What Can we Learn from our Mistakes? Evaluating the Benefits of Correcting Inefficiencies in USDA Cotton Forecasts.

Olga Isengildina-Massa, David Tysinger, Patrick Gerard and Stephen MacDonald¹

Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Corpus Christi, TX, February 5-8, 2011

Copyright 2011 by Olga Isengildina-Massa, David Tysinger, Patrick Gerard and Stephen MacDonald. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

¹ Assistant Professor, Graduate student, Professor in the Department of Applied Economics and Statistics at Clemson University and Senior Economist, ERS, USDA, respectively. Research assistance of Ran Xie is gratefully acknowledged. The funding support of the Economic Research Service of the U.S. Department of Agriculture under the Cooperative Agreement No. 58-3000-9-0077 is gratefully acknowledged. Any opinions, findings, conclusions, or recommendations expressed in this study are those of the authors and do not necessarily reflect the view of the U.S. Department of Agriculture.

It is a commonly held belief of agricultural market participants and analysts that USDA forecasts function as the "benchmark" to which other private and public forecasts are compared. Because of their importance, there is a vast body of literature devoted to analyzing accuracy and efficiency of USDA forecasts (e.g., Gunnelson, Dobson and Pamperin, 1972; Thomson, 1974; Irwin, Gerlow and Liu, 1994; Bailey and Brorsen, 1998; Sanders and Manfredo, 2002; Isengildina, Irwin, and Good, 2004; Isengildina, Irwin, and Good, 2006). These studies focus on production and price forecasts of major U.S. commodities, such as corn, soybeans, wheat, hogs and cattle. Other major commodities and forecast categories received relatively little attention. Even less is known about accuracy and efficiency of WASDE forecasts of the world and foreign supply and demand categories that may affect U.S. markets through trade.

Most of the previous studies find biases and inefficiencies in USDA forecasts. An implication of these findings is that if the inefficiencies are corrected, the forecasts will be improved. However, very little is known about which violations of forecast efficiency cause the biggest problems for forecast performance and the degree to which the forecasts can be improved due to corrections of inefficiency. Only a few studies (e.g., Isengildina, Irwin, and Good, 2006) demonstrate the magnitude of forecast improvement resulting from correction for inefficiencies. The authors examine correction for smoothing in forecast revisions and show that correction for smoothing would decrease root-mean-squared percentage forecast errors an average of 10% in corn and 2% in soybeans.

Published USDA forecasts are always the Department's best estimate of expected future realizations of the variables. However, the Department also publishes analysis of its forecasts, some of which includes evidence of systemic errors. For example, each month's issue of USDA's *World Agricultural Supply and Demand Estimates* (WASDE) includes a set of "Reliability of Projections" tables with average differences between past years WASDE forecasts published in the same month since 1981 and the actual realizations of those variables in percent and volume form. The number of years

USDA's forecasts were too high and too low is also included. Variables include world, U.S. and foreign production, exports, consumption, and ending stocks of wheat, coarse grains, rice, soybeans, and cotton. A table, "Reliability of U.S. Projections," covers corn, sorghum, barley, oats, soybean meal, beef, pork, broilers, turkeys, eggs, and milk (production only for livestock products). These tables indicate persistent tendencies to over- and underestimate certain variables. Similarly, a 2005 USDA study found some export forecasts were significantly less accurate than ARIMA-based forecasts (MacDonald, 2005).

USDA has periodically undertaken efforts to improve its forecasting capability. This included a series of annual interagency conferences from the mid-1990's to 2002. In recent years, USDA's Economic Research Service has at times been successful as it pursued additional funding to upgrade its market analysis program (OMB, 2008, Alfred, Gouge, and Maw, 2009, and OMB, 2009). However, it appears that there is not continuous process to monitor and adjust forecasts based on their past performance. The goal of this study is to evaluate the magnitude of forecast improvements if such quality control system focusing on correction of inefficiencies in USDA cotton forecasts was in place over the last ten years. The aspects of forecast performance included in this study were 1) bias and trends in bias, 2) correlation between forecast error and forecast level, 3) autocorrelation in forecast errors, 4) correlation in forecast revisions. This study will concentrate on USDA cotton forecasts as relatively little is known about these forecasts. Only a few studies have concentrated on a subset of WASDE categories for cotton (MacDonald, 2002) or included examination of cotton in studies of WASDE export forecasts for a number of commodities (MacDonald, 1999 and MacDonald 2005). Data from monthly WASDE balance sheets for the U.S., China and world upland cotton over 1985/86 through 2008/09 including unpublished price forecasts will be analyzed. The framework developed in this study can be used by USDA and other agencies to monitor and improve the performance of their forecasts.

Data

WASDE reports are released by the USDA usually between the 9th and the 12th of each month and contain forecasts of supply and demand for most major crops. Supply and demand estimates are forecasted on a marketing year basis (August through July for cotton). The first forecast for a marketing year is released in May preceding the U.S. marketing year. Estimates are typically finalized 18 months later, by November after the marketing year (Figure 1) except for the U.S. production forecasts which are finalized by May (month 13 of the forecasting cycle). USDA WASDE forecasts are fixed-event forecasts because the series of forecasts is related to the same terminal event (y_T^i), where T is the release month of the final estimate for the category for the i^{th} marketing year. The forecast of the terminal event for month t is denoted as: y_T^i , where t=1, ..., t, t=19, and t=1985/86, ..., 2008/09. Thus, each subsequent forecast is essentially an update of the previous forecast as it describes the same terminal event. The WASDE forecasting cycle generates 18 updates for each forecasted variable except U.S. production (12 updates) within each marketing year for cotton.

