An Evaluation of the USDA Sugar Production and Consumption Forecasts

by

Karen E. Lewis and Mark R. Manfredo

An Evaluation of the USDA Sugar Production and Consumption Forecasts

Karen E. Lewis

and

Mark R. Manfredo*

Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management
St. Louis, Missouri, April 16-17, 2012

* Karen E. Lewis is a Ph.D. Student (kelewis4@asu.edu) and Mark R. Manfredo is a Professor in the Morrison School of Agribusiness and Resource Management at Arizona State University, Mesa, Arizona.

An Evaluation of the USDA Sugar Production and Consumption Forecasts

The performance of the USDA domestic sugar production and consumption forecasts for marketing years 1993/1994 through 2009/2011 was evaluated. Using USDA sugar forecast information, U.S. sugar policy attempts to operate at no cost to the government by maintaining sugar prices above the government loan-rate. Results suggest no evidence that U.S. sugar policy is negatively impacted by the USDA sugar production and consumption forecasts. Also, new policies formed under the 2008 Farm Bill are not impaired by USDA sugar production and consumption forecasts. Overall, the results suggest that the USDA has done an outstanding job of forecasting domestic sugar production and consumption over the sample period.

Keywords: sugar, efficiency, forecast revisions, U.S. sugar policy, 2008 Farm Bill

Introduction

The 1990 Farm Bill, titled the Food, Agriculture, Conservation, and Trade Act of 1990 made it law that the United States Department of Agriculture (USDA) must begin estimating U.S. domestic production and consumption of sugar in its *World Agricultural Supply and Demand Estimates* (WASDE) monthly report (USDA 1). Therefore, on January 12, 1993, the first sugar production and consumption forecast appeared in the *WASDE* report. Every month since then, the USDA has projected total marketing year (October 1-September 30) U.S. sugar production and consumption in its WASDE report.

The goal of this paper is to evaluate the performance of the USDA sugar production and consumption forecasts. Evaluating the performance of the USDA sugar production and consumption forecasts is crucial because the Secretary of Agriculture uses the USDA sugar production and consumption forecasts to properly execute current U.S. sugar policy. Inaccurate and inefficient USDA sugar production and consumption forecasts could result in the Sectary of Agriculture allowing too many imports of sugar into the U.S., thus leading to the implementation of the sugar loan program which would result in the sugar program operating at a cost to the government. Given the importance of sugar production and consumption forecasts in determining sugar policy, the goal of this paper is to determine if inaccurate and inefficient USDA sugar production and consumption forecasts have contributed to improper execution of U.S. sugar policy.

U.S. Sugar Policy

U.S. sugar policy has three main aspects: (1) marketing allotments to U.S. sugar producers which are called the overall allotment quantity (OAQ), (2) a price support system which is a government loan rate set at 18 cents per pound for raw sugarcane and 22.9 cents per pound for refined beet sugar, and (3) tariff-rate quotas (TRQ) which are issued to 41 countries[1].
The Secretary of Agriculture's goal is to maintain the domestic price of sugar above the loan-rate when determining the TRQ and the OAQ (USDA 3). To accomplish this, the Secretary relies on the USDA sugar production and consumption forecasts. The 2008 Farm Bill, states that the

OAQ must not be less than 85% of estimated sugar deliveries for food or human consumption (USDA 2). TRQs are set at the beginning of the year and the 2008 Farm Bill allows the USDA to increase the TRQ on April 1st if the sugar market is under-supplied. Therefore, the USDA sugar production and consumption forecasts are critical to proper implementation of U.S. sugar policy and the goal of this analysis is to evaluate their performance.

Literature Review

Several previous studies have analyzed yearly production and price forecasts of livestock and commodities (e.g. Sanders, Manfredo and Boris 2007; Egelkraut, Garcia, Irwin and Good 2003; Bailey and Brorsen 1998). However, the USDA sugar production and consumptions forecasts are unique compared to many other commonly analyzed forecasts. The USDA predicts total marketing year production and consumption of sugar on a monthly basis in its *WASDE* report, thus creating a sequence of several forecasting revisions which all attempt to predict the final marketing year total production and consumption of sugar as contained in the WASDE. Therefore, this paper will use forecast revision analysis, also known as fixed event forecasting analysis, to evaluate the USDA sugar production and consumption forecasts. Similarly, Isengildina, Irwin, and Good (2006), Mills and Schroeder (2004), Thomson (1974) and Gunnelson, Dobson, and Pamperin (1972) have previously analyzed the USDA forecast revision process.

