Are Revisions to USDA Crop Production Forecasts Smoothed?

by

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Abstract

This article determines the efficiency of the revision process for USDA corn and soybean production forecasts over the 1970/71 through 2004/05 marketing years. Nordhaus’ framework for testing the efficiency of fixed-event forecasts is used. Positive autocorrelation and consistency of directional changes in forecast revisions suggest these forecasts are “smoothed.” Evidence is provided that the loss in forecast accuracy due to smoothing is statistically and economically significant in several cases, which indicates that information about smoothing may be used to make non-trivial improvements in the accuracy of corn and soybean production forecasts. A conservative bias in farm operators’ assessments of yield potential and in the procedure for translating enumerator’ information about plant fruit counts into objective yield estimates are identified as plausible sources of smoothing.

Key Words: Corn, efficiency, fixed-event forecasts, independence, revisions, smoothing, soybeans.
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Agricultural markets are inherently unstable, primarily due to a combination of inelastic demand for food and production technology that is subject to the natural vagaries of weather, disease and pests. Price volatility causes many agricultural firms to rely on forecasts in decision-making. Consequently, the U.S. Department of Agriculture (USDA) devotes substantial resources to agricultural situation and outlook programs (Offutt). Crop production forecasts are an especially prominent example of this effort. These forecasts affect business decisions by farmers and agribusiness firms and also have an impact on government policy. Furthermore, it is a commonly-held belief of market participants that USDA crop production forecasts function as the “benchmark” to which other production estimates are compared. The dominant role of USDA crop production forecasts is not surprising given the classic public goods problem of private underinvestment in information (Wolf, Just and Zilberman) and the critical role that public information plays in coordinating the beliefs of market participants (Morris and Shin). In light of the importance of USDA crop production forecasts and their extensive impact throughout the agricultural sector, it is important to understand the accuracy and reliability of these forecasts.

Several studies examined the accuracy of USDA crop production forecasts (e.g., Egelkraut et al.) and their market impact (e.g., Sumner and Mueller). However, an important aspect of production forecasts generally has been overlooked in the previous literature: the process used to revise the forecasts across the forecasting cycle. For example, the National Agricultural Statistical Service (NASS) of the USDA typically releases five forecasts of annual corn and soybean production for a given marketing year starting in August preceding the marketing year and ending in January of the marketing year. Thus, production forecasts for corn
and soybeans are revised four times each marketing year.\textsuperscript{1} Only one previous study has examined the revision process for USDA crop production forecasts. Gunnelson, Dobson, and Pamperin analyzed first and second revisions for seven crops over 1929-1970 and reported, “While a relatively high percentage of the revisions was successful, the revised forecasts tended to under compensate for the errors in the previous estimate. Thus, for example, if first crop forecasts underestimated or overestimated crop size, the first revision was likely to exhibit similar characteristics.” (pp. 641-42). They did not provide quantitative evidence on the magnitude of the “undercompensation” or conduct formal statistical tests.\textsuperscript{2}

Some analysts argue that USDA production forecasts are “smoothed” or “conservative.” That is, monthly forecasts of the same event are thought to change too slowly compared to available information. For example, a prominent market advisory service made this statement with respect to the June 2000 winter wheat production forecast: “NASS is going to be particularly sensitive about making a drastic reduction in their July and August estimate. ARC anticipates USDA will take a conservative approach and slowly reduce production levels in July, August and September.” (AgResource Company). A related point was made at the 2004 USDA data users meeting, where a representative of a large agribusiness firm, “…commented he had noticed that if NASS corn forecasts go up from September to October they almost always go up from October to November (U.S. Department of Agriculture, p. 8).” Investigation of the efficiency of the revision process for USDA crop production forecasts will provide evidence about the validity of these perceptions.

Nordhaus developed a formal framework to determine the efficiency of fixed-event forecasts, which are a series of forecasts of the same terminal event, like USDA crop production forecasts. Note the difference from a conventional rolling-event framework, where a series of
forecasts of different events is examined. Nordhaus argued that the fixed-event approach may be more powerful than the rolling-event approach, especially in detecting tendencies to systematically adjust forecasts. Rolling-event tests may be unable to detect inefficiency associated with systematic adjustments because forecast errors concerning terminal events occurring at different times are uncorrelated. However, these adjustments would be revealed by the fixed-event approach.

Previous studies of macroeconomic forecasts using Nordhaus’ framework (e.g., Clements, 1995, 1997; Harvey, Leybourne and Newbold) provide substantial evidence of systematic adjustments in forecast revisions. However, this approach has not been applied to agricultural forecasts. Detection of systematic adjustments in forecasts is of interest because it implies that: (1) if forecast revisions are correlated, then forecasts do not efficiently incorporate all available information, and, therefore, may be improved and (2), knowledge about systematic adjustments can be used by market participants to compute adjusted forecasts.

The purpose of this article is to determine the efficiency of the revision process for USDA corn and soybean production forecasts over the 1970/71 through 2004/05 marketing years. These forecasts are of particular interest because corn and soybeans account for about 80 percent of total U.S. grain and oilseed production. Based on Nordhaus’ framework, the analysis includes parametric and non-parametric tests of forecast efficiency. Parametric tests use regression analysis to determine whether revisions in adjacent months are correlated. Non-parametric tests use contingency tables and Pearson Chi-square tests to determine whether revisions in adjacent months are made in the same direction. The use of two different tests provides evidence on the sensitivity of results to the selected test. A simulation is performed to estimate the potential gain in forecast accuracy due to adjustment of USDA corn and soybean
production forecasts for observed smoothing. Finally, potential sources of smoothing are identified in an interview of USDA officials responsible for compilation of USDA crop production forecasts.

