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Olga Isengildina, Scott H. Irwin, and Darrel L. Good

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Olga Isengildina,

Scott H. Irwin,

and

Darrel L. Good[1]

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*Olga Isengildina is a Post-Doctorate Research Associate; Scott H. Irwin is the Laurence J. Norton Professor of Agricultural Marketing and Darrel L. Good is a Professor in the Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign. The funding support of the Economic Research Service of the U.S. Department of Agriculture under Cooperative Agreement No. 43-3AEK-8-80106 is gratefully acknowledged. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the view of the U.S. Department of Agriculture. Comments from Gary Schnitkey are gratefully acknowledged.

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Practitioner's Abstract

This study investigates the nature of the revision process of USDA corn and soybean production forecasts over the 1970/71 through 2002/03 marketing years. Nordhaus' framework for testing the efficiency of fixed-event forecasts is used. In this framework, efficiency is based on independence of forecast revisions. Both parametric and non-parametric tests reject independence of consecutive forecast revisions. Positive correlation and consistency of directional changes in forecast revisions suggest that these forecasts are "smoothed." Estimates of the impact of smoothing on forecast accuracy show that correction for smoothing may result in economically meaningful improvements in accuracy.

Key Words: Corn, efficiency, fixed-event forecasts, independence, revisions, smoothing, soybeans

Introduction

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. 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 private and public estimates are compared. Given 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 have examined the accuracy of USDA crop production forecasts (e.g., Gunnelson, Dobson and Pamperin; Egelkraut, et al.) and their market impact (e.g. Sumner and Mueller; McNew and Espinosa). However, an important aspect of these forecasts has been overlooked in the previous literature. Earlier studies have not investigated the nature of the revision process for USDA crop production forecasts.[1] This process is important because it reveals how production forecasts change across the forecasting cycle. The National Agricultural Statistical Service (NASS) of the USDA releases several forecasts of annual crop production for a given marketing year. For example, the first forecast of corn and soybean production is typically published in August preceding the marketing year.[2] These forecasts are changed monthly through November of the forecast marketing year. "Final" estimates of corn and soybean production are usually released in January of the marketing year. Thus, a series of production forecast revisions for corn and soybeans are released each marketing year.[3]

Analysis of the USDA forecast revision process is an important practical issue because market participants and analysts commonly argue that revisions to USDA crop production forecasts are "smoothed" or "conservative." That is, monthly forecasts of the same event (e.g., the sequence of forecasts for 2001/02 soybean production) change too slowly compared to the available information. For example, AgResource, a prominent market advisory service, made this statement following release of 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." (June 26, 2000). Similar concerns were expressed by Agrivisor-Zwicker, another market advisory service, with respect to the September 1999 corn production forecast: "While some private guesses are coming in as much as 400 million bushels less than the USDA's 9.561 billion bushel August estimate, few expect USDA to come off their August number by more than 200 million bushels" (September 2, 1999). Examination of the revision process for USDA crop production forecasts will provide evidence about the validity of these arguments.

The purpose of this study is to determine the efficiency of the revision process for USDA corn and soybean production forecasts over the 1970/71 through 2002/03 marketing years. These forecasts are of particular interest because corn and soybeans account for about 80 percent of total U.S. grain production. This study uses a framework for testing efficiency of the revision process developed by Nordhaus and previously applied to macroeconomic forecasts (Clements, 1995, 1997; Harvey, Leybourne and Newbold). Based on Nordhaus' framework, the analysis includes parametric and non-parametric tests of forecast efficiency. The parametric tests examine the correlation between consecutive revisions; the non-parametric tests review the consistency in directional changes in forecasts. The analysis is conducted for both the short and long horizon. The results provide the first formal evidence of the efficiency of the revision process for USDA corn and soybean crop production forecasts.

Since the optimality of resource allocation depends upon the accuracy of forecasts at the time decisions are made (e.g., Stein), the relationship between forecast revision efficiency and forecast accuracy also is analyzed. This analysis is needed to understand the economic significance of deviations from forecast efficiency. This knowledge will contribute to the ongoing debate regarding the characteristics and value of USDA situation and outlook information.

Conceptual Framework

The Nordhaus' framework is based on the theory of rational forecasts and is designed to test the efficiency of fixed-events forecasts. A series of forecasts (q_T) of the same terminal event, such as annual crop production where T indicates a production year (e.g., 2000/01), is a fixed-event forecast series. The forecast of the terminal event at time t is denoted as $q_{T/t}$ and the forecasting cycle has a length of T-1. In this context, T is defined as the last observation in the forecast series. For example, assume four monthly forecasts of production are made for a given crop. The time index for the first forecast is t = 1, the second t = 2, etc., and the actual harvest production is $t = T = 5$. Hence, $q_{T/T}$, the last "forecast" in the series, is actual production and identical to q_T. The forecast error at time t is defined as $e_{T/t} = q_T - q_{T/t}$ where $t = 1, \ldots, T$. The forecast revision at time t is denoted as $v_{T/t} = q_{T/t} - q_{T/t-1}$ where $t = 2, \ldots, T$ and the revision cycle has a length of $j = T$-2. Thus, forecasts of the terminal event are revised T-2 times, such as once a month.

According to Nordhaus, weak form efficiency of fixed-event forecasts may be described by two conditions. First, the forecast *error* at time t is independent of all forecast revisions up to time t:

(1) $$\mathrm{E}\left[e_{T/t} \middle| v_{T/t}, \ldots, v_{T/2}\right] = 0 \qquad t = 2, \ldots, T\text{-}1$$

Second, the forecast *revision* at time t is independent of all revisions up to time t-1:

(2) $$\mathrm{E}\left[v_{T/t} \middle| v_{T/t-1}, \ldots, v_{T/2}\right] = 0 \qquad t = 3, \ldots, T$$

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

(3) $$e_{T/t} = q_T - q_{T/t} = v_{T/t+1} + \ldots + v_{T/T}$$

conditions (1) and (2) imply each other. Typically, fixed-event forecast efficiency is tested in terms of revisions. According to equation (2), if forecasts are efficient, their 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 1 provides a hypothetical example of efficient versus inefficient forecast revisions. Efficient forecast revisions appear jagged because they incorporate all new information as soon as it becomes available. Inefficient forecast revisions appear smooth and consistent because new information is incorporated into forecasts slowly.