Nordhuas (1987) developed the formal framework used for determining the efficiency of forecasts by analyzing the forecast revision process. Nordhuas evaluated the forecast efficiency of macroeconomic factors, energy-consumption and oil-price forecasts by evaluating their respective forecast revisions. Clements (1997) advanced Nordhaus' framework to evaluate the efficiency of gross domestic product (GDP) growth and consumer price inflation (CPI) in the United Kingdom by evaluating their forecast revision process. Harvey, Leybourne and Newbold (2001) also determined forecast efficiency of GDP growth, inflation and unemployment in the United Kingdom by evaluating forecast revisions. Isengildina, Irwin, and Good (2006) advanced Nordhaus' revision analysis by investigating forecast revisions to determine if USDA crop production forecasts of corn and soybeans were efficient. They had 35 years of monthly forecast revisions for corn and soybean production. The sugar production and consumption forecasts use similar data which is conducive for the examination of the USDA sugar production and consumption revisions. Thus, this study will determine whether the USDA sugar production and consumption forecasts are accurate and efficient by analyzing the USDA revision process for sugar production and consumption. While previous macroeconomic and commodity forecasts have been analyzed, this is the first study that will determine the accuracy and efficiency of the USDA sugar production and consumption forecasts.

Data and Methods

Monthly estimates of domestic production and consumption of sugar from the monthly *WASDE* reports are used for this study. The first monthly revision forecast used in this study is from the January 12, 1993, *WASDE* issue. The last *WASDE* revision forecast considered in this study is from the November 10, 2011, issue. This results in 18 marketing years of monthly forecast revisions for domestic consumption and production of sugar.

Following Nordhuas (1987) methodology, they defined their forecasts as fixed-event forecasts because the series of monthly forecast revisions are related to the same terminal event (q_T^i) where T is the release month for the final estimate of crop production in the i^{th} marketing year. For this study, November is the release month (T) for the final estimate of sugar production and consumption for the marketing year running from October 1 through September 30.[2]

Following Isengildina, Irwin, and Good (2006), the forecast of the terminal event (T) for month t is denoted as q_t^i where t=1,…,T, and i=1993/1994,...,2010/2011 and the forecast revision at time t is denoted as $v_t^i = q_t^i - q_{t-1}^i$, where t=2,..,T, and i=1993/1994,...,2010/2011. Similar to the figure used by Isengildin, Irwin, and Good, figure 1 displays the revision process visually for marketing year 1993/1994. All marketing year revisions used in this study were created using the same method as the revisions in marketing year 1993/1994. Following Isengildina, Irwin, and Good sugar production and consumption forecast revisions are estimated in log percentage form:

(1)
$$v_t^i = 100 * \ln(q_t^i / q_{t-1}^i)$$
t=2,…,19; i=1993/1994,...,2010/2011,

where the forecasting cycle has a length of T=19 and the revision cycle has a length of T-1=18 for both production and consumption of sugar.

Table 1 and table 2 present the descriptive statistics for sugar production and consumption monthly revisions. On average, the largest forecasting revision for sugar production occurs during the first August considered in the revision process and the largest single monthly revision also occurred on the first August considered in the revision process. This makes sense because there is great uncertainty over how much sugar will be produced during the marketing year that early on in the forecasting sugar. On average, the largest forecasting revisions for sugar consumption took place during the second November considered in the revision process and the largest single month revision was 3.0% and occurred during the second June considered in the revision process. It makes sense that the second November considered in the revision process is the when the largest revision occurs because the second November in the USDA's revision process is when the final marketing year consumption is essentially realized.

Ultimately, there is little volatility in the USDA's sugar production and consumption forecasts which suggests the revision process is fairly accurate. The standard deviation and range of the sugar production revisions illustrate a decreasing pattern of change as the revisions approached the terminal month for the marketing year. This is consistent with expectations because it becomes more apparent what realized sugar production for the marketing year will be as the marketing year comes closer to an end. Interestingly, this pattern is not apparent for sugar consumption, which also is consistent with expectations because sugar consumption does not follow a growing cycle similar to sugar production. Sugar consumption is therefore likely to be more difficult to forecast than sugar production, because as the marketing years comes to an end, additional information regarding sugar consumption is not available like it is for sugar production.

Tests for bias in the sugar production and consumption revisions were also conducted and appear in table 1 and table 2. The sugar production and consumption forecasts do not indicate any evidence of any of the monthly forecasts being biased. The tests of bias, following Isengildina, Irwin, and Good (2006), simply test that the mean percentage revision for a particular month is equal to zero. If the mean percentage revision for a certain month is statistically different from zero, then the revisions are said to be biased.

Table 1 and table 2 demonstrate that there is essentially no bias in sugar production and consumption forecast revisions. Nordhaus (1987) methodology, presented in the next section, suggests that finding no bias in forecast revisions indicates that there is no bias in sugar production and consumption forecasts. However, unbiased forecast revisions are not the same as efficient forecast revisions. Despite being unbiased, forecast revisions can still be inefficient (Isengildina, Irwin, and Good 2006). The next section determines the efficiency of the USDA sugar production and consumption forecasts.

