NCCC-134

APPLIED COMMODITY PRICE ANALYSIS, FORECASTING AND MARKET RISK MANAGEMENT

An Evaluation of How Forecasting Efficiency Leads to Reduced Firm Risks

by

Karen L. DeLong, Carlos O. Trejo-Pech, and Robert Johansson

Suggested citation format:

DeLong, K. L., C. O. Trejo-Pech, and R. Johansson. 2024. “An Evaluation of How Forecasting Efficiency Leads to Reduced Firm Risks.” Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. [http://www.farmdoc.illinois.edu/nccc134].

An Evaluation of how Forecasting Efficiency Leads to Reduced Firm Risks

Karen L. DeLong, Carlos O. Trejo-Pech, and Robert Johansson*

Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2024.

Acknowledgment: Support for this project was provided by the American Sugar Alliance.

* Karen L. DeLong (kdelong39@utk.edu) and Carlos O. Trejo-Pech (ctrejope@utk.edu) are Associate Professors at the Department of Agricultural and Resource Economics, University of Tennessee, Knoxville, TN. Robert Johansson (rob@sugaralliance.org) is Director of Economics and Policy Analysis at American Sugar Alliance, Arlington, VA.

An Evaluation of how Forecasting Efficiency Leads to Reduced Firm Risks

The United States (US) Department of Agriculture (USDA) World Agricultural Supply and Demand Estimates (WASDE) provides forecasts of domestic sugar production and consumption as well as Mexican sugar production. These forecasts are used to assist the USDA in the implementation of US sugar policy. Therefore, this study evaluates the accuracy, bias, and efficiency properties of the USDA WASDE sugar forecasts. Results indicate USDA WASDE domestic sugar production and consumption forecasts, and Mexican sugar production forecasts, are accurate, unbiased, and efficient. US sugar policy helps to ensure the predictability of sugar-related forecasts, which may then generate positive economic effects for sugar-using firms (SUFs) that rely on reliable knowledge and ability to hedge supplies of an important production input. We postulate that forecast predictability, in turn, reduces SUFs' risks compared to other agribusinesses. We further postulate that a lower risk environment leads to a superior economic environment for SUFs in which they can financially outperform other agribusiness firms.

Keywords: Sugar production, sugar consumption, fixed event forecasts.

Introduction

The Sweetener Users Association claims that the United States (US) sugar program negatively affects sugar-using firms (SUFs) because those manufacturers cannot purchase lower-priced world-market sugar. However, Trejo-Pech et al. (2023) documented that SUFs report higher profits and lower risk than their agribusiness (AGB) peers and the whole US market over the last decade. The authors argue that this solid economic performance can in part be explained by the economic benefits SUFs indirectly receive from the implementation of US sugar policy. We posit that due to the mechanisms of US sugar policy, SUFs operate in a more reliable, resilient, and stable domestic sugar market that supplies a relevant portion of the SUFs' needs. That accrues increased profitability and reduced risk for SUFs. The goal of this study is to attempt to measure those potential economic benefits experienced by SUFs by first evaluating government forecasts of sugar supplies for domestic purchases of sugar. We hypothesize that US sugar policy facilitates accurate and efficient sugar-related forecasts, which then produce a cascading positive economic effect for SUFs.

Specifically, this study examines the accuracy, biasness, and efficiency of the United States Department of Agriculture (USDA) *World Agriculture Supply and Demand Estimates* (*WASDE*) sugar forecasts. The analysis will update Lewis and Manfredo's (2012) evaluation of the USDA *WASDE* sugar production and consumption forecasts. They documented that the *WASDE* monthly forecasts were accurate and efficient except for a couple of years. Their analysis covered fiscal years (FYs) 1993/94 to 2010/11. This study extends the analysis from FY 2010/11 to FY 2022/23 and to the analysis of *WASDE* Mexican sugar production forecasts that have been included in the *WASDE* since the 2008/09 crop year (USDA, 2024).

The existence of accurate and efficient predictions for a commodity—at no cost for the firms operating in that industry—is likely to contribute to risk reduction in that industry because firms should be able to prepare more accurate production and financial budgets. While other recent studies have evaluated USDA *WASDE* forecasts (Bora, Katchova, and Kuethe 2021; Ding and Katchova 2023; Isengildina-Massa, Karali, and Irwin 2013), none have included sugar data in their evaluation since Lewis and Manfredo's 2012 study.