WASDE forecasts for the U.S. and the world follow a balance sheet approach to account for supply and utilization (see Vogel and Bange (1999) for a detailed description of the USDA crop forecast generation process). The major components of the balance sheet are beginning stocks, production and imports on the supply side and domestic use, exports and ending stocks reflecting utilization. The balance sheet approach means that individual estimates are cross checked against each other, across commodities and countries. For example, "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, p. 10). WASDE price estimates describe marketing year average prices received by farmers, which is an average of monthly prices weighed by the amounts marketed at these prices. Unlike all other WASDE estimates, price forecasts are published in the form of an interval. Because analysis of interval forecast accuracy is different from point estimate accuracy (e.g.,

Isengildina, Irwin, and Good, 2004), midpoints of price forecasts were used in this study to be consistent with the rest of the analysis.

The focus of this study is monthly WASDE forecasts for the U.S., China, and World Upland Cotton for the marketing years of 1985/86 through 2008/09. Table 1 shows the descriptive statistics for the final estimates (19th forecast for each marketing year) of the supply and demand categories for these regions. The means for various categories reported in this table show that both China and the U.S. are major cotton producers. China is also a major consumer of cotton with the growing textile sector supported by domestic production and supplemented by imports. The demands of China's textile sector are also facilitated by relatively high levels of stocks. The U.S. cotton industry is characterized by a shrinking textile industry and essentially no raw cotton imports. Changes in international cotton trade that occurred in the mid-1990s resulted in the growth of U.S. cotton exports and decline in domestic use and stocks. The U.S. cotton price averaged about 56 cents/lb during the period of this study. Similar to other major U.S. commodities, cotton price has been supported by the farm programs prior to 1985, but has become more market oriented since. Due to the increased export orientation of the U.S. cotton industry, the price of U.S. cotton is becoming increasingly affected by international market forces (Isengildina and MacDonald, 2009).

The standard deviations and the coefficients of variation indicate absolute and relative variability in the forecasted categories. For example, Table 1 shows that China has some of the largest values of coefficients of variation in all categories (except ending stocks). These large values imply that China's supply and demand categories are very volatile and difficult to forecast. In the US, the coefficients of variation for exports and ending stocks were nearly twice as large as the coefficients of variation in other US categories (about 43% and 20%, respectively), indicating higher volatility and potential challenges in forecasting these categories. Similarly, the coefficient of variation for world ending stocks at 26.8%

echoes the pattern observed in the US, suggesting that ending stocks are more difficult to forecast than other supply and demand categories.

Skewness and kurtosis describe the shape of forecast distributions. For the World and China, several WASDE categories exhibit significant positive skewness and leptokurtic distributions. Specifically, production, imports, domestic use, and exports were all shown to have positive skewness and kurtosis values near or above 1. Both of these measures indicate the frequent presence of mostly positive outliers in the data. These outliers illustrate occurrences such as record production in the world and China in 2004, or sharp changes in imports as Chinese imports tripled from 2004 to 2005. These examples illustrate once again that many cotton categories are very difficult to forecast.

Methods

The focus of this study was to evaluate the magnitude of forecast improvements resulting from correction of inefficiencies in USDA cotton forecasts. The corrections were performed in the following manner: the study period (1985-2008) was split into two subsets, an evaluation subset (starting with 1985-1998) and validation subset (1999-2008). The evaluation subset was then used to estimate parameters for 1) the test of bias and trends in bias, 2) correlation between forecast error and forecast level, 3) autocorrelation in forecast errors, 4) correlation in forecast revisions, as explained below. The validation subset was then used to correct published forecasts if significant inefficiencies were detected and evaluate whether these corrections improved the forecasts. Thus, for the first observation in the validation subset, the marketing year of 1999/00, the estimation subset consisted of 1985/86-1998/99 marketing years. The second observation in the validation subset was adjusted based on parameters calculated with 15 observations (1985/86-1999/00) in the evaluation subset. The process was repeated until the evaluation subset consisted of 24 observations to generate parameters used to evaluate the last

year of the validation subset (2008/09) forecasts. Thus, the validation subset consisted of 10 observations (1999/00-2008/09).

Forecast adjustments were based on the properties of USDA cotton forecasts investigated using error and revision analysis. For each category, monthly announcement and marketing year forecast errors and revisions were calculated as following:

1.
$$e^{i}_{t} = y^{i}_{T} - y^{i}_{t}; \quad t=1,...,T-1; \quad i=1985/86,...,2008/09$$
$$r^{i}_{t} = y^{i}_{t} - y^{i}_{t-1}; \quad t=2,...,T; \quad i=1985/86,...,2008/09$$

where e_t^i corresponds to the error, r_t^i is the revision for a given report month t, and marketing year i. As defined earlier, y_t^i is the forecast for marketing year i released in month t and y_T^i corresponds to the final estimate for marketing year i, T=19 for cotton.

The first property investigated in this study was forecast bias. Parameters for the test of bias were estimated using data from the evaluation subset in the following regression:

2.
$$e_t^i = \alpha_0 + \beta_t I + \varepsilon_t^i$$
; $i=1985/86,...,2008/09$, .

Where I is a linear time trend, which starts with the negative value (-14 for 1985/86-1999/00 subsample) in the beginning of the evaluation sub-sample and ends with -1 for the last year of the evaluation subsample. This approach forces I = 0 in the next year, which simplifies the correction as described below. The null hypothesis for an unbiased forecast is $\alpha_0 = 0$. If $\alpha_0 > 0$, forecasts are consistently underestimating the final estimate. If $\alpha_0 < 0$, forecasts are consistently overestimating the final estimate. If α_0 was different from zero at the 5% significance level, the next forecast was corrected for bias by adding the coefficients of the above regression:

3.
$$adj y_t^{i+1} = y_t^{i+1} + \alpha_0$$
.