Forecast Efficiency

A strongly efficient forecast is one that incorporates all possible information into its forecast. Testing for strong form efficiency is not practical because it is essentially impossible to test if a forecast is incorporating all public and private information into its forecast (Nordhaus 1987). Therefore, Nordhaus (1987) presented methodology to test for weak form forecast efficiency. According to Nordhaus, a forecast is weak form efficient if it efficiently incorporates information regarding all past forecasts into its current forecast. Therefore, examining past forecast revisions for efficiency is sufficient when testing a forecast for weak form efficiency (Nordhaus 1987).

Nordhaus' methodology for testing if a forecast is weak form efficient begins by defining forecast errors in terms of forecast revisions

(2) $$e_t = q_T - q_t = v_{t+1} + v_{t+2} \dots + v_T,\ \ t = 1, \dots, T$$

where e_t is the forecast error at time t, q_T is the forecast of the terminal event, q_t is the forecast for time t and v_t is the forecast revision at time t. Equation (2) states that the forecast error in time period t is equal to the sum of the forecast revisions starting in time period t+1 and ending in terminal month T. For example, in terms of our data, the forecast error in time period 20 is equivalent to the sum of forecast revisions 21 through 24. Next, Nordhaus derived two propositions regarding weak form efficiency. The first proposition states that the forecast *error* at date t must be independent of all forecast revisions up to time t:

(3) $$E[e_t | v_t, \dots, v_2] = 0,\ \ t = 2, \dots, T-1.$$

To exemplify, equation (3) for t=5 is the following:

(4) $E[e_5|v_5, v_4, v_3, v_2] = 0.$

Equation (4) demonstrates that the error in time period five is independent of all forecast revisions that transpired prior to time period five. Norhaus' second proposition states that the forecast *revision* at date t is independent of all forecast revisions up to time t-1:

(5) $E[v_t|v_{t-1}, \ldots, v_2] = 0, \quad t = 3, \ldots, T.$

For example, forecast revision v_5 must be independent of forecast revisions v_4, v_3 and v_2 for the forecast to be efficient. From equation (2), forecast errors can be defined in terms of forecast revisions; thus, equation (3) and equation (5) imply each other. Because equation (3) and equation (5) imply each other, analyzing forecast revisions for independence (Nordhaus' proposition 2) is a sufficient test for weak form efficiency (Isengildina, Irwin, and Good 2006).

Equation (5), which is Nordhaus' proposition 2, implies that forecast revisions should follow a random walk. If forecast revisions do not follow a random walk and are correlated, a graph of the forecast revisions will appear smoothed because they are incorporating new information into the forecast too slowly; a graph of forecast revisions that are weak form efficient will appear jagged because the revisions incorporate information as soon as it becomes available (Nordhaus 1987). Alternatively, forecasts are inefficient if forecast revisions are correlated and forecast revisions move consistently up or down (Isengildina, Irwin, and Good 2006).

An obvious test of Nordhaus' proposition 2 is to calculate the first-order autocorrelation coefficient of the revisions and test whether it differs significantly from zero (Clements 1997). Therefore, the model used to test weak form efficiency is the following:

(6) $v_t = \alpha v_{t-1} + \varepsilon_t \qquad t = 3, \ldots 19$

where ε_t is the error term, v_t is the forecast revision at time t and the number of observations is equal to T-2=17. This equation estimates the first-order autocorrelation of revisions for terminal event T. The null hypothesis is that coefficient α=0. If the null hypothesis is rejected, this implies that the forecast revisions are inefficient. For this study 18 different regressions of this model were estimated for each of our 18 marketing years for sugar production and sugar consumption. While initially this appears to be a small sample, a sample size of 17 is consistent with previous studies. Isengildina, Irwin, and Good (2006) did not estimate equation (6) in their analysis because they only had a sample size of three. Nordhaus (1987) estimated equation (6) for five different marketing years and had number of observations for each year varying from 18 to 37. Clements (1997) estimated equation (5) with 14 observations and Harvey, Leybourne and Newbold (2001) estimated equation (6) with 24 observations. Clements did examine the idea of pooling revision data from all marketing years together into one dependent variable to overcome problems associated with his small sample size of 14. Therefore, in addition to estimating equation (6) for all of the marketing years, this model also incorporates Clements approach of pooling all of the marketing year revisions into one variable and then estimating equation (6). Table 3 shows the results of estimating this model for sugar production and consumption revisions for marketing years 1993/1994 through 2010/2011 as well as the results of estimating equation (6) with the pooled data.

