Are Revisions of USDA's Commodity Forecasts Efficient?

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1. Introduction

Recent years have seen increased volatility in international commodity markets. Most major crops' prices have spiked at least once since 2006, and the OECD-FAO, Food and Agricultural Policy Research Institute (FARRI) and the U.S. Department for Agriculture (USDA) drew a consistent conclusion that the prices will remain elevated in the next several years (European Commission: Agriculture and Rural Development, 2011). Financial market developments explain some of the volatility, as the global capital flows have been nearly unprecedented. Additionally, the increasing share of production grown in developing countries with higher yield variability results in unstable prices. Commodity markets' increased volatility makes the USDA forecasting job harder than ever.

World Agricultural Supply and Demand Estimates (WASDE), one of the most influential public sources of commodity forecasts, provides USDA's comprehensive estimates of supply and demand for major U.S. and global crops and U.S. livestock. Industry participants have relied on these forecasts in making production, marketing processing, and retailing decisions for many years. Numerous studies revealed the significant impact of the WASDE reports on commodity markets (e.g., Karali, 2012; Adjemian 2012; Isengildina, Irwin, and Good, 2008). With relatively low reserve stocks of commodities around the world, new information from various sources drives markets with much greater speed than in the past. Therefore, it is essential to assure its high standards of accuracy and efficiency for WASDE reports.

Several recent studies examined the accuracy and efficiency of WASDE forecast. Sanders and Manfredo (2002) found that the beef and pork production forecasts inefficiently incorporated available information. They showed the existence of positive serial correlation in errors of beef and poultry production forecasts. Sanders and Manfredo (2003) examined the WASDE price forecasts for cattle, hogs and broilers and found overestimation in broiler price forecasts and inefficiency in a number of livestock price forecasts due to repeated forecast errors. Isengildina, Irwin, and Good (2004) evaluated corn and soybean price forecasts using interval accuracy tests and rejected forecasts accuracy at the 95%

level for both commodities. Botto et al. (2006) analyzed forecasts accuracy of all categories for corn and soybean, and they found inefficiency in soybean ending stocks and price forecasts. More recently, Isengildina-Massa, MacDonald, and Xie (2012) incorporated a variety of tests to evaluate the forecast performance of WASDE cotton forecasts for the U.S. and China. They discovered that the most pervasive rejection of efficiency across variables and countries occurred in tests of revisions efficiency. Lewis and Manfredo (2012) concluded that the sugar production and consumption forecasts are less problematic as inefficiency was only found in a few cases. Although all these studies demonstrated the inefficiency of WASDE across different commodities, none of them provided guidance on how to improve forecasts accuracy.

Isengildina, Irwin, and Good (2006) focused on forecast revisions efficiency, which has been largely overlooked in the previous studies. The forecast revisions process is an important issue as it reveals how forecasts change across the forecasting cycle and analyzing forecast revisions allows the detection of inefficiency due to systematic under/over-adjustments in forecasts. They found the existence of revisions inefficiency in WASDE corn and soybean production forecasts and suggested a procedure based on Nordhaus's (1987) approach to successfully correct for inefficiency in revisions. However, their procedure was rather simplistic and the results were limited to corn and soybean production forecasts.

This study expands Isengildina, Irwin, and Good's work to develop a statistical procedure for correction of inefficiencies in revisions of WASDE forecasts for U.S. corn, soybeans, wheat, and cotton. The proposed procedure takes into account the issue of outliers, the impact of forecasts size and direction, and the stability of revision inefficiency and could improve forecasts accuracy.

2. Data

This study focuses on monthly WASDE U.S. corn, soybean, wheat, and cotton forecasts from 1984/85 through 2011/12. Vogel and Bange (1999) describe that forecasts of U.S. crop production are independently prepared by the National Agricultural Statistics Services, while supply, demand, and price forecasts are developed jointly by several USDA agencies: the Foreign Agricultural Marketing Service provides information about foreign production, use and trade; the Economic Research Service recognizes the most important economic effects and implications for prices and quantities supplied and demanded; the Farm Service Agency describes the current policy environment and farmers' reactions to current reports; the Agricultural Marketing Service provides current price and market reports for crops and livestock; and the World Agricultural Outlook Board operates the Joint Agricultural Weather Facility and coordinates the high-security interagency process by chairing an Interagency Commodity Estimates Committee (ICEC) of leaders responsible for each commodity. Joint preparation enables USDA analysts to incorporate all available resources and assures the estimates are consistent across all USDA publications.

WASDE supply and demand forecasts apply a full balance-sheet approach for each commodity, which means that the total supply must equal the demand. The total supply of a crop is comprised of beginning stocks, imports, and production. The demand side of the balance sheet includes domestic use, exports, and ending stocks. Domestic use has been further subdivided into feed and residual, and food, seed and industrial for corn; crushings, seed, and residuals for soybeans; and feed and residual, food, and seed for wheat. The ending stocks for a marketing year t become the beginning stocks for year $t+1$. While price forecasts are published in interval form, other categories' forecasts are point estimates. To overcome this inconsistency and keep the analysis consistent across all categories, midpoints of the price forecast intervals are considered in our analysis.[2]

All WASDE estimates are forecasted on a marketing year basis, which spans from September to August for corn and soybean, from June to May for wheat, and from August to July for cotton. The first forecasts for all crops of each marketing year are published in May preceding the marketing year.