If α_0 was not significantly different from zero, no correction was made. This procedure was repeated for each forecast year in the validation subsample.

Weak form of forecast efficiency implies that forecast errors should be orthogonal to forecasts themselves as well as to prior forecast errors (Nordhaus, 1987). Following Pons (2000) weak efficiency was evaluated using the following regressions:

4.
$$e_t^i = \alpha_1 + \beta_1 y_t^i + \varepsilon_t^i$$
 $i=1985/86,...,2008/09$,

and

5.
$$e_t^i = \alpha_2 + \beta_2 e_t^{i-1} + \varepsilon_t^i$$
 $i=1985/86,...,2008/09$.

Note that for fixed event forecasts, the forecast error for the previous event (marketing year) should be used for this test. The null hypotheses for efficient forecasts is $\beta = 0$. When $\beta_I > 0$ in equation (3), larger forecast values are associated with larger positive errors (greater underestimation) and smaller negative errors (smaller overestimation). When $\beta_I < 0$, larger forecast values are correlated with smaller positive errors (smaller underestimation) and larger negative errors (larger overestimation). If $\beta_2 \neq 0$ in equation (6), there is a systematic component in forecast errors that can be predicted using past errors. As before, if β was different from zero at the 5% significance level, the next forecast was corrected for inefficiency by adding the coefficients of the above regressions:

6.
$$adj y_t^{i+1} = y_t^{i+1} + \alpha_t + \beta_t y_t^{i+1}$$
 and $adj y_t^{i+1} = y_t^{i+1} + \alpha_t + \beta_t e_t^{i}$.

If β was not significantly different from zero, no correction was made.

Weak form efficiency of fixed-event forecasts also implies that forecast revisions should follow a random walk (Nordhaus, 1987). Following Isengildina, Irwin, and Good (2006), this property was evaluated using the following regressions:

7.
$$r_t^i = \gamma r_{t-1}^i + \varepsilon_t^i \quad i=1985/86,...,2008/09,$$

For (t=3), γ represents the slope coefficient of all October revisions made from 1985/86 to 2008/09 regressed against previous September revisions (t-1=2) for the same respective years. The null hypothesis for efficiency in forecast revisions is $\gamma = 0$. If $\gamma > 0$, the forecasts are "smoothed" as they are partially based on the previous revision. If $\gamma < 0$, the forecasts are "jumpy" as they tend to over-correct the previous revision. As before, if γ was different from zero at the 5% significance level, the next forecast was corrected for inefficiency by adding the coefficients of the above regression:

8.
$$adj y_{t+1}^{i+1} = y_{t+1}^{i+1} + \gamma_{t+1} r_i^t.$$

If γ was not significantly different from zero, no correction was made.

The magnitude of forecast improvement due to inefficiency correction was evaluated by comparing the errors of the forecasts in the validation sub-sample that underwent the correction procedure described above and uncorrected forecasts published during the same time period. Two measures used to compare forecast performance were mean absolute error (*MAE*) and root mean squared error (*RMSE*), as defined below:

9.
$$MAE_t = \frac{1}{n} \sum_{i=15}^{24} |e_t^i|$$
 and $RMSE_t = \sqrt{\frac{1}{n} \sum_{i=15}^{24} (e_t^i)^2}$.

Both measures are effective at comparing the magnitude of forecast improvements due to corrections of inefficiencies. Specifically, *MAE* describes the average magnitude of the forecast errors, whereas *RMSE* measures how far, on average, the monthly forecasts were from the final value and is more sensitive to outliers than *MAE*.

Results

Results of the empirical analysis were consistent between MAE and RMSE, therefore only MAE results are presented to conserve space. Table 2 presents MAE of unadjusted WASDE cotton forecasts

over 1999/00 to 2008/09 marketing years. This table shows that U.S. exports, ending stocks and prices, China's domestic use, exports and ending stocks, as well as world production, domestic use and ending stocks suffered from some of the largest errors in the respective balance sheets. These MAE values are presented mostly for context purposes to help understand the relative magnitude of forecast improvements due to correction of inefficiencies presented in the subsequent tables.

Changes in MAE due to correction of bias in WASDE cotton forecasts reported in table 3 demonstrate that this correction was beneficial in most cases as we observed significant reduction in MAE for U.S. production, and price; China's production, imports, domestic use, and exports; and world domestic use and exports. The magnitude of the improvements was often substantial, around 1.3 cents per lb improvement in accuracy in U.S. average price in the first two months of the forecasting cycle, about 490 thousand bales improvement in China's production forecasts from October(i) to December(i), and 370 thousand bales improvement in world domestic use forecasts in the first six months of the forecasting cycle. Correction of bias, however, resulted in much larger forecast errors for China and world ending stocks. This result may be due to the fact that USDA was already correcting for bias in these categories during the validation period and the simulation conducted in this study resulted in overcorrection.

Changes in MAE resulting from correction of correlation of error with forecast levels reported in table 4 demonstrate forecast improvements in all but China and world production and import forecasts where no corrections were made. Some of the largest improvements were observed in U.S. exports, domestic use and price forecasts, China's domestic use and ending stocks forecasts and world domestic use, exports and ending stocks forecasts. The magnitude of reductions in MAE were about 70 thousand bales for U.S. domestic use with average reductions of 210 thousand bales in the first five months of the forecasting cycle. Improvements in U.S. price forecasts were also concentrated in the beginning of the forecasting cycle with average improvement from July(i) to September(i) averaging

about 1.31 cents per lb smaller MAE. Improvements in China's domestic use forecasts were spread out through the whole forecasting cycle averaging 0.25 million bales reduction in MAE. The largest average reduction in MAE due to correction for correlation of error with forecast levels was observed for world domestic use forecasts averaging 540 thousand bales reduction in MAE. World export forecasts also benefitted from this correction with the largest reduction in MAE taking place from July(i) to October(i). No average increases in errors were observed.

