies and Lahiri (1995, 1999) models and investigate forecast revisions by emphasizing the link between the forecasts and the forecast target, which is not included in the original Nordhaus test. Our framework also decomposes the errors into the sum of unforecastable shocks, which can be viewed as a structure to address the uneven information flow noted by Lahiri and Sheng (2008), and USDA’s own idiosyncratic residuals. Specifically, we take into account the USDA’s correction of its own errors. If such corrections occur and forecasts are efficient, then adjacent forecast revisions must be negatively correlated as the adjacent forecast revisions contain the same forecast.\(^1\) Thus, the results from the original Nordhaus test are biased if the USDA in fact does correct its own errors.

The present study explores the efficiency and potential biases within the USDA ending stock forecasts. To do so, the model proposed includes an error covariance matrix which is unique for crop ending stock forecasts. The analysis is performed by means of a Bayesian Markov Chain Monte Carlo (MCMC) approach. This method allows the estimation of the regression coefficients and the complex error covariance matrix in one iteration step, which yields the full posterior distributions for the parameters of interest, including the error variances that are likely to be skewed.

The remainder of the study is organized as follows: Section II reviews the background models for analyzing the fixed-event forecasts and introduces the advocated model for evaluating crop ending stock forecasts. Section III describes the data and introduces the estimation methods. Section IV discusses the results, and the final section provides concluding remarks.

**Model**

The present study evaluates USDA crop ending stock forecasts by testing for bias and efficiency. The null hypothesis is as follows:

\[ H_0: \text{USDA crop ending stock forecasts are unbiased and efficient.} \]
A rejection of $H_0$ indicates that USDA forecasts are inefficient and can be improved upon by using existing information.

*Previous Models*

Empirical studies on testing forecast bias and efficiency are typically based on Mincer and Zarnowitz (1969):

$$\ln S_t = a + b \ln F_{t,n} + error_{t,n}. \quad (1)$$

In the present application, $\ln S_t$ represents the logarithm of the realization of the ending stocks of a given crop at the end of marketing year $t$, $F_{t,n}$ is the USDA $n$-month-ahead log forecast of the ending stock $S_t$, $a$ and $b$ are parameters, and $error_{t,n}$ is an error term. Under the null hypothesis, $H_0: (a, b) = (0,1)$, USDA forecasts of ending stocks are unbiased.

A preferred specification is obtained by imposing $b = 1$ in regression (1) and rearranging the terms, which yields

$$\ln S_t - \ln F_{t,n} = a + error_{t,n}. \quad (2)$$

The difference $(\ln S_t - \ln F_{t,n})$ represents the forecast error of the $n$-month-ahead USDA forecast. Regression (2) is widely used because it is more intuitive and does not require the forecast $F_{t,n}$ to be uncorrelated with the residual in regression (1). Another advantage of regression (2) over regression (1) is that standard inference tests can be applied to it, even if ending stocks $S_t$ are non-stationary (as they most likely are).

In the case of forecasts of fixed events, such as ending stocks, the regression errors in (2) are correlated because they cover overlapping periods (i.e., $error_{t,n}$ and $error_{t,m>n}$ overlap over period $n$). To address this issue, the research based on Nordhaus (1987) focuses on forecast revisions $(\ln F_{t,n-1} - \ln F_{t,n})$ instead. He noted that testing for strong efficiency is very difficult because it is impossible to incorporate into the test all of the information available at the time the
forecasts are issued. Nordhaus thus introduced a weak efficiency test which is solely based on past forecasts, because the latter are always available to the forecaster.

A forecast is said to be weakly efficient if both the current forecast error and forecast revision are independent of all past forecast revisions. Nordhaus' test for weak efficiency is based on estimating the following regression for each $t$:

$$
\ln F_{t,n-1} - \ln F_{t,n} = \gamma_t (\ln F_{t,n} - \ln F_{t,n+1}) + \zeta_{t,n},
$$

(3)

where $\zeta_{t,n}$ follows a normal distribution with fixed variance. For each year, the test is performed by pooling over all forecast revisions in that year. A $\gamma_t$ significantly different from zero means rejection of weak efficiency, implying that forecasts can be improved upon by using information from past forecasts.

Isengildina et al. (2006) modified the Nordhaus model by pooling over all forecast revisions for a certain month instead of a certain year to reduce the number of regressions to be estimated. Isengildina et al. (2013) further extended it by including a bias term and additional public information. Lahiri and Sheng (2008) introduced an efficiency test similar to Nordhaus, but under more generalized restrictions, and pooled the forecasts by the forecast horizon.

In contrast, Davies and Lahiri (1995, 1999) focus on forecast errors directly. They postulate that fixed-event forecasts are characterized by two types of errors, namely, the unforecastable shocks within the forecasting cycle, and the forecaster’s idiosyncratic errors. Unforecastable shocks arise from elements which cannot be controlled by the forecaster, such as changes in economic structure, market conditions, or deviations from benchmark assumptions. The forecaster’s idiosyncratic errors, on the other hand, stem from the forecaster’s subjective views and/or model.

In the present notation, the Davies and Lahiri decomposition of regression (2)'s error term can be stated as:

$$
error_{t,n} = \lambda_{t,n} + \epsilon_{t,n},
$$

(4)
where $\lambda_{t,n}$ represents the unforecastable shock for forecast horizon $n$ and marketing year $t$, and $\varepsilon_{t,n} \sim i. i. d. N(0, \sigma^2)$ is the idiosyncratic error. The shock term $\lambda_{t,n}$ can be further decomposed as the sum of $i. i. d.$ monthly unforecastable shocks:

$$\lambda_{t,n} = \sum_{j=0}^{n-1} k_{t,j},$$

(5)

where $k_{t,j} \sim i. i. d. N(0, \sigma_j^2)$. The idea underlying decomposition (5) is that a forecast made at a date closer to the target event tends to be more precise; hence, it should have a smaller forecast error variance. The proposed error structure implies that the unforecastable shocks $\lambda_{t,n}$ are correlated within each marketing year $t$, because of the overlaps of forecast horizons.

Based on the Davies and Lahiri framework, Clements et al. (2007) proposed analyzing forecast revisions. By incorporating the error structure (4)-(5) into regression (2), making the latter’s intercept horizon-specific, and differencing it, the model by Clements et al. can written as

$$\ln F_{t,n-1} - \ln F_{t,n} = a_n - a_{n-1} + \omega_{t,n},$$

(6)

where $\omega_{t,n} \equiv k_{t,n} + \varepsilon_{t,n} - \varepsilon_{t,n-1}$. Importantly, Clements et al. assumed homoscedastic unforecastable shocks $k_{t,n}$, and simplified the estimation of the covariance matrix of the residuals in regression (6) by ignoring the negative correlations generated by the adjacent idiosyncratic errors $\varepsilon_{t,n}$ and $\varepsilon_{t,n-1}$. They also proposed a simplification by restricting the idiosyncratic errors $\varepsilon_{t,n}$’s to be zero.