[2] USDA was prohibited from publishing forecasts of cotton prices from 1929 to 2008, but USDA's Interagency Commodity Estimates Committee for cotton calculated unpublished price forecasts each month as point estimates. Since 2008, cotton price forecasts have been published in interval form. Also, for all four commodities, the price forecasts normally converge to point estimates by April of the marketing year.

Beginning stocks and production forecasts are normally finalized after the harvest time of each crop, by October for wheat and January for corn, soybean, and cotton[3]. Estimates for other forecast categories are generally finalized by November after the marketing year. Therefore, production and beginning stocks' forecasting cycles are 9 months for corn, soybean, and cotton, and 6 months for wheat. The forecasting cycles are 19 months for all crops' other categories. Figure 1 demonstrates marketing years and forecasting cycles for commodities included in this study.

WASDE forecasts are considered fixed-event forecasts because the series of forecasts are related to the same terminal event y_t^J, where J is the release month of the final estimate for a marketing year t, and $t=1(1984/85),\ldots,28(2011/12)$. While for production and beginning stocks forecasts, $J=9$ for corn, soybeans, and cotton and $J=6$ for wheat, $J=19$ for all crops' other categories. The terminal event for supply and demand categories describes a total volume, while it represents a marketing year's average value for price. The forecasted value published in month j is denoted as y_t^j, where $j=1,\ldots,J$. Therefore, each subsequent forecast is an update of the previous forecast describing the same terminal event. Based on the definition of forecast cycles, WASDE generates 18 updates/revisions for each U.S. category except for production and beginning stocks (8 updates for corn, soybean, and cotton, and 5 updates for wheat). Figure 2 illustrates the layout of the fixed event forecasting cycle and the corresponding forecast revisions process using an example of corn and soybean production.

3. Methods

3.1 The Basic Adjustment Procedure to Correct Revision Inefficiency

The basic adjustment procedure for correcting revision inefficiency is described in Isengildina, Irwin and Good (2006). Forecast revisions are defined as the difference between two adjacent forecasts. In

[3] WASDE frequently published the revised estimate of final soybean production in October after the marketing year. The final forecasts of the cotton production were commonly revised in April and May of the subsequent year. Also, WASDE sometimes revised the final forecasts of the wheat beginning stocks and production in January and October, respectively. Because these additional revisions were somewhat sporadic in nature, they are not included in our analysis.

order to standardize for increasing crop size over time, forecast revisions are examined in log percentage form:

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

where r_t^j is a revision of a forecast for marketing year t released in month j-1. For inefficiency correction they used a measure that provides an adjustment parameter γ for a pending, as opposed to a past revision:

(2) $$e_t^j = \alpha + \gamma r_t^{j+1} + \varepsilon_t^j \qquad j = 1, \ldots, J - 1;\; t = 1,\ldots,28,$$

where e_t^j is forecast error of a forecast for marketing year t released in month j, and r_t^{j+1} is the forecast revision for the same marketing year t released in the next month. Consistently with forecast revisions, forecast errors are calculated in log percentage form:

(3) $$e_t^j = 100 * \ln\left(\frac{y_t^J}{y_t^j}\right) \qquad j = 1,\ldots,J-1;\, t = 1,\ldots,28 \;.$$

Equation (2) is based on Nordhaus'(1987) derivation that the forecast error at time j should be fully corrected (on average) by the following revision(s), thus, if revisions are efficient, $\gamma=1$. According to Isengildina, Irwin and Good (2006), out-of-sample correction of revision inefficiency proceeds along the following steps: 1) estimate γ coefficients in equation (2) using the Ordinary Least Square (OLS) method through the data in the estimation subsample, 2) multiply published revisions by γ coefficients to derive efficient revisions[4], and 3) calculate adjusted forecasts by adding efficient revisions to the previous months' forecasts. For example, if $\hat{\gamma}$ is estimated using 1984/85-1993/94 May forecast errors (e_t^j, $t=1,\ldots,10$ and $j=1$) and June forecast revisions (r_t^{j+1}, $t=1,\ldots,10$, and $j=1$), the adjusted revision for June 1994/95 ($\hat{r}_t^{j+1}$, $t=11$ and $j=1$) is the product of $\hat{\gamma}$ and $r_{11}{}^2$. Because the forecast errors and

[4] We follow a more conservative approach by adjusting revisions and forecasts only when the estimated γ coefficients are significant at a significance level of 0.5 Results of adjusting all revisions and forecasts regardless of the significance of the estimated γ coefficients are available upon request.

revisions are defined in logarithm terms in this study, the June 1994/95 adjusted forecast is calculates as $\hat{y}_{11}^{2} = y_{11}^{1} * e^{(\hat{r}_{11}^{2}/100)}$.

