USDA AND PRIVATE ANALYSTS FORECASTS OF ENDING STOCKS:

HOW GOOD ARE THEY?

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ABSTRACT

Forecasts of U.S. ending stocks for corn, soybean, and wheat issued by the USDA and private analysts are evaluated. The null hypothesis that USDA forecasts are unbiased cannot be rejected. The null hypothesis that private analysts' forecasts are unbiased forecasts of USDA forecasts cannot be rejected either. However, there is strong evidence that the forecasts issued by the USDA and private analysts are inefficient. Overall, the precision of the USDA forecasts and the private analysts' forecasts is highest for wheat and lowest for soybean.

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I. 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) report. It can be argued that the public provision of information is valuable for participants and enhances the overall functioning of agricultural markets (Allen (1994)). Researchers have found that farmers, agribusinesses, government and other market participants place substantial value on these forecasts, and adjust their market behavior accordingly (Bauer and Orazem (1994), Garcia *et al*. (1997), Isengildina-Massa *et al*. (2008a, 2008b), Adjemian (2012)). There are many studies devoted to analyzing the accuracy and efficiency of USDA price and production forecasts (e.g. Irwin *et al*. (1994), Sanders and Manfredo (2002, 2003), Isengildina *et al*. (2004)). In contrast, little attention has been paid to ending stocks forecasts; to the best of our knowledge, only Botto *et al*. (2006) have investigated the accuracy of ending stock forecasts, relying on a frequentist approach.

Many private analysts also issue their own agricultural forecasts before the release of the USDA forecasts. Private analysts' forecasts are considered valuable because they reveal opinions from participants who are actively involved in the market, and whose objectives and sources of information need not overlap with the ones from the government. Researchers have found that relatively large differences between the consensus analysts’ forecasts and the forecasts from government agencies often lead to market volatility (French *et al*. (1989)). In the case of crop output forecasts, some studies have found a decline in the informational value of USDA forecasts (Garcia *et al*. (1997)), which is consistent with the rise in the provision of private forecasts. Further, Fortenbery and Sumner (1993) have found that markets no longer react to USDA production forecasts, whereas McKenzie (2008) has arrived at the opposite conclusion.

Previous studies on price and production forecasts have either implicitly assumed that private analysts directly forecast the target outcome (so that their forecasts can be viewed as competing with forecasts from government agency) (e.g., Garcia *et al*. (1997), Egelkraut *et al*. (2003)), or proceeded under the assumption that private forecasts are unbiased estimates of the government forecasts (McKenzie (2008)). The validity of the conclusions from such studies cannot be directly applied to ending stock forecasts, because the relationships among private forecasts, USDA forecasts, and realized ending stocks have not been unexplored.

Using data for corn, soybean, and wheat, the present study proposes and tests a plausible structure of private and USDA forecasts of ending stocks: private analysts forecast USDA ending stock forecasts instead of ending stocks. Under this hypothesis, an analyst's ending stock forecast can be interpreted as a two-stage forecast, or forecast of forecast (FoF). The first stage is the USDA forecast of ending stocks, and the second stage is the analyst's forecast of the USDA forecast. The FoF hypothesis is reasonable for at least two reasons. First, for many private market participants, forecasts of the USDA forecasts are more valuable than forecasts of the ending stocks themselves. Second, previous USDA forecasts are publicly available; therefore, it seems sensible to assume that private analysts incorporate them into their information set when revising their forecasts.

Based on the FoF hypothesis, the present study builds two different models to evaluate forecasts for each stage. The first model evaluates the USDA forecasts of the ending stocks. USDA forecasts are fixed-event forecasts because they are made for a given event – the ending stock – but have different forecast horizons. Previous research on fixed-event forecasts has often examined macroeconomic variables, such as inflation rate, and real and nominal GDP growth rates (Nordhaus (1987), Karamouzis and Lombra (1989), Clements (1995, 1997)), Romer and Romer (2000), Harvey *et al*. (2001), Clements *et al*. (2007)). The present study applies a decomposition of the error term proposed by Davies and Lahiri (1995) to address the possible correlations among forecast errors, and introduces an additional error decomposition to incorporate marketing year random effects. In this way, the covariance structure of forecast errors is specified so as to reduce the bias of the estimated parameters.

The second proposed model evaluates analysts' forecasts under the FoF hypothesis. Under this hypothesis, analysts forecasts can be treated as rolling-event forecasts, i.e., forecasts with a fixed forecasting horizon and a rolling target. We rely on the rolling-event forecast literature to design tests of forecast efficiency. By pooling over all analysts instead of using analysts' consensus forecasts, we avoid the aggregation bias problem found in previous studies (e.g. Figlewski and Wachtel (1983), Keane and Runkle (1990), Bonham and Cohen (2001)).

We perform the econometric analysis by means of a Bayesian Markov Chain Monte Carlo (MCMC) approach. Bayesian methods yield the full posterior distributions for the parameters of interest. Moreover, Bayesian methods are particularly useful in the present application because they allow us to solve the problem of the numerous observations missing from the private analysts' forecast dataset.

The remaining part of the study is organized as follows: Section II proposes two separate models for evaluating USDA forecasts and analysts' forecasts. Section III describes the data and Section IV discusses the empirical methods employed for the estimation. Section V discusses the results, and the final section provides concluding remarks.

II. Description of the Models

The present study seeks to explore the relationships among analysts' forecasts, USDA forecasts, and forecast targets by postulating and testing a special structure for these three objects, namely, analysts forecast USDA forecasts instead of the ending stocks. In this way, an analyst's ending stock forecast can be interpreted as a two-stage forecast, or FoF. Therefore, forecast evaluations can be decomposed as two models, the first of which focuses on USDA forecasts (Model 1), whereas the second looks at analysts' forecasts (Model 2).

Forecasts are evaluated by testing their bias and efficiency. The null hypotheses are the following:

Model 1 H_0: USDA forecasts are unbiased and efficient forecasts of ending stocks.