**Proposed Model**

The (weak) efficiency test used here combines the characteristics of the Nordhaus (1987) and Davies and Lahiri (1995, 1999) models, and expands the one proposed by Clements et al. (2007). Succinctly, the proposed efficiency test is based on the estimation of the following system of equations for the forecast revisions:
\[
\begin{align*}
\ln S_t - \ln F_{t,1} &= \alpha + \beta (\ln F_{t,1} - \ln F_{t,2}) + \varepsilon_{t,1}, \\
\ln F_{t,1} - \ln F_{t,2} &= \alpha + \beta (\ln F_{t,2} - \ln F_{t,3}) + k_{t,2} - \varepsilon_{t,1} + \varepsilon_{t,2}, \\
\vdots \\
\ln F_{t,N-2} - \ln F_{t,N-1} &= \alpha + \beta (\ln F_{t,N-1} - \ln F_{t,N}) + k_{t,N-1} - \varepsilon_{t,N-2} + \varepsilon_{t,N-1},
\end{align*}
\] (7)

where \( N \) is the maximum forecasting horizon for a marketing year. As pointed out in the literature (e.g., Nordhaus 1987), it is impossible to include all past information as explanatory variables in regressions like (7). Therefore, we follow Nordhaus and construct a test for weak efficiency by letting the previous forecast revision be the explanatory variable. Rejection of the null hypothesis \( H_0: \alpha = \beta = 0 \) for all \( n \) indicates that \( F_{t,n} \) is a weakly inefficient forecast of \( S_t \) because previous forecasts can predict forecast errors. In other words, forecasts fail to fully incorporate information contained in past forecasts.\textsuperscript{5}

This system can be viewed as an improvement on both streams of the literature discussed earlier. It reduces the restrictions on the error covariance matrix by allowing for both regression error heteroscedasticity and autocorrelations. At the same time, it introduces an error covariance structure to estimate a minimal number of covariance parameters (see the package of online Supplementary Materials for details about the covariance structure).

Our model builds upon the Nordhaus test by further identifying the unforecastable shocks and the forecaster’s own idiosyncratic residuals. Given the proposed covariance structure, system (7) can no longer be estimated by ordinary least squares, because the explanatory variable \( (\ln F_{t,n} - \ln F_{t,n+1}) \) is negatively correlated with the idiosyncratic residual \( \varepsilon_{t,n} \).\textsuperscript{6} Thus, we estimate the equations as a system by treating the forecast revisions within the same marketing year as a panel.

Allowing for heteroscedastic shocks is reasonable for forecasts of fixed-events, especially for ending stocks whose forecast horizon is long and which are likely characterized by seasonality. For example, larger variances can be expected in early revisions of ending stock forecasts because of the uncertainty from production.\textsuperscript{7} In addition, seasonality in consumption, trade, and production patterns for many crops means that the arrival of new information varies
from month to month, again making it desirable to allow for heteroscedastic shocks. Given the seasonal nature of crop information, we also examine a variation of the model where \(\alpha\) and \(\beta\) are allowed to differ by season, following Isengildina-Massa, MacDonald, and Xie (2012). We divide the time period into four components: pre-harvest, post-harvest but before final production is known, after final production to the first production estimate of the next crop, and after the first production estimate of the next crop to the announcement of the final ending stocks.

Autocorrelations also exist in the residuals of system (7). They stem from the idiosyncratic residuals and can be interpreted as forecasters’ corrections of their own errors. For example, suppose the idiosyncratic residual in a particular year \(\tau\) is zero, except for misinterpreting a piece of information when issuing the \(n\)th forecast, causing it to unduly underestimate the ending stocks. That is, \(\varepsilon_{\tau,m} \neq n = 0\) and \(\varepsilon_{\tau,n} > 0\). Then, the revision for the \(n\)th horizon \((\ln F_{t,n} - \ln F_{t,n+1})\) will be smaller (by \(\varepsilon_{\tau,n}\)) than it should be, and it will be followed by an \((n - 1)\)th revision greater (by \(\varepsilon_{\tau,n}\)) than it would have been otherwise. The Nordhaus model does not build in this feature due to their strong i.i.d. assumptions on the idiosyncratic errors.

In the present application, the maximum horizon \((N)\) exceeds 12 months. Hence, there are instances where ending stock forecasts for two consecutive crop years are issued simultaneously. Since shocks for consecutive crop years are likely to be positively correlated (e.g., a negative demand shock will likely result in higher ending stocks for both the current and the following marketing year), we estimate system (7) two ways, one assuming that concurrent unforecastable shocks for consecutive marketing years (i.e., \(k_{t,n}\) and \(k_{t+1,n+12}\)) are positively correlated, as described in the online Supplementary Materials, and the other assuming no correlation across the years.
Data and Estimation Methods

The data used for the analysis are the U.S. ending stocks and their corresponding USDA monthly forecasts for three major agricultural commodities – corn, soybeans and wheat – for marketing years 1985/86 through 2014/15 (i.e., a total of 30 marketing years).

U.S. ending stocks are obtained from the Grain Stocks Report released by USDA’s National Agricultural Statistics Service (NASS). The report is issued quarterly, typically in early January, and at the end of March, June and September. Specifically, ending stocks data for corn and soybeans are retrieved from the September report (the first report after the end of the U.S. marketing year for these two commodities), whereas ending stock data for wheat are retrieved from the June report.10

The USDA monthly forecasts are retrieved from the WASDE reports. The U.S. marketing year for corn and soybeans starts on September 1st and ends on August 31st of the following calendar year. For both crops, the first USDA ending stock forecast for a marketing year is released in the month of May before the marketing year begins, so that \( N = 17 \) months for corn and soybeans. The last forecast is released in September, after the marketing year ends and before the release of the ending stock of that marketing year.

The U.S. marketing year for wheat is different for corn and soybeans, as it starts on June 1st and ends on May 31st of the following calendar year. However, the first USDA forecast for wheat ending stocks is also released in May (together with the first forecast for corn and soybeans), and the last forecast is released in June of the following calendar year. Thus, \( N = 14 \) months for wheat.

All of the data are transformed into logarithms to fit model (7). Table 1 shows the descriptive statistics for the USDA log forecast revisions \((\ln F_{t,n} - \ln F_{t,n-1})\) for all three commodities. The means of the log forecast revisions for corn and soybeans are slightly negative, at \(-0.3\%\) and \(-1.6\%\) respectively. The mean for wheat is slightly positive, at 0.1%. The medians for corn and wheat are zero, whereas for soybeans it is slightly negative (\(-0.8\%\)). The standard deviations are considerably larger for corn and soybeans (for which they exceed 10%)
than for wheat (6.3%). Given the size of the standard deviations, the means and medians are not significantly different from zero. The range of revisions is largest for soybeans, from −48.8% to 75.7%. Revisions for corn range from −64.8% to 41.0%. The smallest range corresponds to wheat, from −22.2% to 23.0%.