While Isengildina, Irwin and Good (2006) demonstrated that such revision inefficiency correction improved the accuracy of corn and soybean production forecasts in their 1980/81-2004/05 validation subsample, this procedure may suffer from several potential limitations. First, an OLS regression was used to estimate $\hat{\gamma}$ in equation (2), so the estimates may be influenced by the presence of outliers. Second, other variables may affect smoothing. For example, Isengildina, Irwin and Good (2013a) argued that "big crops get bigger and small crops get smaller," which suggests that forecast size and direction should be considered in adjusting forecasts for revision inefficiency. Third, stability of revision inefficiency over time would have implications on how well the correction procedure may improve accuracy: if the inefficiency is unstable, the adjustment procedure would perform poorly and modifications must be made. Our approach to incorporating these additional factors in revision inefficiency correction procedure is described in the following sections.

3.2 Outlier Detection

Rousseeuw and Leroy (2005) argued that regression outliers (either in the dependent or independent variable) pose a serious threat to a standard least squares analysis. They suggested two approaches to deal with outliers, including regression diagnostics and robust regression. Diagnostics include statistics, such as the Hat Matrix and the Cook's D, computed from the data so as to discover influential points. Once these outliers have been removed or corrected, the remaining data is re-evaluated. On the other hand, robust regression tries to develop estimators that are not strongly affected by outliers through assigning less weight to "abnormal" values.

In this study, the existence of outliers in estimating equation (2) using the OLS method is detected by Cook's D. To deal with outliers, robust regression is preferred in estimating the γ coefficients in equation (2) because outliers as forecast errors or forecast revisions cannot be simply removed or corrected, and a detected outlier represents a sudden change in revision inefficiency level.

M-estimator by Huber (1964) and MM-estimator by Yohai (1987) are considered in this study as they are the most commonly used robust estimators and both are accessible in statistical software R.

3.3 Forecast Size and Direction

The influence of forecast size and direction on revision inefficiency should also be considered in the adjustment procedure because Isengildina, Irwin, and Good (2013a) suggested that forecast size and direction are some of the potential sources of smoothing. In order to account for the effect of those two variables, out-of-sample linear trend forecasts are generated using the 5-year rolling approach. Accordingly, the rolling trend forecast for 1989/90 is constructed as a linear trend forecast using data from 1984/85-1988/89 and the rolling trend forecast $\hat{y}_{trend,t}$ for the remaining years are to be predicted consistently using the previous five years' observations. The rolling trend forecasts are estimated using only the final month WASDE estimates for each marketing year, so the trend forecasts remain the same across different months within one marketing year.

The Trend Difference (*TD*) is then defined as the log percentage difference between USDA forecast and the estimated rolling out-of-sample trend forecast:

(4) $$TD_t^j = 100 * \ln\left(\frac{y_t^j}{\hat{y}_{trend,t}}\right) \qquad j = 1, \ldots, J;\ t = 6,\ldots,28.$$

TD captures the influence of both USDA forecast size and direction by comparing the actual forecast to a linear trend forecast. The sign of *TD* indicates the forecast direction with a positive *TD* showing that the actual forecast was higher than the predicted value from the trend. The magnitude of *TD* indicates the forecast size as it communicates how much larger or smaller the actual forecast is relative to the trend value. To take this additional information into account for correction for revision inefficiency, equation (2) is modified as follows:

(5) $$e_t^j = \alpha + \gamma r_t^{j+1} + \beta TD_t^j + \varepsilon_t^j \qquad j = 1, \ldots, J-1;\ t = 6,\ldots,28.$$

Correction for revision inefficiency then proceeds as described in the basic procedure.

3.4 Stability of Revision Inefficiency Over Time

Stability of revision inefficiency is tested using a Quandt Likelihood Ratio (QLR) test[5]. If the structural break in revision inefficiency is identified, the basic correction procedure can be modified in the following ways. The first approach requires the use of data after the breakpoint for the adjustment procedure. Consequently, the full data period of this study will be trimmed and the validation subsample will be shortened as well. Alternatively, a rolling approach to estimating $\hat{\gamma}$ in equation (2) could be applied instead of the recursive approach used by Isengildina, Irwin and Good (2006). With the rolling approach the γ coefficients for any year are estimated consistently by previous five years' forecasts errors and revisions[6]. The use of this 5-year rolling approach may help reduce the influence of potential structural changes that happened more than 5 years ago.

3.5 Accuracy Evaluation

Performances of alternative revision inefficiency correction procedures are evaluated based on their effect on forecast accuracy. In each case, evaluation is conducted out of sample with parameters used to correct for inefficiency calculated in evaluation subsample and the accuracy of corrected forecasts assessed in validation subsample[7]. Following Isengildina, Irwin and Good (2006) study, the average reduction in root mean square percentage errors (RMSPEs) across all months as well as the number of month with smaller RMSPEs relative to the total number of months with changing RMSPEs are used to measure the improvement of forecasts accuracy.

Forecasts accuracy implications of the basic correction procedure are evaluated relative to published WASDE forecasts. Adjustments to the basic procedure are evaluated relative to the basic procedure itself in order to assess if they are offering an improvement and should be included. After all

[5] Due to space limitation, the details on conducting QLR tests and results are not presented here and they are available upon request.
[6] This study also applied 10-year rolling estimation, but 5-year window performed better in dealing with potential structural changes.
[7] The estimation and validation subsamples consist of 1984/85-1993/94 and 1994/95-2011/12 forecasts, respectively, for the basic correction procedure. The validation subsamples for adjusting for outliers is from 1994/95 to 2011/12, for controlling forecast size and direction is from 1999/00 to 2011/12, for using post breakpoint data is from 10 years after the structural break to 2011/12, and for applying rolling approach in equation (3) is from 1994/95 to 2011/12.

useful adjustments are taken into account, the accuracy implications of the advanced correction procedure are evaluated relative to published WASDE forecasts.