US Sugar Policy

US sugar policy, including a trade agreement with Mexico, domestic marketing allotments, and a tariff rate quota (TRQ) system, allows the USDA to ensure the domestic price of sugar remains above the government loan rates for raw sugarcane and refined beet sugar (USDA Economic Research Service (ERS), 2024). The Suspension Agreements for sugar between the US and Mexico sets minimum prices (that are above the aforementioned loan rates) and maximum quantities for sugar shipped into the US (USDA ERS, 2024). Approximately forty other countries have access to the World Trade Organization (WTO) TRQ for sugar, which provides near duty-free access to the US market.

The USDA has been surveying sugar refining companies and farmers in order to publish the *WASDE* domestic sugar forecasts since FY 1993/94. To determine how much sugar from Mexico to allow into the US to stay in compliance with the Mexican suspension agreement, the USDA relies on the *WASDE* Mexican sugar production forecast. When NAFTA became fully effective for sugar in 2008, the USDA was also tasked with including Mexican sugar production forecasts in the *WASDE* (Lewis and Manfredo, 2012). Therefore, in FY 2008/09, the *WASDE* began including Mexican sugar production forecasts. There are several policy implications associated with the accuracy and efficiency of the *WASDE* sugar forecasts.

Data

The USDA routinely asks all domestic producers of sugarbeets and sugarcane their levels of production and also asks domestic beet sugar and cane sugar-producing companies their levels of production and sales. Those surveys are mandatory. Each month, USDA publishes the *WASDE* and provides estimates of domestic production and consumption of sugar as well as estimates Mexican sugar production. Lewis and Manfredo (2012) evaluated the domestic production and consumption forecasts from FY 1993/94 through 2010/11. Provided a complete FY of Mexican estimates did not appear until FY 2009/10, only one year of Mexican production forecasts were evaluated by Lewis and Manfredo. Therefore, this paper will analyze the domestic production and consumption forecasts for FYs 1993/94 through 2022/23 as well as the Mexican production forecasts for FYs 2009/10 through 2022/23.

The *WASDE* sugar forecasts are fixed-event forecasts. Therefore, the methods utilized follow Nordhuas's (1987) framework for evaluating fixed-event forecasts. Using this framework, the terminal event forecast is q_T^i where T is the month of the final estimate of sugar production and consumption in FY i. We consider November as the terminal event, T, for the final estimate of sugar production and consumption even though the USDA does, at times, provide some updates to that number. The sugar FY is October 1 through September 30.

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*. For the domestic sugar production and consumption forecasts, *i*=1993/94,...,2022/23 and the forecast revision at time *t* is denoted as $v_t^i = q_t^i - q_{t-1}^i$, where t=2,..,*T*. For the Mexican production forecasts, *i*=2009/10,…,2022/23 and the forecast revision at time *t* is defined the same as the domestic forecasts. Similar to Isengildina, Irwin, and Good, we estimate the forecast revisions in log percentage form:

(1)
$$v_t^i = 100 * \ln\left(q_t^i / q_{t-1}^i\right)$$
$$t=2,\ldots,19$$

To exemplify how the production forecasts are estimated, for FY 2011/12 (e.g., September 2011/ October 2012), the first forecast appears in the May 2011 *WASDE* and we assume the terminal forecast, *T*, occurs in November 2012
[1]. Thus, June 2011 contains the first revision to the forecast and there are a total of 18 revisions until November 2012 when the terminal forecast occurs and total FY production is essentially known. This process is the same for the domestic and Mexican sugar production forecasts and for sugar consumption.

Methods

Bias Tests

Following Isengildina, Irwin, and Good (2006), tests of bias were conducted to determine whether the mean percentage revision (MPR) is equal to zero. If the MPR is statistically different from zero, then the revisions are said to be biased. If the MPR is positive (negative), this indicates consistent underestimation (overestimation) of sugar production or consumption. Bias tests were conducted on revisions outlined in equation (1) within each FY and, for the domestic forecasts, among adjacent months across all FYs.