The results in table 3 show that the null hypothesis of $\alpha=0$ was rejected at the 5% level for sugar production forecast revisions for marketing year 1994/1995 and marketing year 1999/2000. Table 3 shows that the null hypothesis of $\alpha=0$ was rejected at the 5% level for sugar consumption forecast revisions for marketing years 1998/1999, 2000/2001, 2009/2010 and the 2010/2011. These results suggest that the forecast revisions for sugar production were inefficient for the marketing years 1994/1995 and 1999/2000 and that the forecast revisions for sugar consumption were inefficient for marketing years 1998/1999, 2000/2001, 2009/2010 and 2010/2011. The sugar production estimated coefficients for marketing years 1994/1995, and 1999/2000 were positive 0.52 and 0.48 respectively. The sugar consumption α estimated coefficients for marketing years 1998/1999, 2000/2001 and 2009/2010 were positive 0.52, 1.16, 0.45 and 0.53. All of the significant coefficients are positive which indicates forecast "smoothing." Forecast smoothing indicates that a past history of positive revisions tends to be followed by further positive revisions (Nordhaus 1987). The positive significant coefficients for sugar production and consumption forecast revisions suggests that forecasters consistently display inefficiency in that they fail to incorporate all information from their own past forecasts into the current forecast. Nordhaus (1987) and Harvey, Leybourne and Newbold (2001) suggest that the positive autocorrelation reflects that forecasts react very slowly to new information as it accumulates and perhaps indicates reluctance among forecasters to deviate from the consensus in the previous period.

Inefficient forecasts found for sugar production for marketing years 1994/1995 and 1999/2000 and for sugar consumption for marketing years 1998/1999 and 2000/2001 may have caused the U.S. sugar program to operate at a cost to the government for these particular marketing years. Since marketing year 2001/2002, the U.S. sugar program has operated at no cost to the federal government (American Sugar Alliance 1). Therefore, the inefficient sugar production forecast for marketing year 1994/1995 and 1999/2000 and the inefficient sugar consumption forecasts in 1998/1999 and 2000/2001 may have been a reason that the price of sugar fell below the U.S. government loan-rate. For example, the Secretary of Agriculture may have relied on information from an inefficient sugar production or sugar consumption forecast and allowed too many foreign sugar imports into the U.S. during marketing years 1994/1995, 1998/1999, 1999/2000 and 2000/2001. However, overall results from estimating equation (6) suggest that the USDA is doing a good job of forecasting sugar production and consumption. As well, discovering only two inefficient marketing years for sugar production and only four inefficient marketing years for sugar consumption over a 18 year time frame is an excellent record. Discovering only a few inefficient marketing year forecasts indicates the USDA sugar production and consumption forecasts have been an excellent resource to the Secretary of Agriculture in determining the proper allocation of TRQs to foreign countries who import sugar into the U.S.

Monthly Comparisons of Forecast Efficiency

To further examine if sugar production and consumption forecasts have affected U.S. sugar policy decisions, monthly comparisons of sugar consumption and production revisions are examined. According to the 2008 Farm Bill, if the U.S. sugar market is under-supplied, the USDA can increase the TRQ on April 1 (American Sugar Alliance 2). Therefore, it is important to determine the efficiency of the monthly sugar production and consumption revisions. Therefore, methodology following Isengildina, Irwin, and Good (2006) will be used to test for monthly revision efficiency. Because Isengildina, Irwin, and Good were unable to use equation (6) to model their data because of degrees of freedom issues, they estimated the following model:

(7) $$v_t^i = \alpha v_{t-1}^i + \varepsilon_t \qquad i = 1993/1994, \ldots, 2010/2011$$

where ε_t is the error term, v_t^i is the revisions at month t for marketing year i and the number of observations is equal to the number of marketing years (N), which is 18 for our study. Therefore, all January revisions for all 18 marketing years are regressed against all December revisions and so forth for all of the monthly revisions in the revision process. This is different from equation (6) because instead of estimating all revisions for marketing year 1993/1994, we are analyzing the revisions from month to month. In addition to estimating monthly revision correlations, an approach created by Clements (1997) of pooling data and then estimating equation (7) is also used.

The results from table 4 indicate autocorrelation between consecutive sugar production revisions for months 2nd August/2nd July at the 5% level of significance. Table 4 results indicate autocorrelation between consecutive sugar consumption revisions for months September/August and 2nd August/2nd July at the 5% level of significance. Estimated significant coefficients ranged from -0.47 to positive 0.58. Forecast revisions are estimated in percentage form; thus, they may be interpreted as point elasticicites (Isengildina, Irwin, and Good 2006). The 0.58 coefficient for 2nd August versus 2nd July sugar consumption revisions means that a one percent positive revision in 2nd July is expected to be followed by a 0.62% positive revision in 2nd August. The pooled regression coefficients were not significant for sugar production or sugar consumption.

Once again, these results indicate that the USDA is doing a good job forecasting sugar production and consumption compared to the revisions that have been examined for other commodities. Isengildina, Irwin, and Good (2006) discovered several incidences of inefficiency in the USDA revision process for soybeans and corn. Isengildina, Irwin, and Good results suggested smoothing in every monthly revision for corn, including their pooled results. In the case of soybeans, Isengildina, Irwin, and Good. discovered smoothing in the pooled results and evidence of smoothing in one of the three monthly revisions. Compared to Isengildina et al. results, the USDA does a much better job of forecasting sugar production and consumption than forecasting corn and soybean production. Possible reasons the USDA forecasts for sugar production and consumption are more efficient than the USDA forecasts of corn and soybean production involve differences between U.S. sugar production compared to U.S. corn and soybean production. Sugar, which is produced from both sugarbeets and sugar cane, is only grown in a few states in the U.S while corn and soybeans are produced in several states. In 2009 sugarbeets were grown in 11 states and sugarcane was grown in four states. Meanwhile, soybeans are grown in 31 states and corn is grown in 48 states.