Figures 1a and 1b depict the standard deviations of the log forecast revisions, displayed in order of diminishing forecast horizons. For all three commodities, the standard deviations exhibit a decreasing trend as the forecast horizons shorten, except for the final revision. The largest errors in final revisions occur for soybeans, whereas the smallest ones are observed for wheat. In addition, standard deviations are generally greater for corn and soybeans than for wheat. The patterns highlighted in figure 1 align with other USDA and private crop reports released during the forecast period. For example, the higher peaks in the series occur in the months of March, June, September, and December, which line up with the quarterly updates for the Grain Stocks report. Other reports, such as the weekly export sales and monthly soybean crushing report, also provide periodic, but potentially surprising, information about ending stock levels. It is clear from figure 1 that the standard deviations of log forecast revisions vary substantially by forecast horizon, highlighting the importance of allowing for heteroscedasticity in the estimation model.

The proposed model is estimated using Bayesian MCMC methods. MCMC methods greatly facilitate dealing with heteroscedasticity, autocorrelation, and the complex covariance structure underlying system (7). Another advantage of the Bayesian approach is that it yields full posterior distributions for the parameters of interest. This feature is particularly useful when researchers try to characterize the property of parameters with a skewed posterior, such as error variances. The joint posterior distributions of the parameters of the model, the choice of priors for the parameters, and the steps involved in the MCMC iterations are shown in the online Supplementary Materials.
Results and Discussion

Estimation results for the marketing years 1985/86 through 2014/15 are summarized in tables 2 and 3. These results are for the model given no correlation across the marketing years. The results incorporating correlation across the years are very similar and are reported in the online Supplementary Materials. Gelman and Rubin (1992) test statistics are below 1.01 for all parameters for all three commodities, which strongly suggests convergence of the Markov Chains. Table 2 displays the means and standard deviations for the estimated parameters, including the intercept, slope, and the standard deviations of the unforecastable shocks and the idiosyncratic errors. Table 3 reports the 2.5%, 50%, and 97.5% quantiles of the corresponding parameters. Parameter estimates can be compared among all three commodities, because forecast revisions are all measured in natural logarithms (i.e., percentage values).

The intercept \( \alpha \) represents the bias of the USDA forecast revisions. For corn and wheat, the estimated intercepts are positive but small, with zero contained in the 95% credible interval. Therefore we cannot reject the null hypothesis that USDA corn and wheat forecasts revisions are unbiased. In contrast, for soybeans the mean estimate of \( \alpha \) is \(-1.8\%\), which is statistically significant as zero is not included in the 95% credible interval. This estimate indicates that, on average, the USDA adjusts its forecast down by 1.8% each month. Given the average level of soybean ending stocks over the period is 256 million bushels, this 1.8% monthly adjustment, on average, represents roughly 5 million bushels. Thus, USDA has a tendency to overestimate the ending stocks of soybeans over the course of the marketing year. This downward adjustment may not seem large on a monthly basis, but over a longer period span time it is substantial. The estimate implies that early forecasts of soybean ending stocks are considerably upwardly biased on average; for example, the forecast released in June for the ending stock of the following marketing year \( F_{t,16} \) tends to overestimate the ending stock by over 25%.

Coefficient \( \beta \) measures the association between two adjacent log forecast revisions, accounting for the endogeneity of past revisions. For all three commodities, the mean estimates of \( \beta \) are positive and significant at the 1% level, indicating inefficient forecasts. The mean
estimate for corn is 0.163, meaning that if USDA adjusted its forecast up by 10% in the past month, on average it will revise its forecast up by about 1.6% in the current month. The slope estimate for wheat is slightly higher at 0.182 implying that if USDA adjusted its forecast up by 10% in the past month, on average it will revise its forecast up by about 1.8% in the current month. The largest $\beta$ estimate corresponds to soybeans, which at 0.337 is almost twice as large as the estimate for wheat.

The slope estimates show that the USDA is conservative in adjusting its ending stock forecasts for all three crops. In other words, the most recent USDA forecast does not fully represent the arrival of new information, because it smooths its forecasts. To see this, a positive value of $\beta$ as found here implies that the USDA log forecast issued on a particular month ($\ln F_{t,n}$) is a weighted average of the “optimal” log forecast corresponding to that month ($\ln O_{t,n}$) and the USDA log forecast the month before ($\ln F_{t,n+1}$), i.e.,

$$\ln F_{t,n} = \frac{1}{1+\beta} \ln O_{t,n} + \frac{\beta}{1+\beta} \ln F_{t,n+1}. \quad (8)$$

Alternatively, this expression can be written as

$$\ln F_{t,n} = \ln O_{t,n} + \frac{\beta}{1+\beta} (\ln F_{t,n+1} - \ln O_{t,n}), \quad (9)$$

according to which the USDA log forecast can be interpreted as the optimal forecast plus an adjustment proportional to the extent to which the previous USDA forecast is greater/smaller than the optimal forecast. For the case of corn (soybeans, wheat), expression (8) implies the USDA assigns a weight of 86% (75%, 85%) to the “optimal” forecast, and 14% (25%, 15%) to its own previous forecast.

The present results are consistent with previous research that government agencies have a tendency to smooth their forecasts (e.g., Isengildina et al. 2006). An interesting question to ask is why is the USDA conservative in its crop ending stock forecasts. Isengildina et al. (2006) summarized several reasons that could help explain why government agencies smooth their
forecasts. They claimed that for USDA crop production forecasts, the smoothing stems from conservative farm operators’ assessments, and bias in using information.

Ending stock forecasts, however, are quite different from production forecasts. Whereas the construction of production forecasts is based on surveys and satellite images, ending stock forecasts combine predictions of various components of both demand and supply, which are inherently more subjective. Vogel and Bange (1999) state “Throughout the growing season and afterwards, estimates are compared with new information on production and utilization, and historical revisions are made as necessary.” Therefore, the USDA may include past forecasts when computing revised ending stock forecasts, as the ending stock forecasts require much more subjective analysis on the demand side of the balance sheet. In this way, a revised forecast can possibly be a weighted average of earlier forecasts and current estimates.

Table 2 also reports the standard deviations of the monthly unforecastable shocks. It can be seen that they tend to increase as the forecast horizon lengthens. For corn and soybeans, the shocks are typically large for the first seven months of a forecasting cycle. This is to be expected, because at that stage the actual level of U.S. output hasn’t been fully revealed, adding another layer of uncertainty to the ending stock forecasts. Later forecast revisions are mainly attributed to the demand side only, and hence shocks are typically smaller.

For corn, the standard deviations of the monthly unforecastable shocks range from 2.5% to 23.0%. Large shocks are expected to arrive in revisions in pre-marketing year July\textsuperscript{11} (20.5%), pre-marketing year August (23.0%), October (15.3%), and January (13.2%). These shocks align with the quarterly stock updates from USDA and are consistent across the crops. In addition, the January revision corresponds to the release of the final production forecast of that marketing year, and signals the end of the role of domestic production in USDA ending stock forecasts. Shocks in March (2.6%) and June (2.5%) are the smallest.