4. Results

3.1 The Basic Adjustment Procedure to Correct Revision Inefficiency

Accuracy implications of the basic correction procedure were evaluated by subtracting the monthly RMSPEs of adjusted forecasts from those of the published WASDE forecasts over the validation subsample from 1994/95 to 2011/12. Negative values indicate that on average errors got smaller after correcting for revision inefficiency and show the existence of improvements from adjusting the forecasts using the basic procedure. Positive values indicate that published WASDE forecasts were more accurate than the adjusted forecasts. The summary statistics pertaining to this analysis for corn, soybean, wheat, and cotton, are presented in Panels 1 of tables 1-4, respectively.

Our findings demonstrate that on average, the basic correction procedure in the vast majority of the cases did not improve the accuracy of the forecasts included in this study. All average changes in RMSPEs in corn and wheat are non-negative, showing larger errors resulting from forecast adjustment. The only negative change in RMSPEs among soybean forecasts, is for crushings, but it is very small (0.004). Interestingly, the errors in soybean export forecasts went down in 7 out of 11 months due to adjustment, but the magnitude of the increases in error in the remaining 4 months outweighed the magnitude of improvements and resulted in a positive average change in RMSPEs. Among cotton forecasts, the only case of average reduction in error is associated with production forecasts (0.058), indicative of forecast improvements in 3 out of 5 months. Our findings for corn and soybean production forecasts are in sharp contrast to Isengildina, Irwin, and Good (2006) results exclusively due to the differences in the sample periods (their study used the data from 1970 to 2004), since the basic adjustment procedure is identical. These differences also highlight the importance of the factors that may have an effect on the basic correction procedure investigated in this study.

4.2 Outlier Detection

The existence of outliers in equation (2) was examined using Cook's D. Outliers were found for all categories in all crops. Although MM-estimator is often preferred to the M-estimator in robust regression because the latter could be biased in the presence of high leverage points, we found that the M-estimator performed better in this study[8]. Based on the results comparing the M-estimator and the OLS estimator[9], the M-estimator is preferred for corn and cotton due to accuracy improvements in the majority of cases. On the other hand, the OLS estimator is preferred for soybeans because the forecasts accuracy of 3 out of 7 categories decreased from using the M-estimator. The evidence for using the M-estimator is not dominating based on the results for wheat. Due to the consideration of simplicity, the OLS estimator was preferred for wheat. Therefore, for the rest of this study the M-estimator was chosen in estimating γ coefficients in equation (2) for corn and cotton while the OLS estimator was preferred for soybeans and wheat.

4.3 Forecast Size and Direction

The impact of forecast size and direction on correction for revision inefficiency was investigated by including the variable TD in equation (5), as described in section 3.3. The changes in RMSPEs for four crops over the validation subsample 1999/2000-2011/12 were calculated by subtracting the RMSPEs of adjusted forecasts including TD from those adjusted using the basic procedure for the same time period[10]. This adjustment appeared to have the largest impact on the soybean balance sheet where crushings, seed and residual, and price forecasts show reductions in average error and error improvement in the majority of corrections. Most impressive results were found in corn price and wheat production forecasts, which showed reduction in average error with no instances of accuracy

[8] The comparison results using MM-estimator and M-estimator for all four commodities are available upon request.
[9] Due to space limitation, the comparison results using the M-estimator and the OLS estimator are not included, and the results are available upon request.
[10] Due to space limitation, the assessments of the changes in RMSPEs for corn, soybean, wheat, and cotton are not included, and the results are available upon request.

deterioration. While wheat price forecasts also demonstrate an average reduction, these forecasts' accuracy improved in only 1 out of 5 cases. The lack of accuracy improvement after accounting for forecast size and direction in cotton balance sheet suggests that cotton forecasters already take these factors into account. Based on these results, forecast size and direction was incorporated in correcting inefficiency in revisions of corn price; soybean crushings, seed and residual, and price; and wheat production and price forecasts, but not in any other categories.

4.4 Stability of Revision Inefficiency Over Time

Based on the QLR test results, we concluded that forecast revisions were unstable over the study sample period with structural breaks likely taking place in 1987 and 2006-2007. Due to the lack of effectiveness, the two modifications described in section 3.4 were not included in the adjustment procedure[11]. Instead, we examined the impact of structural breaks on the effectiveness of our correction procedure from another angle by evaluating the changes in their effect on forecast accuracy over time. For this purpose, the validation subsample 1994/95-2011/12 for the correction procedure was divided into three 6-years periods, where 1994/95-1999/00, 2000/01-2005/06, and 2006/07-2011/12 were named stage 1, 2, and 3 respectively.