Model 2 H_0: Analysts' forecasts are unbiased and efficient forecasts of USDA forecasts.

The structure of the advocated models is described in the next subsections.

II.1. Model 1: USDA Forecasts of Ending Stocks

For a given commodity, let S_t denote the realization of its stocks at the end of marketing year t. Let n be the forecast horizon, and $U_t^{(n)}$ represent the n-month-ahead USDA forecast of S_t. The bias of USDA forecasts can be tested using the Mincer and Zarnowitz (1969) regression:

(1) $$S_t = \alpha + \beta U_t^{(n)} + error_t^{(n)},$$

which can be fitted in either levels or logarithms. The null hypothesis $H_0: (\alpha, \beta) = (0, 1)$ implies USDA forecasts are unbiased. By imposing $\beta = 1$, regression (1) can be re-written as

(2) $$S_t - U_t^{(n)} = \alpha + error_t^{(n)},$$

where the difference ($S_t - U_t^{(n)}$) is the USDA forecast error. Regression (2) is preferred by some researchers (e.g., Carmona (2008)) because it does not require $U_t^{(n)}$ to be uncorrelated with $error_t^{(n)}$. Therefore, the present analysis is based on regression (2) using the logarithms of realizations and forecasts, as stocks are non-negative and right-skewed.

The USDA ending stock forecasts are fixed-event forecasts, because they are made for a given event. Since forecast horizons for an event overlap, the regression errors are inherently correlated with each other (i.e., $error_t^{(n)}$ and $error_t^{(m>n)}$ are correlated because they overlap over period n). Parameter estimates may be biased if the covariance structure of the regression errors is not correctly specified. The present study applies the decomposition of regression errors developed by Davies and Lahiri (1995). Specifically, the error term $error_t^{(n)}$ is decomposed into the sum of monthly shocks and an idiosyncratic error:

(3) $$error_t^{(n)} = \sum_{j=1}^{n} u_j + \eta_t^{(n)},$$

where $u_j \sim i.i.d.N(0,\sigma_u^2)$ represents the shock corresponding to month j, and $\eta_t^{(n)} \sim i.i.d.N(0,\sigma_\eta^2)$ is the idiosyncratic error. The idea underlying decomposition (3) is that a forecast made at a date closer to the target event tends to be more precise; hence, it has a smaller forecast error variance. This approach is in line with studies in other areas of inquiry, which have found that forecasts improve as the forecast horizon becomes shorter (Egelkraut *et al*. (2003)). A random effect is assigned to each month, so there are at most twelve monthly effects.

In a panel data setting, forecast errors may also be correlated across time. In the present model, USDA forecast errors for different horizons but corresponding to the same marketing year are likely to be correlated. To allow for such a structure, the term $\eta_t^{(n)}$ is further decomposed as $\eta_t^{(n)} = \mu_t + \varepsilon_t^{(n)}$, where $\mu_t \sim i.i.d.N\left(0,\sigma_\mu^2\right)$ represents marketing year random effects, and $\varepsilon_t^{(n)} \sim i.i.d.N(0,\sigma_\varepsilon^2)$ denotes the idiosyncratic error. Regression (2) then becomes

(4) $$(S_t - U_t^{(n)}) = \alpha + \sum_{j=1}^{n} u_j + \mu_t + \varepsilon_t^{(n)}.$$

The structure of the data can be characterized by two dimensions, namely, forecast horizon n and marketing year t. A pooled analysis offers an overall assessment of USDA forecast performance. The USDA forecasts are sorted first by marketing year t, and then by forecast horizon n. Let T and N be the number of marketing years and the maximum forecast horizon, respectively. The vector of USDA forecasts then takes the following form:

(5) $$U' = (U_1^{(N)}, \dots, U_1^{(1)}, \dots, U_T^{(N)}, \dots, U_T^{(1)}).$$

Thus, the covariance matrix of the error term can be expressed as:

(6) $$\Sigma^U = \sigma_u^2 \begin{bmatrix} B & B & \dots & B \\ B & B & \dots & B \\ \vdots & \vdots & & \vdots \\ B & B & \dots & B \end{bmatrix}_{T\times T} + \sigma_\mu^2 \begin{bmatrix} 1_{N\times N} & 0 & \dots & 0 \\ 0 & 1_{N\times N} & \dots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & 1_{N\times N} \end{bmatrix}_{T\times T} + \sigma_\varepsilon^2 I_{TN\times TN},$$

where $1_{N\times N}$ is an $(N \times N)$ matrix with all elements equal to 1, $I_{TN\times TN}$ is the $(TN \times TN)$ identity matrix, and

(7) $$B = \begin{bmatrix} N & N-1 & \dots & 1 \\ N-1 & N-1 & \dots & 1 \\ \vdots & \vdots & & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix}_{N\times N}.$$

The efficiency test based on regression (4) consists of fitting

(8) $$(S_t - U_t^{(n)}) = \alpha + \beta X_t^{(n)} + \sum_{j=1}^{n} u_j + \mu_t + \varepsilon_t^{(n)},$$

where $X_t^{(n)}$ represents one or more explanatory variables known at the time the forecast is made. The null hypothesis $H_0\colon \beta = 0$ indicates that $U_t^{(n)}$ is efficient, in the sense that forecast errors cannot be predicted using available information. A practical problem with this test is that it is impossible to include all past information in $X_t^{(n)}$. Therefore, given the most frequently used explanatory variables in previous panel data studies, here the variables included in $X_t^{(n)}$ are (a) the n-month-ahead USDA forecast error in the preceding marketing year $(S_{t-1} - U_{t-1}^{(n)})$ (Ali *et al*. (1992)), (b) the USDA forecast revision in the preceding month $(U_t^{(n+1)} - U_t^{(n+2)})$, and (c) the previous marketing year's change in ending stocks $(S_{t-1} - S_{t-2})$ (Abarbanell and Bernard (1992)). Succinctly, the regression estimated to investigate Model 1 is

(9) $$y_t^{(n)} = \boldsymbol{\beta X_t^{(n)}} + \sum_{j=1}^{n} u_j + \mu_t + \varepsilon_t^{(n)},$$

where $y_t^{(n)} \equiv (S_t - U_t^{(n)})$, $\boldsymbol{X_t^{(n)}} \equiv [1\ y_{t-1}^{(n)}\ \ (U_t^{(n+1)} - U_t^{(n+2)})\ (S_{t-1} - S_{t-2})]'$, and $\boldsymbol{\beta} \equiv [\alpha\ \beta_1\ \beta_2\ \beta_3]$.