**USDA Crop Forecasting Process**

All phases of the crop forecasting process are conducted by the National Agricultural Statistics Service (NASS), an agency within the USDA. Production forecasts for corn and soybeans are released in August, September, October, and November, with final estimates published in January. Corn and soybean production forecasts are based on estimates of planted and harvested acreage and two types of yield indications, a farmer-reported survey and an objective yield survey. The acreage figures are obtained from the USDA’s June Agricultural Survey, conducted during the first two weeks of June and reported at the end of June. The June Survey is based on a large farm operator list frame and a separate and independent area frame survey. These acreage estimates are used in subsequent production forecasts until there is evidence (survey or other) to alter the acreage estimates. The farmer and objective yield surveys use the same sampling, survey and estimation procedures from year-to-year. This allows yield and production forecasts to be compared over time.

The farmer-reported yield survey is conducted for states with significant corn and soybean production. In 2004, 33 states were surveyed for corn and 29 for soybeans. Farmers included in the yield survey are randomly selected from the list frame (essentially a list of names, addresses and phone numbers) of individuals that responded to the June Agricultural Survey. This assures that farmers included in the yield surveys are growing the crop of interest. Farmers are asked monthly (August through November) for a subjective prediction of their final corn and
soybean yields. While the list frame changes across years, reflecting changing farming arrangements, the same individuals are surveyed each month for a particular crop year. Farmer-reported yield surveys are conducted primarily by Computer Assisted Telephone Interviewing (CATI), but some data are collected by mail and by face-to-face interviews.

The objective yield survey for corn and soybeans typically has been conducted only for the seven most important production states, but that number was expanded to ten states for corn in 2004. These "speculative" states generate about 70 percent of U.S. production for each of the crops. The objective yield survey is based on an area-frame sampling design, where fields are randomly selected from the total land area used in production of a given crop. Mirroring the procedure for the farmer-reported yield survey, fields for the objective yield survey are randomly selected from the larger number surveyed in USDA’s June Agricultural Survey. Sample fields are selected with a probability proportional to their size.

Objective yields are obtained from two independently located plots in each randomly selected field. Physical counts and measurements of the number of plants and production per plant are conducted. Yield per acre is generated for the field after standardizing for row widths, moisture content and harvest loss. Objective yield indications are derived from models based on observations over the last five years for the corresponding months compared with end of season yields. Separate monthly models are constructed by maturity stage so forecast adjustments are automatically made for early or late maturing crops. At the end of the season, plots are harvested, and yields are calculated based on actual grain weights and harvest losses. In addition, an interview is conducted with the farm operator immediately after harvest to determine acres actually harvested and the yield realized in the sample field.
As noted earlier, yield forecasts are developed monthly from August through November. The data on both yield surveys are collected during the last week of the month previous to the survey month and the first few days of the survey month, generally from the 25th of the previous month through the 3rd of the survey month. Yield forecasts reflect crop conditions at the beginning of the survey month and assume normal growing conditions for the remainder of the season as reflected by historical records.

The farmer and objective yield indications are combined in a multistage process employing statistical and judgmental techniques. Before the actual "lock-up" that precedes the release of a crop report, all available acreage data and farmer-reported yield indications for non-speculative states are reviewed. One part of this review is comparison of yield recommendations for a given state with adjoining states to see if they demonstrate consistency, based on the weather that has already occurred. If there is a need to discuss recommendations with a state office, this can be done but no information is exchanged about yield indications for other states. By the time lock-up occurs, harvested acreage for all states and yields for non-speculative states have been set.

The lock-up for USDA crop reports occurs the night before a report is released. The recommendations and comments for speculative states are transmitted as encrypted data files that are locked in a safe until the lock-up area is secured. For these states, yield indications are available from both the farmer-reported survey and the objective yield survey. During lock-up, the Agricultural Statistics Board reviews all the indications, and in consultation with commodity statisticians, determines production forecasts for speculative states. An explicit formula or rule is not used to combine the farmer and objective yield surveys. Regional production forecasts are then determined. The final step is the generation of national production forecasts. In
commenting on the process used to determine final production estimates Gardner notes that it
“…is not done using a pre-specified formula---in which case a computer could replace the NASS
board---but through a consensus of the Board members based on their experience and the full
information before them.” (p. 1068) A detailed description of the production forecasting process
can be found in NASS/SMB.

Data

USDA forecasts of corn and soybean production over the 1970/71 through 2004/05
marketing years are examined in this study. USDA corn and soybean production forecasts are
considered fixed-event forecasts because the series of forecasts is related to the same terminal
event \( q_T \), where \( T \) is the release month (January) for the final estimate of crop production in the
\( i \)th marketing year. The forecast of the terminal event for month \( t \) is denoted as \( q_t^i \), where \( t = 1, \ldots, T \), and \( i=1970/71, \ldots, 2004/05 \). The forecast revision at time \( t \) is denoted as \( v_{t}^i = q_t^i - q_{t-1}^i \)
where \( t = 2, \ldots, T \), and \( i=1970/71, \ldots, 2004/05 \). This layout of fixed-event forecasts and
corresponding revision process is illustrated for the USDA corn and soybean production
forecasting cycle in figure 1. In order to standardize for increasing crop size over time, revisions
are examined in log percentage form:

\[
(1) \quad v_{t}^i = 100 \times \ln \left( \frac{q_t^i}{q_{t-1}^i} \right) \quad t=2, \ldots, 5; i=1970/71, \ldots, 2004/05
\]

where the forecasting cycle has a length of \( T=5 \), and the revision cycle has a length of \( T-1=4 
months for both crops.\)
Table 1 presents descriptive statistics on monthly revisions for USDA forecasts of corn and soybean production. The data suggest that the first (September) revision of both corn and soybean production was typically the largest. This revision for corn and soybeans was as large as 18 percent. As indicated by standard deviations and ranges, the magnitude of forecast revisions tended to decrease from the first to the last revision, a pattern consistent with resolution of production uncertainty across the forecasting cycle. In general, there was a similarity in the magnitude and range of corn and soybean production forecast revisions during the period of study with soybean revisions being slightly larger than corn revisions.