Weak form efficiency in forecast revisions generally is examined empirically by estimating a regression of the following form:

(4) $$v_{T/t} = \alpha v_{T/t-1} + \zeta_{T/t} \qquad t = 3, \ldots, T$$

where α is the regression slope coefficient, $\zeta_{T/t}$ 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. The null hypothesis here is α=0, which, if not rejected, implies that forecast revisions are efficient. However, Nordhaus's condition for weak form efficiency includes not only the most recent, but *all* revisions up to time t-1. Therefore, another efficiency test is based on the cumulative revision from date t forward as a function of total forecast revisions up to date t:

(5) $$\left(\sum_{\theta=t}^{T} v_{T/\theta}\right) = \beta\left[\sum_{\theta=2}^{t-1} v_{T/\theta}\right] + \zeta_{T/\theta} \qquad t = 3, \ldots, T.$$

The hypothesis tested in equation (5) is similar to that in equation (4), namely, if β=0, forecast revisions are efficient. The difference is that equation (5) tests for higher order correlation in forecast revisions.

Nordhaus's conditions for weak-form efficiency (equations 1 and 2) may also be used to demonstrate a relationship between forecast errors and forecast revisions. This relationship is of interest because it can be used to determine the impact of inefficiency in forecast revisions on forecast errors (or the accuracy of forecasts). The second condition for weak-form forecast efficiency (equation 2) may be restated for the forecast revision at time t + 1:

(6) $$\mathrm{E}\left[v_{T/t+1}\left|v_{T/t},...,v_{T/2}\right.\right]=0 \qquad t = 2,..., T\text{-}1.$$

Note, that in this notation equations (1) and (6) are conditional on the same information set ($v_{T/t},...,v_{T/2}$). Therefore, the difference between equation (1) and equation (6) may be expressed as:

(7) $$\mathrm{E}\left[e_{T/t}-v_{T/t+1}\left|v_{T/t},...,v_{T/2}\right.\right]=0 \qquad t = 2,..., T\text{-}1.$$

This equation implies that, on average, the difference between the forecast error made at time t and the forecast revision between times t and $t + 1$ should be zero. In other words, if forecasts are efficient, the forecast error at time t should be fully corrected (in the expectations sense) by the following revision. This condition may be tested empirically by estimating the following regression:

(8) $$e_{T/t}=\gamma v_{T/t+1}+\varepsilon_{T/t} \qquad t = 2,..., T\text{-}1.$$

The null hypothesis in this case is $\gamma=1$, which would indicate forecast efficiency. If $\gamma\neq1$, this information may be used to determine the impact of forecast revision inefficiency on forecast errors.

Data

The USDA forecasts of corn and soybean production are examined for 1970/71 through 2002/03 marketing years. These forecasts are typically released by the USDA from August through November and finalized in January.[4] Sometimes forecasts are revised after the January "final" estimate. This happens most frequently for soybeans in October following the marketing year. However, due to the sporadic nature of these subsequent revisions they are not included in the analysis. Thus, for the purposes of this study, forecasts are released five times and four revisions are available in each marketing year for each crop. Note that the first forecast is published in August and the fifth "forecast" is the January final estimate. In order to standardize for increasing crop sizes over time, revisions are examined in percentage form:

(9) $$v_{T/t}=100*\ln\left(q_{T/t}/q_{T/t-1}\right) \qquad t=2,..., 5$$

where the revision cycle has a length of $j=T\text{-}2=3$ months for both crops.[5]

Revisions are tested for the presence of bias by examining the null hypothesis:

(10) $$H_0\text{: } \mu_t=0$$

where μ_t is the mean of forecast revisions made in month t during the study period. This hypothesis was tested using a standard t-test:

(11) $$t_t=\frac{\overline{v}_t}{\hat{\sigma}_t/\sqrt{n}}$$

where $\overline{v}_t$ is the mean forecast revision for month t, $\hat{\sigma}_t$ is the standard deviation of the forecast revisions in month t and n is the number of observations included in the test.

Table 1 presents descriptive statistics on monthly revisions for USDA forecasts of corn and soybean production. The data suggests that during the study period the first (September) revision of both corn and soybean production was typically the largest. This first revision tended to be downward, meaning that the September estimate was lower than the August forecast. Both corn and soybean forecasts were revised by as much as about 18 percent down in September. However, according to the *t*-test, there was no statistically significant downward bias in this month's revision. Revisions for other months tended to be upward, with the exception of January for soybeans. In general, there is similarity in the magnitude and range of corn and soybean production forecast revisions during the period of study.

One may expect forecast revisions to become smaller as more information becomes available during the forecasting cycle. This pattern is detected in standard deviations of forecast revisions, which change from 3.86 to 1.52 percent in corn and from 3.96 to 1.84 percent in soybeans. The pattern is not always consistent in soybeans, however, as the standard deviation of November revisions is slightly lower than that of January revisions (1.72 vs 1.84 percent).

The null hypothesis of no bias in USDA production forecast revisions was not rejected on both the monthly level and for the pooled data set, with only two exceptions: January corn production revisions and November soybean production revisions. In both cases, revisions had a positive bias with a mean of about 0.6 percent and the lowest standard deviation compared to the other months. Bias (or lack of it) in forecast revisions also implies bias in forecasts themselves, as revisions are easily traced back to the forecasts (Nordhaus). However, the general lack of bias in USDA crop production forecasts revealed here should not be confused with efficiency. Unbiased forecasts may be systematically adjusted up and/or down during the forecasting cycle with errors canceling out for the entire series of forecasts. Efficiency tests allow detection of any patterns in forecast revisions.