In the case of soybeans, the standard deviations of the unforecastable monthly shocks range from 2.9% to 24.6%. Large shocks are expected in revisions in all of the first five months of the forecasting cycle from July to November. The October shock is the largest at 24.6%,
whereas the other four early shocks are at around 14% each. October is also the time of the first revision of the corresponding soybean production forecasts. Contrary to the case of corn, the January shock (8.1%) is not large compared to other early shocks.

For wheat, the standard deviations of unforecastable shocks lie in a much narrower range, namely, 3.1% to 10.9%. Large shocks are expected in revisions occurring in July (10.9%), August (9.8%), and October (8.7%).

For all three crops, there is a noticeable jump in the standard deviations of the shocks corresponding to the final forecast revisions. This shock measures the difference between the USDA’s final forecasts and the actual ending stocks, which is different in nature from the other forecast revisions. The estimate is largest for soybeans (16.9%) and smallest for wheat (6.7%). For corn, the estimate is 8.8%. A possible explanation for this finding could be that the models used by the USDA may not incorporate some important information which can last for as long as the full forecasting cycle. Hence, when the final stocks are released, that information becomes suddenly captured as unforecastable shocks in the proposed model, resulting in large final revisions. Another possible reason could be that USDA obtains a backlog of additional information prior to the final revision that changes the usage patterns from what was previously expected. A third potential reason could be that unexpected large demand changes occur during the final month of the marketing year.

The estimates of $\sigma$ represent the standard deviations of USDA idiosyncratic residuals, the forecast errors that remain after the bias, inefficiency, and unforecastable shocks are accounted for. The mean estimates of $\sigma$ are 0.9% for corn, 1.9% for soybeans, and 1.1% for wheat. These results reveal that the idiosyncratic residuals are quite small (less than 2% of the final crop stocks), as their standard deviation is smaller than the standard deviations of all of the unforecastable shocks for the respective crop.
Have USDA Crop Ending Stocks Improved Over Time?

To verify the robustness of the results, and to investigate whether the USDA forecasts have improved over time, we also estimated the model for each of the three decades 1985/86-1994/95, 1995/96-2004/05, and 2005/06-2014/15. The results are summarized in table 4.

Overall, the decadal estimates are remarkably consistent with the estimates obtained using the entire period. In the case of the intercept $\alpha$, all of the three sub-period mean estimates are small and non-significant for corn and wheat, but significantly negative for soybeans. The mean estimates of the slope $\beta$ are all significantly positive, except for wheat in the most recent decade (for which the mean estimate is 0.113, but not significantly different from zero). Perhaps the most intriguing finding is the noticeably greater slope estimate for soybeans in the most recent decade ($\beta = 0.500$), implying that if USDA adjusted its soybean forecast down by 10% in the past month, on average it will revise its forecast down by about 5% in the current month. This result is consistent with the recent concerns raised in the soybean industry regarding the performance of the USDA ending stock forecasts for soybeans. Over the past ten years, soybean exports have grown substantially, moving from one-third of the crop’s usage in 2005/06 to nearly half of the crop’s usage currently. Within the soybean industry, there has been concern that the USDA demand and ending stock estimates were not adequately capturing the export demand growth, resulting in higher ending stock estimates and lower crop prices. The findings here tend to support that supposition.

Seasonal Patterns in the Inefficiency?

Given the results shown above and the seasonal pattern of the information flow during the marketing year with production, demand, and ending stock estimates, we modified the model to allow the intercept and slope terms to vary across sub-periods, determined by the set of information within each sub-period. The sub-periods are: (a) pre-harvest, (b) post-harvest but before final production is known, (c) after final production to the first production estimate of the
next crop, and (d) after the first production estimate of the next crop to the announcement of the final ending stocks.

In the pre-harvest sub-period, both supply and demand are forecast from economic models and expert experience. For corn and soybean, this sub-period covers June to August before harvest. For wheat, this sub-period is not defined, nor estimated. We refer to the pre-harvest sub-period with the subscript IV. In the post-harvest sub-period, supply estimates are informed by producer surveys and in-field observations, while demand estimates are still derived from economic models and expert experience. For corn and soybean, this sub-period covers August to February. For wheat, this sub-period covers June to October. We refer to the post-harvest sub-period with the subscript III. In the final production sub-period, supplies are essentially set, while demand estimates are updated with ongoing usage. For corn and soybean, this sub-period covers February to May. For wheat, this sub-period covers October to May. We refer to the final production sub-period with the subscript II. In the first production estimate of the next crop sub-period, information about the next crop could influence forecasts of crop usage in the months just before harvest. For corn and soybean, this sub-period covers May to October. For wheat, this sub-period covers May to July. We refer to the final sub-period with the subscript I. The results are summarized in table 5.

Overall, the sub-period estimates are consistent with the earlier estimates. In the case of the intercepts $\alpha$, the vast majority of the sub-period mean estimates are small and non-significant for corn and wheat, with the exception being in the final sub-period for wheat. Three of the four intercepts are significantly negative for soybeans, with the only exception being the post-harvest sub-period ($a_{III}$). Since the $\alpha$s represent bias, the corn and soybean ending stock estimates have the largest bias in the pre-harvest sub-period (IV), while the wheat stocks have the largest bias in the final sub-period (I). The mean estimates of the slopes $\beta$s are all significantly positive. As the $\beta$s measure the association between adjacent log forecast revisions, the associations grow stronger as the final ending stocks numbers approaches for soybean and wheat. For corn, the associations are stronger in sub-periods II and IV. Meanwhile, the standard deviations for the
unforecastable monthly shocks remain very close to the estimates from the restricted model, but the standard deviation for the idiosyncratic residuals increases.

Conclusions
We develop a framework to investigate the efficiency of USDA crop ending stock forecasts based on the works of Clements et al. (2007), Nordhaus (1987) and Davies and Lahiri (1995, 1999). The proposed model analyzes adjacent forecast revisions with emphasis on the link between forecasts and the forecast target. The residuals are decomposed as the sum of monthly unforecastable shocks and USDA’s own idiosyncratic errors. The postulated error covariance matrix then exhibits heteroscedasticity (due to the unforecastable shocks), as well as autocorrelation (due to the idiosyncratic errors).

We apply our estimation framework to USDA ending stock forecasts for three major agricultural commodities – corn, soybeans and wheat. A total of 30 marketing years, from 1985/86 to 2014/15 are investigated. Estimation is conducted by means of a Bayesian MCMC approach. This method allows us to estimate the coefficients and the error covariance matrix in the same iteration. The MCMC method also allows the parameters to vary freely, so that the estimation results can be used to validate the postulated structure of the residual covariance matrix.

