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Smoothing in USDA's Commodity Forecasts

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Abstract

This study investigates the rationality of monthly revisions in annual forecasts of supply, demand, and price for U.S. corn, cotton, soybeans, and wheat, published in the *World Agricultural Supply and Demand Estimates* over 1984/85 through 2011/12. The findings indicate that USDA's forecast revisions are not independent across months, and that forecasts are typically smoothed. Adjustment for smoothing in a subset of forecasts (2002/03 – 2011/12) showed weak results: marginal improvements in accuracy were limited to wheat production and cotton production and domestic use while deterioration in accuracy was observed in all other cases. Smoothing coefficients were highly unstable over time. Case studies for corn focused on correction for a structural break and the impact of forecast size and direction, but did not lead to improvements in accuracy. Case studies for October revisions of soybean production forecasts suggest that ten year rolling estimation and correcting for outliers using leverage may help improve accuracy in the adjusted forecasts.

Keywords: rationality, efficiency, forecast revisions, fixed event forecasts, WASDE, smoothing, corn, soybean, wheat, cotton

1. Introduction

Recent years have seen the greatest volatility in world commodity markets in decades. Wheat, rice, corn, and cotton prices have each spiked at least once since 2005, increasing risks for low-income consumers in developing countries, and livestock and clothing producers around the world. Financial market developments account for some of the volatility, as swings in global income have been nearly unprecedented. But with relatively low reserve stocks of commodities around the world, new information from many sources now drives markets with much greater speed than in the past. In this environment, concerns have surfaced about USDA's ability to reliably provide markets with information needed to find equilibrium quickly, minimizing the need for costly corrections along the food supply chain. In December 2011, the Wall Street Journal reported that over the last two years, USDA's monthly forecasts of farmer's production quantities have been, "off the mark to a greater degree than any other two consecutive years in the last 15 [years]."

Evaluation of USDA's forecasts in academic literature stretches back to the previous cycle of commodity price shocks of the 1970s. Gunnelson, Dobson and Pamperin (1972), in a publication just before prices entered a period of volatility, showed that USDA tended to underestimate crop size, underestimate changes, and revise their forecasts inefficiently. The General Accounting Office in 1988 found that errors in USDA's projections of corn forecasts were a key component of downward bias in forecasts of budgetary outlays. Bailey and Brorsen (1998) and Sanders and Manfredo (2002) found underestimation in forecasts of beef, pork, and broiler production. Sanders and Manfredo (2003) found overestimation of broiler price forecasts and serial correlation in a number of livestock price forecasts. Isengildina, Irwin, and Good (2006) examined corn and soybean production forecasts for revision efficiency and rejected efficiency for the period 1970-2004, with strong evidence that USDA under-adjusts its U.S. production forecast revisions. Isengildina, MacDonald, and Xie (2012) examined USDA's cotton forecasts for both the U.S. and China across a number of supply and demand variables, and found that the most pervasive rejection of efficiency across variables and countries occurred in tests of revision efficiency. In every such case, inefficiency took the form of under-adjustment or smoothing.

The framework for analysis of efficiency in forecast revisions was developed by Nordhaus (1987). In this context, systematic under-adjustments of the forecasts are termed "smoothing" and over-adjustments are called "jumpiness." 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 this forecast inefficiency can be used by USDA forecast providers to improve their forecasts. Therefore, the goal of this study was to:

- a) Evaluate the extent of smoothing in monthly revisions of annual forecasts of all supply, demand, and price categories for U.S. corn, cotton, soybeans, and wheat,

published in the *World Agricultural Supply and Demand Estimates (WASDE)* over 1985/86 through 2011/12.

- b) Explore potential sources of smoothing, such as the size and the direction of the forecast.
- c) Develop a forecast adjustment procedure that can be used to correct smoothing in these forecasts and evaluate its potential effectiveness within the last ten years of the study sample.

This study focuses on forecasts for all US corn, soybeans, wheat, and cotton categories published within the World Agricultural Supply and Demand Estimates (WASDE) reports over the 1984/85 through 2011/12 marketing years. These forecasts are of particular interest because corn, soybeans, and wheat account for over 90% of total U.S. grain and oilseed production. The U.S. is also the third largest producer and the largest exporter of cotton in the world. While revision efficiency in corn and soybean production forecasts and cotton forecasts has been examined before (Isengildina et al., 2006, 2012), adjustment for smoothing in these forecasts has not been explored.

2. Data

WASDE reports are typically released by the USDA between the 9th and the 12th of each month and contain forecasts of supply and demand for most major crops. WASDE forecasts follow a balance sheet approach, accounting for each component of supply and utilization (see Vogel and Bange, 1999 for a detailed description of the USDA crop forecast generation process). The supply side of the balance sheet consists of beginning stocks, production, and imports. Utilization includes domestic use (or consumption), exports, and ending stocks. The ending stocks for year t become beginning stocks for year $t + 1$. The balance sheet approach requires that 'total supply must equal domestic use plus exports and ending stocks. Prices tie both sides of the balance sheet together by rationing available supplies between competing uses' (Vogel and Bange, 1999, p. 10). Unlike all other estimates, price forecasts are published in interval form. To be consistent with analysis of forecasts for all other categories, midpoints of the published price intervals are considered.

Several agencies within USDA are involved in preparing forecasts: National Agricultural Statistics Service (NASS) collects data on U.S. crop production and stocks; Farm Service Agency (FSA) describes the current policy environment and farmers' reactions to current policies; Agricultural Marketing Service (AMS) provides current price and marketing reports; Foreign Agriculture Service (FAS) provides information regarding foreign production, use, and trade; Economic Research Service (ERS) identifies important economic effects and implications for prices, quantities supplied and demanded; World Agricultural Outlook Board (WAOB), with separate leaders for each commodity, coordinates the interagency process used to produce WASDE estimates. This involvement of these agencies ensures that the best available data are used and the estimates are consistent across all USDA publications.

All estimates are forecasted on a marketing year basis (September through August for corn and soybeans, June through May for wheat, and August through July for cotton), thus forecasted values represent marketing year averages. Figure 1 demonstrates marketing years and forecast months for the four commodities studied. The first forecast for a marketing year is released in May preceding the U.S. marketing year. Production and beginning stocks forecasts are generally finalized by October (for wheat) and January (for corn, soybeans, and cotton) of the marketing year. All other estimates are typically finalized by the next September (for wheat) or November (for corn, soybeans, and cotton). Thus, there is a 9 (6) month forecasting cycle for production and beginning stocks forecasts, and a 19 (17) month cycle for all other categories for corn, soybeans, and cotton (wheat).

The different categories are realizations of quite different processes. For example, consumption is typically a variable more likely to embody trend behavior over time, while production forecasts can fluctuate strongly from year-to-year—and within a year—due to weather shocks. The forecasts also exhibit different patterns reflecting how USDA forecasters develop their information sets. Therefore, the efficiency differences in this study are to some extent a function of the differences in the physical processes, but also a function of USDA's organization and access to private information.

USDA's WASDE forecasts are considered fixed-event forecasts because the series of forecasts is related to the same terminal event (y_t^J), where J is the release month of the final estimate for marketing year t . The forecasted value published in month j of marketing year t is denoted as y_t^j , where $j = 1, \dots, J$, and $J = 19$ for corn, soybeans, and cotton, and $J = 17$ for wheat. Thus, each subsequent forecast is an update of the previous forecast describing the same terminal event. The terminal event for each category describes a marketing year total (for production, consumption, and stocks categories) or average (for price) values. Based on our definition of a 19 (17) month forecasting cycle, WASDE generates 18 (16) updates for each U.S. category forecasted except production and beginning stocks (eight updates for corn, soybeans, and cotton, and five updates for wheat) within each marketing year. The marketing years covered in this study are $t = 1(1984/85), \dots, T(2011/12)$, where $T=28$. This layout of fixed-event forecasts and corresponding revision process is illustrated for the USDA corn and soybean production forecasting cycle in Figure 2. In order to standardize for increasing crop size over time, forecast revisions and forecast errors are examined in log percentage form:

$$(1) \quad r_t^j = 100 * \ln \left(\frac{y_t^j}{y_t^{j-1}} \right) \quad j = 2, \dots, J; t = 1, \dots, 28$$

where r_t^j is a revision of a forecast for marketing year t released in month $j-1$, and

$$(2) \quad e_t^j = 100 * \ln \left(\frac{y_t^J}{y_t^j} \right) \quad j = 1, \dots, J - 1; t = 1, \dots, 28$$

where e_t^j is the error associated with forecast for marketing year t released in month j .