Panels 2-5 of tables 1-4 report the summary of changes in forecast accuracy for corn, soybean, wheat, and cotton respectively over the full validation subsample following with three stages. The changes were computed by subtracting the RMSPEs of published WASDE forecasts from those of adjusted forecasts using the advanced revision inefficiency correction procedure. The advanced procedures for four crops were formed according to the results of the previous two sections as follows: equation (5) was used for correcting corn price forecasts; soybean crushings, seed and residual, and price forecasts; and wheat production and price forecasts; while equation (2) was used for all other categories. The M-estimator was used for corn and cotton and the OLS estimator was applied for

[11] The comparison results using the two modified approaches are available upon request.

soybean and wheat.

A direct comparison of the advanced correction procedure with the basic correction procedure can be made based on the results of the full validation subsample in Panel 1 and 2 of table 1-4[12]. Relative to the basic correction procedure, the advanced procedure improved forecast accuracy in 5 out of 7 categories in corn, 3 out of 7 categories in soybeans, 2 out of 8 categories in wheat, and 4 out of 6 categories in cotton. The advanced procedure reduced the accuracy of corn beginning stocks and feed and residual forecasts, and cotton beginning stocks and price forecasts, while leaving the accuracy of other forecast categories unchanged.

The results for 3 stages in tables 1-4 reveal the performance of the advanced correction procedure over time. Our results for corn production forecasts shown in table 1 demonstrate that the advanced adjustment procedure reduced average RMSPEs in stage 1 and stage 3 but not in stage 2. This finding helps illustrate how instability in revision inefficiency is likely the reason for the inconsistency between our findings and those of Isengildina, Irwin, and Good (2006). Our adjustment procedure performed very well for corn export forecasts in stage 2 but not in other stages. Among soybean forecasts, our adjustment procedure performed the best in stage 3 with average RMSPEs reductions in beginning stocks, exports, and price of 0.134, 0.232, and 0.076, respectively. The results are probably the strongest for soybean exports, where forecast accuracy improved in 8 out of 11 months. In terms of raw units, our findings for soybean exports imply a reduction in forecasts error in December of 2011/12 marketing year due to correction for forecasts revision inefficiency as large as 3 million bushels for a 1.3 billion bushel soybean crop. However, prior to stage 3, our adjustment procedure did not perform that

[12] Notice the validation subsample for category price in corn, crushings, seed and residuals, and price in soybean, and production and price in wheat in panel 1 of table 1-4 starts in 1994/95, while the validation subsample of these categories in panel 2 of table 1-4 starts in 1999/00. Therefore, the results for these categories in panel 2 using the advanced correction procedure should be compared with the ones using the basic procedure over the same validation subsample 1999/00-2011/12. The average RMSPEs has decreased from 0.07 to 0.059 for corn price; from 0.014 to 0.003 for crushings, from 0.525 to 0.505 for seed and residuals, and from 0.102 to 0.059 for price in soybean; from 0.02 to -0.043 for production and from 0.167 to 0.141 for price in cotton.

well for these forecasts. Wheat forecasts were the least affected by revision inefficiency, but we still find potential accuracy improvements due to our adjustment procedure in production forecasts in stages 2 and 3 and in price forecasts in stage 3. In the cotton balance sheet our adjustment procedure was most appropriate for production forecasts, where accuracy improved in 3 out of 5 months in each stage and average RMSPE went down in stages 2 and 3 by 0.172 and 0.208, respectively. Accuracy improvements due to correction for revision inefficiency in other cotton forecasts were more sporadic. These findings demonstrate the challenges in correcting revision inefficiency when this inefficiency is unstable over time.

5. Summary and Conclusions

Numerous previous studies demonstrated inefficiencies in WASDE commodity forecasts. Our study focused on inefficiency in revisions of WASDE forecasts of U.S. corn, soybeans, wheat, and cotton. We attempted to develop an adjustment procedure that could be used to correct revision inefficiency and improve the accuracy of these forecasts.

Setting the revision inefficiency correction procedure suggested by Isengildina, Irwin, and Good (2006) study as the basic procedure, we incorporated the issue of outliers and the impact of forecasts size and direction on revision inefficiency. After a series of comparisons, the advanced correction procedures for four commodities were selected as following: using the OLS estimator for soybeans and wheat and the M-estimator for corn and cotton; only considering forecasts size and direction for corn price; soybean crushings, seed and residuals, and price; and wheat production and price forecasts. We also found that revisions inefficiencies were unstable during our sample period, resulting in changes in the accuracy correction ability of the advanced procedure over time.

Our findings suggest that our adjustment procedure has the highest potential for improving accuracy in wheat and cotton production and soybean export forecasts. It is important to note that applying such correction procedure over time should remove or decrease the degree of revision inefficiency, which should be taken into account in the continued adjustment of the correction procedure to be focused on the most relevant data.