Corrections for correlation of error with previous year's error also resulted in more accurate forecasts as shown in table 5. While these improvements were relatively smaller in magnitude, they were significantly different from zero for U.S. production and exports averaging about 10 thousand bales reduction in MAE, as well as China and world imports with average reductions in MAE of 270 and 90 thousand bales, respectively, and China and world domestic use forecasts with average reductions in MAE of 100 thousand bales. The largest improvements were observed in China's imports forecasts with average reduction in MAE between September(i) and April(i+1) of 550 thousand bales.

Corrections for correlation in forecast revisions resulted in very minor improvements and often caused increases in forecast error as demonstrated in table 6. These adjustments were not beneficial for WASDE cotton forecasts.

Overall the results of this study demonstrate that some corrections of forecast inefficiencies, such as correction of correlation of error with forecast levels and correlation of error with previous year's error resulted in consistent improvement of USDA cotton forecasts, while correction for correlation in forecast revisions did not benefit the forecasts. Correction for bias yielded mixed results likely because USDA has already been applying those corrections to some of the categories and thus our analysis resulted in over-correcting.

Summary and Conclusions

This study investigated the magnitude of forecast improvements resulting from correction of inefficiencies in USDA cotton forecasts over 1999/00 to 2008/09 marketing years. The aspects of forecast performance included in this study were 1) bias and trends in bias, 2) correlation between forecast error and forecast level, 3) autocorrelation in forecast errors, 4) correlation in forecast revisions. Data from monthly WASDE balance sheets for the U.S., China and world upland cotton over 1985/86 through 2008/09 including unpublished price forecasts was included in the empirical analysis.

Overall the results of this study demonstrated that some corrections of forecast inefficiencies, such as correction of correlation of error with forecast levels and correlation of error with previous year's error resulted in consistent improvement of USDA cotton forecasts, while correction for correlation in forecast revisions did not benefit the forecasts. The magnitude of improvements was as much as 540 thousand bales (or 22%) average reduction in MAE of world domestic use forecasts due to correction of correlation with forecast levels and 270 thousand bales (or 19%) average reduction in MAE of China's imports forecasts due to correction of correlation with past errors. Correction for bias yielded mixed results likely because USDA has already been applying those corrections to some of the categories and thus our analysis resulted in over-correcting.

The findings of this study focus on errors in USDA cotton forecasts. A lot of these errors are justified by challenges in forecasting supply and demand factors for a very dynamic industry undergoing structural changes and faced with data quality and availability issues from foreign countries. Regardless of these limitations USDA is providing a very important service to information-starved cotton market. In this sense this study will echo multiple previous authors that argue that USDA provide valuable information to market participants that can be used to accommodate and improve private forecasts and enhance welfare by reducing price uncertainty (e.g., Sanders and Manfredo, 2003; Isengildina, Irwin and

Good, 2006). However, it would be constructive if USDA would use the findings of this study to "learn from their mistakes." An on-going forecast quality analysis similar to the one presented in this study would allow USDA to identify problem areas in their forecasting procedures and to address them in a timely manner in order to ensure the highest quality of information that they provide. The framework developed in this study can be also be used by other agencies to monitor and improve the performance of their forecasts.

References

Allred, E., E. Gouge, and I. Maw, "R&D in the U.S. Department of Agriculture," In, Intersociety Working Group (ed.) AAAS Report XXXIII Research And Development FY 2009, American Association for the Advancement of Science, 2008.

Bailey, D.V., and B.W. Brorsen. "Trends in the Accuracy of USDA Production Forecasts for Beef and Pork." Journal of Agricultural and Resource Economics 23 (1998): 515–26.

Gunnelson, G., W. Dobson, and S. Pamperin. "Analysis of the Accuracy of USDA Crop Forecasts." *American Journal of Agricultural Economics*, 54(1972):639-645.

Irwin, S.H., M.E. Gerlow, and T.R. Liu. "The Forecasting Performance of Livestock Futures Prices: A Comparison to USDA Expert Predictions." Journal of Futures Markets, 14(1994): 861-875.

Isengildina, O. Irwin, S., and Darrel L. Good. "Evaluation of USDA Interval Forecasts of Corn and Soybean Prices," American Journal of Agricultural Economics, 86(2004): 990-1004.

Isengildina, O., S.H. Irwin, D.L. Good. "Are Revisions to USDA Crop Production Forecasts Smoothed?" American Journal of Agricultural Economics, 88(4) (2006): 1091-1104.

Isengildina, O. and S. MacDonald. "Cotton Prices and the World Cotton Market: Forecasting and Structural Change." Economic Research Report, Economic Research Service, U.S. Department of Agriculture, 2009.

MacDonald, S. "A Preliminary Evaluation of USDA's Export Forecasts," The 10th Federal Forecasters Conference 1999: Papers and Proceedings and Selected Papers of 19th International Symposium on Forecasting, U.S. Department of Education Office of Educational Research and Improvement, pages 305-316.

MacDonald, S. "Rational Commodity Forecasts: Improving USDA's Cotton Analysis," 12th Federal Forecasters Conference—Papers and Proceedings. 2002, Veterans Health Administration, U.S. Department of Veterans Affairs, 355-360.