3. Methods

3.1 Test for Smoothing in Revisions

The theoretical framework for evaluation of revision efficiency developed by Nordhaus (1987) 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 t the forecast *error* at time j is independent of all forecast revisions up to time j :

$$(3) \quad E[e^j | r^j, \dots, r^2] = 0 \quad j = 2, \dots, J - 1.$$

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

$$(4) \quad E[r^j | r^{j-1}, \dots, r^2] = 0 \quad j = 3, \dots, J.$$

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

$$(5) \quad e^j = 100 * \ln\left(\frac{y^J}{y^j}\right) = r^{j+1} + \dots + r^J \quad j=2, \dots, J.$$

conditions (3) and (4) imply each other. Thus, analysis of independence in forecast revisions is sufficient to test for weak-form efficiency. According to equation (4), 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.

This property is considered here using the approach outlined in Isengildina, Irwin, and Good (2006):

$$(6) \quad r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j \quad j = 2, \dots, J; \quad t = 1, \dots, 28.$$

As an example, for $j = 3$, λ represents the slope coefficient of all July revisions made from 1984/85 to 2011/12 regressed against the June revisions ($j - 1 = 2$) for the same respective years. The null hypothesis for efficiency in forecast revisions is that $\lambda = 0$. If $\lambda > 0$, the forecasts are “smoothed” as they are partially based on the previous revision. If $\lambda < 0$, the forecasts are “jumpy” as they tend to partially offset the previous revision. Within this approach, revision inefficiency in one month (rejection of H_0 that $\lambda = 0$), signals a failure in the previous month to appropriately incorporate all new information.

The test of H_0 that $\lambda = 0$ requires at least 3 rolling-event forecasts to generate a revision and a lagged revision. This limits our ability to analyze the first few forecasts of any given marketing year, and month 3 is the first month analyzed. Test statistics for the data pooled across all marketing years and forecast months were estimated using panel least squares methods with White cross-section correction in standard error calculation. The White cross-section method treats the pooled regression as a multivariate regression (with an equation for each cross-section), and computes White-type robust standard errors for the system of equations. This estimator is robust to cross-equation correlation as well as different error variances in each cross-section (Wooldridge, 2002, p 148-153 and Arellano,

1987). Ordinary least squares regression analyses were used to test forecasts for each month.

3.2 Correction for smoothing

3.2.1 Basic Model

Adjustment for smoothing is based on the relationship described in equation 5, which implies that the forecast error at time j should be fully corrected (on average) by the following revision(s):

$$(7) \quad e_t^j = a + gr_t^{j+1} + e_t^j \quad j = 1, \dots, J - 1; \quad t = 1, \dots, 28.$$

If revisions are efficient, equations (3) and (4) imply that $\gamma=1$. This is an alternative measure of revision inefficiency that provides an adjustment parameter for a pending, as opposed to a past, revision. Complete correction of the forecast error is an attribute of the final revision, but this property holds for earlier revisions as well since all future revisions can be expressed as a function of previous revisions using equation (6). The second step in the adjustment procedure is to use the estimated γ coefficients to adjust the actual USDA forecasts for revision inefficiency. Specifically, actual revisions are multiplied by the estimated γ coefficients in equation (7) to derive a series of efficient revisions. Adjusted USDA forecasts are then calculated by adding the adjusted (efficient) revisions to the previous months' forecasts. This adjustment procedure insures the forecasts at the beginning and the end of the forecasting cycle are unchanged and only the intermediate path is adjusted to satisfy efficiency. All regression equations are estimated using ordinary least squares for each month.

To realistically reflect the information available to USDA forecasters, γ coefficients are computed in the estimation sub-sample, which starts with data from years 1984/85-2001/02 and is used recursively for out-of-sample correction of smoothing in the following years, with the evaluation sub-sample consisting of 2002/03-2011/12 forecasts. For instance, estimated γ coefficient from regression (7) using 1984-2001 May forecasts errors and June forecasts revisions can be used to adjust June 2002 forecasts. The adjusted revision can be calculated by multiplying published June revision by $\hat{\gamma}$. Because this study defines the forecast errors and revisions in natural logarithm terms, the June 2002 adjusted forecast is equal to the product of May forecast and the exponential function of the adjusted June revision. The change in forecast accuracy is evaluated by subtracting the root mean square percentage errors (RMSPE) of adjusted forecasts from those of published WASDE forecasts.

3.2.2 Stability of Smoothing Over Time

Stability of smoothing over time needs to be considered in this study because we are using the recursive approach to adjust forecasts and have a relatively long sample period (28 marketing years). Stability of smoothing coefficient can be reviewed by blocking the full data period 1984/85-2011/12 into consecutive 10 year sub-samples, such as 1984/85-1993/94, 1985/86-1994/95, etc. The estimated λ coefficients ($\hat{\lambda}$) from equation (6) can be

computed for each sub-sample. Plotting those \hat{f} 's provides a general view of existence of instability in smoothing over time. Furthermore, the structural change can be tested through formal tests. In recent studies (Hansen, 2001; Isengildina, Irwin, and Good, 2006), the Quandt Likelihood Ratio (QLR) test is used to consider breakpoints. The QLR test has been found to be superior to the traditional Chow test because the latter suffers from the arbitrary nature of the selected breakpoints. The QLR test statistic is the maximum of all the Chow F-statistics over a range of potential breakpoints, with a conventional search for such breakpoints within the inner 70% of the observations from the study period (excluding the first and last 15% observations in the sample period).

The QLR test will be applied to test the stability of smoothing using equation (6). If QLR test indicates the existence of a structural change in smoothing, the adjustment procedure described for the basic model will be applied only to the data occurring after the breakpoint. Consequently, the RMSPEs for the evaluation sub-sample from 2002/03 to 2011/12 can be calculated and the change in accuracy from the basic model can be evaluated by subtracting the RMSPEs of forecasts adjusted using breakpoint forward data from those adjusted using the basic model.

3.2.3 Forecast Size and Direction

Previous studies (e.g., Isengildina et al. 2012), suggest that forecast size and direction may be potential sources of smoothing. In order to correct for the influence of forecast size and direction on smoothing, out-of-sample linear trend forecasts are generated. A recursive approach was used by Isengildina et. al (2012). However, the 5-year rolling out-of-sample trend forecast approach is applied in this study because USDA commodity forecasts in the long term are volatile. Accordingly, the rolling trend forecast for 1989/90 is calculated using a linear trend for forecast from 1984/85-1988/89 and the rolling forecast for the remaining years is calculated consistently using the previous five years' observations.

The Trend Difference (TD) is defined as the log percentage difference between USDA forecast (y_t^j) and the out-of-sample trend forecast ($y_{trend,t}$):

$$(8) \quad TD_t^j = 100 * \ln \left(\frac{y_t^j}{y_{trend,t}} \right) \quad j = 1, \dots, J; \quad t = 6, \dots, 28.$$

TD captures both USDA forecast size and direction by comparing the actual forecast with a linear trend forecast. The sign of TD indicates direction with a positive TD showing that the actual forecast was higher than predicted value from the trend. The magnitude of TD indicates size as it communicates how much larger or smaller the actual forecast was from the trend value.

To take this additional information into account for adjustment for smoothing, equation (7) was modified as follows:

$$(9) \quad e_t^j = a + gr_t^{j+1} + bTD_t^j + e_t^j \quad j = 1, \dots, J - 1; \quad t=6, \dots, 28.$$

Following the adjustment procedure in section 3.2.1, the estimated γ coefficient in equation (9) was used to adjust revision and forecast. Finally, subtracting the RMSPEs of forecasts adjusted in this section from those adjusted using the basic model provides the assessment of changes in forecast accuracy in the evaluation sub-sample (2002/03-2011/12).