Our limited ability to correct revision inefficiency using multiple statistical methods explored in this study makes us think about the nature of this inefficiency commonly called smoothing. Most previous studies (Nordhaus, 1987; Isengildina, Irwin and Good, 2006; Coibon and Gorodnichenko, 2010) argue that smoothing is associated with conservativeness or inability of forecasters to adjust to innovations in a timely manner. However, if this conservativeness was systematic, we should be able to adjust it using statistical methods. Instead, our findings show that smoothing is very unstable over time, yet a persistent characteristic of most forecasts reviewed in this study. These observations suggest that perhaps correlations in forecast revisions (inefficiency) illustrate that forecasters tend to make the same mistakes within the forecasting cycle. In fact, some of the biggest improvements in suggested revision inefficiency correction procedure were due to incorporating forecast size and direction for some forecasts. If repeating the same mistakes causes inefficiency, it can only be corrected by knowing what these mistakes are. In this case, studies that investigate efficiency of these forecasts with respect to outside factors (e.g., macro forces in Isengildina and Karali, 2013b) may provide some guidance.

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Table 1. Evaluation of Revision Inefficiency Correction Procedures for Corn Forecasts

	Beginning Stocks	Production	Feed and Residual	Food, Seed, and Industrial	Exports	Ending Stocks	Price
Panel 1: Changes in RMSPEs: Adjusted forecasts based on the basic correction procedure versus the WASDE published forecasts, 1994/95-2011/12[a]							
Average	0.044	0.037	0.029	0.023	0.152	0.308	0.067
Count of Improvements/Count of Changes	0/1	0/3	0/3	1/3	2/6	0/7	0/3
Panel 2: Changes in RMSPEs: Adjusted forecasts based on the advanced correction procedure versus the WASDE published forecasts, 1994/95-2011/12[b]							
Average	0.208	0.003	0.033	0.004	0.093	0.256	0.059
Count of Improvements/Count of Changes	1/4	1/3	0/3	1/3	4/7	0/7	0/2
Panel 3: Stage 1 (1994/95-1999/00)							
Average	0.207	-0.042	0.000	0.006	0.065	0.312	
Count of Improvements/Count of Changes	1/3	1/3	0/0	0/1	3/4	1/5	
Panel 4: Stage 2 (2000/01-2005/06)							
Average	0.170	0.074	0.003	0.060	-0.240	0.378	0.022
Count of Improvements/Count of Changes	1/3	2/3	1/2	0/1	5/6	0/5	0/2
Panel 5: Stage 3 (2006/07-2011/12)							
Average	0.110	-0.014	0.062	0.194	0.233	0.176	0.096
Count of Improvements/Count of Changes	1/3	2/3	0/3	2/5	1/4	1/3	0/1

Notes: [a]The changes in RMSPEs in panel 1 are computed by subtracting the RMSPEs of published WASDE forecasts from those of forecasts adjusted using the basic procedure.
[b]The evaluation is carried out by subtracting the RMSPEs of published WASDE forecasts from those of forecasts adjusted using the advanced correction procedure.
The advanced revision inefficiency correction procedure for corn includes the use the M-estimator in estimating the γ coefficients, use of equation (6) for category price, and use of equation (3) for other categories.
The validation subsamples for equation (6) are from 1999/00-2011/12. So, no results are given for price in stage 1.
Negative values indicate the improvement in forecast accuracy and positive values illustrate the deterioration in forecast accuracy.
Average and the count of improvements out of the count of changes are summary statistics across all forecast months.

Table 2. Evaluation of Revision Inefficiency Correction Procedures for Soybean Forecasts

	Beginning Stocks	Production	Crushings	Seed and Residual	Exports	Ending Stocks	Price
Panel 1: Changes in RMSPEs: Adjusted forecasts based on the basic correction procedure versus the WASDE published forecasts, 1994/95-2011/12[a]							
Average	0.805	0.021	-0.004	0.456	0.013	0.286	0.090
Count of Improvements /Count of Changes	1/3	0/1	2/3	1/6	7/11	1/6	2/7
Panel 2: Changes in RMSPEs: Adjusted forecasts based on the advanced correction procedure versus the WASDE published forecasts, 1994/95-2011/12[b]							
Average	0.805	0.021	0.003	0.505	0.013	0.286	0.059
Count of Improvements /Count of Changes	1/3	0/1	2/3	1/6	7/11	1/6	2/7
Panel 3: Stage 1 (1994/95-1999/00)							
Average	2.079	0.000			0.166	0.585	
Count of Improvements /Count of Changes	1/3	1/3			3/4	1/5	
Panel 4: Stage 2 (2000/01-2005/06)							
Average	0.335	0.046	-0.001	0.846	0.169	0.265	0.205
Count of Improvements /Count of Changes	0/1	0/1	1/2	1/4	3/7	0/4	1/7
Panel 5: Stage 3 (2006/07-2011/12)							
Average	-0.134	0.001	0.008	0.308	-0.232	0.054	-0.076
Count of Improvements /Count of Changes	1/2	0/1	1/3	0/3	8/11	2/5	2/3

Notes: [a]The changes in RMSPEs in panel 1 are computed by subtracting the RMSPEs of published WASDE forecasts from those of forecasts adjusted using the basic procedure.
[b]The evaluation is carried out by subtracting the RMSPEs of published WASDE forecasts from those of forecasts adjusted using the advanced correction procedure.
The advanced revision inefficiency correction procedure for soybean includes the use of the OLS estimator in estimating the γ coefficients, use of equation (6) for category crushings, seed and residual, and price, and use of equation (3) for other categories.
The validation subsamples for equation (6) are from 1999/00-2011/12. So, no results are given for crushings, seed and residual, and price in stage 1.
Negative values indicate the improvement in forecast accuracy and positive values illustrate the deterioration in forecast accuracy.
Average and the count of improvements out of the count of changes are summary statistics across all forecast months.