FY Weak Form Efficiency Tests

Provided it is essentially impossible to test if a forecast is strongly efficient, we follow Nordhaus's (1987) methodology to test for weak form forecast efficiency. This test involves calculating the first-order autocorrelation coefficient of the forecast revisions and testing whether it differs significantly from zero (Clements, 1997). The regression used to test weak form efficiency is the following:

(2)
$$v_t = \alpha v_{t-1} + \varepsilon_t \qquad t = 3, \ldots 19$$

where ε_t is the error term, v_t is the FY forecast revision at time *t* and the number of observations is equal to *T-2*=17. Equation (2) estimates the first-order autocorrelation of revisions for

[1] The USDA *WASDE* contains terminal event estimates until April of the following year, but due to the lack of variation in these revisions, we considered the terminal event to occur in November. The mean absolute revision across all studied years was 0.02 from November to December and in all but eight years this revision was 0.

terminal event *T*. The null hypothesis is that α=0; if the null hypothesis is rejected, this implies the forecast revisions are inefficient. Equation (2) implies that forecast revisions should follow a random walk. If forecast revisions do not follow a random walk and are correlated, a forecast revisions graph would appear smoothed because new information is being incorporated into the forecast too slowly. Forecast revision graphs that are weak form efficient should appear jagged because the revisions are incorporating information as it becomes available (Nordhaus 1987). If the forecast revisions are correlated, then the forecasts are inefficient since the forecast revisions move consistently up or down (Isengildina, Irwin, and Good, 2006) rather than following a random walk.

Adjacent Month Efficiency Tests

Monthly comparisons of sugar forecast revisions are also examined provided certain forecasting months have significance as to how sugar policy is implemented. In general, forecasts prior to April are utilized to determine how to operate the Mexican suspension agreement. After April, the forecasts are primarily used to determine how to operate the TRQs and whether to increase them. If the USDA considers the US sugar market under supplied, beginning on April 1 the TRQ can be increased. Thus, examining *WASDE* forecasting efficiency by using a monthly approach is also important to consider.

To accomplish this, we follow Isengildina, Irwin, and Good (2006) methods. They did not have enough observations to estimate equation (2) and developed the following procedure to analyze USDA forecasts:

(3) $$v_t^i = \alpha v_{t-1}^i + \varepsilon_t$$

where ε_t is the error term, v_t^i is the *t* month revisions for FY *i* and the number of observations is equal to the number of FYs. For the US sugar production and consumption forecasts we analyze *i*=1993/94 ,…, 2022/23 FYs (n=30). To exemplify how the regression works, all January revisions for all 30 FYs of domestic sugar forecasts are regressed against all December revisions. Thus, different from equation (2), instead of analyzing all the revisions for FY 1993/94, for example, all of the monthly revisions across all FYs are analyzed. Provided only 14 FYs of Mexican forecasts exist, we did not analyze adjacent month forecasts for Mexican production due to the low number of observations.

Results

FY Descriptive Statistics and Bias Tests

Tables 1 and 2 show the descriptive statistics and bias test results for the domestic sugar production and consumption forecasts for FYs 1993/94 through 2022/23. Table 3 shows the descriptive statistics and bias tests for the Mexican sugar production forecasts for FYs 2009/10 through 2022/23. Only the FY 1997/98 and 2004/05 domestic sugar production forecasts indicate bias (p<0.05) (Table 1). The MPR for FY 1997/98 is positive (0.37) which indicates consistent underestimation of sugar production in this FY. Meanwhile, the MPR for FY 2004/05 is negative (-0.48) which indicates consistent overestimation of sugar production. Finding only two biased FY forecasts across 30 FYs suggests the USDA has done a solid job forecasting domestic sugar production. Further, the mean absolute values of the forecast revisions were rarely above 1%. This also suggests the forecasts are quite accurate. Further, there has been no indication of bias in the production forecasts in over 18 years.

The sugar consumption forecasts indicate bias in only three FYs (2000/01, 2007/08, 2010/11) ($p<0.05$) (Table 2). All of the MPRs are less than 0.40, and two of the three are positive, which indicates underestimation of sugar consumption. The mean absolute value of the forecast revisions are all below 0.43%, which is very low. There also are no indications of bias in over 13 years.

For the Mexican production forecasts, there were instances of bias in FY 2013/14 and FY 2021/22 ($p<0.05$) (Table 3). In FY 2013/14 the USDA consistently underestimated the Mexican sugar crop by almost 2% in each monthly estimate. Interestingly, this was the timeframe Mexico was found to be dumping sugar on the US market (US International Trade Commission, 2024). Meanwhile, in FY 2021/22 the USDA consistently overestimated the crop, on average, by 0.36%.