II.2. Model 2: Analysts' Forecasts of USDA Forecasts

Under the FoF hypothesis, analysts' forecasts are typical rolling-event forecasts, which are different from the fixed-event USDA forecasts discussed in the previous subsection. However, except for the Davies and Lahiri (1995) decomposition of regression errors, similar arguments apply to Model 2. Letting $a_{it}^{(n)}$

denote analyst i's n-month-ahead forecast of the ending stocks of marketing year t, the analog of the transformed Mincer and Zarnowitz (1969) regression (2) is[1]

(10) $$U_t^{(n)} - a_{it}^{(n)} = \alpha + error_{it}^{(n)}.$$

The errors in regression (10) are likely to be correlated if they correspond to the same analyst. The reason for this assertion is that each analyst may follow a specific information collection process, rely on a particular forecast model, or even hold personal views on the commodity. Therefore, it necessary to include a separate term to address the possible correlation among each analyst's forecast errors. In addition, similar to Model 1, the errors in regression (10) are likely to be correlated if the forecasts target ending stocks for the same marketing year because, e.g., information on commodity production and consumption is generally more stable within than across marketing years. In short, $error_{it}^{(n)}$ is decomposed as:

(11) $$error_{it}^{(n)} = \lambda_i + \mu_t + \varepsilon_{it}^{(n)},$$

where $\lambda_i \sim i.i.d.N\left(0, \sigma_\lambda^2\right)$ represents a random effect associated with analyst i, $\mu_t \sim i.i.d.N\left(0, \sigma_\mu^2\right)$ is a random effect for marketing year t, and $\varepsilon_{it}^{(n)} \sim i.i.d.N(0, \sigma^2)$ is the idiosyncratic error.

The Model 2 data are characterized by three dimensions, namely, analyst i, marketing year t, and forecast horizon n. Let I, T, and N be the total number of analysts, the total number of marketing years, and the maximum number of forecast horizons, respectively. Sorting analysts' forecasts by analysts first, then by marketing years, and lastly by forecast horizons, the vector of analysts' forecasts takes the form:

(12) $$A = [a_{11}^{(N)}, \ldots, a_{11}^{(1)}, \ldots, a_{1T}^{(N)}, \ldots, a_{1T}^{(1)}, a_{21}^{(N)}, \ldots, a_{2T}^{(1)}, \ldots, a_{IT}^{(N)}, \ldots, a_{IT}^{(1)}]'.$$

Thus, the covariance matrix of $error_{it}^{(n)}$ can be characterized as:

(13) $$\Sigma^A = \sigma_\lambda^2 \begin{bmatrix} 1_{TN\times TN} & 0 & \ldots & 0 \\ 0 & 1_{TN\times TN} & \ldots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \ldots & 1_{TN\times TN} \end{bmatrix}_{I\times I} + \sigma_\mu^2 \begin{bmatrix} C & C & \ldots & C \\ C & C & \ldots & C \\ \vdots & \vdots & & \vdots \\ C & C & \ldots & C \end{bmatrix}_{I\times I} + \sigma^2 I_{ITN\times ITN},$$

[1] Notation distinguishing between Model 1 and Model 2 is omitted for simplicity.

where

$$(14) \qquad C = \begin{bmatrix} 1_{N\times N} & 0 & \dots & 0 \\ 0 & 1_{N\times N} & \dots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & 1_{N\times N} \end{bmatrix}_{T\times T}.$$

As for Model 1, efficiency test based on regression (10) are performed by incorporating explanatory variables containing past information. In model (2), such variables are (a) the analyst's own n-month-ahead forecast error in the past marketing year ($U_{t-1}^{(n)} - a_{i(t-1)}^{(n)}$), (b) the USDA forecast revision in the preceding month ($U_t^{(n+1)} - U_t^{(n+2)}$), and (c) the analyst's own forecast error in the previous month ($U_t^{(n+1)} - a_{it}^{(n+1)}$) (Ali *et al.* (1992)). The full regression corresponding to Model 2 can be written as:

$$(15) \qquad y_{it}^{(n)} = \boldsymbol{\beta X_{it}^{(n)}} + \lambda_i + \mu_t + \varepsilon_{it}^{(n)},$$

where $y_{it}^{(n)} \equiv (U_t^{(n)} - a_{it}^{(n)})$, $\boldsymbol{X_{it}^{(n)}} \equiv [1\ y_{i(t-1)}^{(n)}\ (U_t^{(n+1)} - U_t^{(n+2)})\ y_{it}^{(n+1)}]'$, and $\boldsymbol{\beta} = [\alpha\ \beta_1\ \beta_2\ \beta_3]$.

III. Data

Model 1 is investigated using data on U.S. ending stocks and their corresponding USDA monthly forecasts for corn, soybean and wheat. U.S. ending stocks for marketing years 1984/85 through 2012/13 are obtained from the quarterly Grain Stocks Report released by the USDA's National Agricultural Statistics Services (NASS). Ending stocks data for corn and soybean (wheat) are retrieved from the September (June) report - the first report after the marketing year ends in August (May). For each commodity, a total of $T = 29$ marketing years are used to analyze Model 1.

The USDA monthly forecasts of US ending stocks are retrieved from the WASDE report. The U.S. marketing year for corn and soybean (wheat) starts in September (June) and ends in August (May) of the next calendar year. Marketing-year ending-stock forecasts for corn and soybean (wheat) are released between May, before the marketing year begins, and September (May), after (when) the marketing year ends. Thus, for each marketing year there are $N = 17$ forecasts for corn and soybean, and $N = 14$ forecasts for wheat.