The null hypothesis of no bias in USDA production forecast revisions was not rejected at the 5% significance level with two exceptions: January corn production revisions and November soybean production revisions. In both cases, revisions had a positive bias with a mean of 0.5% in corn and 0.6% in soybeans and the lowest standard deviation compared to the other months. The general lack of bias in forecast revisions also implies no bias in forecasts themselves, as revisions are easily traced back to the forecasts (Nordhaus). However, limited evidence of bias in USDA crop production forecast revisions revealed here should not be confused with efficiency. Unbiased forecast revisions may be systematically adjusted up and/or down during the forecasting cycle with errors canceling out for the entire series of forecasts. Efficiency tests introduced in the next section allow detecting any patterns in the forecast revision process.

**Conceptual Framework**

The theoretical framework developed by Nordhaus is based on the theory of rational forecasts and is designed to test the efficiency of fixed-event forecasts. According to Nordhaus, weak-form efficiency of fixed-event forecasts may be described by two conditions. First, for any
given marketing year \((i)\) the forecast \textit{error} at time \(t\) is independent of all forecast revisions up to time \(t\):

\[
(2) \quad E\left[ e_t \mid v_t, \ldots, v_2 \right] = 0 \quad t = 2, \ldots, T-1.
\]

Second, the forecast \textit{revision} at time \(t\) is independent of all revisions up to time \(t-1\):

\[
(3) \quad E\left[ v_t \mid v_{t-1}, \ldots, v_2 \right] = 0 \quad t = 3, \ldots, T.
\]

Because forecast errors may be defined in terms of future revisions:

\[
(4) \quad e_t = q_T - q_t = v_{t+1} + \ldots + v_T
\]

conditions (2) and (3) imply each other. Thus, analysis of independence in forecast revisions is sufficient to test for weak-form efficiency. According to equation (3), if forecasts are weak-form efficient, revisions should follow a random walk. If, instead, forecast revisions are correlated and forecasts move consistently up or down, they are said to be inefficient. Figure 2 provides a hypothetical example of efficient versus inefficient (in this case smoothed) forecast revisions. Efficient forecast revisions appear jagged because they incorporate all new information as soon as it becomes available. Inefficient forecast revisions are smoother because new information is incorporated into forecasts too slowly.

In previous studies (e.g., Nordhaus), weak-form efficiency generally has been tested by estimating a regression of the following form for each terminal event:

\[
(5) \quad v_t = \alpha v_{t-1} + \zeta_t \quad t=3,\ldots, T
\]

where \(\alpha\) is the regression slope coefficient, \(\zeta_t\) is a standard, normal error term and the number of observations is equal to \(T-2\). This equation provides an estimate of the first-order serial correlation of revisions for a particular event. The null hypothesis is \(\alpha=0\), which, if not rejected, implies that forecast revisions are efficient. However, applying the above specification in the
current study will result in a large number of regressions (35) estimated based on only a few observations ($T-2=3$). This problem was less severe in previous studies of macroeconomic forecasts because a larger number of revisions for each terminal event typically was available. Therefore, the specification is adapted to the present setting by estimating the correlation between two adjacent revisions across marketing years rather than consecutive revisions within the same marketing year. For a given pair of consecutive revisions, $t$ and $t-1$, this regression is:

$$\nu_i = \alpha \nu_{i-1} + \xi_i \quad i=1970/71, \ldots, 2004/05$$

where $\alpha$ is the regression slope coefficient, $\xi_i$ is an error term and the number of observations is equal to $N$ (35 in this case). Thus, all October revisions ($t=3$) made from 1970/71 to 2004/05 are regressed against previous September revisions ($t-1=2$) in the respective years, rather than reviewing all pairs of revisions for, say, 2004/05 crop production. Because two adjacent revisions of the same event are analyzed, the ability to detect systematic adjustments is preserved. This does, however, place an emphasis on whether revisions from one month to the next are independent rather than whether the entire series of revisions within the same marketing year is efficient. This modification has the advantage that forecast revisions are compared at the same time from year-to-year, which should be based on similar points in the production cycle for corn and soybeans.

In addition to correlations estimated separately for each pair of forecast revisions, the correlation of USDA forecast revisions is estimated using a pooled data set in order to further improve the power of statistical tests. This approach was proposed by Clements (1997), who argued that the power of efficiency tests may be improved by estimating equation (6) using $(T-2) \times N$ observations and ordinary least squares (OLS), rather than running separate regressions for
each of the $N$ terminal events. The resulting pooled regression estimates the average correlation between all consecutive revisions within the study period.

**Correlation Test Results**

Results of the correlation efficiency tests are reported in table 2. These tests demonstrate that correlation between consecutive corn forecast revisions was statistically significant at the 5% level in all months. Estimated correlation coefficients ranged from 0.25 to 0.68. Tests of soybean production forecast revisions revealed statistically significant correlation in forecast revisions in November at the 5% level, with an estimated coefficient of 0.25. Because forecast revisions were in percentage form, estimated coefficients may be interpreted as point elasticities. Thus, a 0.68 coefficient for November versus October corn production revisions means that a one percent positive revision in October is expected to be followed by 0.68 percent positive revision in November. Results of the pooled estimation confirm the presence of smoothing in both commodities with the average correlation in corn equal to 0.36 and in soybeans equal to 0.19. Both pooled estimates were significant at the 1% level.