Table 3. Evaluation of Revision Inefficiency Correction Procedures for Wheat Forecasts

	Beginning Stocks	Production	Food	Seed	Feed and Residual	Exports	Ending Stocks	Price
Panel 1: Changes in RMSPEs: Adjusted forecasts based on the basic correction procedure versus the WASDE published forecasts, 1994/95-2011/12[a]								
Average	0.142	0.032	0.000	0.016	0.076	0.183	0.000	0.124
Count of Improvements /Count of Changes	0/1	1/3	0/0	0/1	0/2	0/5	0/0	0/4
Panel 2: Changes in RMSPEs: Adjusted forecasts based on the advanced correction procedure versus the WASDE published forecasts, 1994/95-2011/12[b]								
Average	0.142	-0.043	0.000	0.016	0.076	0.183	0.000	0.141
Count of Improvements /Count of Changes	0/1	1/2	0/0	0/1	0/2	0/5	0/0	1/5
Panel 3: Stage 1 (1994/95-1999/00)								
Average	0.519		0.000	0.000	0.025	0.309	0.000	
Count of Improvements /Count of Changes	0/1		0/0	0/0	0/1	0/4	0/0	
Panel 4: Stage 2 (2000/01-2005/06)								
Average	0.000	-0.093	0.000	0.000	0.000	-0.012	0.000	0.337
Count of Improvements /Count of Changes	0/0	1/2	0/0	0/0	0/0	1/2	0/0	1/5
Panel 5: Stage 3 (2006/07-2011/12)								
Average	0.000	-0.004	0.000	0.189	0.144	0.191	0.000	-0.017
Count of Improvements /Count of Changes	0/0	1/1	0/0	0/2	0/2	0/3	0/0	1/3

Notes: [a]The changes in RMSPEs in panel 1 are computed by subtracting the RMSPEs of published WASDE forecasts from those of forecasts adjusted using the basic procedure.
[b]The evaluation is carried out by subtracting the RMSPEs of published WASDE forecasts from those of forecasts adjusted using the advanced correction procedure.
The advanced revision inefficiency correction procedure for wheat includes the use of the OLS estimator in estimating the γ coefficients, use of equation (6) for category production and price, and use of equation (3) for other categories.
The validation subsamples for equation (6) are from 1999/00-2011/12. So, no results are given for production and price in stage 1.
Negative values indicate the improvement in forecast accuracy and positive values illustrate the deterioration in forecast accuracy.
Average and the count of improvements out of the count of changes are summary statistics across all forecast months.

Table 4. Evaluation of Revision Inefficiency Correction Procedures for Cotton Forecasts

Month	Beginning Stocks	Production	Domestic Use	Exports	Ending Stocks	Price
Panel 1: Changes in RMSPEs: Adjusted forecasts based on the basic correction procedure versus the WASDE published forecasts, 1994/95-2011/12[a]						
Average	0.200	-0.058	0.079	0.126	0.153	0.151
Count of Improvements/Count of Changes	0/2	3/5	2/8	5/9	2/8	2/7
Panel 2: Changes in RMSPEs: Adjusted forecasts based on the advanced correction procedure versus the WASDE published forecasts, 1994/95-2011/12[b]						
Average	0.207	-0.064	0.064	0.099	0.051	0.156
Count of Improvements/Count of Changes	0/4	4/5	1/8	4/9	1/6	3/7
Panel 3: Stage 1 (1994/95-1999/00)						
Average	0.452	0.127	0.034	0.682	-0.262	-0.050
Count of Improvements/Count of Changes	0/2	3/5	2/8	5/9	2/8	2/7
Panel 4: Stage 2 (2000/01-2005/06)						
Average	-0.105	-0.172	0.261	-0.456	0.014	0.378
Count of Improvements/Count of Changes	0/2	3/5	2/8	5/9	2/8	2/7
Panel 5: Stage 3 (2006/07-2011/12)						
Average	0.454	-0.208	-0.084	0.110	0.443	0.109
Count of Improvements/Count of Changes	0/2	3/5	2/8	5/9	2/8	2/7

Notes: [a]The changes in RMSPEs in panel 1 are computed by subtracting the RMSPEs of published WASDE forecasts from those of forecasts adjusted using the basic procedure.
[b]The evaluation is carried out by subtracting the RMSPEs of published WASDE forecasts from those of forecasts adjusted using the advanced correction procedure.
The advanced revision inefficiency correction procedure for cotton includes the use of the M-estimator in estimating the γ coefficients and use of equation (3) for all categories.
Negative values indicate the improvement in forecast accuracy and positive values illustrate the deterioration in forecast accuracy.
Average, max, min, and the count of improvement out of the count of changes are summary statistics across all forecast months.