All data are measured in billions of bushels and transformed into logarithms. The structure of Model 1 prevents us from using the entire forecast dataset to compute the dependent variable. The first two forecasts of each marketing year can be used to calculate the explanatory variable representing the forecast revision in the previous month, but cannot be used to compute the dependent variable. Similarly, the ending stocks and their forecasts in the first two marketing years ($t = 1984/1985$ and $t = 1985/1986$) cannot be used to construct the dependent variable. Thus, the dependent variable consists of forecast errors over the marketing years 1986/87 through 2012/13, with maximum forecast horizons of $N = 15$ for corn and soybean, and $N = 12$ for wheat. In summary, the corn and soybean regressions comprise 405 (= 27 years × 15 forecasts) observations, whereas the regressions for wheat have 324 (= 27 years × 12 forecasts) observations.

Model 2 is analyzed using the USDA monthly forecasts of U.S. ending stocks of corn, soybean and wheat for marketing years 2004/05 through 2012/13. The source and format of the USDA forecasts are the same as those used in Model 1, but cover a shorter period because private analysts' forecasts could not be obtained for marketing years prior to 2004/05. Private analysts' forecasts of US ending stocks for corn, soybean and wheat for marketing years 2004/05 through 2012/13 are reported in the monthly Survey of U.S. Grain and Soybean Carryout Forecasts released by Dow Jones Commodities Service. Each survey is published a few days before the release of the monthly WASDE report. Out of 49 analysts who provide at least one forecast in the surveys, the present study investigates those analysts who constantly report over 60% of the time.[2] For corn and soybean, forecast data from 12 analysts are investigated. Out of a total 1836 (= 9 years × 17 forecasts × 12 analysts) potential observations, there are 1510 non-missing observations for corn and 1508 for soybean. In the case of wheat, forecast data

[2] Unlike USDA forecasts, private analysts' forecasts are often missing because, e.g., analysts sometimes fail to respond to the survey, they change business, or issues arise when collecting their responses.

from 9 analysts are adopted, yielding 974 non-missing observations out of 1134 (= 9 years $\times$ 14 forecasts $\times$ 9 analysts) potential observations.

Similar to Model 1, the dependent variable only consists of forecasts over marketing years 2005/06 through 2012/13, with maximum forecast horizons of $N = 15$ for corn and soybean, and $N = 12$ for wheat. Data are also measured in billions of bushels and transformed into logarithm values.

IV. Estimation Methods

The parameters of Models 1 and 2 are estimated using Bayesian Markov Chain Monte Carlo (MCMC) methods. Unlike frequentist methods, an advantage of the Bayesian approach is that it yields full posterior distributions for the parameters of interest. An additional advantage of adopting Bayesian methods is that they provide a straightforward solution to the problem of the large number of missing observations associated with Model 2. This section outlines the joint posterior distributions of the parameters for each model, the choice of priors for the parameters, and the main steps in the MCMC iterations.

IV.1. Bayesian Estimation of Model 1

Estimation of Model 1 is performed by means of Gibbs Sampling. Let Λ_1 denote the set of parameters of Model 1, i.e., $\Lambda_1 = \{\boldsymbol{\beta}, \{u_j\}_{j=1}^{N}, \{\mu_t\}_{t=1}^{T}, \sigma^2, \sigma_u^2, \sigma_\mu^2\}$. The joint posterior density of Λ_1 can be written as:

(16) $$p(\Lambda_1) = \prod_{nt} \Phi\left(y_t^{(n)} \middle| \boldsymbol{\beta}, u_j, \mu_t, \sigma^2\right) \prod_{j=1}^{N} \Phi(u_j |\, \sigma_u^2)$$
$$\prod_{t=1}^{T} \Phi(\mu_t |\, \sigma_\mu^2) * \Phi(\boldsymbol{\beta} |\, \boldsymbol{M}, \boldsymbol{V}) p(\sigma^2) p(\sigma_u^2) p(\sigma_\mu^2)$$

Conditionally conjugate priors are adopted for the present analysis. In particular, the priors chosen for the parameters are:

(17) $\boldsymbol{\beta} \sim N(\boldsymbol{M}, \boldsymbol{V})$,

(18) $\varepsilon_t^{(n)} \sim N(0, \sigma^2)$,

(19) $u_j \sim N(0, \sigma_u^2), j = 1, \ldots, N$,

(20) $\mu_t \sim N\left(0, \sigma_\mu^2\right), t = 1, \ldots, T$, and

(21) $\sigma, \sigma_u, \sigma_\mu \sim Uniform(0, \infty)$.

The prior distribution for the coefficient vector $\boldsymbol{\beta}$ is multivariate normal with mean $\boldsymbol{M} = \mathbf{0}_4$ and covariance matrix $\boldsymbol{V} = 1000\boldsymbol{I}_{4\times4}$, where $\mathbf{0}_4$ is a (4×1) vector of zeros. The scale is chosen to be large so that the priors are non-informative. The uniform prior for the standard deviation parameters is chosen following Gelman (2006). This prior is non-informative and can be viewed as a limit of the half-t family distributions, which is conditionally conjugate to the extent of more general folded-noncentral-t distributions.[3] The conditional posterior distribution for each parameter is outlined in the Appendix.

For each commodity, the Gibbs sampler is run for three Markov Chains for 100 thousand iterations each. In each iteration, each parameter is updated from the posterior distributions conditional on the most recent updated values of other parameters in the following sequence: $\boldsymbol{\beta}, \{u_j\}_{j=1}^N, \{\mu_t\}_{t=1}^T, \sigma^2, \sigma_u^2, \sigma_\mu^2$. The first half of each chain is discarded as a burn-in period. Gelman and Rubin (1992) tests are applied to check the convergence of the remaining part of the chains.