Results show that USDA forecasts are weakly inefficient for all three commodities. Forecast revisions for soybeans are biased: the USDA has a tendency to overestimate the ending stocks for soybeans. We cannot reject the null hypothesis that USDA forecasts for corn and wheat are unbiased. The slope coefficients for three commodities are all positive and significant, providing strong evidence against efficiency. The significantly positive slope estimates suggest that the USDA is conservative in adjusting its forecasts, and it puts positive weight on its past forecasts. Based on the seasonal analysis, this weight tends to increase as the marketing year ends. We also find that the unforecastable shocks are heteroscedastic. Unforecastable shocks corresponding to early forecast revisions are typically large. Interestingly, shocks corresponding
to the final forecast revisions (i.e., the difference between the USDA’s final forecasts and the actual ending stocks) are also large for all three crops. The large percentage final adjustment may be due to the tendency for the final stock number to be smaller, hence any adjustment would look larger on a percentage basis. In their analysis of stocks, Irwin, Sanders, and Good (2014) summarized that the USDA, via the WAOB, may not be directly forecasting stocks, but instead are forecasting crop usage, with the stocks being determined by an accounting identity (ending stocks = beginning stocks + yearly supplies – yearly usage). The results from Botto et al. (2006) outline how the errors in forecasting production and usage will transfer to stock forecasts.

Our estimates also suggest that the overall quality of USDA ending stock forecasts has remained largely unchanged over the last 30 years. At the individual crop level, however, forecasts for wheat seem to have become less inefficient in the most recent decade, whereas for soybeans they have become substantially more inefficient. There are some distinct seasonal patterns to the inefficiencies, especially for soybeans. These inefficiencies could have significant impacts as Congress has shown that it is willing to incorporate USDA projections into agricultural and energy policies, as displayed by the efforts to tie the Renewable Fuels Standard to crop ending stock estimates. As Irwin and Good (2016) point out, inefficiencies in ending stock projections likely lead to inefficiencies in crop price estimates. Such inefficiencies would affect projected government payments and budget baselines for determining federal agricultural policies. For example, under previous farm bills, advance farm bill payments were based on preliminary crop price estimates. Such the projection inefficiencies can have a direct impact on government expenditures.

Concerns, such as those voiced by the soybean industry, that the USDA ending stock estimates were not adequately capturing the export demand growth (for example, see Alumbaugh (2016)), resulting in higher ending stock estimates and lower crop prices likely have some merit. In the past, the USDA has held conferences to explore improvements to its forecasting capacity. Our results suggest the potential for some systematic improvement by incorporating the implicit smoothing that seems to be occurring in the forecasts. As Isengildina-Massa, MacDonald, and
Xie (2012) suggest, USDA may wish to establish a systematic process to evaluate forecast performance to outline potential improvements to the models and data sources used. However, it also points to the need for additional information on potential export demands and the coordination of the WAOB staff with their colleagues filing export briefs for the Foreign Agricultural Service of USDA. Thus, the importance of efficient ending stock projections is for both market and policy reasons.

Given that USDA forecasts are found to be inefficient, an interesting question worth exploring is whether there are any forecasters who can provide better forecasts. In recent years, private analysts provide their own ending stocks forecasts. For crop production, Garcia et al. (1997) found a decline in the informational value of USDA forecasts. However, the comparisons between USDA and analysts’ stock forecasts have never been addressed before. Thus, it would be worth investigating whether analysts are efficient in forecasting ending stocks, and whether the analysts’ forecasts can improve upon USDA forecasts.
References


**Endnotes**

1. If the current forecast revision equals $F_t - F_{t-1}$ and the previous forecast revision equals $F_{t-1} - F_{t-2}$, then they share the error related to $F_{t-1}$. Given the signs of $F_{t-1}$ in each revision, this creates the negative correlation between the forecast revisions.

2. Regression (1) can also be run in levels, depending on the specific application. We perform the analysis using logarithms, because ending stocks cannot be negative and the residuals appear to be better behaved than using levels.

3. For agricultural forecasts, prime examples of unforecastable shocks are weather shocks.

4. Davies and Lahiri developed their model for a three-dimensional analysis of panel data. The notation representing individual forecasters is omitted because we only consider a single forecaster – the USDA.

5. As noted earlier in the discussion of equations (2) and (3), this is a test of weak efficiency because the regressions are solely based on past forecasts. System (7) does not involve separate intercepts and slopes by marketing years (i.e., $\alpha_t$ and $\beta_t$) or by forecast horizon (i.e., $\alpha_n$ and $\beta_n$) to avoid overparameterization and the well-known biases in the estimated autocorrelations from short panels (e.g., Nickell 1981; Solon 1984; Mudelsee 2001).

6. This negative correlation biases the OLS estimate of the slope coefficient ($\beta$) toward zero, as the problem is analogous to the well-known “attenuation” caused by measurement errors in the explanatory variables.

7. For example, shocks to production output, such as weather conditions, can be substantial.

8. Which is a concern in the forecasting literature, as noted by Lahiri and Sheng (2008).

9. We thank a reviewer for suggesting this modification.

10. In rare occasions there have been revisions of the ending stocks in the Grain Stocks Report, but they have been typically quite small. Irwin, Sanders, and Good (2014) detail many of the reasons these adjustments occur. In this situation, we use the finalized ending stocks in later reports.
11. For the revisions, the monthly label indicates the month of the revision. For example, the July revision is the change in the forecast from June to July.