Interpretation of these results should take into account the average absolute magnitude of underlying revisions. For example, even though the estimated coefficient for January corn revisions was slightly larger than for October revisions (0.31 versus 0.25), because of the larger average absolute magnitude of September revisions compared to November revisions (2.23% and 1.68%, respectively, table 1), smoothing has a greater impact in absolute terms on October forecasts than on January forecasts. Finally, note that all estimated coefficients were positive, which indicates positive correlation in forecast revisions, consistent with Nordhaus’ hypothesis of forecast “smoothing.”
The OLS model assumes that the covariance matrix of the error term is diagonal. According to Clements (1997) this may be a poor assumption since revisions to forecasts at different target dates may be heteroskedastic. Revisions were tested for the presence of heteroskedasticity across time and within events using Goldfield-Quandt tests. Time-related heteroskedasticity was tested by partitioning the sample period into two approximately equal sub-periods (1970/71-1986/87 vs. 1987/88-2004/05). Likewise, event-related heteroskedasticity was tested by partitioning the events into two groups (October-September revisions vs November-October and January-November revisions). The values of the Goldfield-Quandt statistics were 0.65 ($p=0.062$) for corn and 0.52 ($p=0.011$) for soybeans for time-related tests and 2.14 ($p=0.004$) for corn and 3.61 ($p=0.00$) for soybeans for event-distance tests. These test values suggest the presence of both time-related and event-distance heteroskedasticity in corn and soybean production forecast revisions. In order to take into account heteroskedasticity detected in the sample, Harvey’s model of multiplicative heteroskedasticity was used (Harvey, p.99). A trend variable for marketing years and an event-distance variable (months before January) were included in the variance equation. As shown in table 2, correction for both time-related and event-distance heteroskedasticity yielded coefficient estimates and $t$-values quite close to those obtained from the OLS pooled model estimation.

Another relevant issue is potential structural change in model parameters across time, particularly in view of the relatively long sample period (35 marketing years). A traditional approach would be to pick an arbitrary sample breakpoint, often the midpoint of the sample, and use a Chow test for structural change. This could be further refined by associating breakpoints with major events relevant to the data series. Either of these approaches suffers from the arbitrary nature of the selected breakpoints. Recent literature suggests the Quandt Likelihood
Ratio (QLR) test as a superior test for detecting structural change of unknown timing (e.g., Hansen, 2001). The QLR test consists of taking the largest Chow statistic over all possible breakdates, while making sure that subsample points are not too close to the end points of the sample. The QLR test was applied to the pooled data in this study with 15% trimming. The highest value of the Chow statistic was 3.73 for corn and 3.53 for soybeans. The critical value of the QLR statistic at the 10% significance level is 7.12 (Stock and Watson, p. 471), which indicates that the null hypothesis of no structural change cannot be rejected. Hence, the pattern of smoothing detected in revisions to USDA corn and soybean production forecasts was stable across the 1970/71-2004/05 time period.

**Directional Test Results**

Nordhaus’ approach is extended in this study to include non-parametric tests. These tests are of interest because they relax distributional assumptions necessary for the parametric regression-based tests. Specifically, a Pearson chi-squared test can be used to determine whether revisions in two consecutive months are likely to be made in the same direction. The Pearson chi-squared statistic for this case is calculated as:

\[ S = \frac{N(O_{t-1, negative} \cdot O_{t, positive} - O_{t-1, positive} \cdot O_{t, negative})^2}{n_{t-1}C_{negative}^C_{positive}} \]

where \( O \) refers to the number of observations in a particular month that are positive or negative, \( n \) is the number of observations for a particular month, \( C \) is the number of positive or negative observations across the two months, and \( N \) is the total number of observations. This statistic is used to test the null hypothesis that the number of positive (or, equivalently, negative) revisions is equal between months \( t \) and \( t-1 \). The null distribution of \( S \) is given approximately by the chi-
squared distribution with 1 degree of freedom (Conover, p. 200). A significant value of the Pearson chi-squared statistic indicates consistency in directional changes between consecutive revisions, and thereby, reveals inefficiency.

Results of the directional efficiency tests of corn and soybean production forecast revisions are presented in terms of conditional probabilities in table 3. Conditional probabilities indicate the likelihood that the revision for month \( t \) will be made in a given direction based on the revision direction in the previous month. For example, the number of positive revisions of September corn production forecasts that remained positive in October, 11, divided by the total number of positive revisions in October, 21, gives a conditional probability of 73%. If revisions followed a random walk, the conditional probability of consecutive revisions made in the same direction would be 50% (like flipping a fair coin). Inefficient revisions, on the other hand, would have conditional probabilities significantly different from 50%.

Conditional probabilities for corn production forecast revisions demonstrate a tendency for positive revisions to remain positive and for negative revisions to be closer to independence between two consecutive months. On average, corn production revisions remained positive 79% of the time and remained negative 56% of the time. The strongest evidence of smoothing was detected between October and November revisions, which remained positive 100% of the time and remained negative 64% of the time. This pattern reveals that USDA forecasters were mainly conservative in revising corn forecasts upwards. The Pearson chi-squared statistic was significant at the 1% level for October-November and the pooled data set, confirming the tendency of corn revisions to be made in the same direction.

Conditional probabilities for soybean production forecast revisions demonstrate a tendency for both positive and negative revisions to be made in the same direction an average of
66% of the time. The tendency for positive revisions to remain positive was the strongest between October and November (83 percent) and for negative revisions to remain negative between November and January (92 percent). This pattern is consistent with the concept of forecast “smoothing” discussed above. At the same time, soybean revisions between September and October were close to independence in both directions, suggesting forecast efficiency in this case. These observations are confirmed by Pearson chi-squared statistics, which were significant at the 1% level in all cases for soybeans except for September-October.