MacDonald, S. "A Comparison of USDA's Agricultural Export Forecasts with ARIMA-based Forecasts," 14th Federal Forecasters Conference—Papers and Proceedings, 2005, Veteran's Health Administration, U.S. Department of Veterans Affairs, pages 155-161.

Nordhaus, W.D. "Forecasting Efficiency: Concepts and Applications." *Review of Economics and Statistics* 69(1987):667-674.

Office of Management and Budget, Statistical Programs of the United States Government Fiscal Year 2009. 2008.

Office of Management and Budget, Statistical Programs of the United States Government Fiscal Year 2010. 2009.

Pons, J. "The Accuracy of IMF and OECD Forecasts for G7 Countries." Journal of Forecasting 19 (2000): 53-63.

Sanders, D.R., and M.R. Manfredo. "USDA Production Forecasts for Pork, Beef, and Broilers: An Evaluation." Journal of Agricultural and Resource Economics 27 (2002): 114–28.

Thompson, J.M. "Analysis of the Accuracy of USDA Hog Farrowings Statistics." *American Journal of Agricultural Economics*, 34(1974):1213-1217.

Vogel, F.A., and G.A. Bange. 1999. "Understanding USDA Crop Forecasts." Miscellaneous Publication No. 1554, US Department of Agriculture, National Agricultural Statistics Service and Office of the Chief Economist, World Agricultural Outlook Board.

Table 1. Summary of Descriptive Statistics for WASDE Cotton Forecasts, 1985/86-2008/09

	Category	Production (M.Bal)	Imports (M.Bal)	Domestic Use (M.Bal)	Exports (M.Bal)	Ending Stocks (M.Bal)	Price (¢/lb)
World	Mean	92.42	28.80	93.23	28.46	40.58	N/A
	Std Deviation	14.50	5.35	13.22	5.82	10.87	N/A
	Coeff Variation (percent)	15.69	18.58	14.18	20.45	26.80	N/A
	Skewness	0.92	1.31	1.20	1.39	0.70	N/A
	Kurtosis	0.03	1.81	0.53	1.97	-0.29	N/A
China	Mean	22.94	3.72	26.79	0.76	12.56	N/A
	Std Deviation	6.01	4.76	10.63	0.90	4.85	N/A
	Coeff Variation (percent)	26.22	127.89	39.69	118.74	38.65	N/A
	Skewness	1.43	1.92	1.42	1.50	-0.11	N/A
	Kurtosis	1.19	3.94	0.63	1.53	-0.92	N/A
US	Mean	17.12	N/A	8.22	8.92	5.22	55.82
	Std Deviation	3.41	N/A	2.27	3.84	2.20	10.71
	Coeff Variation (percent)	19.89	N/A	27.61	43.04	42.21	19.19
	Skewness	-0.01	N/A	-0.35	0.63	0.84	-0.29
	Kurtosis	0.07	N/A	-0.87	-0.09	-0.03	0.12

Notes: N=24 years One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

Table 2. MAE of Unadjusted WASDE Cotton Forecasts, 1999/00-2008/09 Marketing Years.

			U.S.		_	_		China			World					
Month of Forecasting Cycle	Production	Exports	Domestic Use	Ending Stocks	Average Farm Price	Production	Imports	Domestic Use	Exports	Ending Stocks	Production	Imports	Domestic Use	Exports	Ending Stocks	
]	Million 48	0 lb. bales-		cents/lb		Mil	lion 480 lb.	bales			Mill	ion 480 lb. b	ales	,	
$1 \text{ May}_{(i)}$	1.90	2.27	0.73	1.70	9.44						5.96	3.72	3.84	3.84	7.22	
$2 \operatorname{June}_{(i)}$	1.90	2.30	0.68	1.65	9.34						5.64	3.60	4.10	3.83	7.54	
$3 \operatorname{July}_{(i)}$	2.02	2.24	0.61	1.63	6.58	2.88	3.56	2.99	2.99	3.27	4.99	3.57	3.91	2.99	7.08	
$4 \text{ August}_{(i)}$	1.56	2.06	0.56	1.80	5.44	2.78	3.37	2.79	2.79	3.19	4.02	3.35	3.73	2.79	6.47	
$5 \operatorname{September}_{(i)}$	1.19	1.91	0.51	1.78	5.79	2.53	2.95	2.65	2.65	3.11	3.72	3.02	3.66	2.65	6.25	
6 October _(i)	0.84	1.72	0.49	1.62	3.85	2.08	2.61	2.80	2.80	2.29	3.12	2.62	3.81	2.80	4.65	
7 November $_{(i)}$	0.43	1.49	0.44	1.47	3.10	1.54	2.18	2.31	2.31	2.16	3.01	2.20	3.48	2.31	4.56	
8 December _(i)	0.27	1.44	0.36	1.48	3.16	1.49	1.95	2.12	2.12	2.12	2.77	1.88	3.11	2.12	3.90	
9 January $_{(i+1)}$	0.13	1.34	0.32	1.33	2.33	1.09	1.66	1.84	1.84	2.38	2.18	1.44	2.81	1.84	3.46	
10 February $_{(i+1)}$	0.13	1.16	0.31	1.20	2.38	0.73	1.53	1.76	1.76	2.00	1.71	1.26	2.39	1.76	2.69	
11 $March_{(i+1)}$	0.13	0.78	0.27	0.80	1.68	0.79	1.01	1.46	1.46	2.11	1.49	0.82	1.73	1.46	2.51	
$12 \operatorname{April}_{(i+1)}$	0.05	0.64	0.24	0.63	1.63	0.79	0.75	1.31	1.31	2.07	1.23	0.76	1.66	1.31	2.58	
13 $May_{(i+1)}$		0.51	0.20	0.47	1.23	0.71	0.62	1.42	1.42	1.56	1.02	0.57	1.53	1.42	1.83	
14 $\operatorname{June}_{(i+1)}$		0.43	0.17	0.47	1.23	0.67	0.33	1.26	1.26	1.76	0.97	0.54	1.34	1.26	1.76	
15 $July_{(i+1)}$		0.30	0.15	0.43	1.03	0.51	0.29	1.00	1.00	1.14	0.77	0.49	1.14	1.00	0.92	
16 August _{$(i+1)$}		0.14	0.13	0.27	1.12	0.51	0.05	0.95	0.95	1.12	0.65	0.21	1.02	0.95	1.11	
17 September _{$(i+1)$}	1)	0.08	0.09	0.11	0.98	0.39	0.00	0.44	0.44	0.99	0.51	0.25	0.58	0.44	1.10	
18 October $_{(i+1)}$		0.00	0.00	0.04	0.53	0.00	0.00	0.10	0.10	0.25	0.06	0.18	0.23	0.10	0.51	
Average	0.88	1.16	0.35	1.05	3.38	1.22	1.43	1.70	1.70	1.97	2.44	1.69	2.45	1.94	3.68	