Adjacent Month Descriptive Statistics and Bias Tests

Tables 4 and 5 show the adjacent month descriptive statistics and bias test results for the domestic sugar production and consumption forecasts for FYs 1993/94 through 2022/23 (n=30). For sugar production, results indicate bias in only the November and April forecasts ($p<0.05$) (Table 4). This result may relate to the fact that November is the first month following the fiscal-year end and April is particularly relevant to the US sugar program because it is when quota import adjustments can be made. These revisions are both negative and less than 1%. To exemplify, the April forecast is, on average, consistently 0.34% lower than the March forecasts. It is important to note that the adjacent month bias tests are only examining the relationship between revisions (forecasts from one month to the next) and are not indicating the accuracy of the forecasts (the accuracy of the monthly forecast relative to the terminal event). Also, as expected, the mean absolute value column shows that the forecast revissions tend to be lower (i.e., forecasts more accurate) as the November terminal event month approaches.

Similar to the sugar production forecasts, only two months indicate bias for the sugar consumption forecasts (February and 2nd July) ($p<0.05$) (Table 5). In February, the revisions were, on average, consistently lowered from the January estimates by 0.27%. The second July forecast was consistently 0.22% higher than the second June forecast. Ultimately, these results indicate both sugar production and consumption forecasts are relatively stable from month to month over the considered FYs.

FY Weak Form Efficiency Tests

Table 6 provides the weak form efficiency test results for the domestic sugar production and consumption forecasts and Table 7 provides them for the Mexican production forecasts. The weak form efficiency test estimated coefficients for the sugar production forecasts in FYs 1994/95, 1999/00, and 2016/17 were positive and significant (p<0.05) (Table 6). This suggests those forecasts were inefficient with evidence of "smoothing" which indicates positive forecast revisions are typically followed by positive forecast revisions (Nordhaus, 1987). Thus, the forecasts are not efficiently incorporating new information in these years since a graph of the revisions would not appear jagged nor appear to follow a random walk. However, this only occurred in three of the 30 years considered; thus, overall, the USDA has efficient forecasts in 90% of the considered FYs.

Sugar consumption forecasts were only inefficient in FYs 1998/99 (p<0.05), 2000/01 (p<0.001), 2009/10 (p<0.05), 2010/11 (p<0.05), and 2014/15 (p<0.05) (Table 6). In four of the five inefficient years, the estimated coefficient from equation (2) indicate smoothing, which is similar to the sugar production forecasts. The Mexican sugar production forecasts were only inefficient in FY 2009/10 (p<0.05) (Table 7) and this year had a positive coefficient that indicates smoothing.

Adjacent Month Weak Form Efficiency Tests

The adjacent month weak form efficiency test results appear in Table 8 for domestic sugar production and consumption. There are only two months that suggest inefficient forecasts for sugar production (April and 2nd August) (p<0.05). For the April forecast, the coefficient is interpreted as the following: a 1% positive revision in the March forecast is expected to be followed by a 0.40% forecast revision in April. Thus, the revisions in the March and April (and 2nd July and 2nd August) forecasts are correlated. While those tests indicate a random walk was possibly not witnessed in the forecast revisions from March to April (and from 2nd July to 2nd August), this does not provide an indication of the accuracy of these forecasts.

Future Research

Results in this study show that with a few exceptions, sugar production and consumption quantity forecasts have been accurate, unbiased, and efficient over the past thirty years. That is in large part due to the sugar policy, which provides USDA the authority to survey all domestic sugarbeet and sugarcane production as well as the beet sugar and cane sugar being produced and sold into the US market, and because the sugar policy increases the ability of USDA to forecast import levels. Those forecast properties are likely to contribute to a more reliable and stable business environment in the US sugar industry and should, in turn, facilitate sugar-using firms' forecasts. For instance, the easiness of predicting input quantity facilitates predicting input prices and, as an extension, predicting firm profits. Therefore, future research can evaluate the forecast properties of financial analysts' earnings forecasts among SUFs. Sometimes guided by firm management (Hirst et al. 2008), equity analysts forecast several financial metrics that investors widely use to assess firms' future value and evaluate managerial performance (Kaplan, Martin, and Xie 2021). A firm's earnings per share (EPS) forecast constitutes one highly valuable piece of information for investors and firms (Graham, Harvey, and Rajgopal 2006).