Empirical Tests

This study combines several tests to determine the efficiency of the revision process of USDA forecasts of corn and soybean production. The first two tests investigate whether forecast revisions for the current period were independent of previous forecast revisions, which corresponds to Nordhaus' condition for weak form efficiency. The third test was applied to determine the relationship between forecast revisions and forecast errors. This relationship was in turn used to analyze the impact of inefficiency on forecast accuracy.

Correlation Efficiency Tests.

First, following Nordhaus, the correlation of USDA forecast revisions of corn and soybean production was estimated via OLS regressions described by equation (4). This analysis concentrates on the short-horizon correlation as only two consecutive revisions are analyzed. Nordhaus' approach was adapted to an agricultural setting by analyzing correlation between two adjacent revisions across marketing years (all marketing years, fixing t and t-1) rather than consecutive revisions within the same marketing year (all t and t-1, same marketing year) as is customarily done in the macroeconomic literature. Thus, all October revisions (t=3) made from 1970/71 to 2002/03 were regressed against previous September revisions (t=2) in the respective years, rather than reviewing all pairs of revisions for, say, 2002/03 crop production. Because two adjacent revisions of the same event are analyzed, the ability to detect systematic adjustments is preserved. However, emphasis is placed 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 allows comparing forecast revisions made at the same point in time from year-to-year, which should be based on similar information. This approach is also consistent with the way market participants apparently perceive efficiency of agricultural forecast revisions. An additional benefit of this approach is the improved power of statistical tests due to the fact that combining revisions across years allows for substantially more degrees of freedom than combining across revisions for the same year.

The short-horizon correlation structure of WASDE forecast revisions was also examined using a pooled data set in order to improve the power of statistical tests. This approach has been proposed by Clements (1997), who argued that the power of efficiency tests may be improved by estimating equation (4) using $(T\text{-}2)\times n$ observations and ordinary least squares (OLS), rather than running separate regressions for each of the n terminal events. Thus, a regression model that includes pairs of consecutive revisions of production forecasts pooled across different years should be statistically more powerful than a similar model for each particular year. One of the disadvantages of using OLS for the pooled model is that it assumes the covariance matrix of the error term is diagonal, which may be a poor assumption since revisions to forecasts at different target dates may be heteroscedastic (Clements, 1997). Revisions were tested for the presence of heteroscedasticity across time (from 1970/71 through 2002/03) and within events (from September to January). The values of the Goldfield-Quandt statistics were 0.86 (p=0.30) for corn and 0.84 (p=0.19) for soybeans for time-related tests and 1.88 (p=0.02) for corn and 2.43 (p=0.00) for soybeans for event-distance tests. These test values suggest the presence of event-distance but not time-related heteroscedasticity in both corn and soybean production forecast revisions. In order to take into account the event-distance heteroscedasticity detected in the sample, Harvey's model of multiplicative heteroscedasticity was applied (Harvey, p.99). This model yielded coefficient estimates very similar to the ones obtained from the OLS model estimation: 0.39 (p=0.000) for corn and 0.19 (p=0.009) for soybeans assuming linear heteroscedasticity; and 0.40 (p=0.000) for corn and 0.22 (p=0.002) for soybeans assuming quadratic heteroscedasticity.

Results of the short-horizon correlation efficiency tests are reported in table 2. These tests demonstrate significant short-horizon correlation for corn forecast revisions in all months. Estimated correlation coefficients ranged from 0.25 to 0.79. These findings suggest that corn production forecasts were inefficient.[6] Because forecast revisions were analyzed in percentage form, obtained coefficients may be interpreted as point elasticities. Thus, a 0.79 coefficient for November versus October revisions means that a one percent positive revision of the corn production forecast in October is expected to be followed by 0.79 percent positive revision in November. Results of the pooled estimation confirm the findings of the monthly tests demonstrating the presence of short-horizon correlation. All estimated coefficients were positive, which indicates positive correlation in forecast revisions, consistent with Nordhaus' hypothesis of forecast "smoothing."

Short-horizon correlation tests of soybean production forecast revisions detected statistically significant correlation in forecast revisions in November and January, but not in October. Estimated coefficients ranged from 0.08 to 0.32, lower than was found in most cases for corn.

Thus, a 0.32 coefficient for November versus October revisions implies that a one percent positive revision in October would have been followed by only about three-tenths of a percent positive revision in November. Significant short-term correlation was also detected in the pooled regression. Similar to the results of corn efficiency tests, all coefficients were positive, again suggesting a tendency for forecast "smoothing."

Because the study period is rather long (33 years), the issue of structural changes that may have taken place during this time was examined. Some previous studies (Fortenbery and Sumner; Garcia et al.) found that the market impact of USDA forecasts changed after 1984, suggesting that there may have been structural changes in forecasting practices around this time. Therefore, the sample period was divided into two sub-periods: 1970/71-1984/85 and 1986/87-2002/03 marketing years. A standard Chow test was applied to examine if OLS regressions corresponding to equation (4) for the pooled data sets were equal in the first and second sub-periods. The value of the Chow test was 2.55 (p=0.09) for corn and 0.17 (p=0.84) for soybean production revisions. Thus, there was only marginal evidence of a structural shift in corn production forecast revisions and no evidence of structural changes in soybeans. The correlation between two consecutive revisions was higher in the later period in corn, changing from 0.30 during 1970/71-1984/85 to 0.58 during 1986/87-2002/03. This evidence suggests that the efficiency of corn production forecast revisions declined somewhat over the sample period.

Also of interest is the issue of longer-term correlation, where the focus is on persistence of revisions across several months. This was examined by analyzing the cumulative revision from date t forward as a function of total forecast revisions up to time t-1 (equation 5). Correlation was tested for the following combinations of revisions: the sum of October, November, and January vs. September; the sum of November and January vs. the sum of September and October; and January vs. the sum of September, October and November. As shown in table 3, the long-horizon correlation tests yielded statistically significant results for corn at the beginning and the middle of the forecasting cycle. September revisions had a strong impact on remaining revisions in the forecasting cycle. The coefficient estimate (β=0.41) suggests that if September forecast was revised up by 10 percent, the following three forecasts overall would be revised up by about four percent. In addition, the first half (September and October) was correlated (0.26) with the second half (November and January) of the revisions in the forecasting cycle. These results indicate that, for example, optimistic forecasts remained optimistic throughout most of the forecasting cycle. Only January revisions appeared independent from the sum of the previous revisions. Positive correlation coefficients again suggest a tendency for forecast smoothing. No significant long-horizon correlation was detected in soybean production forecast revisions during the study period.