Notes: N=10 marketing years. May_i and June_i, forecasts for China were not published before 2005/06 and therefore were not included in this analysis.

Table 3. Change in MAE Resulting from the Correction of Bias in WASDE Cotton Forecasts, 1999/00-2008/09 Marketing Years.

			U.S.				World								
Month of Forecasting Cycle	Production	Exports	Domestic Use	Ending Stocks	Average Farm	Production	Imports	Domestic Use	Exports	Ending Stocks	Production	Imports	Domestic Use	Exports	Ending Stocks
		Million 48	30 lb. bales-		cents/lb		Milli	on 480 lb. b	ales			Millio	on 480 lb.	bales	
$1 \text{ May}_{(i)}$	-0.18	-0.05	0.04	0.00	-1.38						0.00	0.00	-0.44	0.00	2.63 *
$2 \operatorname{June}_{(i)}$	0.00	-0.04	0.04	0.00	-1.26						0.00	0.00	-0.43	0.00	2.91 **
$3 \text{ July}_{(i)}$	-0.17	-0.05	0.01	0.00	0.00	-0.29	-0.20	-0.20	-0.09	0.84	0.00	0.00	-0.36	0.00	2.15 *
$4 \text{ August}_{(i)}$	0.00	-0.04	0.02	0.00	0.00	-0.28	-0.19	-0.16	-0.08	1.21 *	0.00	0.00	-0.35	0.00	1.98 *
$5 \text{ September}_{(i)}$	0.00	0.08	0.01	0.00	0.00	0.13	-0.17	-0.08	-0.07	1.13 *	0.00	0.00	-0.36	-0.19	2.05 *
$6 \operatorname{October}_{(i)}$	-0.07	0.19	0.04	0.00	0.00	-0.43	-0.14	0.09	-0.06	0.72	0.00	0.00	-0.29	-0.19	1.67 *
7 November $_{(i)}$	0.00	-0.03	-0.04	0.00	0.00	-0.56	0.00	-0.09	-0.07	0.29	0.00	0.00	0.00	-0.15	1.29 *
$8 \operatorname{December}_{(i)}$	0.00	0.01	-0.04	0.00	-0.81	-0.47	0.00	-0.16	-0.06	0.70 *	0.00	0.00	0.00	0.00	0.60
9 January $_{(i+1)}$	-0.01	0.10	0.00	0.00	-0.49	0.02	0.00	-0.23	-0.05	0.85 *	0.00	0.00	0.00	0.00	0.79
10 February $_{(i+1)}$	-0.01	0.03	0.00	0.00	-0.26	-0.16	-0.06	0.00	-0.04	0.64 *	0.00	0.00	0.00	0.00	0.03
11 $March_{(i+1)}$	-0.01	-0.02	0.00	0.00	-0.14	-0.22	0.00	0.00	0.00	0.63 *	0.00	0.00	0.00	0.00	-0.34
$12 \operatorname{April}_{(i+1)}$	0.00	-0.06	0.00	0.00	-0.04	-0.02	0.00	-0.07	0.00	0.34	0.00	0.00	0.00	0.00	0.04
$13 \operatorname{May}_{(i+1)}$		-0.06	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	0.45 *	0.00	0.00	0.00	0.00	-0.36
14 $\operatorname{June}_{(i+1)}$		-0.03	0.00	0.00	-0.03	0.09	0.00	0.00	0.00	0.44 *	0.00	0.00	0.00	0.00	-0.05
15 $July_{(i+1)}$		-0.09	0.00	-0.05	-0.06	0.07	-0.02	0.00	0.00	0.21 *	0.00	0.00	0.00	0.00	-0.25
16 $\operatorname{August}_{(i+1)}$		-0.03	0.00	0.00	-0.06	0.07	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.07
17 September _{$(i+1)$}		-0.02	0.00	0.00	-0.08	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.03
18 October $_{(i+1)}$		0.00	0.00	-0.01	-0.25 **	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Average	-0.04 *	-0.01	0.00	0.00	-0.27 **	-0.13 **	-0.05 **	-0.06 **	-0.03 ***	0.54 ***	0.00	0.00	-0.12 **	-0.03 *	0.85 ***

Notes: N=10 marketing years. May_i and June_i, forecasts for China were not published before 2005/06 and therefore were not included in this analysis. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 4. Change in MAE Resulting from the Correction of Correlation with Forcast Levels in WASDE Cotton Forecasts, 1999/00-2008/09 Marketing Years.