Estimating equation (7) provides no evidence for sugar policy inefficiencies associated with the 2008 Farm Bill mandating April 1 as the official USDA TRQ reallocation date. The USDA does not publish its WASDE sugar production and consumption estimates until the middle of each month; therefore, it relies on forecast estimates from the March *WASDE* when determining whether to increase the TRQ. Estimating equation (7) reveals the March revisions for sugar production and consumption were efficient at the 5% significance level.

Sugar Forecasting Accuracy

To further test the performance of the 2008 Farm Bill policy of making April 1 the TRQ reallocation date, the next section will determine how the sugar production and consumption revisions from the March forecast have performed over time. The March forecast revision sequences for sugar production and consumption have proven to be unbiased and efficient. In addition to being unbiased and efficient, it is possible that the March forecast revision sequences have improved or worsened over the past 18 years that the USDA has been publishing the estimates in the *WASDE*. It is possible that predicting sugar production has become more difficult because of increased globalization and increases in the number of free trade agreements the U.S. has signed. For example, under the North American Free Trade Agreement (NAFTA), starting January 1, 2008 sugar from Mexico now can enter the U.S. tariff free (USDA 4). According to the USDA, "the main challenge to the U.S. sugar program comes from sugar imports from Mexico that now enter duty-free under the terms of the NAFTA (USDA 2)." Forecasting sugar consumption may have also become more complicated to forecast because of the addition of several new artificial sweeteners substitutes (e.g. Splenda, Stevia) into the market which could change consumers' consumption behaviors regarding sugar.

The following model will be utilized to determine if forecasting sugar production and consumption has become more difficult over time:

(8) $|\xi_t| = \theta_1 + \theta_2 Trend_t + u_t, \quad t = 1, \ldots, 18$

where $|\xi_t|$ is the absolute value of the forecast error at time t, $Trend_t$ is a time trend variable equal to the 1 through 18, and $u_t$is the random disturbance term (Bailey Brorsen 1998). Only 18 observations are used to model equation (8), which is a small sample size and may indicate our results are not very robust. Modeling equation (8) results in four different regressions. The forecast error (ξ_t) in the first regression is equal to the difference between the sugar production estimate in March and the actual (realized) total marketing year sugar production. Similarly, the error in the second regressions is equal to the difference between the sugar consumption estimate in March and the realized total marketing year sugar consumption. The null hypothesis of equation (8) is that $\theta_2 = 0$. A failure to reject the null suggests that, over time, there is no systematic increase or decrease in the absolute value of the forecast error, $|\xi_t|$. If the null hypothesis is significant, then forecasts have either improved or worsened over time. If θ_2 is negative ($\theta_2 < 0$) then the forecast has improved over time. Otherwise, if θ_2 is positive ($\theta_2 > 0$) then the forecast has worsened over time. Table 5 displays the results of estimating equation (8).

The estimated θ_2 is not significant for sugar production or sugar consumption forecasts for the March forecasts. The results suggest that there is no evidence that sugar production and consumption forecasts associated with the April 1 TRQ reallocation date have become better or worse through time.

Future Research

The previous section determines that the sugar production forecast has not worsened over time despite an increase in the number of countries being able to import sugar into the U.S. tariff free because of free trade agreements. The USDA has stated that Mexican sugar that now enters the market tariff free may increase the difficulty of implementing U.S. sugar policy (USDA 2). To help make this transition smoother, the 2008 Farm Bill made it law that the Secretary of Agriculture must collect information on production, consumption, stocks and trade of sugar in Mexico and publish this information in each edition of the USDA's monthly WASDE (USDA 3). Therefore, determining the accuracy and efficiency of the USDA forecast of monthly Mexican imports into the U.S. is also important to analyze when determining how efficiently U.S. sugar policy is operating.

Using Nordhaus (1987) methodology used previously, equation (6) was estimated for Mexican sugar imports into the U.S. However, because it wasn't until January 1, 2008, that Mexican sugar started being imported tariff free under NAFTA rules, there are only two complete marketing year to examine to determine if the forecast was efficient. Using 17 observations, marketing year 2009/2010 and 2010/2011 was estimated using equation (6). The results from this regression are presented in table 6 and suggest that Mexican forecasts of sugar imports into the U.S. have been efficient. The accuracy and efficiency of the Mexican sugar imports into the U.S. forecast is an area that can be analyzed in the future as free trade of sugar between the U.S. and Mexico advances.