Implications of Smoothing for Forecast Accuracy

Overall, the results of the correlation and directional tests were the same, as both revealed the presence of smoothing in most corn and soybean production forecast revisions. Economic theory implies that the smoothing detected in revisions to the USDA production forecasts reduces economic welfare because forecasts are not fully efficient. More specifically, Falk and Orazem show theoretically that less accurate government crop production forecasts reduce social welfare because market prices after release of the forecasts are not as close to the equilibrium prices that would prevail if actual production were known with certainty. It follows that the economic welfare implications of forecast smoothing depend on the magnitude of the difference in accuracy between USDA forecasts and efficient (unsmoothed) forecasts. 7

A simulation was performed to estimate the potential gain in forecast accuracy due to adjustment for smoothing in USDA corn and soybean production forecasts. The first step was to estimate regressions of the form $\epsilon_t^i = \gamma v_{t+1}^i + \epsilon_t^i$ for September, October and November forecasts for each crop. If revisions were efficient, equations (2) and (3) imply that $\gamma=1$. In other words, the forecast error at time $t$ should be fully corrected (on average) by the following revision. 8
realistically reflect the information available to market participants, the regression was first estimated over 1970/71-1979/80 and used to project the degree of smoothing expected by market participants in 1980/81. Similar out-of-sample projections were made for remaining years by adding an additional observation to each regression estimation. As expected, all estimated $\gamma$ coefficients for corn were greater than one indicating under-adjustment, or smoothing, in revisions. Estimated $\gamma$ coefficients for soybeans in September were generally lower than one (but not statistically different from one) and generally greater than one otherwise (with an exception of one October regression and three November regressions).

The second step in the simulation was to use the estimated $\gamma$ coefficients to adjust actual USDA forecasts for smoothing. Specifically, actual revisions were multiplied by the estimated $\gamma$ coefficients to derive a series of efficient revisions. For example, the estimated $\gamma$ coefficient for August forecast errors and September revisions over 1970/71-1994/95 was 1.44. This coefficient was multiplied by the actual revision for September 1995/96 (-3.64%) to obtain an adjusted revision (-5.24%) for that month. Adjusted USDA forecasts were calculated by adding the adjusted (efficient) revision to the previous months’ forecast. Note that this procedure does not change forecasts at the beginning or the end of the forecasting cycle, only the intermediate path is adjusted to satisfy efficiency.

In proportional terms, the results show that the correction for smoothing decreased root mean squared percentage forecast errors an average of 10% in corn and 2% in soybeans. The reduction in forecast error variation was as large as 21% and 5% for October revisions of corn and soybean production forecasts, respectively. In terms of raw units, the results imply a reduction in forecast error variation due to correction for forecast smoothing as large as 69 million bushels for a 10 billion bushel corn crop and 5 million bushels for a 2.8 billion bushel
soybean crop. Overall, the evidence indicates that information about smoothing may be used to make non-trivial improvements in the accuracy of USDA corn and soybean production forecasts and, therefore, has potential economic value to market participants.

**Sources of Smoothing**

The smoothing found in revisions to USDA forecasts of corn and soybean production is statistically and economically significant in several cases, consistent with empirical evidence in previous studies of macroeconomic forecasts (e.g., Nordhaus; Harvey, Leybourne and Newbold), and corroborates the arguments of market participants presented in the introduction. Such smoothing may take place on either of two levels involved in the forecasting procedure: (1) data sources and/or estimation procedures used by USDA analysts to generate these forecasts may contain a conservative bias and/or (2) USDA analysts may be too conservative in incorporating data into their forecasts. A discussion of possible sources of smoothing in USDA crop production forecasts is presented in this section.

The first possible source of the observed smoothing may be the weather assumption used by the USDA. As noted earlier, the USDA uses a “normal weather” assumption for the remainder of the growing season to condition all forecasts of corn and soybean crop production. This conditioning implies that the direction, and possibly the magnitude, of the USDA revision for a given month may be predicted based on weather conditions in the month preceding the revision. For example, the September revision may be predicted based on August weather, as shown below:
In the same manner, October revisions may be predicted based on September weather and so on. However, the ability to predict the revision for the current month based on the previous month’s weather does not necessarily mean that revisions can be predicted from the previous revision. If all information based on current (e.g., August) weather conditions is efficiently incorporated in the upcoming (e.g., September) forecast revision, following revisions (October, November, January) will be correlated with the September revision only if weather conditions are correlated across the same time period. For example, a positive (negative) September revision followed by a positive (negative) revision in October, would imply that weather conditions in both August and September were “good” (“bad”). Previous studies demonstrate that weather conditions are approximately independent for the time horizons relevant to USDA crop revisions (e.g., Hill and Mjelde). Thus, it is unlikely that the weather conditioning assumption used by the USDA is the cause of forecast smoothing observed in this study.

From a more theoretical perspective, Bradford and Kelejian developed a model that suggests smoothing may result from a measurement error correction process. Specifically, they developed a theoretical model where the latest yield observations do not result in an optimal forecast of crop production due to measurement error. Instead, the model indicates a better procedure would be to form a weighted-average of earlier forecasts and the current estimate with weights depending on the parameters of the joint distribution of the monthly forecasts. Therefore, due to measurement error, previous forecasts would be included along with new information in forming the current optimal forecast. This is similar to using GLS regression to
correct for measurement error, with earlier forecasts viewed as independent estimates (instruments) of the same variable. This logic was supported by Gardner, who asserted that the USDA does not in fact publish an independent production forecast each month: “If the current estimate is substantially different from earlier estimates there is a tendency not to adjust the prior NASS estimates fully to rely only on the current month’s information. Thus, the NASS estimate already does with its prior information what Bradford and Kelejian recommend doing with published NASS estimates.” (p.1068) Gardner also indicated that the role of earlier forecasts in forming the current month’s forecast is not discussed in USDA publications. He advocated a full and detailed disclosure of how forecasts are constructed to aid in the intelligent use of the forecasts.