IV.2. Bayesian Estimation of Model 2

Let Λ_2 denote the set of parameters of Model 2, i.e., $\Lambda_2 = \{\boldsymbol{\beta}, \{\lambda_i\}_{i=1}^C, \{\mu_t\}_{t=1}^T, \sigma^2, \sigma_\lambda^2, \sigma_\mu^2, A_m\}$, where A_m is a vector representing the missing observations for analysts' forecasts. As noted earlier, to

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[3] The uniform prior serves a better role than the weakly-informative inverse gamma $(\varepsilon, \varepsilon)$ prior distribution for the variance, where ε is a positive value close to zero. When using a gamma $(\varepsilon, \varepsilon)$ instead of the uniform prior to estimate Model 1, inferences are found to be very sensitive to the choice of ε, because the value of estimated standard deviation parameters are quite small. In this way, the results from applying inverse gamma $(\varepsilon, \varepsilon)$ priors are less likely to be non-informative in the present study if ε is not small enough relative to the estimated variances. Importantly, results similar to the ones obtained under uniform priors are found when employing inverse gamma $(\varepsilon, \varepsilon)$ priors with $\varepsilon = 0.01$ and 0.001. Moreover, no significant changes are found in the results if other non-informative priors (e.g., $\sigma, \sigma_u, \sigma_\mu \sim U(0{,}1000)$, or $\sigma^2, \sigma_u^2, \sigma_\mu^2 \sim 1$) are applied.

estimate Model 2 the Bayesian MCMC method has the advantage that it allows us to deal with missing observations A_m in a straightforward manner. More specifically, missing observations are treated in the same way as parameters for estimation purposes.

The estimation of Model 2 is more involved than the estimations performed in related studies, because both the dependent variables and the explanatory variables are characterized by missing data. It seems unwise to simply neglect those observations which contain missing data, as doing so may result in a relatively large loss of information. To solve this problem, the present study utilizes the connections among observations based on the proposed model. In particular, it can be seen from the model that an analyst's forecast $a_{it}^{(n)}$ appears in the following three regressions:

i. $(U_t^{(n)} - a_{it}^{(n)})$ on $[1\ (U_{t-1}^{(n)} - a_{i(t-1)}^{(n)})\ (U_t^{(n+1)} - U_t^{(n+2)})\ (U_t^{(n+1)} - a_{it}^{(n+1)})]$,

ii. $(U_t^{(n-1)} - a_{it}^{(n-1)})$ on $[1\ (U_{t-1}^{(n-1)} - a_{i(t-1)}^{(n-1)})\ (U_t^{(n)} - U_t^{(n)})\ (U_t^{(n)} - a_{it}^{(n)})]$,

iii. $(U_{t+1}^{(n)} - a_{i(t+1)}^{(n)})$ on $[1\ (U_t^{(n)} - a_{it}^{(n)})\ (U_{t+1}^{(n+1)} - U_{t+1}^{(n+2)})\ (U_{t+1}^{(n+1)} - a_{i(t+1)}^{(n+1)})]$,

where (i) represents the original model, (ii) is the one-month forwarded version, and (iii) is the one-year forwarded version. At each MCMC iteration, the remaining two variables which do not contain $a_{it}^{(n)}$ are treated as given. An imputed value for $a_{it}^{(n)}$ is then obtained by predicting $(U_t^{(n)} - a_{it}^{(n)})$ using the remaining two variables updated in the previous iteration and the most recently updated parameters.[4]

The initial values of the missing $a_{it}^{(n)}$ data are set equal to the mean of the non-missing analysts' forecasts for the same horizon and marketing year.[5] To avoid unrealistic predictions from inverting parameter draws which are close to zero, the following alternative regressions are used for situations (ii) and (iii) above:

ii'. $(U_t^{(n)} - a_{it}^{(n)})$ on $[1\ (U_{t-1}^{(n-1)} - a_{i(t-1)}^{(n-1)})\ (U_t^{(n)} - U_t^{(n)})\ (U_t^{(n-1)} - a_{it}^{(n-1)})]$,

[4] Note that the USDA forecast data are complete; hence, the explanatory variable representing past month USDA forecast change does not need to be updated.

[5] The choice of initial values does not affect the draws after convergence, due to the characteristics of Markov Chains.

iii'. $(U_t^{(n)} - a_{it}^{(n)})$ on $[1\ (U_{t+1}^{(n)} - a_{i(t+1)}^{(n)})\ (U_{t+1}^{(n+1)} - U_{t+1}^{(n+2)})\ (U_{t+1}^{(n+1)} - a_{i(t+1)}^{(n+1)})]$.

The missing data are imputed by a calculating a weighted average of the predictions from (i), (ii') and (iii'), with the weights assigned based on the precisions of the idiosyncratic errors. Specifically, the weight for the prediction from regression $k\ \in \{i, ii', iii'\}$ is defined by:

(22) $$w_k = \frac{\frac{1}{\sigma_k^2}}{\frac{1}{\sigma_i^2}+\frac{1}{\sigma_{ii'}^2}+\frac{1}{\sigma_{iii'}^2}},$$

where σ_k^2 is the estimated variance of regression k's idiosyncratic errors.

The prior distributions for parameters in Model 2 are as follows:

(23) $$\boldsymbol{\beta} \sim N(\mathbf{0_4}, 1000\boldsymbol{I}_{4\times 4}),$$

(24) $$\varepsilon_{it}^{(n)} \sim N(0, \sigma^2),$$

(25) $$\lambda_i \sim N\left(0, \sigma_\lambda^2\right), j = 1, \dots, C,$$

(26) $$\mu_t \sim N\left(0, \sigma_\mu^2\right), t = 1, \dots, T,$$

(27) $$\sigma, \sigma_u\ , \sigma_\mu\ \sim Uniform(0, \infty).$$

The choice of prior distributions for Model 2 follows a similar rationale as the one for Model 1.