Summary and Conclusions

Determining the accuracy and efficiency of the USDA sugar production and consumption forecast is important for several reasons. From a methodological perspective, evaluating the USDA sugar production and consumption forecast is important because this paper continues to add to literature that examines the USDA forecasting revision process (Isengildina, Irwin, and Good 2006; Mills and Schroeder 2004; Thomson 1974; and Gunnelson, Dobson, and Pamperin 1972). Of those studies, only Isengildina, Irwin, and Good (2006) used Nordhaus (1987) methodology for their analysis. Evaluating the USDA sugar production and consumption forecast is also important from a policy perspective. When implementing U.S. sugar policy the Secretary of Agriculture must rely heavily on the USDA sugar production and consumption forecast in order to determine how many foreign sugar imports are allowed into the U.S. each year. Inaccurate and inefficient USDA sugar production and consumption forecasts may cause the Secretary of Agriculture to allow too many foreign sugar imports into the U.S., thus causing the price of sugar to fall below the government loan-rate. This would cause the U.S. sugar program to operate at a cost to the government; a situation that is currently the goal of U.S. sugar policy to avoid according to the 2008 Farm Bill.

Nordhaus (1987) methodology determined marketing years 1994/1995, 1998/1999, 1999/2000 and 2000/2001 to all be marketing years when either the sugar production or sugar consumption forecasts were inefficient. According to the American Sugar Alliance (2011), the U.S. sugar program has operated at no cost to the government since marketing year 2001/2002. This indicates that inefficient sugar production and consumption forecasts during marketing years 1994/1995, 1998/1999, 1999/2000 and 2000/2001 may have led to the U.S. allowing too many sugar imports into the U.S., thus lowering the price of sugar below the government loan-rate.

Overall, the USDA has done a good job forecasting domestic sugar production and consumption. Based on Nordhaus (1987) methodology, there are very few marketing years when the sugar production and consumption forecasts are inefficient. There are also very few inefficiencies in adjacent monthly forecasts as tested by methodology created by Isengildina, Irwin, and Good (2006). Bias in the sugar production and consumption forecast revisions also rarely exists. Additionally, there is no evidence of USDA sugar production and consumption forecasts worsening over time. New policies formed under the 2008 Farm Bill are not negatively impacted by USDA sugar production and consumption forecasts. Together these results suggest that the USDA has does an outstanding job of forecasting domestic sugar production and consumption from marketing year 1993/1994 through 2010/2011.

References

American Sugar Alliance (1). 2011. Press Releases. Sugar Policy Projected to Reach Two-Decade Milestone. http://www.sugaralliance.org/newsroom/sugar-policy-projected-to-reach-two-decade-milestone.html. Accessed May 23, 2011.

American Sugar Alliance (2). 2012. U.S Sugar Policy. How it Works. http://www.sugaralliance.org/images/stories/Sugar_Fact_Sheets_2012/how-it-works.pdf. Accessed April 12, 2012.

Bailey, DeeVon and B.Wade Brorsen. 1998. Trends in the Accuracy of USDA Production Forecasts for Beef and Pork. *Journal of Agricultural and Resource Economics.* 23:515-525.

Clements, Michael P. 1997. Evaluating the Rationality of Fixed-Event Forecasts. *Journal of Forecasting* 16:225-239.

Egelkraut, Thorsten M., Philip Garcia, Scott H. Irwin, and Darrel L. Good. 2003. An Evaluation of Crop Forecast Accuracy for Corn and Soybeans: USDA and Private Information Agencies. *Journal of Agricultural and Applied Economics* 25:79-95.

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

Harvey, I. David, Stephen J. Leybourne, and Paul Newbold. 2001. Analysis of a Panel of UK Macroeconomic Forecasts. *Econometrics Journal* 4:S37-S55.

Isengildina, Olga, Scott H. Irwin and Darrel L. Good. 2006. Are Revisions to USDA Crop Production Forecasts Smoothed? *American Journal of Agriculture Economics* 88,4:1091-1104.

Mills, Jeffery B. and Ted C. Schroeder. 2004. Are Cattle on Feed Report Revisions Random and Does Industry Anticipate Them? *Journal of Agribusiness.*20, 3: 363-374.

Nordhaus, William D. 1987. Forecasting Efficiency: Concepts and Applications. *The Review of Economics and Statistics.* 4:667-674.

Sanders, R. Dwight, Mark R. Manfredo, Keith Boris. 2007. Accuracy and Efficiency in the U.S. Department of Energy's Short-Term Supply Forecasts. *Journal of Energy Economics.* 30:1192-1207.

Thomson, James M. 1974. Analysis of the Accuracy of USDA Hog Farrowing Statistics. *American Journal of Agricultural Economics*. 56:1213-1217.

United States Department of Agriculture. (1). 2011. Economic Research Service. Provisions of the Food, Agriculture, Conservation, and Trade Act of 1990. http://www.ers.usda.gov/publications/aib624/. Accessed March 12, 2011.

United States Department of Agriculture. (2). 2011. Economic Research Service. 2008 Farm Bill. http://www.ers.usda.gov/farmbill/2008/titles/titleicommodities.htm#sugar. Accessed March 10, 2011.