4. Results

4.1 Test for Smoothing in Revisions

Table 1 shows the summary of results for a pooled data set combining all forecast months (3 - 17 or 18 for most variables, 3 - 9 or 10 for beginning stocks, and 3 - 13 for production²) and all years (1984/85-2011/12). Production, price, exports, and ending stocks forecast revisions were inefficient and smoothed for each commodity. The results indicate that a 10% revision in month i is usually followed by a 2.6% revision in the same direction in month $i+1$ in cotton and soybean production forecasts. Smoothing is slightly larger in corn production forecasts (3.0%) and slightly smaller in wheat (1.95%). Domestic use forecasts are efficient for corn and wheat, and beginning stocks are forecast efficiently for corn and soybeans. Inefficiency takes the form of smoothing in every case, except the forecasts for feed and residual use of wheat. These forecasts exhibit jumpiness, or negative correlation across months of revisions. Thus, a 10% revision in wheat feed and residual use in month i tends to be partly offset with the 0.8% revision in the opposite direction the following month. The finding of smoothing in production forecasts is consistent with the results of Isengildina, Irwin, and Good (2006) and Isengildina-Massa, MacDonald, and Xie (2012). The preponderance of smoothing rather than jumpiness also mirrors other studies, such as Nordhaus (1987) and Coibon and Gorodnichenko (2012).

The inefficiencies shown for a summary estimate of USDA's performance over the entire forecasting cycle in Table 1 are the average inefficiencies across the forecasting cycle. Figures 3-6 show the values of inefficiency test coefficients on the monthly level that reject the null hypothesis of zero. Corn exports are smoothed mostly in the middle and later months of the forecasting cycle. Price smoothing for corn is largely in the middle of the cycle, but use estimate smoothing largely happens later. Cotton forecasts have smoothing for a number of variables in the middle of the cycle. For cotton production and ending stock estimates smoothing seems more frequent than it is for corn. USDA's wheat forecasts

² Note that USDA's forecast cycle start later with respect to the wheat marketing year than it does for the other commodities. Therefore, USDA's late-season estimates of the wheat variables are finalized a few months earlier than for other variables. In each case, months were included in the panel if the mean absolute percent error (MAPE) of the variable's forecast was > 0 for 1985-2010.

generally have less smoothing than those for other commodities. Soybean forecasts have more smoothing than the other commodities. Note that wheat's production cycle is distinct from that of the other commodities here, with two harvests in North America corresponding to spring- and winter-sown crops. Soybeans differ in having a much larger role for Southern Hemisphere production in the world market. This may account for the extensive late-season smoothing in USDA's soybean forecasts.

The "jumpiness" in the wheat feed and residual forecast revisions is confined to only one month, August, in the late-season revisions. Closer examination of USDA's pattern of revisions for its wheat feed and residual estimates explains how to reconcile the apparent inconsistency of one single inefficient month driving the panel result for the entire forecasting cycle. The feed and residual variable for wheat is only adjusted by USDA at distinct points in the forecasting cycle. Virtually no revisions are undertaken in months 7, 8, 10, 11, 13, and 14. Revisions are common in months 6, 9, 12, 15, and 16. NASS quarterly stocks estimates, and Census mill grind reports drive this pattern in the residual component of the forecast. It appears that the combination of infrequent adjustments, and the residual nature of the category resulted in a large role of a single month.

4.2 Correction for smoothing

4.2.1 Basic Model

Results of the forecast accuracy test for the recursively estimated basic model (equation 7) are presented in terms of changes in RMSPEs in Table 1-4. Positive values indicate that RMSPEs get smaller after adjusting for smoothing and show the existence of improvements by adjusting the forecasts using the basic model. Negative values indicate that the published USDA forecasts are actually more accurate than the adjusted forecasts. Corn and soybean results (Table 1 and 2, respectively) show that the RMSPEs for the adjusted forecasts are bigger than that of the original forecasts for many months across all supply and consumption categories. The average differences in RMSPEs further show that the basic model adjustment procedure leads to less accurate forecasts for corn and soybeans. While the findings of smoothing in corn and soybean production forecasts are similar to the findings of Isengildina, Irwin, and Good (2006), the adjustment simulation in this study resulted in a deterioration of production forecast accuracy, which differs from the conclusion in Isengildina, Irwin, and Good (2006) reflecting the different time periods used in the analysis (1970-2004 sample in the previous study).

Table 3 shows that the basic adjustment procedure results in deterioration of accuracy for most categories for U.S. wheat forecasts, except production (Table 3). Among the four crops considered in this study, cotton has the biggest accuracy improvement in both production and domestic use forecasts; with the mean RMSPE decreasing by 1.088 due to adjusting for smoothing with the basic model. However, the change in the mean RMSPE for price is -1.045, which indicates that adjustment increases the forecast error.

4.2.2 Stability of Smoothing Over Time

Because of the space considerations, sections 4.2.2 and 4.2.3 include results only for corn. Figure 7 gives an example of the stability of smoothing over time for corn production using the consecutive 10-year subsamples described in Section 3.2.2. For example, the bars in the plot for July represent the λ coefficients calculated by equation (6) for each block of observations. The coefficients vary depending on time periods used. The results of the QLR test for corn production are reported in Figure 8 as an example. The figure illustrates the detection of structural changes in November 1993. The QLR results for all other categories of corn indicate that 1995 was the breakpoint. Our next adjustment approach focused on post 1995 to calculate λ coefficients to adjust for smoothing. Table 5 shows the difference between the RMSPE of the forecasts adjusted using post 1995 data and the RMSPE using all of the data from the basic model. The negative values in all categories indicate that using post 1995 data for forecast adjustment does not improve the accuracy of corrected forecasts relative to the basic model.

4.2.3 Forecast Size and Direction

As mentioned in section 3.2.3, this study selected the 5-year rolling linear trend to measure relative size and direction of the forecasts. TD was constructed using equation (8), and the forecasts were adjusted by using the estimated γ coefficients from equation (9). The changes in RMSPEs for corn over the period 2002/03-2011/12 after accounting for forecast size and direction are provided in Table 6. More negative changes in RMSPEs exist than positive changes, and the mean RMSPE are negative for all categories in corn. These results indicate that compared with the basic model this approach does not improve the accuracy of adjusted forecasts.

4.2.4 Soybean production case study

The disappointing results of several adjustment approaches described above led to a more in depth investigation of smoothing in the case of October soybean production forecasts. USDA's October-November production forecasts were smoothed across all four commodities and soybean forecasts had a greater prevalence of smoothing than other commodities. Using a dataset with USDA's 1984-2011 September, October, and November estimates of that year's U.S. soybean production, revision efficiency test statistics were estimated using equation 6. Simulations were run through 2011, starting with the 1999 forecast, by adjusting the October forecast when data for the previous years showed inefficient past revisions. The baseline approach followed MacDonald and Isengildina (2012) and Isengildina, Irwin, and Good (2006)—recursive estimation with the full historical sample. The baseline simulation showed a slight deterioration in average accuracy, unlike both previous studies (Isengildina, Irwin, and Good, 2006; and MacDonald and Isengildina-Massa, 2012). Both of these earlier works, while recursive like the baseline simulation in this case study, differed in applying the alternative adjustment derived using equation 7, and in the sample period. Table 3's month 7 results correspond to those found

in this case study, and show an improvement of accuracy when equation 7 is applied over that particular time period (2002-12).

Additionally, we undertook two approaches to limit the estimation sample to a subset that is more relevant to a one-year out, out-of-sample forecast of smoothing. The first approach was to apply a rolling rather than recursive estimation approach, using a sample of constant size, dropping the oldest year as a new one became available. This limits the sample to the most recent data. The second approach was to limit the sample by excluding outlying forecasts: for both recursive and rolling estimates, a first stage involves estimating the test statistic with the full sample, and then a second stage involves re-estimating the statistic after excluding years that pass designated thresholds (described below) for having outsized influence on the test statistic. This limits the sample to more “typical” years.

Outlier identification was undertaken by measuring leverage, Cook’s distance D , and DF beta statistics (see Williams, 1987, for more discussion). Based on typical cut-off points applied in the literature, outliers were excluded when the test statistics exceeded $6/N$, $4/N$, and $2/\sqrt{N}$, respectively, where N is a sample size. Alternatives in the application of outlier exclusion included using a given test statistic to choose years for exclusion, and excluding years that failed any of the tests or pairs of them. Thus, a total of 16 alternatives were examined for simulating forecast adjustment to correct revision inefficiency in USDA’s forecasts of U.S. soybean production forecasts for the 1999-2011 crops.