Directional Efficiency Tests.

Nordhaus' approach was extended to include non-parametric tests. These tests are of interest because they relax distributional assumptions necessary for the parametric tests. Specifically, non-parametric tests examine whether revisions were likely to be made in the same direction. Patterns in directional changes of revisions also are of great practical interest to market participants. In order to perform this test, forecast revisions were categorized as positive or not and compiled into a 2x2 contingency table. The tables were constructed so that the rows contained data for revisions in period *t* and the columns for period *t*-1. Each contingency table was analyzed using a Pearson chi-squared test which calculates the following test statistic:

$$\sqrt{S} = \frac{\sqrt{P}(O_{11}O_{22} - O_{12}O_{21})}{\sqrt{p_1 p_2 \; C_1 C_2}} \tag{14}$$

where *O* refers to a number of observations in a particular period (first number of the subscript: 1=(*t*-1), 2=*t*) belonging to a particular category, positive or negative (second number of the subscript: 1=negative, 2=positive), *p* describes a number of observations for a particular period, *C* describes a number of observations for a particular category, and *P* describes a total number of observations. This statistic tests the null hypothesis that the number of revisions in pairs of periods is equal in different categories. The null distribution of *S* is given approximately by the chi-squared distribution with 1 degree of freedom (Conover, 1999). Consistent with correlation efficiency tests, these tests were conducted on a monthly and a pooled level for short-horizon analysis and for combinations of months (as described for correlation tests) for long-horizon analysis.

The results of the directional efficiency tests of corn and soybean production forecast revisions are presented in Tables 4 through 7. These results are presented in two formats: counts and conditional probabilities. Counts describe actual cases of forecast revisions being positive or negative and are used for the Pearson Chi-Square test. Conditional probabilities describe the likelihood of a revision to be made in a given direction based on the revision direction in the previous month. If revisions followed a random walk, the conditional probability of consecutive revisions made in the same direction would be 50 percent (like flipping a fair coin). Inefficient revisions, on the other hand, would have conditional probabilities significantly different from 50 percent. The following discussion will focus on conditional probabilities because they can be compared directly across categories and commodities.

Short-horizon conditional probabilities for corn production forecast revisions are reported in Table 4 and demonstrate a tendency for positive revisions to remain positive and for negative revisions to be closer to independence between two consecutive months. For example, panel A indicates that negative September revisions remained negative in October about half of the time. On the other hand, positive September revisions were followed by positive October revisions about 70 percent of the time. This pattern reveals that USDA forecasters were mainly conservative in revising forecasts upwards. The pooled conditional probabilities for corn were 0.79 for positive revisions remaining positive and 0.57 for negative revisions remaining negative. The results are consistent with monthly tests, which demonstrate the strongest likelihood for positive revisions to remain positive between October and November (100%). The tendency for revisions to be made in the same direction was also suggested by Pearson Chi-Square statistics which were significant for October-November and for the pooled data set.

Short-horizon conditional probabilities for soybean production forecast revisions are found in Table 5 and on a pooled basis show a tendency for positive revisions to remain positive and for negative revisions to remain negative about two-thirds of the time. This pattern is consistent with the concept of forecast "smoothing" discussed above. Monthly tests demonstrate the strongest likelihood for positive revisions to remain positive between October and November (82 percent) and for negative revisions to remain negative between November and January (92 percent). At the same time, 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-Square statistics which were significant in all cases except for September-October.

The long-horizon directional tests for corn reported in Table 6 suggest that only positive revisions were likely to remain positive. A positive revision in September remained positive overall for the rest of the forecasting cycle 79 percent of the time. If September and October revisions were overall positive, they remained positive 85 percent of the time. This relationship weakened somewhat toward the end of the forecasting cycle, as there were roughly only two out of three chances for positive revisions to remain positive between the cumulative September through November revision and January revision. Negative corn production forecast revisions did not demonstrate such persistent long-horizon patterns. The long-horizon consistency for corn production revisions to remain in the same direction was confirmed by Pearson Chi-Square test only in the middle of the forecasting cycle.

The long-horizon directional tests for soybeans shown in Table 7 yielded mixed results. September revisions were independent from cumulative revisions for the rest of the forecasting cycle. There was roughly a two out of three chance for positive cumulative revisions to remain positive and for negative cumulative revisions to remain negative in the middle of the forecasting cycle. This tendency intensifies in negative revisions toward the end of the forecasting cycle, but disappears in positive revisions, which become close to independent. These findings are consistent with Pearson Chi-Square statistics which were not significant in the beginning and became significant toward the middle and the end of the forecasting cycle.

Overall, the results of correlation and directional tests consistently reveal the presence of smoothing in most corn and soybean forecast revisions. Smoothing is stronger in corn forecast revisions with correlation coefficients about twice as high as the ones in soybeans. Smoothing is prevalent in the short horizon in both commodities, evidence of long-horizon smoothing is detected only in corn.

Impact on Forecast Accuracy.

This section examines the impact of smoothing detected in revisions of USDA corn and soybean production forecasts on forecast accuracy. This analysis is needed to understand the economic significance of forecast smoothing. According to Stein, the optimality of resource allocation depends upon the accuracy of forecasts at the time decisions are made. Therefore, any changes in forecast accuracy due to forecast smoothing would reflect the economic implications of deviations from efficiency. As discussed in the conceptual framework, Nordhaus' conditions for weak-form efficiency may be used to determine the relationship between forecast errors and forecast revisions. To be consistent with forecast revisions measurement, forecast errors were also measured in percentage form:

(15) $$e_{T/t} = 100 \times \ln\left(q_T \big/ q_{T/t} \right) \qquad t=1,\ldots, T\text{-}1$$

The relationship between forecast errors and forecast revisions was examined empirically by estimating equation (8) using an OLS regression.