The MCMC iteration steps for Model 2 are:

- Step 1: Set up initial values for the parameters in Λ_2.
- Step 2: Sequentially draw $\boldsymbol{\beta}, \{\lambda_i\}_{i=1}^C, \{\mu_t\}_{t=1}^T, \sigma^2, \sigma_\lambda^2, \sigma_\mu^2$ based on most recent draws of other parameters and A_m.
- Step 3: Update A_m by the criteria mentioned above.
- Step 4: Repeat Step 2 and 3 until the maximum iteration is reached and check for convergence.

V. Results and Discussion

Estimation results are summarized in Tables 1 and 2 for Models 1 and 2, respectively. Means and standard deviations for the estimated parameters are shown in panel A of each table, whereas medians and 95% credible intervals are reported in panel B. Gelman and Rubin (1992) test statistics are below 1.01 for all seven parameters, which strongly suggests convergence of the Markov chains.

V.1. Model 1

The point estimates of the intercept α are positive and in the order of about 5% for the three commodities. Although the null hypothesis that USDA forecasts are unbiased cannot be rejected at the 5% significance level for any of the commodities, it is rejected at the 10% level for corn and wheat. In other words, USDA forecasts of ending stocks for corn and wheat have a weak tendency to be biased, on average underestimating the ending stocks by approximately 5%.[6]

Point estimates of the coefficient associated with the n-month-ahead USDA forecast error in the previous marketing year (β_1) are negative for all commodities, but significant only for soybean. This result suggests that USDA forecasts for soybean are inefficient, as the n-month-ahead USDA forecast tends to underestimate this marketing year's ending stocks if the previous marketing year overestimated them at the same horizon. The null hypothesis that USDA forecasts are efficient with respect to forecasts made during the same period of past marketing year cannot be rejected for corn and wheat.

Coefficient β_2 measures the association between the USDA forecast errors and the changes to the forecast made in the preceding month ($U_t^{(n+1)} - U_t^{(n+2)}$). The estimates of β_2 are all negative and significant, indicating inefficiency for all three commodities. According to the point estimates, an upward forecast revision of 1% on a given month is associated with an average ending stock

[6] Recall that forecasting errors are defined as $y_t^{(n)} \equiv (S_t - U_t^{(n)})$, so a positive α indicates that the USDA forecast underestimates the true value.

overestimation of 0.2% to 0.5%. One possible explanation of this finding is that the USDA is overconfident about the information on the trend. That is, if information shows that ending stocks will likely be higher than previously estimated, the USDA may put more weight on it than is warranted, causing it to overestimate the actual figure. Another possible explanation may be the neglect of feedback effects. An upward revision indicates a higher supply of the commodity, which tends to lower the market price. In turn, the lower price stimulates consumption of the commodity, which reduces the ending stocks. If the latter effect is ignored, the ending stocks are more likely to be overestimated.

The preceding change in ending stocks ($S_{t-1} - S_{t-2}$) has mixed results, as the point estimate of β_3 is positive and significant for corn, but negative and non-significant for soybean and wheat. For corn, the positive β_3 suggests that the USDA tends to underestimate this marketing year's ending stocks if ending stocks increased over the past marketing year. In other words, USDA seems cautious about making forecasts on the trend of ending stocks changes for corn; if there is a trend, the USDA forecast tends to consider it unsustainable.

The estimated standard deviations of the random effects and the idiosyncratic errors are all significantly greater than zero for each commodity. Regardless of the commodity, the largest and smallest standard deviations correspond to the idiosyncratic errors and the monthly effects, respectively. The standard deviations of the marketing year effects are relatively large, indicating differences among marketing years. Overall, the standard deviations of the forecast error regressions reveal that the quality of the USDA forecasts is highest for wheat and worst for soybean.

V.2. Model 2

Based on the estimated intercepts shown in Table 2, the null hypothesis that analysts' forecasts are unbiased forecasts of USDA forecasts cannot be rejected for any commodity. In short, the FoF hypothesis appears to be valid. However, the estimated slopes (βs) strongly indicate that analysts' forecasts are inefficient.

The estimate of β_1 is positive for all commodities, but significantly different from zero only for wheat. This implies that if analysts underestimated the n-month-ahead USDA wheat forecast in the past marketing year, they tend to underestimate it again in the current marketing year. In other words, analysts are slow in adjusting their forecasts based on information from the previous marketing year.

Changes in the n-month-ahead USDA forecast over the previous month are significantly associated with analysts' forecast errors, because the estimates of β_2 are significantly different from zero for all three commodities. However, the estimated coefficients are negative for corn and wheat, and positive for soybean. For corn and wheat (soybean), the negative (positive) coefficient indicates that analysts tend to overestimate (underestimate) the USDA forecast following an upward USDA forecast revision over the past month. Therefore, analysts tend to believe that the trend will (not) continue.

By far, the strongest evidence of inefficiency is provided by the positive effect of analysts' forecasting error in the previous month on their current forecasting error, captured by β_3. Estimates of β_3 are positive, relatively large, and significant for all three commodities. The magnitude of the estimated β_3 indicates that if analysts underestimated the USDA forecast by 1% in the past month, they underestimate the USDA forecast in the current month by about 0.2% to 0.3% on average. A possible explanation of this finding is that analysts under-react, adjusting their forecasts to new information more slowly than is warranted.

The estimated standard deviations are all significantly different from zero regardless of the commodity. For each commodity, the largest standard deviation corresponds by far to the idiosyncratic errors. In contrast, the standard deviation of the random analyst effects is always the smallest, suggesting that the quality of forecasts is relatively homogeneous across analysts. Similar to Model 1, analysts' forecasts appear to be most precise for wheat, and least accurate for soybean.

VI. Conclusions

The present study evaluates forecasts of U.S. ending stocks for corn, soybean, and wheat issued by the USDA and private analysts. USDA forecasts are treated as fixed-event forecasts of the target ending stock. In contrast, analysts' forecasts are hypothesized to be forecasts of the USDA forecasts, or "forecasts of forecasts" (FoF), which allows us to analyze them as rolling-event forecasts. The econometric analysis is conducted by applying of a Bayesian Markov Chain Monte Carlo approach. Bayesian methods are especially useful to study the private analysts' data, because it is characterized by a large number of missing observations.