We found very limited evidence that exclusion of selected data through outlier adjustment when recursively estimating forecast adjustments may improve accuracy (Figure 9). On the contrary, a rolling estimation approach excluding data points that exceeded the leverage threshold resulted in the most accurate of the 16 alternatives on average over 1999-2011. As Figure 10 indicates, out the 16 alternatives examined, the only improvement in accuracy (measured by reduced Mean Absolute Percent Error, MAPE) was the application of a rolling estimation while excluding observations exceeding the leverage threshold. Most outlier adjustment approaches reduced accuracy. Further research is needed to determine if leverage is a generalizable approach to improving accuracy or if the success here is an idiosyncratic characteristic of this particular dataset.

Examining the results across years revealed two things: instability in the degree of inefficiency over time, and varying distributions over time of increases and decreases in accuracy between alternative adjustment simulations. Figure 8 illustrates the instability in estimated efficiency statistics over time for corn, and the observed parameter variation of soybean production in October suggests similar results are likely. Table 8 illustrates how different forecast adjustment approaches not only differ with respect to the average change in accuracy they introduce, but also in the range of positive and negative changes. The average change in accuracy over the simulation period mentioned above conceals variation with a set of years, with adjustment reducing accuracy rather than increasing it in some years.

5. Conclusions

Numerous previous studies demonstrate inefficiencies in USDA commodity forecasts. An obvious implication of these findings is that correction of these inefficiencies would result in more accurate forecasts. This study focused on one of the most common forms of inefficiency, smoothing in forecast revisions, to explore potential improvements to forecast accuracy that may result from its correction. We found that production, price, export, and ending stock forecast revisions were inefficient and smoothed for each of the major field crops forecast in USDA's WASDE report.

The widespread evidence of smoothing suggests that forecast accuracy could be improved if this inefficiency is corrected. However, our simulations of correction for smoothing yielded mixed results with respect to accuracy. This finding highlights the challenges with correction for smoothing. The above regressions were estimated using a recursive estimation procedure and adding an additional year to the estimation subsample. This is a suitable procedure if smoothing is consistent over time, but we found widespread evidence of changes in smoothing over time, suggesting it would be appropriate to undertake a systemic search for parameter instability. However, our attempts to use only post-structural change data for forecast adjustment did not result in accuracy improvement relative to the basic approach. Neither did our attempts to account for several sources of smoothing, such as forecast size and direction.

Additional approaches that focus on weighted methods and rolling windows were considered in soybean production forecasts case study. This case study demonstrated that average accuracy of adjusted forecasts may be improved by limiting the data used to calculate an adjustment factor. It also highlighted that the simple average of accuracy improvement might not be a sufficient criterion to choose among adjustment strategies. A strategy that results in large decreases in accuracy in some years that are offset by larger improvements in other years might not be preferable to a strategy that avoids introducing larger errors.

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Table 1. Estimated λ for test of independence of forecast revisions for WASDE crop forecasts.^a

Variable	Corn	Cotton	Soybeans	Wheat
Beginning stocks	0.077	0.309 ***	0.091	0.171 **
(N)	162	324	162	162
Production	0.302 ***	0.257 ***	0.259 ***	0.195 ***
(N)	270	270	405	405
Feed & residual	0.014			-0.084 ***
(N)	432			432
Food, seed, & other.	0.105 **		0.024	0.075 **
(N)	432		432	405
Crush			0.362 ***	
(N)			432	
Domestic use	0.077	0.346 ***	0.335 ***	0.013
(N)	405	432	432	405
Exports	0.398 ***	0.329 ***	0.329 ***	0.258 ***
(N)	405	432	432	432
Ending stocks	0.168 ***	0.206 ***	0.263 ***	0.112 **
(N)	405	405	405	405
Price	0.1294 *	0.160 ***	0.228 ***	0.290 ***
(N)	405	432	405	378

Notes: r is forecast revision. Months 3 through 17 or 18 included for most variables. Forecast months included up to point where 1985-2010 MAPE = 0, which is earlier for production and earliest for beginning stocks. Regressions estimated using panel least squares with White heteroscedasticity correction. N is the number of observations. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%, respectively.

$$^a r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$$

Table 2. Changes in RMSPE for corn forecasts, 2002/03-2011/12 using all data

Month	Production	Feed and Residual	FSI	Exports	Domestic Use	Ending Stocks	Price
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	-0.049	0.013	0.015	-1.034	-0.057	-3.098	-0.314
3	0.001	-0.231	0.003	-1.215	-0.105	4.039	-0.179
4	-0.049	-0.233	-0.046	-0.756	-0.029	-1.218	-0.561
5	-0.115	0.343	0.198	-1.322	0.190	-3.868	-0.234
6	-0.843	0.192	0.261	0.826	-0.158	-0.882	0.067
7	0.058	0.221	0.000	1.590	0.099	-0.202	0.198
8	0.000	0.019	-1.042	-0.002	-0.084	-0.455	-0.206
9	-0.003	-0.117	-0.033	-0.986	-0.044	-1.683	-0.594
10	0.000	0.000	0.317	-0.222	0.005	-2.223	-0.176
11	0.000	0.000	0.000	-0.881	0.000	0.137	-0.105
12	0.000	0.031	0.136	0.302	-0.054	-0.445	0.188
13	0.000	0.143	-0.295	0.147	-0.053	-1.301	-0.098
14	0.000	0.070	0.012	0.414	0.029	0.143	-0.783
15	0.000	-0.161	0.048	0.384	-0.028	-3.215	-0.009
16	0.000	0.000	-0.018	-0.399	0.020	-0.405	-0.065
17	0.000	-0.362	0.055	0.001	-0.163	-0.325	-0.033
18	0.000	-0.042	-0.004	-0.032	-0.012	-0.095	0.000
Average	-0.056	-0.006	-0.022	-0.177	-0.025	-0.839	-0.161

Note: The values are computed by subtracting the RMSPEs of adjusted forecasts from those of published WASDE forecasts. Positive values are shaded in dark grey, indicating the improvements of forecast accuracy by adjusting the forecasts using the basic model. Negative values, shaded in light grey, illustrate the negative effect on forecast accuracy.

Table 3. Changes in RMSPE for soybean forecasts, 2002/03-2011/12 using all data

Month	Production	Crushing	Export	Seed and Residual	Domestic Use	Ending Stocks	Price
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	-0.099	-0.043	-0.674	-0.174	-0.108	-5.021	-0.292
3	-0.306	0.001	-2.115	-1.317	0.003	0.140	-0.368
4	0.267	-0.035	-3.883	1.317	-0.049	-0.900	-1.045
5	0.043	-0.300	-1.082	0.109	-0.196	1.626	-0.445
6	-0.143	0.026	0.133	-4.069	0.344	1.402	-0.490
7	0.043	-0.152	0.499	-0.289	-0.107	0.141	-0.092
8	0.000	-0.675	1.837	3.615	-2.516	-3.996	-2.652
9	-0.006	-0.545	-0.542	0.090	-0.298	-0.433	-0.401
10	0.000	-0.299	0.479	-3.105	-0.326	-2.691	0.295
11	0.000	0.067	1.073	-1.173	0.047	-1.408	0.832
12	0.000	-0.009	0.849	-0.178	0.225	3.165	-0.155
13	0.000	0.161	1.026	0.057	0.052	-1.722	0.007
14	0.000	0.063	0.437	0.000	0.009	-3.290	-0.109
15	0.000	0.256	0.358	-0.789	0.003	0.877	-0.046
16	0.000	0.077	0.109	-1.098	0.026	-1.093	-0.012
17	0.000	-0.024	-0.187	-2.028	-0.050	-1.136	-0.001
18	0.000	-0.032	-0.004	-0.882	-0.029	0.000	-0.167
Average	-0.011	-0.081	-0.094	-0.551	-0.165	-0.797	-0.286

Note: The values are computed by subtracting the RMSPEs of adjusted forecasts from those of published WASDE forecasts. Positive values are shaded in dark grey, indicating the improvements of forecast accuracy by adjusting the forecasts using the basic model. Negative values, shaded in light grey, illustrate the negative effect on forecast accuracy.