In order to provide more direct evidence on the source of smoothing in USDA corn and soybean production forecasts, NASS officials responsible for compilation of these forecasts were interviewed on January 11, 2005 in Washington, D.C. The three NASS officials who participated in the interview were Richard D. Allen, Deputy Administrator, Programs and Products, and Chair of the Agricultural Statistics Board; Steven D. Wiyatt, Director of the Statistics Division; and Joseph J. Prusacki, Chief of the Crops Branch of the Statistics Division. Each has long experience with the crop production forecasting process and is highly knowledgeable about all aspects of the process. They uniformly indicated that NASS does not approach the forecasting task in terms of revisions. Instead, the officials explained that NASS attempts to make the best possible interpretation of production potential each month based upon available information in order to minimize forecast error versus the final estimate. In other words, NASS starts with a clean slate and makes a “new” forecast each month, rather than altering the previous forecast in some way. This was reinforced at the 2004 USDA Data Users
Meeting, where it was emphasized that every month “...judgments are made independently, based on the data available. NASS does not set a target figure in October and then “sneak” up to it.” (U.S. Department of Agriculture, p.8) Taken as a whole, these comments suggest that the smoothing observed in USDA corn and soybean production forecasts is unlikely to be driven by a measurement error correction procedure as suggested by Bradford and Kelejian and Gardner.

Another potential cause of smoothing suggested in the previous literature is strategic behavior. Nordhaus first suggested that bureaucratic organizations may intentionally smooth forecasts, because efficient forecasts would be too unstable. Batchelor and Dua argued that minimization of expected squared errors may not be the only objective of forecast suppliers because demand for economic forecasts may be related to factors other than accuracy, such as stability. Therefore, forecasters may have incentives to adjust their published figures so as to tradeoff expected accuracy against stability. In a similar vein, Scotese argued that if a forecast is subject to large and frequent revisions it is difficult to rely on as a guide to future actions. The result is that a forecaster’s reputation is enhanced by incorporating new information slowly into forecasts. Scotese developed a formal model where the forecaster’s objective function is based on minimization of the loss associated with both large errors and large revisions. Evidence of this tradeoff was found for Federal Reserve Staff forecasts of real GNP, but not for inflation. NASS officials strongly disagreed with the idea that their forecasting efforts were driven by strategic behavior and emphasized again that their sole objective is to minimize forecast errors versus the final estimate.

The discussions with NASS officials suggested that smoothing in USDA crop production forecasts is more likely associated with systematic tendencies in the two yield indications that underlie the published forecasts. The first source of smoothing may be a
bias in farm operators’ assessments of production potential. Bias in this indicator would be consistent with behavioral psychology studies (e.g., Tversky and Kahneman; Arrow) that suggest people tend to hold on to prior views too long and are therefore conservative with regard to future assessments. That is, there is a tendency in human decision-making to process news slowly, trusting familiar notions rather than incorporating surprises into forecasts, which may lead to “forecast stickiness” in Nordhaus terms. If this conservative bias is present in farmers’ assessments of yield potential, it may be carried over into USDA production forecasts. Additionally, if conservativeness is an aspect of normal decision-making and analysis, as behavioral psychologists argue, it cannot be ruled out that NASS analysts are conservative in the way they process available information.

The second source of smoothing may be a bias in the procedure used to translate enumerators’ information about plant fruit counts early in the production season into objective yield estimates. Specifically, the information on fruit counts is used to predict yield potential based on regression models of the relationship between fruit counts and fruit weight for the last five production seasons. It is possible that the use of a fixed five-year window may result in misleading estimates if crop conditions in the forecast year are not considered. As an illustration, consider corn production forecasts for the 2004/05 marketing year. From the beginning of the season the yield forecast for corn was too low at least partially because the relationship between fruit counts and weight during the previous five years did not reflect the exceptionally good growing conditions in the summer of 2004. Since there is considerable information available on crop conditions even for the first August forecast, this can be viewed as a form of omitted variable bias in the estimated relationship between fruit counts and weight. Thus, the use of data for the
previous five years resulted in significant understatements of production potential in August and September of 2004, which was subsequently corrected by a record positive revision in October when actual observations on the count/weight relationship became available.

Summary and Conclusions

Previous studies of U.S. Department of Agriculture (USDA) crop production forecasts generally overlooked an important aspect of these forecasts, namely, the nature of forecast revisions. The forecast revisions process is an important issue because it reveals how forecasts change across the forecasting cycle. In particular, examination of forecast revisions allows detection of deviations from efficiency due to systematic under- or over- adjustment, which is not revealed in conventional analyses of forecast errors. Systematic under-adjustment of forecasts is commonly referred to as “smoothing.”

This study examined the efficiency of the revision process for USDA corn and soybean production forecasts over the 1970/71 through 2004/05 marketing years. Analysis was based on a fixed-event approach developed by Nordhaus. Correlation tests rejected the null hypothesis of forecast efficiency in all cases except for October and January revisions of soybean production forecasts. Positive correlation coefficients between consecutive revisions were higher in corn, ranging from 0.25 to 0.68, compared to soybeans, which ranged from 0.14 to 0.26. Directional tests for corn revealed that positive revisions remained positive an average of 79% of the time and negative revisions remained negative an average of 56% of the time. In soybeans, positive and negative revisions were followed by revisions in the same direction an average of 66% of the
time. Overall, the results of the correlation and directional tests were consistent, as both revealed the presence of smoothing in most corn and soybean production forecast revisions.