12. We thank the reviewers for suggesting this avenue of research.
Figure 1a. Standard deviations of USDA log forecast revisions of ending stocks ($\ln F_{t,n-1} - \ln F_{t,n}$) by forecast month and horizon for corn and soybean, 1985/86-2014/15.
Figure 1b. Standard deviations of USDA log forecast revisions of ending stocks ($\ln F_{t,n-1} - \ln F_{t,n}$) by forecast month and horizon for wheat, 1985/86-2014/15.
Table 1. Descriptive statistics of USDA log forecast revisions of ending stocks ($\ln F_{t,n-1} - \ln F_{t,n}$), 1985/86-2014/15.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Number of Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>-0.003</td>
<td>0.000</td>
<td>0.105</td>
<td>-0.648</td>
<td>0.410</td>
<td>510</td>
</tr>
<tr>
<td>Soybeans</td>
<td>-0.016</td>
<td>-0.008</td>
<td>0.113</td>
<td>-0.488</td>
<td>0.757</td>
<td>510</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.001</td>
<td>0.000</td>
<td>0.063</td>
<td>-0.222</td>
<td>0.230</td>
<td>420</td>
</tr>
</tbody>
</table>
Table 2. Means and standard deviations of regression estimates of USDA log forecast revisions of ending stocks (\(\ln F_{t,n-1} - \ln F_{t,n}\)), 1985/86-2014/15.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Corn</th>
<th></th>
<th>Soybeans</th>
<th></th>
<th>Wheat</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>(St. Dev.)</td>
<td>Mean</td>
<td>(St. Dev.)</td>
<td>Mean</td>
<td>(St. Dev.)</td>
</tr>
<tr>
<td>Intercept ((\alpha))</td>
<td>0.003</td>
<td>(0.002)</td>
<td>-0.018***</td>
<td>(0.003)</td>
<td>0.002</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Slope ((\beta))</td>
<td>0.163***</td>
<td>(0.043)</td>
<td>0.337***</td>
<td>(0.059)</td>
<td>0.182***</td>
<td>(0.065)</td>
</tr>
<tr>
<td>Standard Deviations of Unforecastable Shocks:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\sigma_1) (Sept., May)</td>
<td>0.088</td>
<td>(0.012)</td>
<td>0.169</td>
<td>(0.023)</td>
<td>0.067</td>
<td>(0.010)</td>
</tr>
<tr>
<td>(\sigma_2) (Aug., Apr.)</td>
<td>0.033</td>
<td>(0.008)</td>
<td>0.029</td>
<td>(0.013)</td>
<td>0.034</td>
<td>(0.007)</td>
</tr>
<tr>
<td>(\sigma_3) (July, Mar.)</td>
<td>0.045</td>
<td>(0.007)</td>
<td>0.064</td>
<td>(0.012)</td>
<td>0.032</td>
<td>(0.007)</td>
</tr>
<tr>
<td>(\sigma_4) (June, Feb.)</td>
<td>0.073</td>
<td>(0.011)</td>
<td>0.072</td>
<td>(0.012)</td>
<td>0.047</td>
<td>(0.008)</td>
</tr>
<tr>
<td>(\sigma_5) (May, Jan.)</td>
<td>0.025</td>
<td>(0.008)</td>
<td>0.041</td>
<td>(0.012)</td>
<td>0.031</td>
<td>(0.008)</td>
</tr>
<tr>
<td>(\sigma_6) (Apr., Dec.)</td>
<td>0.054</td>
<td>(0.008)</td>
<td>0.069</td>
<td>(0.011)</td>
<td>0.043</td>
<td>(0.007)</td>
</tr>
<tr>
<td>(\sigma_7) (Mar., Nov.)</td>
<td>0.083</td>
<td>(0.012)</td>
<td>0.061</td>
<td>(0.012)</td>
<td>0.062</td>
<td>(0.010)</td>
</tr>
<tr>
<td>(\sigma_8) (Feb., Oct.)</td>
<td>0.026</td>
<td>(0.007)</td>
<td>0.043</td>
<td>(0.012)</td>
<td>0.054</td>
<td>(0.009)</td>
</tr>
<tr>
<td>(\sigma_9) (Jan., Sept.)</td>
<td>0.053</td>
<td>(0.008)</td>
<td>0.058</td>
<td>(0.010)</td>
<td>0.034</td>
<td>(0.008)</td>
</tr>
<tr>
<td>(\sigma_{10}) (Dec., Aug.)</td>
<td>0.132</td>
<td>(0.018)</td>
<td>0.081</td>
<td>(0.014)</td>
<td>0.087</td>
<td>(0.013)</td>
</tr>
<tr>
<td>(\sigma_{11}) (Nov., July)</td>
<td>0.059</td>
<td>(0.009)</td>
<td>0.064</td>
<td>(0.011)</td>
<td>0.068</td>
<td>(0.010)</td>
</tr>
<tr>
<td>(\sigma_{12}) (Oct., June)</td>
<td>0.080</td>
<td>(0.012)</td>
<td>0.136</td>
<td>(0.020)</td>
<td>0.098</td>
<td>(0.014)</td>
</tr>
<tr>
<td>(\sigma_{13}) (Sept., May)</td>
<td>0.153</td>
<td>(0.021)</td>
<td>0.246</td>
<td>(0.034)</td>
<td>0.109</td>
<td>(0.015)</td>
</tr>
<tr>
<td>(\sigma_{14}) (Aug.)</td>
<td>0.101</td>
<td>(0.015)</td>
<td>0.149</td>
<td>(0.021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\sigma_{15}) (July)</td>
<td>0.230</td>
<td>(0.032)</td>
<td>0.149</td>
<td>(0.021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\sigma_{16}) (June)</td>
<td>0.205</td>
<td>(0.028)</td>
<td>0.145</td>
<td>(0.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Deviation of Idiosyncratic Residuals ((\sigma))</td>
<td>0.009</td>
<td>(0.006)</td>
<td>0.019</td>
<td>(0.009)</td>
<td>0.011</td>
<td>(0.007)</td>
</tr>
</tbody>
</table>

Note: *** (**, *) denotes that the parameter estimate is different from zero at the 1% (5%, 10%) level of significance, because the posterior probability of the parameter estimate being greater than zero is either less than 0.5% (2.5%, 5%) or greater than 99.5% (97.5%, 95%). Probability indicators are omitted for the standard deviations of unforecastable errors and idiosyncratic errors, because they are non-negative by construction.

\(\sigma_n\) is the standard deviation of the unforecastable shock corresponding to the \(n\)-month forecast horizon. For example, for corn and soybeans, \(\sigma_{16}\) is the standard error of unforecastable shocks between June and July for forecasts of the following marketing year's ending stocks. \(\sigma_1\) is the standard deviation of the shock corresponding to the final forecast revision, i.e., the final forecast error.

\(a\)The first month listed is for corn and soybean, the second month listed is for wheat.
Table 3. Quantiles of regression estimates of USDA log forecast revisions of ending stocks \((\ln F_{t,n} - \ln F_{t,n-1})\), 1985/86-2014/15.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Corn</th>
<th></th>
<th></th>
<th>Soybeans</th>
<th></th>
<th></th>
<th>Wheat</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.5%</td>
<td>Median</td>
<td>97.5%</td>
<td>2.5%</td>
<td>Median</td>
<td>97.5%</td>
<td>2.5%</td>
<td>Median</td>
<td>97.5%</td>
</tr>
<tr>
<td>Intercept ((\alpha))</td>
<td>-0.002</td>
<td>0.003</td>
<td>0.007</td>
<td>-0.025</td>
<td>-0.018</td>
<td>-0.012</td>
<td>-0.003</td>
<td>0.002</td>
<td>0.007</td>
</tr>
<tr>
<td>Slope ((\beta))</td>
<td>0.083</td>
<td>0.161</td>
<td>0.253</td>
<td>0.228</td>
<td>0.334</td>
<td>0.455</td>
<td>0.070</td>
<td>0.176</td>
<td>0.327</td>
</tr>
<tr>
<td>Standard Deviations of Unforecastable Shocks: (\sigma_n)</td>
<td>(\sigma_1) (Sept., May) (\sigma_2) (Aug., Apr.) (\sigma_3) (July, Mar.) (\sigma_4) (June, Feb.) (\sigma_5) (May, Jan.) (\sigma_6) (Apr., Dec.) (\sigma_7) (Mar., Nov.) (\sigma_8) (Feb., Oct.) (\sigma_9) (Jan., Sept.) (\sigma_{10}) (Dec., Aug.) (\sigma_{11}) (Nov., July) (\sigma_{12}) (Oct., June) (\sigma_{13}) (Sept., May) (\sigma_{14}) (Aug.) (\sigma_{15}) (July) (\sigma_{16}) (June)</td>
<td>0.067</td>
<td>0.087</td>
<td>0.116</td>
<td>0.130</td>
<td>0.166</td>
<td>0.222</td>
<td>0.051</td>
<td>0.066</td>
</tr>
</tbody>
</table>

\(\sigma_n\) is the standard deviation of the unforecastable shock corresponding to the \(n\)-month forecast horizon. For example, for corn and soybeans, \(\sigma_{16}\) is the standard error of unforecastable shocks between June and July for forecasts of the following marketing year’s ending stocks. \(\sigma_1\) is the standard deviation of the shock corresponding to the final forecast revision, i.e., the final forecast error.