The null hypothesis that USDA forecasts are unbiased cannot be rejected at the 5% significance level for any of the commodities. However, there is strong evidence that the USDA forecasts are inefficient. In particular, USDA forecast errors are very strongly associated to the forecast change made in the preceding month. An upward forecast revision of 1% on a given month is associated with an average ending stock overestimation of about 0.2% for corn and wheat, and of approximately 0.5% for soybean. Overall, the precision of the USDA forecasts is highest for wheat and lowest for soybean.

In the case of private analysts' forecasts, the null hypothesis that they are unbiased forecasts of USDA forecasts cannot be rejected for any commodity, i.e., there is no evidence against the FoF hypothesis. However, the null hypothesis that analysts' forecasts are efficient is soundly rejected. Changes in the n-month-ahead USDA forecast over the previous month are significantly associated with analysts' current forecast errors. The results indicate that following an upward revision in the USDA forecast over the past month of 1%, on average analysts overestimate the USDA forecast by 0.05% for corn and 0.12% for wheat, but underestimate it by 0.12% for soybean. The strongest evidence against efficiency is provided by the positive effect on the current forecasting error of analysts' forecasting errors in the previous month. If analysts underestimated the USDA forecast by 1% in the previous month, they tend to underestimate the USDA forecast in the current month by about 0.24% for corn, 0.22% for soybean, and 0.3% for wheat.

As for USDA forecasts, the forecasts of private analysts are most precise for wheat and least accurate for soybean. Interestingly, the quality of forecasts is found to be relatively homogeneous across analysts.

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Appendix: Conditional Posterior Distributions for Parameters in the Gibbs Sampler

For Model 1, the hierarchical model consists of regression (9) and priors (17) through (21). In matrix form, regression (9) becomes

(A.1) $\boldsymbol{Y} = \boldsymbol{\beta X} + \boldsymbol{WZ} + \boldsymbol{\Sigma}$,

where $\boldsymbol{Z}$ is a vector containing all random effects, and $\boldsymbol{W}$ is a matrix with each row indicating the random effects of the corresponding observation. Therefore, given $\{\boldsymbol{\beta}, u_j, \mu_t, \sigma^2\}$, the dependent variable $y_t^{(n)}$ follows a normal distribution:

(A.2) $y_t^{(n)} \mid \boldsymbol{\beta}, u_j, \mu_t, \sigma^2 \sim N(\mathbf{1}_{TN\times 4}\boldsymbol{\beta} + \sum_{j=1}^{n} u_j + \mu_t, \sigma^2)$,

and the likelihood is $\prod_{nt} \Phi\left(y_t^{(n)} \middle| \boldsymbol{\beta}, u_j, \mu_t, \sigma^2\right)$. The posterior density of the set of model parameters is given by expression (16).

The conditional posterior density for $\boldsymbol{\beta}$ is

(A.3) $p(\boldsymbol{\beta}|\Lambda_1\backslash\boldsymbol{\beta}) = \prod_{nt} \Phi\left(y_t^{(n)} \middle| \boldsymbol{\beta}, u_j, \mu_t, \sigma^2\right) * \Phi(\boldsymbol{\beta}|\ \boldsymbol{M}, \boldsymbol{V})$.

Hence:

(A.4) $\boldsymbol{\beta}|\Lambda_1\backslash\boldsymbol{\beta} \sim \boldsymbol{N}((\boldsymbol{X'X}/\sigma^2 + \boldsymbol{V}^{-1})^{-1}(\boldsymbol{X'}(\boldsymbol{Y} - \boldsymbol{WZ})/\sigma^2 + \boldsymbol{V}^{-1}\boldsymbol{M}), (\boldsymbol{X'X}/\sigma^2 + \boldsymbol{V}^{-1})^{-1})$.

The conditional posterior density of $u_j, j = 1, \dots, N$ is

(A.5) $p(u_j|\Lambda_1\backslash u_j) = \prod_{u_j} \Phi\left(y_t^{(n)} \middle| \boldsymbol{\beta}, u_j, \mu_t, \sigma^2\right) * \Phi(u_j|\ \sigma_u^2)$.

Therefore:

(A.6) $u_j|\Lambda_1\backslash u_j \sim N\left(\frac{\boldsymbol{W}'_{u_j}\left(\boldsymbol{Y} - \boldsymbol{X\beta} - \boldsymbol{W}_{-u_j}\boldsymbol{Z}_{-u_j}\right)/\sigma^2}{\boldsymbol{W}'_{u_j}\boldsymbol{W}_{u_j}/\sigma^2 + 1/\sigma_u^2}, \frac{1}{\boldsymbol{W}'_{u_j}\boldsymbol{W}_{u_j}/\sigma^2 + 1/\sigma_u^2}\right)$,

where $\boldsymbol{W}_{u_j}$ is the column of $\boldsymbol{W}$ which indicates the random effect u_j. The conditional posterior density of $\mu_t, t = 1, \dots, T$ is analogous to the one of u_j's.

The conditional posterior density of σ^2 is

(A.7) $p(\sigma^2|\Lambda_1\backslash\sigma^2) = \prod_{nt} \Phi\left(y_t^{(n)} \middle| \boldsymbol{\beta}, u_j, \mu_t, \sigma^2\right) * p(\sigma^2)$, so that

(A.8) $\sigma^2 | \Lambda_1 \backslash \sigma^2 \sim IG((TN-1)/2, (\boldsymbol{Y}-\boldsymbol{X\beta}-\boldsymbol{WZ})'(\boldsymbol{Y}-\boldsymbol{X\beta}-\boldsymbol{WZ})/2)$.

Finally, the conditional posterior density of σ_u^2 is

(A.9) $p(\sigma_u^2 | \Lambda_1 \backslash \sigma_u^2) = \prod_{j=1}^{N} \Phi(u_j | \sigma_u^2) * p(\sigma_u^2)$.