Economic theory shows that the welfare implications of forecast smoothing depend on the magnitude of the difference in accuracy between USDA forecasts and efficient (unsmoothed) forecasts. A simulation was performed to estimate the potential gain in forecast accuracy due to adjustment for smoothing. In proportional terms, the correction for smoothing decreased root mean squared percentage forecast errors an average of 10% in corn and 2% in soybeans. The reduction in forecast error variation was as large as 21% and 5% for October revisions of corn and soybean production forecasts, respectively. This evidence indicates that information about smoothing may be used to make non-trivial improvements in the accuracy of USDA corn and soybean production forecasts and, therefore, has potential economic value to market participants.

As a final step, this study investigated potential sources of smoothing in USDA crop production forecasts. An interview of officials responsible for compilation of USDA forecasts revealed that smoothing was unlikely the result of a measurement error correction procedure or strategic behavior on the part of USDA analysts. The officials repeatedly expressed that independent forecasts are made each month with the sole objective of forecast error minimization. Discussions with the USDA officials identified two plausible sources of smoothing: (1) a conservative bias in farm operators’ assessments of yield potential, and (2) a conservative bias in the procedure for translating enumerators’ information about plant fruit counts into objective yield indications. Adjustment for both sources of smoothing may improve the efficiency of USDA corn and soybean production forecasts.

An important remaining issue is how USDA forecasts are interpreted and used by the market participants. If market participants are unaware of or misunderstand the nature of the
revisions process, welfare losses may result. The potential magnitude of the losses is illustrated by the analysis in this article. If instead market participants are aware of the smoothing process and account for it in forming expectations, economic losses may be negligible or non-existent (Orazem and Falk). The quotes in the introduction to this paper suggest that market analysts are aware, at least in general terms, of smoothing in USDA crop production forecasts. The degree to which market participants actually use this knowledge in forming their own crop production forecasts is an interesting area for further research.
References


Endnotes

1 It is important to emphasize that the term “revision” does not necessarily imply that NASS produces a forecast for a given month by simply altering the previous forecast. The term “change in forecast” may be more descriptive. This paper employs the term “revision” as it is consistent with usage in the forecasting literature (e.g., Nordhaus).

2 Thomson reports a small “conservative” pattern in revisions to farrowing intentions in USDA Hogs and Pigs Reports. Mills and Schroeder analyze USDA cattle on feed inventory revisions and find evidence of positive correlation in revisions.

3 The USDA also publishes corn and soybean production forecasts for July. These forecasts were generated by NASS using the same procedures outlined in this paper until 1988/89. Since that time, USDA July production forecasts are based on NASS June acreage estimates and trend yield projections by the World Agricultural Board (WAOB). In addition, prior to 1986/87 “final” estimates were released in February rather than January.

4 Prior to May 1994 corn and soybean crop reports were released at 4 p.m. EST. Since May 1994 reports have been released at 8:30 a.m. EST. There has been only one documented breach in lockup security for USDA crop reports (SRS, pp. 45-46). The Associate Statistician for the USDA in 1905, E.S. Holmes, Jr., collaborated with a cotton trader, Lewis Van Riper, to leak advance information from cotton production reports. At one point in their collaboration a signaling system was developed that involved lowering or raising a window shade in the lock-up room. Since that time, all shades in the lockup area have been sealed while crop reports are prepared.

5 Sometimes the January “final” estimates are subsequently revised. This happens most
frequently in January following the end of the marketing year. Due to the sporadic nature and long time lag of the subsequent revisions they are not considered in this analysis.

6 Raw revisions \((q_t - q_{t-1})\) measured in million bushels were also included in the original analysis and yielded similar results. These results are available from the authors upon request.

7 This statement assumes that the information contained in USDA corn and soybean production forecasts is not fully anticipated by market participants. In other words, USDA production reports are assumed to contain important and relevant “news.” Large and significant futures price reactions after the release of USDA corn and soybean production forecasts indicate that the forecasts provide important new information to the market (e.g., Sumner and Mueller; Garcia et al.).

9 It is interesting to note that the \(\gamma\) estimates from these regressions equal the inverse of Theil’s R-ratio (Theil, 1965, pp. 62-63). This form of a “revision ratio” was examined by Gunnelson, Dobson, and Pamperin and Thomson. Unfortunately these studies only reported the percentage of revision ratios falling in certain ranges \((R<0; 0<R<1; 1<R<2; R>2)\), so a direct comparison to the \(\gamma\) estimates obtained in this study cannot be made.

9 Full results of the simulation analysis are available from authors upon request.
Table 1. Descriptive Statistics and Test of Bias for Revisions of USDA Corn and Soybean Production Forecasts, 1970/71 - 2004/05 Marketing Years.