The results of the regression analysis are presented in the first three columns of table 8. This analysis examines whether the forecast error made at time *t* was fully "corrected" by the following revision, or H_0: $\gamma = 1$. The results confirm the previous findings of this study by rejecting forecast efficiency for all cases except September soybeans. The values of $\hat{\gamma}$ that were statistically different from one ranged from 1.32 to 1.92 for corn and from 1.26 to 1.36 for soybeans. Thus, corn forecast revisions should have been 1.32 to 1.92 times larger to be efficient. For example, a 10 percent October corn revision should have been 19.2 percent if all information available since the previous revision was incorporated as implied by forecast efficiency.

These regression coefficient estimates ($\hat{\gamma}$) can also be used to "adjust" actual forecasts for smoothing. If $\hat{\gamma} \neq 1$, the actual revisions should be multiplied by $\hat{\gamma}$ to impose efficiency. A re-estimation of equation (8) using revisions adjusted in this manner would necessarily yield $\hat{\gamma}=1$. These adjusted revisions may be further applied to calculate adjusted forecasts and adjusted forecast errors. Adjusted forecasts are calculated by adding adjusted revisions to the previous forecasts. Adjusted forecast errors are calculated according to equation (15) but using adjusted forecasts for $q_{T/t}$. 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.

To help illustrate the adjustment procedure, the exact computations for September 1995 corn production forecast revisions are presented here. The September 1995 corn production forecast published by USDA was lower than the August 1995 forecast by 3.64 %, thus the October revision was equal to -3.64 %. To impose efficiency, this revision should be multiplied by 1.41, the relevant $\hat{\gamma}$ obtained from estimation of equation 8. The resulting adjusted revision is therefore -5.11 %. If this efficient revision had taken place the September forecast value would have been $exp\left(\frac{\text{September adjusted revision}}{100}\right) * \text{August forecast} = exp\left(\frac{-5.11}{100}\right) * 8{,}122 = 7{,}717$ million bushels, where *exp* is the anti-log. The error for this adjusted forecast is 100*ln(January final/September adjusted forecast) = 100*ln(7,374/7,717) = -4.55 %. The actual published September forecast was 7,832 million bushels and the actual forecast error was -6.03 %.

The adjusted forecast errors represent errors associated with an efficient revision process and may be compared to actual forecast errors in order to determine the impact of forecast inefficiency on forecast accuracy. Root mean squared percentage error (RMSPE) was applied in this study to perform the comparison. Note that RMSPE is approximately equal to the standard deviation of percentage forecast errors, so long as bias is negligible, as is the case here. Therefore, the difference in actual and adjusted RMSPE indicates the difference in error variances due to forecast inefficiency. Because the procedure for generating adjusted forecast errors assumes perfect knowledge of the degree of inefficiency (available in ex-post analysis), the difference between the RMSPE of actual and adjusted forecasts indicates the maximum possible reduction in error variance due to correction of revisions for inefficiency.

Comparison of accuracy of actual versus adjusted forecasts is presented in the last three columns of table 8. Correction for smoothing may reduce forecast error variation by an average of 0.38 percentage points in corn and 0.08 percentage points in soybeans. Relative to the magnitude of the errors, these results imply a potential drop in error variation by an average of 13 % for corn and 3 % for soybeans. Reduction in forecast error variation could be as large as 22 % in October revisions of corn production forecasts. Differences in RMSPE ranged from 0.17 to 0.73 percentage points in corn and from 0.03 to 0.16 percentage points in soybeans, reflecting potential improvement consistent with the degree of smoothing detected by the previous tests. In absolute terms, these results imply a potential reduction in forecast error variation by about 17 to 73 million bushels for a 10 billion bushel corn crop or about 1 to 4.5 million bushels for a 2.8 billion bushel soybean crop due to correction for forecast smoothing. Thus, the potential improvement in forecast accuracy appears substantial for corn production forecasts and modest for soybean production forecasts which again is consistent with the degree of smoothing detected in these forecast revisions.

The differences in accuracy between the USDA and private forecasts of corn and soybean production reported by Egelkraut et al. for the same months and a similar sample period (1971-2000) provide a useful frame of reference for evaluating the economic significance of the differences in accuracy found in table 8. Egelkraut et al. report that the difference in RMSPE between USDA and private forecasts averaged 0.66 percentage points for corn and 0.35 percentage points for soybeans. The potential improvement in USDA forecast accuracy due to correction for smoothing found in this study represents more than half of the difference in accuracy between USDA and private forecasts for corn and about a quarter for soybeans. Overall, this analysis suggests that correction for smoothing may result in economically meaningful improvements in forecast accuracy.

Summary and Conclusions

Previous studies of USDA crop production forecasts overlooked one 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." Numerous arguments have been made about the presence of smoothing in USDA crop production forecasts. This study is a first formal analysis of this issue. Deviations from efficiency, such as smoothing, result in greater errors relative to efficient forecasts. Since the optimality of resource allocation depends upon the accuracy of forecasts at the time decisions are made (e.g. Stein), the impact of smoothing on forecast accuracy illustrates the economic significance of deviations from efficiency.

The efficiency of the revision process for USDA corn and soybean production forecasts over the 1970/71 through 2002/03 marketing years was examined in this study. Analysis was based on a Nordhaus' framework and included parametric and non-parametric tests of forecast efficiency. Both tests were applied to pairs of forecast months across years, as well as to pairs of forecast months pooled across all forecast months.

Short-horizon tests examined forecast efficiency between two consecutive months. Correlation tests rejected a null hypothesis of forecast efficiency in all cases except for October revisions of soybean production forecasts. Positive correlation between consecutive revisions ranged from 0.25 to 0.79 percent for corn and from 0.08 to 0.32 percent for soybeans. The positive correlation in forecast revisions indicates forecast smoothing. Directional tests revealed a tendency for positive revisions to remain positive and for negative revisions to be closer to independence for corn production forecasts. This pattern suggests that USDA forecasters were conservative in revising corn production forecasts upwards. In soybeans, positive revisions were likely to remain positive and negative revisions were likely to remain negative about two-thirds of the time. This pattern is also consistent with forecast smoothing suggested by correlation tests.