Thus

(A.10) $\sigma_u^2 | \Lambda_1 \backslash \sigma_u^2 \sim IG((N-1)/2, \sum_{j=1}^{n} u_j^2/2)$. The conditional posterior density of $\sigma_\mu^2, t = 1, \ldots, T$ is similar to the one of σ_u^2.

The conditional posterior distributions of the parameters for Model 2 are similar to the ones for Model 1, and are omitted in the interest of space.

Table 1: Parameter Estimates for Evaluation Model of USDA Forecasts (Model 1).

A. Means and Standard Deviations.

Parameter (Variable)	Corn		Soybean		Wheat	
	Mean	(St. Dev.)	Mean	(St. Dev.)	Mean	(St. Dev.)
α (Constant)	0.054*	(0.032)	0.054	(0.045)	0.044*	(0.024)
β_1 $(S_{t-1} - U_{t-1}^{(n)})$	-0.070	(0.051)	-0.113**	(0.047)	-0.064	(0.058)
β_2 $(U_t^{(n+1)} - U_t^{(n+2)})$	-0.199**	(0.076)	-0.500**	(0.089)	-0.237**	(0.090)
β_3 $(S_{t-1} - S_{t-2})$	0.072**	(0.025)	-0.026	(0.038)	-0.011	(0.049)
σ_u	0.014**	(0.010)	0.038**	(0.013)	0.050**	(0.015)
σ_μ	0.132**	(0.022)	0.179**	(0.029)	0.076**	(0.013)
σ	0.1619**	(0.0061)	0.1901**	(0.0072)	0.0960**	(0.0041)

Note: (*) and (**) denote parameter estimates significant at 10% and 5% respectively.

B. Median and Credible Intervals.

Parameter (Variable)	Corn			Soybean			Wheat		
	2.5% Qnt.	Median	97.5% Qnt.	2.5% Qnt.	Median	97.5% Qnt.	2.5% Qnt.	Median	97.5% Qnt.
α (Constant)	-0.0083	0.0541	0.1179	-0.0333	0.0530	0.1437	-0.0019	0.0443	0.0909
β_1 $(S_{t-1} - U_{t-1}^{(n)})$	-0.1690	-0.0699	0.0295	-0.2044	-0.1128	-0.0198	-0.1779	-0.0642	0.0488
β_2 $(U_t^{(n+1)} - U_t^{(n+2)})$	-0.3466	-0.1993	-0.0506	-0.6752	-0.4998	-0.3250	-0.4137	-0.2365	-0.0609
β_3 $(S_{t-1} - S_{t-2})$	0.0231	0.0725	0.1217	-0.1001	-0.0256	0.0488	-0.1072	-0.0106	0.0854
σ_u	0.0010	0.0124	0.0391	0.0197	0.0356	0.0684	0.0270	0.0474	0.0854
σ_μ	0.0953	0.1294	0.1825	0.1314	0.1756	0.2460	0.0538	0.0743	0.1062
σ	0.1505	0.1618	0.1745	0.1767	0.1899	0.2048	0.0883	0.0959	0.1046

Note: (*) and (**) denote parameter estimates significant at 10% and 5% respectively.

Table 2: Parameter Estimates for Evaluation Model of Analysts' Forecasts (Model 2).

A. Means and Standard Deviations.

Parameter (Variable)	Corn		Soybean		Wheat	
	Mean	(St. Dev.)	Mean	(St. Dev.)	Mean	(St. Dev.)
α (Constant)	0.004	(0.012)	0.0017	(0.0083)	0.0021	(0.0076)
β_1 $(U_{t-1}^{(n)} - a_{i(t-1)}^{(n)})$	0.033	(0.028)	0.037	(0.028)	0.125**	(0.033)
β_2 $(U_t^{(n+1)} - U_t^{(n+2)})$	-0.052**	(0.021)	0.118**	(0.028)	-0.115**	(0.040)
β_3 $(U_t^{(n+1)} - a_{it}^{(n+1)})$	0.244**	(0.027)	0.218**	(0.030)	0.295**	(0.037)
σ_λ	0.0106**	(0.0047)	0.0131**	(0.0060)	0.0025**	(0.0021)
σ_μ	0.030**	(0.011)	0.0169**	(0.0078)	0.0186**	(0.0074)
σ	0.0898**	(0.0017)	0.1140**	(0.0022)	0.0551**	(0.0013)

Note: (*) and (**) denote parameter estimates significant at 10% and 5% respectively.

B. Median and Credible Intervals.

Parameter (Variable)	Corn			Soybean			Wheat		
	2.5% Qnt.	Median	97.5% Qnt.	2.5% Qnt.	Median	97.5% Qnt.	2.5% Qnt.	Median	97.5% Qnt.
α (Constant)	-0.0198	0.0041	0.0276	-0.0146	0.0016	0.0184	-0.0134	0.0021	0.0179
β_1 $(U_{t-1}^{(n)} - a_{i(t-1)}^{(n)})$	-0.0217	0.0329	0.0876	-0.0185	0.0372	0.0929	0.0594	0.1246	0.1898
β_2 $(U_t^{(n+1)} - U_t^{(n+2)})$	-0.0926	-0.0522	-0.0118	0.0639	0.1179	0.1719	-0.1932	-0.1149	-0.0370
β_3 $(U_t^{(n+1)} - a_{it}^{(n+1)})$	0.1907	0.2439	0.2976	0.1599	0.2179	0.2759	0.2232	0.2946	0.3659
σ_λ	0.0022	0.0102	0.0670	0.0026	0.0126	0.0264	0.0001	0.0020	0.0077
σ_μ	0.0157	0.0274	0.0583	0.0059	0.0155	0.0114	0.0092	0.0170	0.0371
σ	0.0866	0.0898	0.0932	0.1098	0.1139	0.1183	0.0526	0.0551	0.0578

Note: (*) and (**) denote parameter estimates significant at 10% and 5% respectively.