\(\sigma_n\) The first month listed is for corn and soybean, the second month listed is for wheat.
<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\alpha$)</td>
<td>0.000</td>
<td>0.003</td>
<td>-0.002</td>
<td>-0.012***</td>
<td>-0.024***</td>
<td>-0.021***</td>
<td>0.000</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>Slope ($\beta$)</td>
<td>0.141**</td>
<td>0.172***</td>
<td>0.138**</td>
<td>0.205***</td>
<td>0.147**</td>
<td>0.500***</td>
<td>0.233***</td>
<td>0.181**</td>
<td>0.113</td>
</tr>
<tr>
<td>Standard Deviations of Unforecastable Shocks:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_1$ (Sept., May)</td>
<td>0.032</td>
<td>0.051</td>
<td>0.162</td>
<td>0.152</td>
<td>0.141</td>
<td>0.248</td>
<td>0.090</td>
<td>0.037</td>
<td>0.085</td>
</tr>
<tr>
<td>$\sigma_2$ (Aug., Apr.)</td>
<td>0.009</td>
<td>0.029</td>
<td>0.057</td>
<td>0.043</td>
<td>0.016</td>
<td>0.028</td>
<td>0.014</td>
<td>0.059</td>
<td>0.030</td>
</tr>
<tr>
<td>$\sigma_3$ (July, Mar.)</td>
<td>0.024</td>
<td>0.060</td>
<td>0.054</td>
<td>0.093</td>
<td>0.019</td>
<td>0.066</td>
<td>0.058</td>
<td>0.011</td>
<td>0.020</td>
</tr>
<tr>
<td>$\sigma_4$ (June, Feb.)</td>
<td>0.039</td>
<td>0.064</td>
<td>0.117</td>
<td>0.051</td>
<td>0.066</td>
<td>0.106</td>
<td>0.038</td>
<td>0.062</td>
<td>0.051</td>
</tr>
<tr>
<td>$\sigma_5$ (May, Jan.)</td>
<td>0.015</td>
<td>0.022</td>
<td>0.030</td>
<td>0.033</td>
<td>0.055</td>
<td>0.028</td>
<td>0.025</td>
<td>0.020</td>
<td>0.051</td>
</tr>
<tr>
<td>$\sigma_6$ (Apr., Dec.)</td>
<td>0.035</td>
<td>0.038</td>
<td>0.084</td>
<td>0.023</td>
<td>0.020</td>
<td>0.121</td>
<td>0.039</td>
<td>0.054</td>
<td>0.043</td>
</tr>
<tr>
<td>$\sigma_7$ (Mar., Nov.)</td>
<td>0.065</td>
<td>0.106</td>
<td>0.104</td>
<td>0.065</td>
<td>0.049</td>
<td>0.080</td>
<td>0.053</td>
<td>0.088</td>
<td>0.054</td>
</tr>
<tr>
<td>$\sigma_8$ (Feb., Oct.)</td>
<td>0.016</td>
<td>0.040</td>
<td>0.018</td>
<td>0.039</td>
<td>0.063</td>
<td>0.031</td>
<td>0.083</td>
<td>0.027</td>
<td>0.051</td>
</tr>
<tr>
<td>$\sigma_9$ (Jan., Sept.)</td>
<td>0.059</td>
<td>0.060</td>
<td>0.053</td>
<td>0.049</td>
<td>0.065</td>
<td>0.069</td>
<td>0.033</td>
<td>0.044</td>
<td>0.026</td>
</tr>
<tr>
<td>$\sigma_{10}$ (Dec., Aug.)</td>
<td>0.125</td>
<td>0.168</td>
<td>0.140</td>
<td>0.088</td>
<td>0.083</td>
<td>0.090</td>
<td>0.105</td>
<td>0.075</td>
<td>0.109</td>
</tr>
<tr>
<td>$\sigma_{11}$ (Nov., July)</td>
<td>0.039</td>
<td>0.020</td>
<td>0.103</td>
<td>0.030</td>
<td>0.058</td>
<td>0.090</td>
<td>0.059</td>
<td>0.098</td>
<td>0.063</td>
</tr>
<tr>
<td>$\sigma_{12}$ (Oct., June)</td>
<td>0.096</td>
<td>0.102</td>
<td>0.052</td>
<td>0.172</td>
<td>0.039</td>
<td>0.165</td>
<td>0.136</td>
<td>0.103</td>
<td>0.075</td>
</tr>
<tr>
<td>$\sigma_{13}$ (Sept., May)</td>
<td>0.119</td>
<td>0.208</td>
<td>0.168</td>
<td>0.187</td>
<td>0.366</td>
<td>0.219</td>
<td>0.128</td>
<td>0.126</td>
<td>0.103</td>
</tr>
<tr>
<td>$\sigma_{14}$ (Aug.)</td>
<td>0.074</td>
<td>0.123</td>
<td>0.126</td>
<td>0.112</td>
<td>0.201</td>
<td>0.178</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$\sigma_{15}$ (July)</td>
<td>0.198</td>
<td>0.304</td>
<td>0.246</td>
<td>0.203</td>
<td>0.147</td>
<td>0.156</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{16}$ (June)</td>
<td>0.207</td>
<td>0.152</td>
<td>0.296</td>
<td>0.152</td>
<td>0.125</td>
<td>0.191</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Deviation of Idiosyncratic Residuals ($\sigma$)</td>
<td>0.008</td>
<td>0.019</td>
<td>0.011</td>
<td>0.015</td>
<td>0.023</td>
<td>0.027</td>
<td>0.015</td>
<td>0.011</td>
<td>0.013</td>
</tr>
</tbody>
</table>

Note: *** (**, *) denotes that the parameter estimate is different from zero at the 1% (5%, 10%) level of significance, because the posterior probability of the parameter estimate being greater than zero is either less than 0.5% (2.5%, 5%) or greater than 99.5% (97.5%, 95%). Probability indicators are omitted for the standard deviations of unforecastable errors and idiosyncratic errors, because they are non-negative by construction.

*aOver the period analyzed, the timing of the NASS grain stocks report release has shifted in some instances. For example, the quarterly update for December used to be released at the end of December and is now released in mid-January, in tandem with the release of the WASDE report.