The long-horizon tests examined forecast efficiency between cumulative revision from date *t* forward and a sum of forecast revisions up to date *t*. Correlation tests revealed significant long-horizon inefficiency in corn production forecast revisions in the beginning and the middle of forecasting cycle. No evidence of statistically significant long-horizon correlation was found in soybeans. This analysis revealed that except for the first half of the forecasting cycle in corn, smoothing was not carried over more then one month.

The impact of forecast smoothing on accuracy was examined by comparing root mean squared errors (RMSPE) of actual forecasts and forecasts corrected for smoothing. This analysis revealed that to fully adjust the forecast, as implied by forecast efficiency, revisions had to be as much as 1.92 times greater than that actually observed. Correction for smoothing could result in about a 13 % drop in forecast error variation for corn and 3 % drop for soybeans. Reduction in forecast error variation could be as large as 22 % in October revisions of corn production forecasts. Because this analysis assumed perfect knowledge of the degree of smoothing (available ex-post), the results represent an upper bound of improvement in forecast accuracy due to correction for inefficiency. Improvement in forecast accuracy was potentially larger in corn than in soybeans, consistent with the degree of smoothing demonstrated by correlation tests. This analysis suggested that correction for smoothing may result in economically meaningful improvements in forecast accuracy.

The analysis in this study was based on standard assumptions of rational forecast theory (e.g., minimization of squared errors, Gaussian errors), and therefore did not take into account the presence of measurement errors in the information collected for the forecasts. The issue of measurement error correction in forecasting has been explored by Bradford and Kelejian, among others. These researchers suggested that in the presence of measurement error, previous forecasts should be included along with new information in forming the current optimal (minimum mean squared error) forecast. Gardner argued that the USDA follows a measurement error correction procedure similar to the one proposed by Bradford and Kelejian. Clearly, forecasts adjusted for the presence of measurement error by using previous information would result in revisions that are not independent. Thus, correction for measurement errors is a possible explanation for the observed smoothing of corn and soybean crop production forecasts.

Another deviation from rational forecast assumptions presents itself when the utility function of forecast providers includes arguments other than minimization of squared errors. Nordhaus argued that bureaucratic organizations may intentionally smooth forecasts because efficient forecasts would be too unstable. Stability as a desirable feature of economic forecasts has been discussed by several researchers in the forecasting literature. Nordhaus and Durlauf and Clements (1997) argued that stable forecasts protect the credibility of forecasters. Batchelor and Dua argued that forecasters may have incentives to adjust their published figures so as to trade-off expected accuracy against continuity (stability). It is also possible that USDA forecasters are concerned about the market reaction to their forecasts, and given strategic and political considerations, are averse to making large adjustments in production forecasts.

In reality, some combination of the above mentioned deviations from rational forecast assumptions probably explains most of the observed smoothing of USDA corn and soybean production forecasts. An important and related issue is how these forecasts are interpreted and used by the public. As the analysis in this paper demonstrates, misunderstanding of the nature of forecast revisions may cause suboptimal allocation of resources. However, if the public is aware of the smoothing process and accounts for it in forming expectations, economic losses may be negligible or non-existent. The quotes in the introduction to this paper suggest that market analysts are aware of smoothing in USDA crop production forecasts. An investigation of the degree to which market analysts use this knowledge in forming their own forecasts is an interesting area of future research.

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Table 1. Descriptive Statistics and Test of Bias for Revisions of USDA Corn and Soybean Production Forecasts, 1970/71 - 2002/03 Marketing Years

Crop	Descriptive Statistics					Test of Bias	
Revision Month	Mean	Standard Deviation	Minimum	Maximum	Range	*t*-statistic	*p*-value
Corn			-----percent-----				
September	-0.70	3.86	-17.64	4.44	22.08	-1.05	0.304
October	0.14	2.29	-5.71	3.66	9.36	0.35	0.729
November	0.48	2.25	-6.82	4.28	11.10	1.23	0.229
January	0.58	1.52	-2.48	5.21	7.69	2.19	0.036
Soybeans							
September	-0.52	3.96	-18.29	5.17	23.46	-0.76	0.456
October	0.04	2.69	-4.19	6.24	11.17	0.08	0.937
November	0.59	1.72	-3.61	4.35	7.96	1.97	0.057
January	-0.18	1.84	-5.64	3.70	9.34	-0.58	0.569

Note: 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.

Table 2. Short Horizon Correlation Tests for USDA Corn and Soybean Production Forecast Revisions, 1970/71-2002/03 Marketing Years

Crop	Revisions Dependent Variable	Revisions Independent Variable	Estimated Coefficient	*t* -statistic	*p* -value
Corn					
	October	September	0.25	2.78	0.009
	November	October	0.79	7.31	0.000
	January	November	0.32	2.49	0.018
	Pooled_t	Pooled_{t-1}	0.37	6.24	0.000
Soybeans					
	October	September	0.08	0.67	0.505
	November	October	0.32	3.19	0.003
	January	November	0.26	1.80	0.082
	Pooled_t	Pooled_{t-1}	0.17	2.34	0.022

Notes: All tests are based on percentage revisions and use OLS regressions. Pooled tests include all pairs of consecutive revisions (t vs t- 1) pooled across years. The number of observations for monthly tests is 33, and the number of observations for pooled tests is 99.

Table 3. Long Horizon Correlation Tests for USDA Corn and Soybean Production Forecast Revisions, 1970/71-2002/03 Marketing Years

Crop	Revisions Dependent Variable	Revisions Independent Variable	Estimated Coefficient	*t*-statistic	*p*-value
Corn					
	Oct + Nov + Jan	September	0.41	1.85	0.073
	Nov + Jan	Sep + Oct	0.26	2.51	0.017
	January	Sep + Oct + Nov	0.04	0.94	0.353
Soybeans					
	Oct + Nov + Jan	September	-0.12	-0.59	0.558
	Nov + Jan	Sep + Oct	-0.02	-0.22	0.828
	January	Sep + Oct + Nov	-0.04	-0.65	0.519

Notes: All tests are based on percentage revisions and use OLS regressions. The number of observations is 33.