			U.S.				World								
Month of Forecasting Cycle	Production	Exports	Domestic Use	Ending Stocks	Average Farm	Production	Imports	Domestic Use	Exports	Ending Stocks	Production	Imports	Domestic Use	Exports	Ending Stocks
		0 lb. bales-	cents/lb		Milli	on 480 lb. b	ales		Million 480 lb. bales						
$1 \operatorname{May}_{(i)}$	0.00	-0.10	-0.24	0.00	0.00						0.00	0.00	-1.47 ***	0.00	-0.29
$2 \operatorname{June}_{(i)}$	0.00	-0.13	-0.19	0.00	-0.40						0.00	0.00	-1.47 ***	0.00	-0.17
$3 \text{ July}_{(i)}$	-0.11	-0.10	-0.23	0.00	-1.10	0.00	0.00	-0.84	0.00	-0.16	0.00	0.00	-1.31 **	-0.53	-0.27
$4 \text{ August}_{(i)}$	-0.13	-0.06	-0.19	0.00	-1.54	0.00	0.00	-0.60	0.00	-0.15	0.00	0.00	-1.25 **	-0.52	-0.35
5 September $_{(i)}$	0.00	0.13	-0.20 *	0.00	-1.28	0.00	0.00	-0.50	0.00	-0.02	0.00	0.00	-0.84 *	-0.51	0.00
$6 \operatorname{October}_{(i)}$	0.00	-0.10	-0.09 *	0.00	-0.54	0.00	0.00	-0.37 *	0.00	-0.64	0.00	0.00	-0.65 *	-0.42	-0.59
7 November $_{(i)}$	0.00	-0.19	-0.05	0.00	0.00	0.00	0.00	-0.14	0.00	-0.30	0.00	0.00	-0.57 *	-0.33	0.00
8 December _(i)	0.00	-0.03	-0.02	-0.07	0.00	0.00	0.00	-0.15	0.00	-0.14	0.00	0.00	-0.28 *	0.00	0.00
9 January $_{(i+1)}$	-0.01	0.09	-0.03	0.00	0.00	0.00	0.00	-0.30	-0.09 **	-0.06	0.00	0.00	-0.29 *	-0.25	0.00
10 February _{$(i+1)$}	-0.01	0.02	-0.02	-0.03	0.00	0.00	0.00	-0.15	-0.09 **	-0.15	0.00	0.00	-0.19 *	0.00	0.00
11 $March_{(i+1)}$	-0.01	-0.07	-0.02	0.01	0.00	0.00	0.00	-0.16	-0.07	-0.08	0.00	0.00	-0.24 *	0.00	0.00
$12 \operatorname{April}_{(i+1)}$	0.00	-0.06	0.00	-0.07	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	-0.16	0.00	0.00
13 $May_{(i+1)}$		-0.04	0.00	-0.08	0.00	0.00	0.00	-0.15	-0.01	0.00	0.00	0.00	-0.20	0.00	0.00
14 $\operatorname{June}_{(i+1)}$		-0.13 *	0.00	0.00	0.00	0.00	0.00	-0.16	-0.05	0.00	0.00	0.00	-0.19	0.00	0.00
15 $\operatorname{July}_{(i+1)}$		-0.13 **	0.00	-0.01	0.00	0.00	0.00	-0.18	-0.05 ***	0.00	0.00	0.00	-0.18	-0.04	0.00
16 August _{$(i+1)$}		-0.04 *	0.00	0.00	0.00	0.00	0.00	-0.19	-0.03 **	0.00	0.00	0.00	-0.17	0.00	-0.08
17 September _{$(i+1)$}		-0.04 *	0.00	-0.01	0.00	0.00	0.00	-0.14	0.00	0.00	0.00	0.00	-0.16	-0.03	-0.26 *
18 October _{$(i+1)$}		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	0.00
Average	-0.02	-0.05 ***	-0.07 ***	-0.02 **	-0.27 **	0.00	0.00	-0.25 ***	-0.02 ***	-0.11 **	0.00	0.00	-0.54 ***	-0.15 ***	-0.11 **

Notes: N=10 marketing years. May_i and June_i, forecasts for China were not published before 2005/06 and therefore were not included in this analysis. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 5. Change in MAE Resulting from the Correction of Correlation of Error with Previous Error in WASDE Cotton Forecasts, 1999/00-2008/09 Marketing Years.