United States Department of Agriculture. (3). 2011. Economic Research Service. Sugar and Sweeteners: Policy. http://www.ers.usda.gov/Briefing/Sugar/Policy.htm. Accessed March 11, 2011.

United States Department of Agriculture. (4). 2011. Economic Research Service. Sugar and Sweeteners: Policy. http://www.ers.usda.gov/Briefing/Sugar/Trade.htm. Accessed June 20, 2011.

Footnotes

---

[1]The price support system is a nonrecourse loan program operated by the USDA Commodity Credit Corporation.

[2]For example, sugar production and consumption estimates for marketing year 1993/1994 (October 1st, 1993-September 30, 1994) begin being estimated in May, 1993, and continue being estimated monthly through November, 1995.

Tables

Table 1. Descriptive Statistics and Test of Bias for Sugar Production Revisions (Percent): 1993/1994-2010/2011 Marketing Years

Revision Month	Mean	Mean Abs. Value	Std. Dev.	Min	Max	Range	Test of Bias t-Stat	Test of Bias p-Value
June	-0.05	0.05	0.16	-0.62	0.00	0.62	-1.34	0.20
July	-0.09	0.78	1.16	-3.63	1.39	5.01	-0.32	0.75
August	0.22	1.52	1.99	-3.23	4.49	7.72	0.47	0.64
September	-0.16	1.01	1.37	-3.52	1.47	4.99	-0.49	0.63
October	-0.09	0.77	1.54	-5.27	2.67	7.94	-0.24	0.81
November	-0.54	1.46	2.01	-4.57	3.35	7.93	-1.14	0.27
December	0.31	1.24	1.54	-3.27	2.59	5.87	0.86	0.40
January	-0.03	0.97	1.20	-1.51	2.55	4.06	-0.11	0.92
February	-0.02	0.57	0.87	-1.24	1.85	3.09	-0.11	0.91
March	-0.27	0.54	0.67	-1.48	1.28	2.76	-1.72	0.10
April	-0.24	0.47	0.57	-1.41	0.75	2.16	-1.81	0.09
May	-0.04	0.46	0.77	-1.24	2.59	3.83	-0.25	0.81
2nd June	-0.13	0.42	0.60	-1.76	0.84	2.60	-0.91	0.30
2nd July	-0.15	0.36	0.61	-1.46	1.22	2.68	-1.06	0.30
2nd August	0.19	0.35	0.49	-0.72	1.33	2.05	1.67	0.11
2nd September	0.00	0.33	0.54	-1.27	1.24	2.52	-0.02	0.99
2nd October	-0.09	0.41	0.63	-1.55	1.24	2.79	-0.59	0.57
2nd November	-0.16	0.52	0.65	-1.64	1.19	2.83	-1.01	0.33

*Note: The forecasting revision cycle includes 18 months; therefore 2nd June refers to the 2nd June in the forecasting revision cycle and so forth.

Table 2. Descriptive Statistics and Test of Bias for Sugar Consumption Revisions: 1993/1994-2010/2011 Marketing Years

	Descriptive Statistics for Revisions (Percent)							
		Mean	Std.				Test of Bias	
Revision Month	Mean	Abs. Value	Dev.	Min	Max	Range	t-Stat	p-Value
June	-0.09	0.21	0.56	-2.05	1.03	3.08	-0.69	0.50
July	0.17	0.17	0.45	0.00	1.68	1.68	1.60	0.13
August	0.10	0.35	0.76	-1.18	1.96	3.14	0.57	0.57
September	0.03	0.26	0.73	-1.53	2.59	4.12	0.17	0.87
October	0.21	0.27	0.48	-0.49	1.58	2.07	1.88	0.08
November	-0.22	0.46	0.87	-2.61	1.00	3.61	-1.07	0.30
December	0.11	0.11	0.30	-0.05	1.17	1.23	1.53	0.14
January	-0.01	0.01	0.04	-0.15	0.00	0.15	-1.00	0.33
February	-0.28	0.43	0.71	-2.16	1.14	3.30	-1.69	0.11
March	0.05	0.29	0.53	-1.02	1.07	2.09	0.44	0.67
April	-0.16	0.23	0.45	-1.50	0.37	1.87	-1.54	0.14
May	0.13	0.58	0.89	-1.44	1.77	3.21	0.63	0.54
2nd June	0.31	0.34	0.80	-0.22	3.00	3.21	1.66	0.11
2nd July	0.18	0.20	0.45	-0.11	1.70	1.80	1.72	0.10
2nd August	0.13	0.36	0.57	-1.03	1.15	2.18	0.96	0.35
2nd September	-0.11	0.22	0.45	-1.20	0.95	2.15	-1.07	0.30
2nd October	0.07	0.40	0.63	-1.05	1.51	2.56	0.48	0.64
2nd November	0.24	0.90	1.27	-2.41	2.81	5.23	0.80	0.43

*Note: The forecasting revision cycle includes 18 months; therefore 2nd June refers to the 2nd June in the forecasting revision cycle and so forth.