Table 4. Short Horizon Directional Tests for USDA Corn Production Forecast Revisions, 1970/71-2002/03 Marketing Years

Counts | **Conditional Probabilities**

Panel A: October (*t*) vs September (*t-1*)

		Revision (*t*-1)					Revision (*t*-1)	
		-	+	Total			-	+
Rev (*t*)	-	10	4	14	Rev (*t*)	-	0.53	0.29
	+	9	10	19		+	0.47	0.71
	Total	19	14	33		Total	1.00	1.00

Pearson Chi-Square: 1.91 (0.167)

Panel B: November (*t*) vs October (*t-1*)

		Revision (*t*-1)					Revision (*t*-1)	
		-	+	Total			-	+
Rev (*t*)	-	9	0	9	Rev (*t*)	-	0.64	0.00
	+	5	19	24		+	0.36	1.00
	Total	14	19	33		Total	1.00	1.00

Pearson Chi-Square: 16.80 (0.000)

Panel C: January (*t*) vs November (*t-1*)

		Revision (*t*-1)					Revision (*t*-1)	
		-	+	Total			-	+
Rev (*t*)	-	5	8	13	Rev (*t*)	-	0.56	0.33
	+	4	16	20		+	0.44	0.67
	Total	9	24	33		Total	1.00	1.00

Pearson Chi-Square: 1.35 (0.245)

Panel D: Pooled

		Revision (*t*-1)					Revision (*t*-1)	
		-	+	Total			-	+
Rev (*t*)	-	24	12	36	Rev (*t*)	-	0.57	0.21
	+	18	45	63		+	0.43	0.79
	Total	42	57	99		Total	1.00	1.00

Pearson Chi-Square: 13.61 (0.000)

Notes: Numbers in parentheses are *p*-values.

Table 5. Short Horizon Directional Tests for USDA Soybean Production Forecast Revisions, 1970/71-2002/03 Marketing Years

Panel A: October (*t*) vs September (*t-1*)

Counts		Revision (*t*-1) -	Revision (*t*-1) +	Total	Conditional Probabilities		Revision (*t*-1) -	Revision (*t*-1) +
Rev (*t*)	-	8	8	16	Rev (*t*)	-	0.53	0.44
	+	7	10	17		+	0.47	0.56
	Total	15	18	33		Total	1.00	1.00

Pearson Chi-Square: 0.26 (0.611)

Panel B: November (*t*) vs October (*t-1*)

Counts		Revision (*t*-1) -	Revision (*t*-1) +	Total	Conditional Probabilities		Revision (*t*-1) -	Revision (*t*-1) +
Rev (*t*)	-	9	3	12	Rev (*t*)	-	0.56	0.18
	+	7	14	21		+	0.44	0.82
	Total	16	17	33		Total	1.00	1.00

Pearson Chi-Square: 5.31 (0.021)

Panel C: January (*t*) vs November (*t-1*)

Counts		Revision (*t*-1) -	Revision (*t*-1) +	Total	Conditional Probabilities		Revision (*t*-1) -	Revision (*t*-1) +
Rev (*t*)	-	11	8	19	Rev (*t*)	-	0.92	0.38
	+	1	13	14		+	0.08	0.62
	Total	12	21	33		Total	1.00	1.00

Pearson Chi-Square: 8.97 (0.003)

Panel D: Pooled

Counts		Revision (*t*-1) -	Revision (*t*-1) +	Total	Conditional Probabilities		Revision (*t*-1) -	Revision (*t*-1) +
Rev (*t*)	-	28	19	47	Rev (*t*)	-	0.65	0.34
	+	15	37	52		+	0.35	0.66
	Total	43	56	99		Total	1.00	1.00

Pearson Chi-Square: 9.49 (0.002)

Notes: Numbers in parentheses are *p*-values.

Table 6. Long Horizon Directional Tests for USDA Corn Production Forecast Revisions, 1970/71-2002/03 Marketing Years

Counts | **Conditional Probabilities**

Panel A: October + November + January (*t*) vs September (*t*-1)

		Revision (*t*-1) -	Revision (*t*-1) +	Total			Revision (*t*-1) -	Revision (*t*-1) +
Rev (*t*)	-	7	3	10	Rev (*t*)	-	0.37	0.21
	+	12	11	23		+	0.63	0.79
	Total	19	14	33		Total	1.00	1.00

Pearson Chi-Square: 0.91 (0.341)

Panel B: November + January (*t*) vs September + October (*t*-1)

		Revision (*t*-1) -	Revision (*t*-1) +	Total			Revision (*t*-1) -	Revision (*t*-1) +
Rev (*t*)	-	8	3	11	Rev (*t*)	-	0.62	0.15
	+	5	17	22		+	0.38	0.85
	Total	13	20	33		Total	1.00	1.00

Pearson Chi-Square: 7.679 (0.006)

Panel C: January (*t*) vs September + October + November (*t*-1)

		Revision (*t*-1) -	Revision (*t*-1) +	Total			Revision (*t*-1) -	Revision (*t*-1) +
Rev (*t*)	-	6	7	13	Rev (*t*)	-	0.46	0.35
	+	7	13	20		+	0.54	0.65
	Total	13	20	33		Total	1.00	1.00

Pearson Chi-Square: 0.41 (0.522)

Notes: Numbers in parentheses are *p*-values.