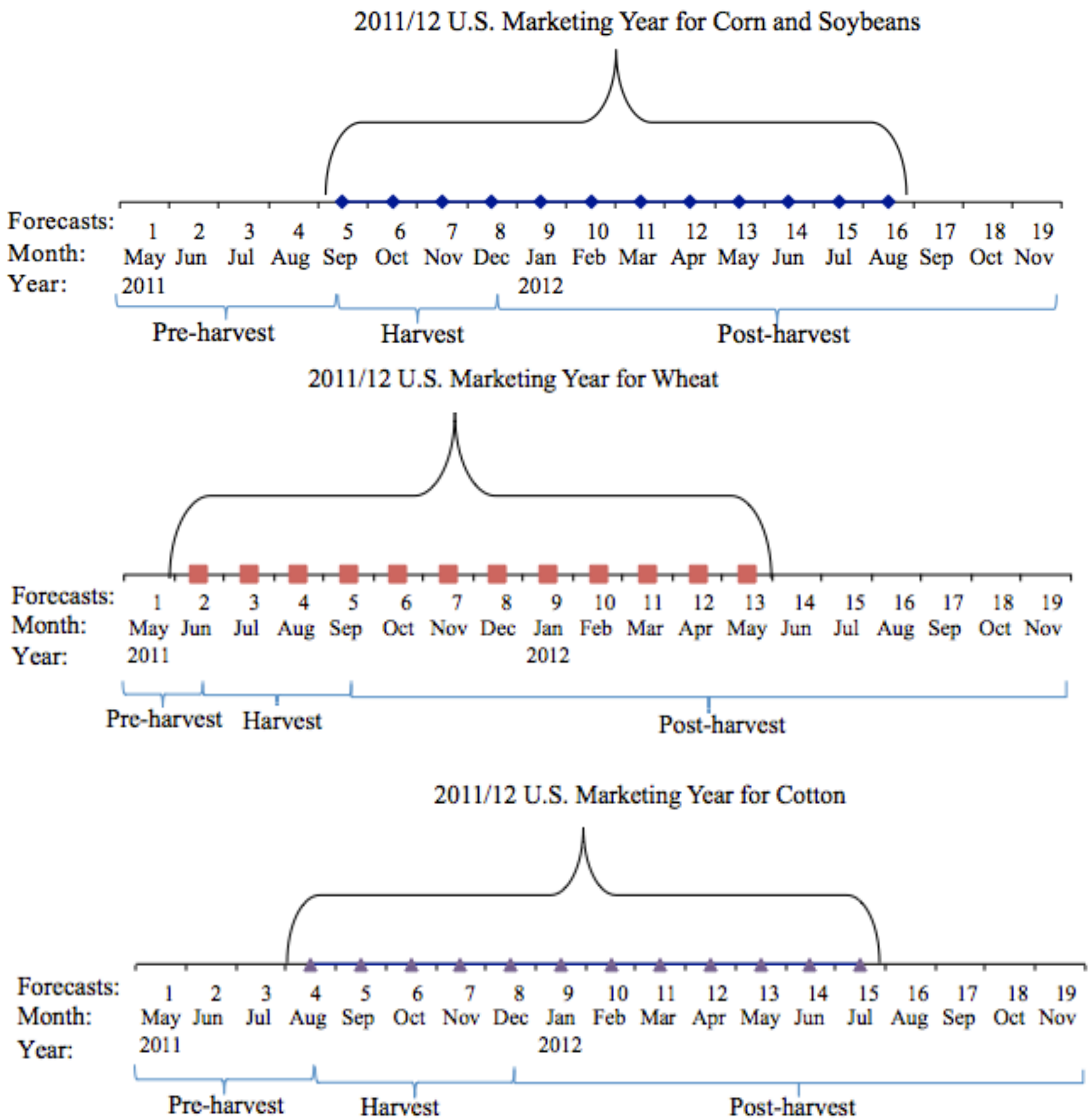

Figure 1. The WASDE Forecasting Cycle for Corn, Soybeans, Cotton and Wheat Relative to the 2011/12 U.S. Marketing Year

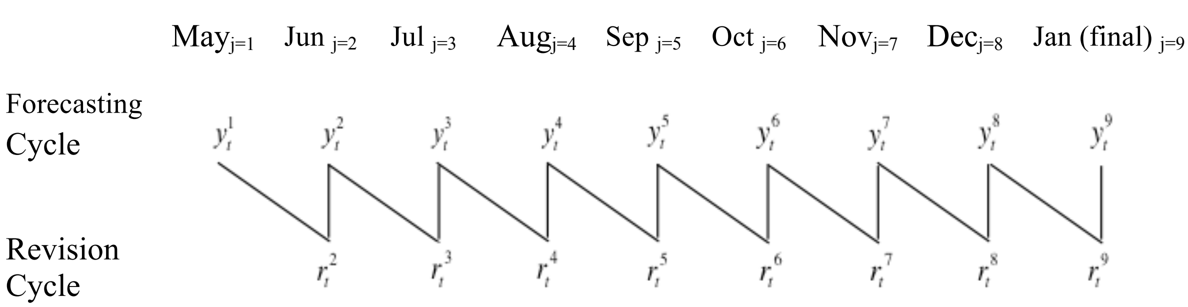

Figure 2. Corn and Soybean Production Forecasting Cycle and Corresponding Revision Cycle for a Marketing Year