			U.S.					China			World					
Month of Forecasting Cycle	Productio n	Exports	Domestic Use	Ending Stocks	Average Farm	Production	Imports	Domestic Use	Exports	Ending Stocks	Productio n	Imports	Domestic Use	Exports	Ending Stocks	
		Million 48	30 lb. bales-		cents/lb	Million 480 lb. bales					Million 480 lb. bales					
$1 \text{ May}_{(i)}$	0.00	0.00	-0.05	0.00	-1.32						0.00	0.00	-0.41	0.00	0.00	
$2 \operatorname{June}_{(i)}$	0.00	0.00	-0.03	0.00	0.00						0.00	0.00	-0.36	0.00	0.00	
$3 \text{ July}_{(i)}$	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	-0.23	0.00	0.00	
4 August $_{(i)}$	0.00	0.00	0.04	0.00	0.00	0.00	0.00	-0.07	0.00	0.00	0.00	-0.58	-0.22	0.00	0.00	
5 September _(i)	0.00	0.00	0.00	0.00	0.00	0.00	-0.83	-0.08	0.00	0.00	0.00	-0.59	-0.21	0.00	0.00	
6 October _(i)	0.00	0.00	-0.07	0.00	0.00	0.00	-0.71	0.00	0.00	0.00	0.00	-0.50	0.00	0.00	0.00	
7 November _(i)	0.00	0.00	0.00	0.00	0.00	0.00	-0.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
8 December _(i)	0.00	0.00	0.00	0.00	-0.34	0.00	-0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
9 January $_{(i+1)}$	-0.02	0.00	0.00	0.00	-0.07	0.00	-0.54	0.00	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	
10 February _{$(i+1)$}	-0.02	0.00	0.00	0.00	0.00	0.00	-0.43	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	
11 $March_{(i+1)}$	-0.02	0.00	0.00	-0.04	0.00	0.00	-0.25	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	
$12 \operatorname{April}_{(i+1)}$	0.00	0.00	0.00	0.00	0.00	0.00	-0.22	-0.10	0.00	0.00	0.00	0.00	0.10	0.00	0.00	
13 $May_{(i+1)}$		0.00	0.00	0.00	0.00	0.00	0.00	-0.30	0.00	0.00	0.00	0.00	-0.02	0.00	0.00	
$14 \operatorname{June}_{(i+1)}$		-0.07	0.00	0.00	0.00	0.00	0.00	-0.53	0.00	0.04	0.00	0.00	-0.18	0.00	0.00	
15 $\operatorname{July}_{(i+1)}$		-0.08	0.00	0.00	0.00	0.00	0.00	-0.22	0.00	-0.02	0.00	0.00	-0.04	0.00	0.00	
16 August _{$(i+1)$}		-0.05	0.00	-0.01	0.00	0.00	0.00	-0.35	0.00	0.14	-0.20	0.00	-0.28	0.00	0.00	
17 September _{$(i+1)$})	-0.06	-0.09	0.00	0.00	0.00	0.00	0.00	0.00	-0.23	0.00	0.00	0.00	0.00	0.00	
18 October _(i+1)	,	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	
Average	0.00 *	-0.01 **	-0.01	0.00	-0.10	0.00	-0.27 ***	-0.10 **	0.00	0.00	-0.01	-0.09 *	-0.10 ***	0.00	0.00	

Notes: N=10 marketing years. May, and June, forecasts for China were not published before 2005/06 and therefore were not included in this analysis. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 6. Change in MAE Resulting from the Correction of Correlation in Revisions of WASDE Cotton Forecasts, 1999/00-2008/09 Marketing Years.

			U.S.					China			World							
Month of Forecasting Cycle	Production	Exports	Domestic Use	Ending Stocks	Average Farm	Production	Imports	Domestic Use	Exports	Ending Stocks	Production	Imports	Domestic Use	Exports	Ending Stocks			
		Million 48	80 lb. bales		cents/lb		Million 480 lb. bales					Million 480 lb. bales						
$1 \operatorname{May}_{(i)}$	0.00	0.00	0.00	0.00	0.00						0.00	0.00	0.00	0.00	0.00			
$2 \operatorname{June}_{(i)}$	0.00	0.00	0.00	0.00	0.00						0.00	0.00	0.00	0.00	0.00			
$3 \text{ July}_{(i)}$	0.00	0.06	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.15			
$4 \text{ August}_{(i)}$	0.00	0.00	0.00	-0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
$5 \text{ September}_{(i)}$	0.00	0.00	0.00	0.07	0.00	0.08	0.11	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.00			
$6 \operatorname{October}_{(i)}$	0.11	-0.03	0.00	0.00	0.00	0.00	0.21	0.07	0.00	0.00	0.00	0.11	0.03	0.00	0.00			
7 November $_{(i)}$	0.05 **	0.00	-0.01	0.01	0.00	0.00	0.36	-0.14	0.00	0.00	0.00	0.00	-0.08	0.00	0.00			
8 December $_{(i)}$	0.05	0.00	0.01	0.02	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.16	0.00	0.00			
9 January $_{(i+1)}$	-0.04	0.04	0.00	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.27			
10 February _{$(i+1)$}	0.00	0.04	0.01	0.08	0.00	0.00	-0.06	0.00	0.00	0.00	0.00	-0.02	0.14	-0.03	0.00			
11 $March_{(i+1)}$	0.00	-0.02	0.00	0.05	0.00	0.00	-0.05	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	-0.12			
$12 \operatorname{April}_{(i+1)}$	0.00	0.10	0.01	0.07	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00			
13 $May_{(i+1)}$		0.02	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
$14 \operatorname{June}_{(i+1)}$		0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	-0.05	0.00	0.00	0.00	0.01	0.00			
15 $July_{(i+1)}$		0.00	0.00	0.01	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02			
16 $August_{(i+1)}$		-0.02	0.00	-0.04	-0.02	0.00	-0.03	0.00	-0.02	0.00	-0.01	0.00	0.00	0.00	0.02			
17 September _($i+1$) 18 October _($i+1$)		0.01 0.00	0.00 0.00	-0.03 -0.01	0.00 0.00	0.00 0.00	0.00	0.00 -0.44	-0.03 0.00	0.00 0.00	0.00 0.00	0.00 0.00	-0.05 0.00	0.05 0.00	0.00 0.00			
Average	0.01	0.01	0.00	0.01	0.00	0.00	0.04	-0.03	0.00	0.00	0.00	0.01	0.02	0.00	0.00			

Notes: N=10 marketing years. May_i and June_i, forecasts for China were not published before 2005/06 and therefore were not included in this analysis. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1% levels, respectively.