Table 4. Changes in RMSPE for wheat forecasts, 2002/03-2011/12 using all data

Month	Production	Food	Seed	Feed and Residual	Export	Domestic Use	Ending Stocks	Price
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.671	-0.047	0.011	0.226	-0.829	-0.040	-1.447	-2.076
3	0.022	0.000	-0.443	-0.492	-0.901	-0.130	-0.160	0.809
4	0.392	-0.110	0.000	-5.395	-2.432	-0.092	-1.227	0.576
5	0.000	-0.654	0.224	-1.356	-0.499	0.008	-0.397	-0.205
6	0.007	0.000	-0.088	-1.494	-0.394	-0.285	-1.392	-0.215
7	0.002	0.000	-0.061	0.000	0.133	0.002	-0.100	-0.198
8	0.000	0.023	0.000	0.000	-0.444	-0.194	-0.011	-0.043
9	0.000	0.012	-0.102	-0.767	-0.157	0.070	-2.117	-0.093
10	0.000	0.000	-0.014	1.660	-0.033	0.093	-0.443	-0.167
11	0.000	-0.076	0.000	0.000	0.043	-0.284	-1.108	-0.047
12	0.000	0.000	0.160	-1.186	-0.131	-0.143	0.444	0.037
13	0.000	-0.002	-1.715	0.000	-0.070	0.011	-0.146	0.032
14	0.000	0.012	0.000	0.000	-0.215	0.004	0.228	-0.055
15	0.000	0.000	0.021	2.738	-0.240	-0.010	0.001	-0.013
16	0.000	-0.003	0.000	-0.423	-0.002	-0.002	0.000	0.000
17	0.000	-0.038	0.000	0.017	0.000	-0.008	0.000	0.000
18	-0.001	-0.001	0.000	-0.012	0.000	-0.030	-0.001	0.000
Average	0.061	-0.049	-0.111	-0.360	-0.343	-0.057	-0.437	-0.092

Note: The values are computed by subtracting the RMSPEs of adjusted forecasts from those of published WASDE forecasts. Positive values are shaded in dark grey, indicating the improvements of forecast accuracy by adjusting the forecasts using the basic model. Negative values, shaded in light grey, illustrate the negative effect on forecast accuracy.

Table 5. Changes in RMSPE for cotton forecasts, 2002/03-2011/12 using all data

Month	Production	Domestic Use	Export	Ending Stocks	Price
1	1.115	1.216	-1.207	5.917	-0.200
2	0.112	1.966	-0.641	5.086	-0.481
3	0.669	1.415	-0.037	-1.769	-0.030
4	0.282	1.089	0.666	0.196	-2.009
5	0.818	1.742	-0.126	-3.703	-2.518
6	0.941	1.208	-6.122	-3.412	-1.630
7	0.623	1.566	-2.798	-6.977	-3.027
8	0.445	3.024	0.424	1.116	-4.787
9	0.219	1.151	0.605	4.483	-1.175
10	0.155	0.147	1.611	1.783	-1.370
11	0.155	0.677	1.942	-6.698	-0.437
12	0.092	0.426	1.304	-0.303	-0.872
13	-0.006	0.710	-0.183	-3.859	0.099
14	0.000	0.898	0.111	-3.459	0.109
15	0.000	0.607	1.071	0.726	0.247
16	0.000	0.913	0.121	-0.450	-0.234
17	0.000	0.890	-0.033	-0.107	0.045
18	0.000	-0.066	0.006	-0.012	-0.539
Average	0.312	1.088	-0.183	-0.636	-1.045

Note: The values are computed by subtracting the RMSPEs of adjusted forecasts from those of published WASDE forecasts. Positive values are shaded in dark grey, indicating the improvements of forecast accuracy by adjusting the forecasts using the basic model. Negative values, shaded in light grey, illustrate the negative effect on forecast accuracy.

Table 6. Changes in RMSPE for corn over 2002/03-2011/12 after adjustment using post 1995 data relative to full data

Month	Production	Feed and Residual	FSI	Exports	Domestic Use	Ending Stocks	Price
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	-0.063	-0.014	0.042	0.003	-0.030	-3.703	-0.028
3	-0.283	-0.253	-0.116	-0.634	-0.282	-4.520	-1.225
4	-1.489	-0.785	-0.128	0.009	-0.610	-15.554	-5.534
5	-0.018	-0.015	-0.009	0.340	-0.003	0.597	-0.303
6	0.989	-0.201	0.025	-0.309	0.136	-0.559	-0.385
7	-0.028	-0.217	-1.591	-0.736	0.040	-0.382	-0.048
8	0.000	0.009	0.711	-4.241	-0.356	-0.002	-0.938
9	0.002	-0.010	-0.031	-0.098	-0.019	1.275	0.213
10	0.000	-0.001	0.105	-0.072	-0.446	-0.898	0.166
11	0.000	0.000	0.000	0.381	0.000	-0.211	-0.429
12	0.000	-0.130	0.072	-0.079	-0.057	-0.277	0.048
13	0.000	-0.239	-0.178	-0.403	-7.007	-1.267	0.221
14	0.000	-0.033	0.003	-0.112	-0.006	-0.169	0.890
15	0.000	-0.243	-0.041	-0.217	-0.056	-1.242	-0.008
16	0.000	0.000	-0.018	0.030	-0.042	-0.192	-0.062
17	0.000	0.362	-0.001	0.020	-0.062	0.167	0.033
18	0.000	0.033	-0.014	-0.006	0.000	0.095	0.000
Average	-0.049	-0.096	-0.065	-0.340	-0.489	-1.491	-0.411

Note: The values are computed by subtracting the RMSPEs of forecasts adjusted using post 1995 data from those adjusted using full data. Positive values are shaded in dark grey, indicating positive changes in forecast accuracy from the basic model by following the estimated structural break. Negative values, shaded in light grey, illustrate the basic model adjustment produce more accurate forecasts.

Table 7. Changes in RMSPE for corn over 2002/03-2011/12 after accounting for forecast size and direction

Month	Production	Feed and Residual	FSI	Exports	Domestic Use	Ending Stocks	Price
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	-0.044	0.023	-0.240	0.157	-0.027	-1.099	-0.193
3	-0.531	-0.467	-0.138	-2.855	-0.235	-0.778	-1.002
4	-0.169	-0.090	0.061	-0.284	-0.077	-0.810	-0.247
5	0.107	-0.076	0.157	0.576	-0.089	-0.034	0.158
6	0.420	-0.387	-0.138	0.149	0.065	-0.076	0.035
7	0.002	0.107	0.039	0.390	0.063	-0.145	0.162
8	0.000	-0.003	-0.014	-3.710	0.021	-0.845	-0.006
9	0.002	0.061	0.024	-0.117	0.011	0.647	0.135
10	0.000	-0.001	0.135	-0.006	-0.137	-1.852	0.156
11	0.000	0.000	0.000	0.299	0.000	-0.112	-0.509
12	0.000	-0.088	0.048	-0.011	0.000	-0.093	-0.030
13	0.000	-1.004	-0.070	-0.769	-0.071	-0.861	0.077
14	0.000	0.000	-0.053	0.047	-0.004	0.030	0.984
15	0.000	-0.127	-0.013	0.205	-0.012	-0.975	0.005
16	0.000	0.000	-0.050	0.024	-0.027	0.045	0.015
17	0.000	-0.178	0.001	0.026	-0.032	0.519	-0.009
18	0.000	0.017	-0.011	-0.016	0.004	0.095	0.000
Average	-0.012	-0.123	-0.015	-0.327	-0.030	-0.352	-0.015