Like the USDA *WASDE* forecasts, EPS forecasts are fixed-event forecasts (Nordhaus 1987). Therefore, future research can evaluate the properties of EPS forecasts of SUFs relative to comparable firms or to other benchmark models such as naïve earnings growth models that are used as reference when evaluating earnings forecasts (Brown 1993). Given our study results, we expect earnings surprises to be lower in magnitude and frequency for SUFs compared to companies operating in non-sugar-related industries. This would lead to a superior economic environment for SUFs in which they can financially outperform other agribusinesses [as demonstrated by Trejo-Pech, DeLong, and Johansson (2023)].

Conclusions

This work updated that of Lewis and Manfredo (2012) to evaluate the accuracy, bias, and efficiency of USDA domestic sugar production and consumption forecasts, and Mexican sugar production forecasts. Results indicate that those forecasts are accurate, unbiased, and efficient over the majority of the FYs considered (e.g., thirty years of domestic forecasts and fourteen years of Mexican forecasts). Thus, it is possible that the predictability in supply and demand in the sugar market, that is likely aided by US sugar policy, contributes to the success of SUFs who have the luxury of sourcing a stable and reliable primary ingredient for their products. Future research can evaluate the properties of SUFs' earnings forecasts provided by equity financial analysts. Assessing the properties of EPS forecasts of SUFs against comparable non-sugar-related firms will shed light on the degree of risk upon which SUFs operate. Given our study results, we expect SUF's earnings surprises to be lower in magnitude and frequency than those of other agribusinesses.

References

Bora, S., A. Katchova, and T. Kuethe. 2021. "The Rationality of USDA Forecasts under Multivariate Asymmetric Loss." *American Journal of Agricultural Economics* 103(3):1006–33.

Brown, L. 1993. "Earnings Forecasting Research: Its Implications for Capital Markets Research." International Journal of Forecasting 9 (3): 295–320.

Clements, M. P. (1997). "Evaluating the Rationality of Fixed-Event Forecasts." *Journal of Forecasting* 16, 225-239.

Ding, K., and A. Katchova. 2023. "Testing the Optimality of USDA's WASDE Forecasts under Unknown Loss." *Agribusiness* n/a(n/a):1–20. doi: 10.1002/agr.21850.

Graham, J., C. Harvey, and S. Rajgopal. 2006. "Value Destruction and Financial Reporting Decisions." *Financial Analysts Journal* 62(6):27–39.

Hirst, D., Koonce, L., and Venkataraman, S. 2008. "Management Earnings Forecasts: A Review and Framework" Accounting Horizons, 22 (3): 315–338

Isengildina-Massa, Olga, Berna Karali, and Scott H. Irwin. 2013. "When Do the USDA Forecasters Make Mistakes?" *Applied Economics* 45(36):5086–5103. doi: 10.1080/00036846.2013.818213.

Kaplan, Z., X. Martin, and Y. Xie. 2021. "Truncating Optimism." *Journal of Accounting Research* 59(5):1827–84. doi: 10.1111/1475-679X.12397.

Lewis, K., and M. Manfredo. 2012. "An Evaluation of the USDA Sugar Production and Consumption Forecasts." *Journal of Agribusiness* 30(2):155–72.

Nordhaus, W. 1987. "Forecasting Efficiency: Concepts and Applications." *The Review of Economics and Statistics* 69(4):667–74. doi: 10.2307/1935962.

Trejo-Pech, C., K. DeLong, and R. Johansson. 2023. "How Does the Financial Performance of Sugar-Using Firms Compare to Other Agribusinesses? An Accounting and Economic Profit Rates Analysis." *Agricultural Finance Review* 83(3):453–77.