<table>
<thead>
<tr>
<th>Crop/Revision Month</th>
<th>Mean</th>
<th>Absolute Value</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>t-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>September</td>
<td>-0.69</td>
<td>2.23</td>
<td>3.75</td>
<td>-17.64</td>
<td>4.44</td>
<td>22.08</td>
<td>-1.08</td>
<td>0.29</td>
</tr>
<tr>
<td>October</td>
<td>0.37</td>
<td>1.92</td>
<td>2.45</td>
<td>-5.71</td>
<td>5.78</td>
<td>11.48</td>
<td>0.90</td>
<td>0.38</td>
</tr>
<tr>
<td>November</td>
<td>0.50</td>
<td>1.68</td>
<td>2.19</td>
<td>-6.82</td>
<td>4.28</td>
<td>11.10</td>
<td>1.36</td>
<td>0.18</td>
</tr>
<tr>
<td>January</td>
<td>0.51</td>
<td>1.15</td>
<td>1.52</td>
<td>-2.48</td>
<td>5.21</td>
<td>7.69</td>
<td>2.01</td>
<td>0.05</td>
</tr>
<tr>
<td>Soybeans</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>September</td>
<td>-0.76</td>
<td>2.44</td>
<td>4.04</td>
<td>-18.29</td>
<td>5.17</td>
<td>23.46</td>
<td>-1.11</td>
<td>0.27</td>
</tr>
<tr>
<td>October</td>
<td>0.10</td>
<td>2.42</td>
<td>3.26</td>
<td>-6.85</td>
<td>9.13</td>
<td>15.98</td>
<td>0.18</td>
<td>0.86</td>
</tr>
<tr>
<td>November</td>
<td>0.58</td>
<td>1.41</td>
<td>1.69</td>
<td>-3.61</td>
<td>4.35</td>
<td>7.96</td>
<td>2.02</td>
<td>0.05</td>
</tr>
<tr>
<td>January</td>
<td>-0.22</td>
<td>1.40</td>
<td>1.80</td>
<td>-5.64</td>
<td>3.70</td>
<td>9.34</td>
<td>-0.73</td>
<td>0.47</td>
</tr>
</tbody>
</table>

Notes: Percentage revisions are calculated as the natural logarithm of the forecast in month $t$ minus the natural logarithm of the forecast in month $t-1$, times 100. $N=35$. The test of bias tests the null hypothesis that the mean percentage revision equals zero.
Table 2. Correlation Test Results for USDA Corn and Soybean Production Forecasts Revisions, 1970/71-2004/05 Marketing Years.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Dependent Variable</th>
<th>Independent Variable</th>
<th>Coefficient</th>
<th><em>t</em>-statistic</th>
<th><em>p</em>-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>October</td>
<td>September</td>
<td>0.25</td>
<td>2.39</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>November</td>
<td>October</td>
<td>0.68</td>
<td>6.58</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>January</td>
<td>November</td>
<td>0.31</td>
<td>2.81</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>Pooled&lt;sub&gt;t&lt;/sub&gt;</td>
<td>Pooled&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.36</td>
<td>5.81</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Pooled&lt;sub&gt;t&lt;/sub&gt;*</td>
<td>Pooled&lt;sub&gt;t-1&lt;/sub&gt;*</td>
<td>0.38</td>
<td>6.11</td>
<td>0.00</td>
</tr>
<tr>
<td>Soybeans</td>
<td>October</td>
<td>September</td>
<td>0.14</td>
<td>1.06</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>November</td>
<td>October</td>
<td>0.25</td>
<td>3.02</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>January</td>
<td>November</td>
<td>0.26</td>
<td>1.54</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>Pooled&lt;sub&gt;t&lt;/sub&gt;</td>
<td>Pooled&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.19</td>
<td>2.72</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>Pooled&lt;sub&gt;t&lt;/sub&gt;*</td>
<td>Pooled&lt;sub&gt;t-1&lt;/sub&gt;*</td>
<td>0.22</td>
<td>3.04</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Notes: Correlation tests use the OLS regression $v'_t = v'_{t-1} + \zeta'_t$, where $v'_t$ is the percentage revision in month $t$, except for pooled regressions marked with an asterisk, which were estimated using Harvey's model to correct for hetroskedasticity. $N=35$ for monthly regressions. $N=105$ for pooled regressions.
Table 3. Directional Test Results for USDA Corn and Soybean Production Forecast Revisions, 1977-71-2003-04 Marketing Years.

<table>
<thead>
<tr>
<th>Revision t</th>
<th>Revision t-1</th>
<th>Corn</th>
<th></th>
<th>Soybeans</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Negative</td>
<td>Positive</td>
<td>Pearson Chi-Square Statistic</td>
<td>Negative</td>
</tr>
<tr>
<td>October</td>
<td>September</td>
<td>0.50</td>
<td>0.27</td>
<td>1.94 (0.16)</td>
<td>0.53</td>
</tr>
<tr>
<td>November</td>
<td>October</td>
<td>0.64</td>
<td>0.00</td>
<td>18.17 (0.00)</td>
<td>0.59</td>
</tr>
<tr>
<td>January</td>
<td>November</td>
<td>0.56</td>
<td>0.35</td>
<td>1.22 (0.27)</td>
<td>0.92</td>
</tr>
<tr>
<td>Pooled</td>
<td></td>
<td>0.56</td>
<td>0.21</td>
<td>13.51 (0.00)</td>
<td>0.66</td>
</tr>
</tbody>
</table>

---Conditional Probabilities---

Note: Numbers in parentheses are $p$-values.
Forecasting Cycle

August \( t=1 \)  
September \( t=2 \)  
October \( t=3 \)  
November \( t=4 \)  
January (final) \( t=5=T \)

Revision Cycle

Figure 1. Corn and soybean production forecasting cycle and corresponding revision cycle for a marketing year

Note: Forecast revisions are generated using the following model: 
\[ v_j = a v_{(j-1)} + b \epsilon_j, \text{ where } \epsilon_j \sim \text{N}(0,2) \]  
and the first revision is set to equal two. Efficient forecast revisions assume \( a=0, b=1 \); inefficient forecast revisions assume \( a=0.6, b=0.4 \). Thus, the inefficient revisions are based 60% on the previous revision and allow news to seep in at a rate of 40% per period.

Figure 2. Hypothetical example of efficient versus inefficient forecast revisions