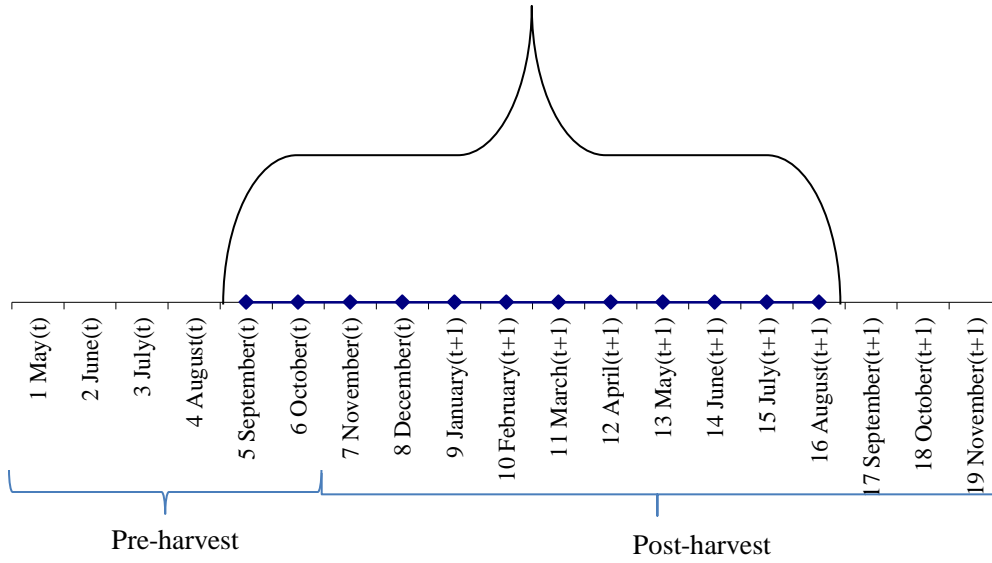
Note: The values are computed by subtracting the RMSPEs of forecasts adjusted by adding forecast size and direction into the basic model from those adjusted using the basic model. Positive values are shaded in dark grey, indicating positive changes in forecast accuracy from the basic model by including the additional information. Negative values, shaded in light grey, illustrate the basic model adjustment produce more accurate forecasts.

Table 8. Changes in MAPE for October soybean production over 1999/2000-2011/12 after adjustment for smoothing using equation (6) estimated with rolling 15-year samples with and without adjustment for high leverage, and with leverage-adjusted recursive samples starting in 1984/85.

Year	Rolling gain	Rolling loss	Adj-Rolling gain	Adj-Rolling loss	Adj-Recursive gain	Adj-Recursive loss
1999			1.21		1.22	
2000					0.92	
2001						
2002						
2003						-1.26
2004						-2.11
2005					1.34	
2006		-0.78		-0.95		-1.16
2007		-0.20		-0.24		-0.29
2009						
2010	0.40		0.49		0.80	
2011						
Average	0.15	-0.49	0.85	-0.60	0.73	-0.81

Note: The values are computed by subtracting the MAPEs of forecasts adjusted using alternative estimations of equation (6). Positive values are shaded in dark grey, indicating improvements in forecast accuracy from the basic model by adjusting for outliers. Negative values, shaded in light grey, illustrate the basic model adjustment produced more accurate forecasts. Years with no adjustment or with accuracy changes of less than 0.1 percent are left blank. Averages in final row include these minor changes.

US Marketing Year for Corn, Soybeans and Cotton



US Marketing Year for Wheat

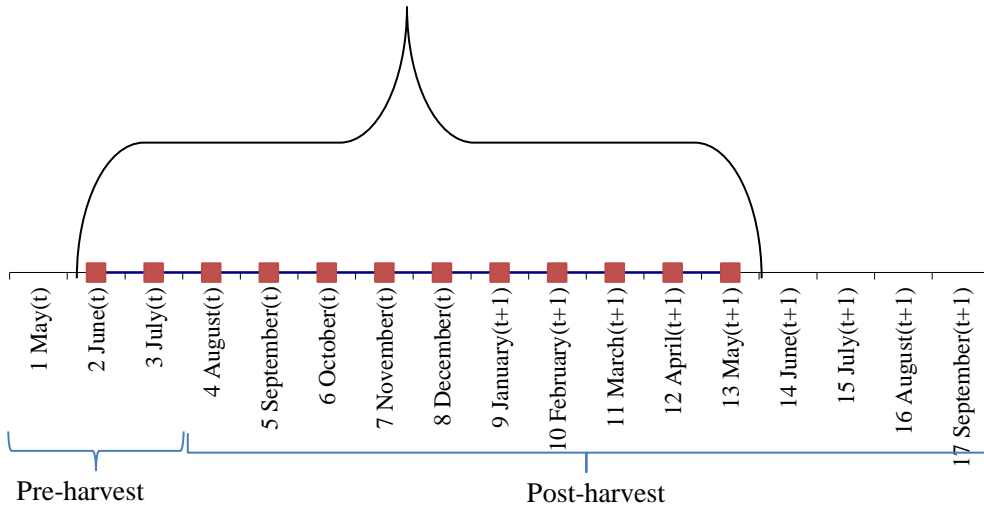


Figure 1. The WASDE forecasting cycle for corn, soybeans, cotton and wheat relative to the U.S. marketing year

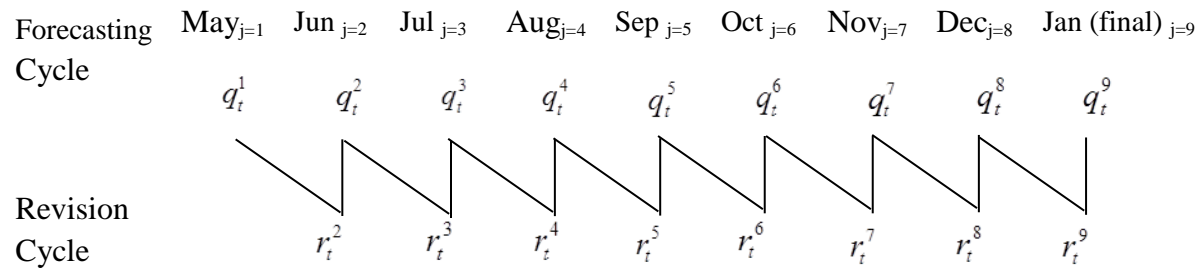
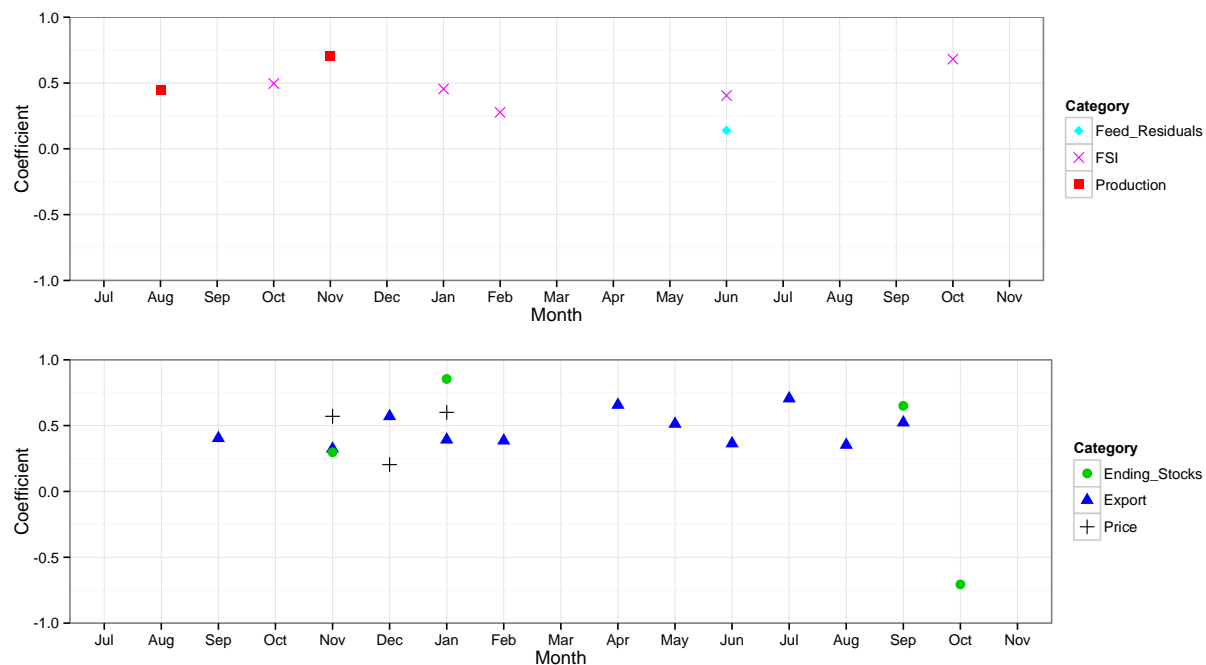
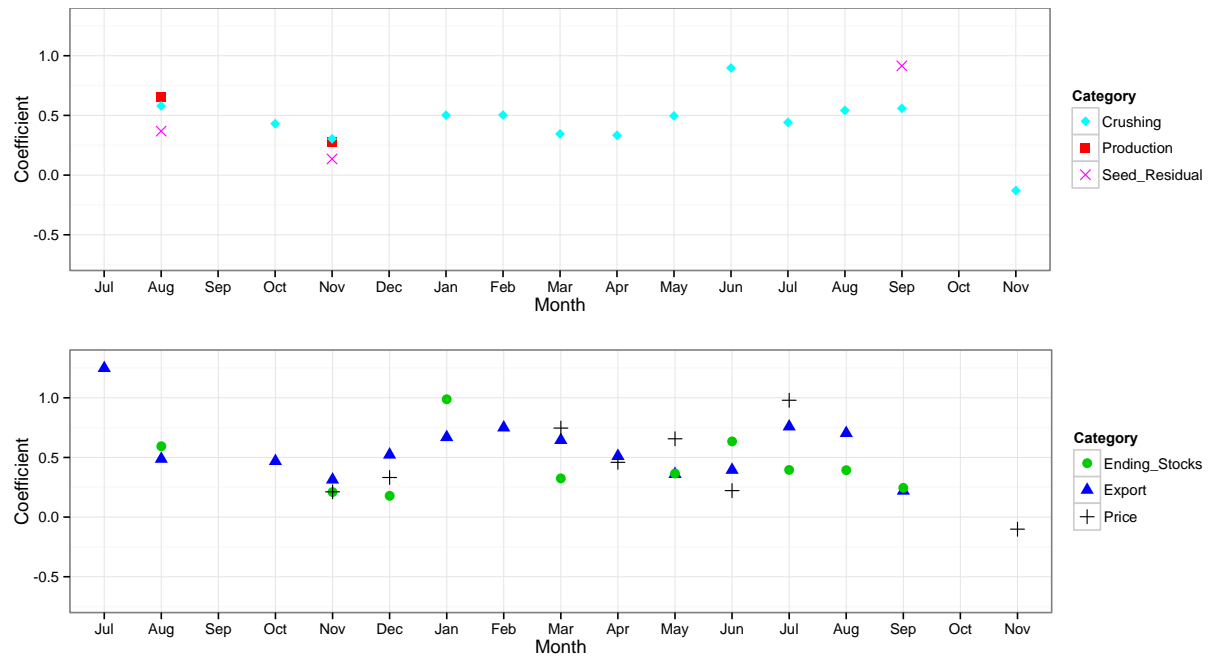