USDA ERS. 2024. Sugar and Sweeteners Policy. Retrieved from: https://www.ers.usda.gov/topics/crops/sugar-and-sweeteners/policy/

USDA. 2024. World Agricultural Supple and Demand Estimates. https://usda.library.cornell.edu/concern/publications/3t945q76s?locale=en&page=20#release-items

US International Trade Commission. 2024. USITC Votes to Continue Cases on Sugar From Mexico. https://www.usitc.gov/press_room/news_release/2014/er0509mm1.htm

Table 1. FY Descriptive Statistics and Test of Bias for Domestic Sugar Production Revisions (Percent): FYs 1993/94 – 2022/23

Fiscal Year	Mean	Mean Abs. Value	Std. Dev.	Min	Max	Range	Bias Test t-Stat
1993/94	0.06	0.53	0.82	-0.93	2.55	3.49	0.28
1994/95	0.18	0.69	1.06	-1.41	3.35	4.76	0.74
1995/96	-0.24	0.36	0.58	-1.76	0.68	2.43	-1.79
1996/97	0.08	0.46	0.75	-1.42	2.08	3.50	0.43
1997/98	0.37	0.47	0.61	-0.39	1.54	1.93	2.60*
1998/99	0.30	0.67	0.83	-1.48	1.59	3.07	1.53
1999/00	0.41	0.68	1.10	-1.81	3.43	5.24	1.58
2000/01	-0.22	0.87	1.54	-5.27	2.59	7.86	-0.60
2001/02	-0.36	0.58	0.97	-3.66	0.75	4.41	-1.58
2002/03	-0.24	0.81	1.24	-3.23	2.59	5.83	-0.83
2003/04	0.03	0.76	1.29	-1.64	4.49	6.13	0.11
2004/05	-0.48	0.74	0.96	-3.27	1.25	4.53	-2.13*
2005/06	-0.53	0.90	1.33	-4.57	1.92	6.50	-1.69
2006/07	0.14	0.50	0.76	-0.92	2.06	2.98	0.77
2007/08	-0.07	0.52	0.66	-1.11	1.32	2.43	-0.45
2008/09	-0.45	1.10	1.55	-3.63	2.67	6.30	-1.23
2009/10	-0.07	1.01	1.60	-3.97	3.07	7.03	-0.20
2010/11	-0.23	0.58	0.84	-1.87	1.21	3.07	-1.16
2011/12	0.19	0.64	0.96	-2.18	1.64	3.82	0.86
2012/13	0.31	0.64	0.98	-1.98	2.02	4.00	1.28
2013/14	-0.22	0.66	1.15	-2.22	2.91	5.14	-0.76
2014/15	0.10	0.75	1.02	-1.66	1.78	3.45	0.42
2015/16	0.34	0.81	1.09	-1.05	3.15	4.20	1.34
2016/17	0.16	0.97	1.39	-2.91	2.84	5.75	0.49
2017/18	0.37	0.82	1.34	-1.09	4.52	5.61	1.16
2018/19	-0.04	1.13	1.56	-2.70	3.49	6.20	-0.11
2019/20	-0.62	1.15	1.93	-6.43	1.72	8.16	-1.36
2020/21	0.14	0.77	1.14	-2.92	2.16	5.09	0.51
2021/22	-0.11	0.82	1.14	-3.30	1.63	4.93	-0.39
2022/23	0.13	0.71	1.09	-2.44	2.29	4.73	0.49

Note: The forecasting revision cycle includes 19 months; thus, there are 18 revisions (n=18) per FY. Note three FYs did not have two monthly revisions so n=16 in FYs 2019, 2014, and 2013. Column Mean is the mean percentage revision (MPR) which is the average of the monthly forecast revisions. The forecast revisions are calculated with equation (1). The test of bias test whether the MPR is statistically different from zero and $*P < 0.05$, $**P < 0.01$ $***P<0.001$.

Table 2. FY Descriptive Statistics and Test of Bias for Domestic Sugar Consumption Revisions (Percent): FYs 1993/94 – 2022/23