*b$\sigma_n$ is the standard deviation of the unforecastable shock corresponding to the $n$-month forecast horizon. For example, for corn and soybeans, $\sigma_{16}$ is the standard error of unforecastable shocks between June and July for forecasts of the following marketing year’s ending stocks. $\sigma_1$ is the standard deviation of the shock corresponding to the final forecast revision, i.e., the final forecast error.

*cThe first month listed is for corn and soybean, the second month listed is for wheat.
Table 5. Means and standard deviations of regression estimates of USDA log forecast revisions of ending stocks (In $F_{t,n-1} - \ln F_{t,n}$), 1985/86-2014/15.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Corn</th>
<th>Soybeans</th>
<th>Wheat</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (St. Dev.)</td>
<td>Mean (St. Dev.)</td>
<td>Mean (St. Dev.)</td>
</tr>
<tr>
<td>Intercept:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.004 (0.003)</td>
<td>-0.015*** (0.005)</td>
<td>0.016*** (0.006)</td>
</tr>
<tr>
<td>$\alpha_II$</td>
<td>0.001 (0.005)</td>
<td>-0.016** (0.007)</td>
<td>-0.002 (0.003)</td>
</tr>
<tr>
<td>$\alpha_{III}$</td>
<td>0.002 (0.006)</td>
<td>-0.012 (0.007)</td>
<td>-0.004 (0.008)</td>
</tr>
<tr>
<td>$\alpha_{IV}$</td>
<td>-0.028 (0.030)</td>
<td>-0.049** (0.019)</td>
<td></td>
</tr>
<tr>
<td>Slope:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_I$</td>
<td>0.220** (0.102)</td>
<td>0.503*** (0.095)</td>
<td>0.634** (0.238)</td>
</tr>
<tr>
<td>$\beta_{II}$</td>
<td>0.314*** (0.096)</td>
<td>0.442*** (0.143)</td>
<td>0.281*** (0.087)</td>
</tr>
<tr>
<td>$\beta_{III}$</td>
<td>0.115** (0.049)</td>
<td>0.288*** (0.061)</td>
<td>0.168* (0.099)</td>
</tr>
<tr>
<td>$\beta_{IV}$</td>
<td>0.323* (0.194)</td>
<td>0.341* (0.173)</td>
<td></td>
</tr>
<tr>
<td>Standard Deviations of Unforecastable Shocks:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_1$ (Sept., May)</td>
<td>0.086 (0.012)</td>
<td>0.168 (0.024)</td>
<td>0.056 (0.009)</td>
</tr>
<tr>
<td>$\sigma_2$ (Aug., Apr.)</td>
<td>0.027 (0.011)</td>
<td>0.021 (0.013)</td>
<td>0.024 (0.011)</td>
</tr>
<tr>
<td>$\sigma_3$ (July, Mar.)</td>
<td>0.045 (0.008)</td>
<td>0.056 (0.013)</td>
<td>0.018 (0.011)</td>
</tr>
<tr>
<td>$\sigma_4$ (June, Feb.)</td>
<td>0.070 (0.011)</td>
<td>0.068 (0.012)</td>
<td>0.037 (0.009)</td>
</tr>
<tr>
<td>$\sigma_5$ (May, Jan.)</td>
<td>0.021 (0.009)</td>
<td>0.027 (0.014)</td>
<td>0.021 (0.011)</td>
</tr>
<tr>
<td>$\sigma_6$ (Apr., Dec.)</td>
<td>0.051 (0.009)</td>
<td>0.066 (0.012)</td>
<td>0.035 (0.010)</td>
</tr>
<tr>
<td>$\sigma_7$ (Mar., Nov.)</td>
<td>0.080 (0.012)</td>
<td>0.056 (0.013)</td>
<td>0.055 (0.011)</td>
</tr>
<tr>
<td>$\sigma_8$ (Feb., Oct.)</td>
<td>0.020 (0.010)</td>
<td>0.032 (0.015)</td>
<td>0.047 (0.010)</td>
</tr>
<tr>
<td>$\sigma_9$ (Jan., Sept.)</td>
<td>0.050 (0.009)</td>
<td>0.052 (0.012)</td>
<td>0.022 (0.011)</td>
</tr>
<tr>
<td>$\sigma_{10}$ (Dec., Aug.)</td>
<td>0.133 (0.019)</td>
<td>0.080 (0.015)</td>
<td>0.080 (0.014)</td>
</tr>
<tr>
<td>$\sigma_{11}$ (Nov., July)</td>
<td>0.056 (0.009)</td>
<td>0.062 (0.013)</td>
<td>0.064 (0.012)</td>
</tr>
<tr>
<td>$\sigma_{12}$ (Oct., June)</td>
<td>0.081 (0.013)</td>
<td>0.131 (0.020)</td>
<td>0.091 (0.015)</td>
</tr>
<tr>
<td>$\sigma_{13}$ (Sept., May)</td>
<td>0.177 (0.020)</td>
<td>0.295 (0.031)</td>
<td>0.123 (0.016)</td>
</tr>
<tr>
<td>$\sigma_{14}$ (Aug.)</td>
<td>0.100 (0.014)</td>
<td>0.148 (0.022)</td>
<td></td>
</tr>
<tr>
<td>$\sigma_{15}$ (July)</td>
<td>0.220 (0.032)</td>
<td>0.153 (0.021)</td>
<td></td>
</tr>
<tr>
<td>$\sigma_{16}$ (June)</td>
<td>0.230 (0.031)</td>
<td>0.161 (0.021)</td>
<td></td>
</tr>
<tr>
<td>Standard Deviation of Idiosyncratic Residuals ($\sigma$)</td>
<td>0.014 (0.007)</td>
<td>0.027 (0.008)</td>
<td>0.023 (0.006)</td>
</tr>
</tbody>
</table>
Note: *** (**, *) denotes that the parameter estimate is different from zero at the 1% (5%, 10%) level of significance, because the posterior probability of the parameter estimate being greater than zero is either less than 0.5% (2.5%, 5%) or greater than 99.5% (97.5%, 95%). Probability indicators are omitted for the standard deviations of unforecastable errors and idiosyncratic errors, because they are non-negative by construction.

Subscripts for slopes and intercepts increase with the length of the forecast period of the equation involved. For corn and soybean, coefficients with subscript I (II, III, IV) correspond to equations where the dependent variables are the Final-September, September-August, August-July, July-June, and June-May (May-April, April-March, and March-February; February-January, January-December, December-November, November-October, October-September, and September-August; August-July and July-June) innovations. For wheat, coefficients with subscript I (II, III) correspond to equations where the dependent variables are the Final-June and June-May (May-April, April-March, March-February, February-January, January-December, December-November, and November-October; October-September, September-August, August-July, and July-June) innovations.

\( \sigma_n \) is the standard deviation of the unforecastable shock corresponding to the \( n \)-month forecast horizon. For example, for corn and soybeans, \( \sigma_{16} \) is the standard error of unforecastable shocks between June and July for forecasts of the following marketing year’s ending stocks. \( \sigma_f \) is the standard deviation of the shock corresponding to the final forecast revision, i.e., the final forecast error.