Figure 2. Corn and soybean production forecasting cycle and corresponding revision cycle for a marketing year



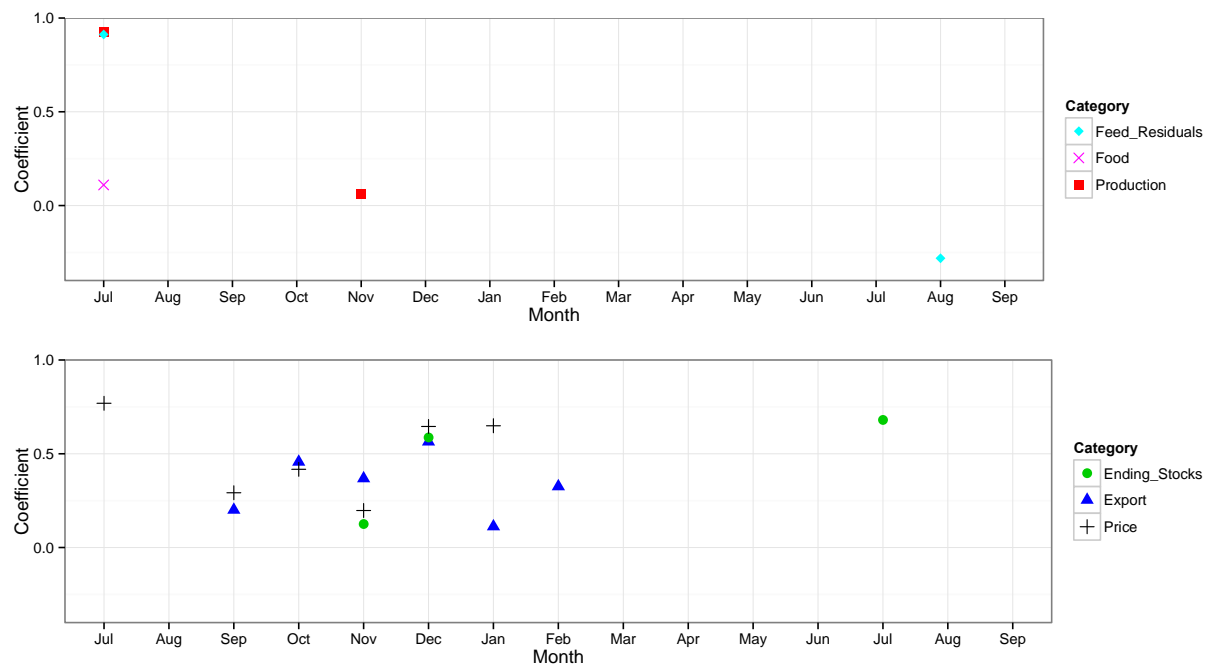
Notes: The efficiency test is conducted by $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$; only significant coefficients (at significance level of 0.1) are presented in the plot.

Figure 3. Revision efficiency test result for corn forecasts, 2002/03-2011/12



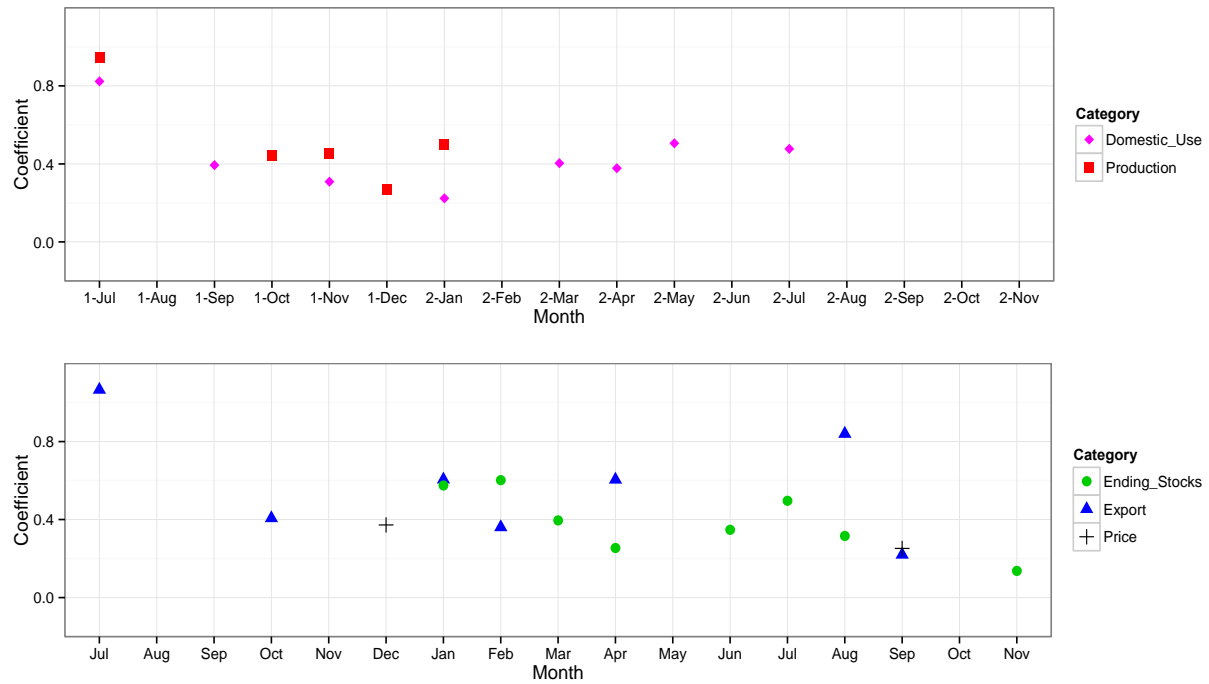
Notes: The efficiency test is conducted by $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$; only significant coefficients (at significance level of 0.1) are presented in the plot.