Table 3. Weak Form Efficiency Test Results: 1993/1994-2010/2011 Marketing Years

Marketing	Sugar Production			Sugar Consumption		
Year Forecast	Coefficient	t-Stat	p-value	Coefficient	t-Stat	p-value
1993/1994	0.10	0.40	0.69	0.11	0.42	0.68
1994/1995	0.52	2.37	0.03	0.09	0.37	0.72
1995/1996	0.10	0.41	0.69	0.04	0.15	0.89
1996/1997	0.25	1.03	0.32	0.02	0.09	0.93
1997/1998	0.39	1.55	0.14	0.01	0.04	0.97
1998/1999	0.20	0.83	0.42	0.52	2.41	0.03
1999/2000	0.48	2.19	0.04	0.28	0.84	0.41
2000/2001	0.02	0.08	0.94	1.16	7.20	0.00
2001/2002	0.09	0.37	0.72	0.24	0.77	0.45
2002/2003	0.00	0.00	1.00	-0.46	-1.30	0.21
2003/2004	-0.29	-1.13	0.27	0.05	0.21	0.84
2004/2005	0.24	1.00	0.33	0.36	1.10	0.29
2005/2006	-0.08	-0.32	0.75	0.18	0.74	0.47
2006/2007	0.04	0.17	0.87	0.00	0.00	1.00
2007/2008	0.18	0.72	0.48	0.20	0.80	0.44
2008/2009	-0.01	-0.04	0.97	-0.10	-0.29	0.72
2009/2010	-0.14	-0.55	0.59	0.45	2.15	0.05
2010/2011	0.43	1.89	0.08	0.53	2.50	0.02
Pooled	0.06	1.11	0.27	0.06	1.15	0.25

Note: Tests use the OLS regression $v_t = \alpha v_{t-1} + \varepsilon_t$ and N=17. The pooled regression N=306

Table 4. Isengildina, Irwin, and Good (2006) Weak Form Efficiency Test Results: 1993/1994-2010/2011 Market Years

Dependent Variable	Independent Variable	*Sugar Production* Coef.	t-stat	p-value	*Sugar Consumption* Coef.	t-stat	p-value
July	June	0.00	0.00	1.00	0.00	0.00	1.00
August	July	0.27	0.65	0.52	-0.07	-0.18	0.86
September	August	-0.07	-0.43	0.67	0.50	2.51	0.02
October	September	-0.11	-0.39	0.70	0.23	1.42	0.17
November	October	0.27	0.84	0.41	0.26	0.64	0.53
December	November	0.09	0.52	0.61	-0.08	-0.92	0.37
January	December	-0.08	-0.44	0.67	-0.04	-1.72	0.10
February	January	-0.01	-0.08	0.93	0.00	0.00	1.00
March	February	0.37	2.01	0.06	0.17	1.01	0.33
April	March	0.36	1.87	0.08	0.22	1.05	0.31
May	April	0.33	1.16	0.26	0.56	1.27	0.22
2nd June	May	0.18	0.97	0.35	-0.25	-1.12	0.28
2nd July	2nd June	0.41	1.80	0.09	0.23	1.88	0.08
2nd August	2nd July	-0.47	-2.75	0.01	0.58	2.27	0.04
2nd September	2nd August	0.28	1.15	0.27	0.01	0.04	0.97
2nd October	2nd September	0.30	1.09	0.29	0.25	0.76	0.46
2nd November	2nd October	0.37	1.55	0.14	0.13	0.26	0.80
Pooledt	Pooledt-1	-0.03	-0.55	0.58	0.08	1.46	0.15

Note: Tests use the OLS regression $v_t^i = \alpha v_{t-1}^i + \varepsilon_t$ where v_t^i is the percentage revision in month t and N=18 except for the pooled version which has (T-2)*N=323 observations.

Table 5. Time Improvement Test, $|\xi_t| = \theta_1 + \theta_2 Trend_t + u_t$, Marketing Years 1993/1994-2010/2011

	March (April 1 TRQ adjustment date)
Sugar Production	
estimated	-0.024
(t-statistic)	(-0.43)
p-value	0.675
Sugar Consumption	
estimated	0.16
(t-statistic)	(1.56)
p-value	0.138*

* Standard errors for the sugar consumption regression was estimated with White's covariance estimator

Table 6. Mexico Weak Form Efficiency Test Results: 2009/2010 & 2010/2011 Marketing Years

Marketing Year Forecast	Coefficient	t-stat	p-value
2009/2010	0.02	0.07	0.95
2010/2011	0.10	0.80	0.43

Note: Tests use the OLS regression $v_t = \alpha v_{t-1} + \varepsilon_t$ and N=17.

Figures

Figure 1. Forecast Revisions For Marketing Year 1993/1994