Table 7. Long Horizon Directional Tests for USDA Soybean Production Forecast Revisions, 1970/71-2002/03 Marketing Years

Counts | **Conditional Probabilities**

Panel A: October + November + January (*t*)

vs September (*t*-1)

		Revision (*t*-1)			Revision (*t*-1)	
		-	+	Total	-	+
Rev (*t*)	-	7	9	16	0.47	0.50
	+	8	9	17	0.53	0.50
	Total	15	18	33	1.00	1.00

Pearson Chi-Square: 0.04 (0.849)

Panel B: November + January (*t*)

vs September + October (*t*-1)

		Revision (*t*-1)			Revision (*t*-1)	
		-	+	Total	-	+
Rev (*t*)	-	9	6	15	0.64	0.32
	+	5	13	18	0.36	0.68
	Total	14	19	33	1.00	1.00

Pearson Chi-Square: 3.48 (0.062)

Panel C: January (*t*)

vs September + October + November (*t*-1)

		Revision (*t*-1)			Revision (*t*-1)	
		-	+	Total	-	+
Rev (*t*)	-	10	9	19	0.77	0.45
	+	3	11	14	0.23	0.55
	Total	13	20	33	1.00	1.00

Pearson Chi-Square: 3.29 (0.070)

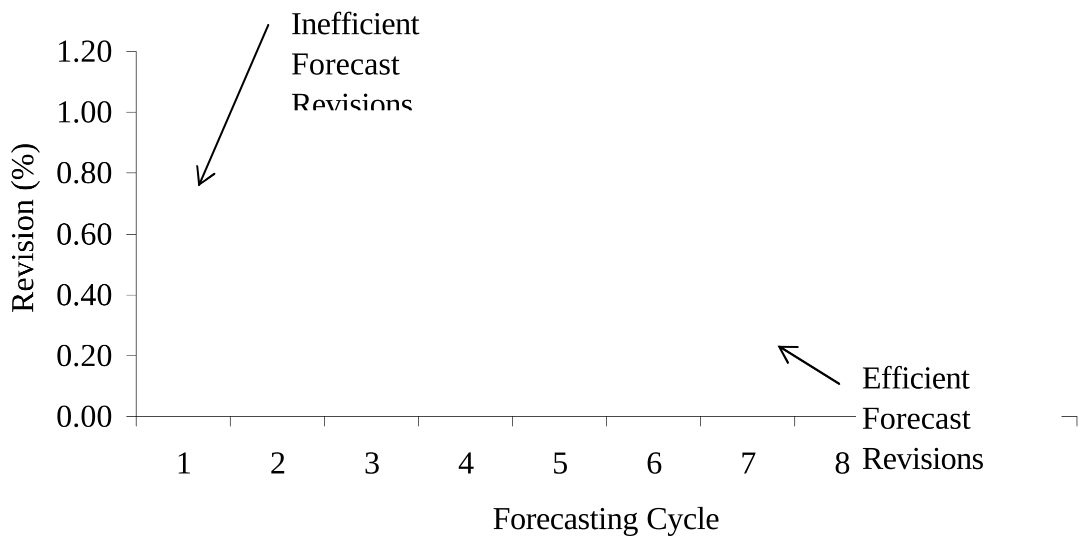
Notes: Numbers in parentheses are *p*-values.

Table 8. Analysis of the Economic Effect of USDA Corn and Soybean Production Forecast Revisions Smoothing, 1970/71 - 2002/03 Marketing Years

		Revision and Forecast Error Regression			Forecast Accuracy Comparison		
Crop	Month	Estimated Coefficient	*t* -statistic	*p* -value	Actual Forecast RMSPE	Adjusted Forecast RMSPE	Difference
Corn						-----%-----	
	September	1.41	-1.85	0.032	5.05	4.80	0.25
	October	1.92	-4.56	0.000	3.31	2.58	0.73
	November	1.32	-2.84	0.002	1.60	1.43	0.17
Soybeans							
	September	0.88	0.59	0.723	4.50	4.47	0.03
	October	1.36	-1.98	0.024	2.87	2.71	0.16
	November	1.26	-1.50	0.067	1.82	1.76	0.06

Notes: The revision and forecast error regression is $e_{T/t} = ?v_{T/t+1} + e_{T/t}$, where $e_{T/t}$ is the forecast error for month t and $v_{T/t+1}$ is the forecast revision for month $t+1$. The t-statistic tests the null hypothesis of ?=1. Number of observaions for each regression is 33. RMSPE stands for root mean squared percentage error.

Figure 1. Hypothetical Example of Efficient versus Inefficient Forecast Revisions



Note: Forecast revisions are generated using the following model: $v_j = av_{(j-1)} + be_j$, where e_j~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 inefficent revisions are based 60% on the previous revision and allow news to seep in at a rate of 40% per period.

Footnotes

[1] One previous study (Mills and Schroeder) addressed this issue for USDA livestock inventory revisions and found evidence of positive correlation in revisions.

[2] Prior to 1989/90 the first forecast of annual corn and soybean production generally was released in July. However, because July forecasts were discontinued in 1989/90, they were not included in the analysis.

[3] The term "revision" does not imply that NASS produces a forecast for a given month by simply altering the previous forecast. Instead, NASS attempts to make the best possible interpretation of production potential each month based upon available information. In other words, NASS makes a "new" forecast each month. It therefore could be argued that the term "change in forecast" is a more accurate description of NASS procedures. This paper employs the term "revision" as it is consistent with usage in the forecasting literature (e.g., Nordhaus).

[4] Prior to 1986/87, "final "estimates were released in February.

[5] Absolute revisions (q_t - q_{t-1}) were also included in the original analysis and yielded similar results. These results are available from the authors upon request.

[6] It may be argued that smoothing in production forecasts is caused by the weather assumptions used by the USDA. Specifically, the USDA uses a "normal weather" assumption for the remainder of the growing season to condition all forecasts of corn and soybean crop production (NASS/SMB). This conditioning implies that the direction, and possibly the magnitude, of USDA revisions may be predicted based on weather conditions in the month after a USDA forecast is released. For example, the September revision may be predicted based on August weather, as shown below:

August Forecast	August Weather	Expected September Revision
10 billion bushels	"Bad"	Down
10 billion bushels	"Normal"	None
10 billion bushels	"Good"	Up

In the same manner, October revisions may be predicted based on September weather and so on. However, the ability to predict revisions based on the previous month's weather does not necessarily mean that revisions from one month to the next can be predicted. 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 weather conditioning used by the USDA was the cause of forecast smoothing observed in this study.