Figure 4. Revision efficiency test result for soybean forecasts, 2002/03-2011/12



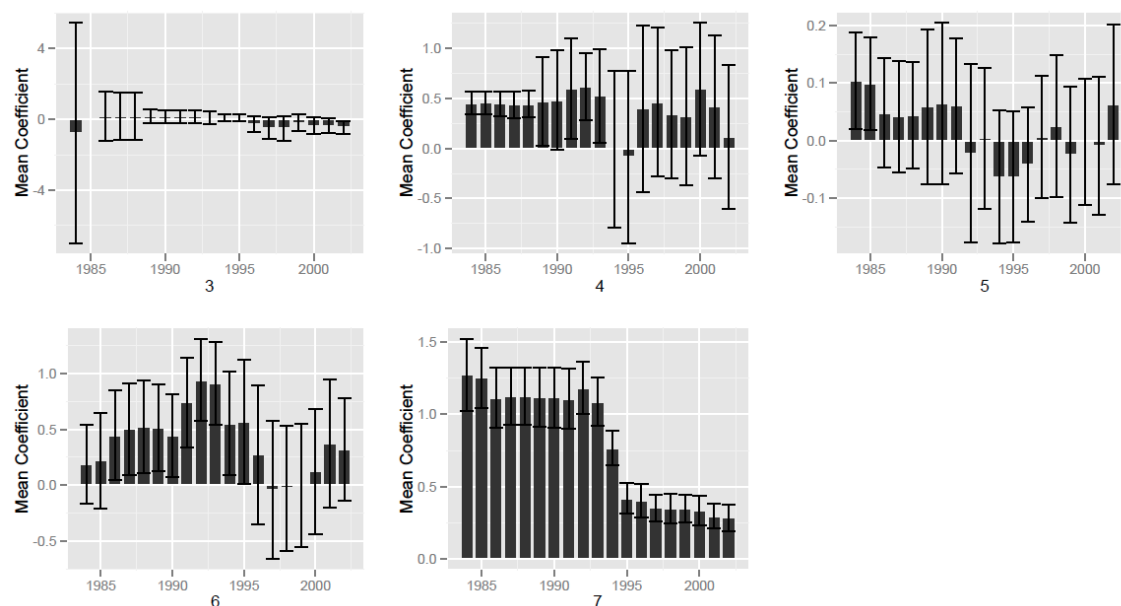
Notes: The efficiency test is conducted by $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$; only significant coefficients (at significance level of 0.1) are presented in the plot.

Figure 5. Revision efficiency test result for wheat forecasts, 2002/03-2011/12



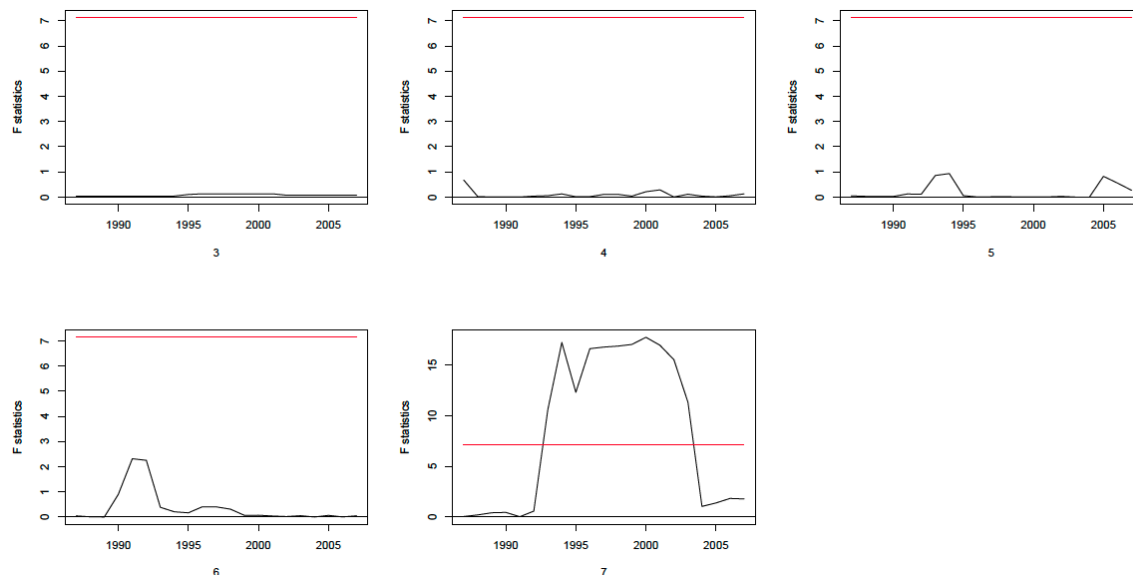
Notes: The efficiency test is conducted by $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$; only significant coefficients (at significance level of 0.1) are presented in the plot.

Figure 6. Revision efficiency Test Result for Cotton Forecasts, 2002/03-2011/12



Notes: The dependent variable is the λ coefficient calculated by $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$; the independent variable 3=July, 4=August, 5=September, 6=October, 7=November. The bar labeled 1985 means the 10 year sub-sample starting in 1985.

Figure 7. Stability of smoothing over time: corn production



Note: F statistic for a QLR test for equation $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$ with the independent variable 3=July, 4=August, 5=September, 6=October, 7=November; the upper horizontal line represents the critical value (7.12) for each month.

Figure 8: Structural change test (QLR) for corn production: 1984/85-2011/12

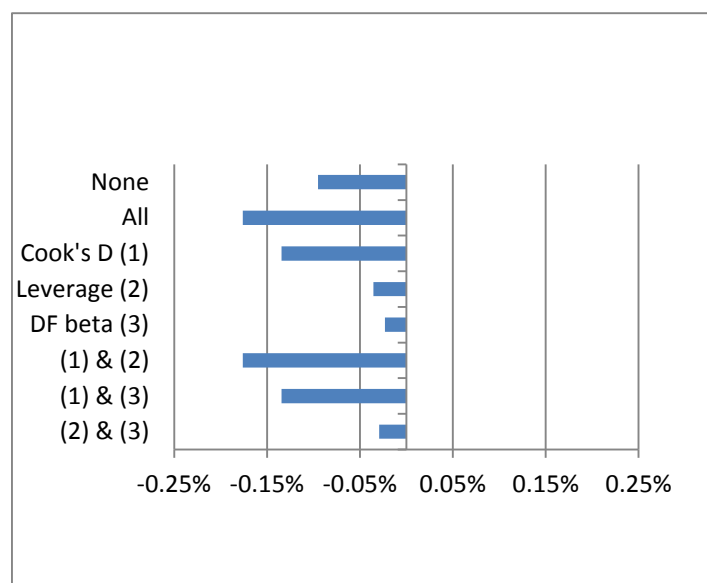


Figure 9: Changes in MAPE for soybean forecasts, 1999/2000-2011/12 using recursive estimation for equation 6 adjustment parameter calculation, with and without adjustment for outliers

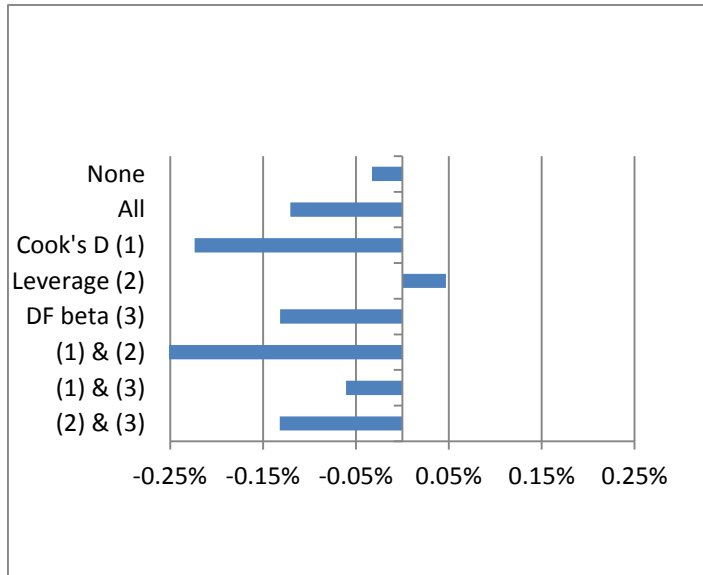


Figure 10: Changes in MAPE for soybean forecasts, 1999/2000-2011/12 using rolling estimation for equation 6 adjustment parameter calculation, with and without adjustment for outliers.