Fiscal Year	Mean	Mean Abs. Value	Std. Dev.	Min	Max	Range	Bias Test t-Stat
1993/94	0.07	0.21	0.42	-0.55	1.51	2.06	0.67
1994/95	0.08	0.23	0.44	-0.54	1.58	2.12	0.75
1995/96	0.05	0.35	0.65	-1.18	1.72	2.90	0.30
1996/97	-0.02	0.34	0.56	-1.04	1.05	2.09	-0.12
1997/98	0.01	0.33	0.62	-1.02	1.96	2.98	0.07
1998/99	-0.02	0.16	0.26	-0.51	0.51	1.02	-0.25
1999/00	0.02	0.16	0.35	-0.97	1.00	1.97	0.27
2000/01	-0.13	0.13	0.24	-0.77	0.00	0.77	-2.28*
2001/02	-0.21	0.61	0.98	-2.16	2.49	4.66	-0.89
2002/03	-0.07	0.39	0.91	-2.06	2.81	4.87	-0.34
2003/04	-0.11	0.36	0.85	-2.61	1.77	4.38	-0.54
2004/05	0.19	0.19	0.38	0.00	1.20	1.20	2.05
2005/06	0.13	0.13	0.27	0.00	0.99	0.99	2.03
2006/07	-0.19	0.25	0.55	-1.50	0.54	2.03	-1.49
2007/08	0.31	0.37	0.63	-0.50	1.73	2.22	2.10*
2008/09	0.08	0.64	1.16	-2.41	3.00	5.41	0.30
2009/10	0.27	0.50	0.84	-2.05	1.83	3.88	1.38
2010/11	0.40	0.43	0.79	-0.28	2.59	2.87	2.15*
2011/12	-0.04	0.47	0.90	-2.25	1.90	4.15	-0.20
2012/13	0.10	0.23	0.44	-0.70	1.13	1.83	0.86
2013/14	0.12	0.24	0.42	-0.95	0.95	1.91	1.17
2014/15	0.12	0.34	0.56	-1.06	1.06	2.12	0.88
2015/16	-0.04	0.24	0.48	-0.92	1.43	2.35	-0.33
2016/17	0.02	0.25	0.44	-0.82	0.83	1.65	0.22
2017/18	-0.12	0.30	0.49	-1.11	0.82	1.93	-1.08
2018/19	-0.20	0.28	0.42	-1.22	0.62	1.83	-1.91
2019/20	0.03	0.19	0.32	-0.62	0.83	1.45	0.36
2020/21	-0.01	0.14	0.30	-0.75	0.62	1.37	-0.10
2021/22	0.16	0.27	0.44	-0.64	1.20	1.84	1.49
2022/23	0.01	0.21	0.36	-0.60	0.80	1.40	0.12

Note: The forecasting revision cycle includes 19 months; thus, there are 18 revisions (n=18). Note three FYs did not have two monthly revisions so n=16 in FYs 2019, 2014, and 2013. Column Mean is the mean percentage revision (MPR) which is the average of the monthly forecast revisions. The forecast revisions are calculated with equation (1). The test of bias test whether the MPR is statistically different from zero and $^*P < 0.05$, $^{**}P < 0.01$ $^{***}P<0.001$.

Table 3. FY Descriptive Statistics and Test of Bias for Mexican Sugar Production Revisions (Percent): FYs 1993/94 – 2022/23

Fiscal Year	Mean	Mean Abs. Value	Std. Dev.	Min	Max	Range	Bias Test t-Stat
2010/11	-0.40	0.89	1.70	-4.00	3.71	7.71	-1.01
2011/12	-0.28	0.68	1.71	-5.83	3.60	9.43	-0.69
2012/13	-0.63	0.96	2.15	-6.39	2.52	8.91	-1.24
2013/14	1.91	2.06	3.04	-0.95	9.58	10.53	2.50*
2014/15	-0.15	1.17	2.32	-5.29	5.18	10.47	-0.27
2015/16	-0.46	0.56	1.41	-5.70	0.75	6.45	-1.38
2016/17	0.11	0.23	0.60	-1.06	2.09	3.15	0.76
2017/18	-0.13	0.61	1.35	-3.30	3.23	6.53	-0.41
2018/19	-0.20	0.27	0.61	-2.03	0.65	2.68	-1.36
2019/20	0.40	0.40	0.92	0.00	3.17	3.17	1.76
2020/21	-0.80	1.48	2.54	-8.69	2.03	10.72	-1.34
2021/22	-0.36	0.39	0.69	-2.17	0.14	2.31	-2.22*
2022/23	0.35	0.40	0.89	-0.45	3.10	3.55	1.66

Note: The forecasting revision cycle includes 19 months; thus, there are 18 revisions (n=18). Note three FYs did not have two monthly revisions so n=15 in FYs 2019, 2014, and 2013. Column Mean is the mean percentage revision (MPR) which is the average of the monthly forecast revisions. The forecast revisions are calculated with equation (1). The test of bias test whether the MPR is statistically different from zero and $*P < 0.05$, $**P < 0.01$ $***P<0.001$.

Table 4. Adjacent Month Descriptive Statistics and Test of Bias for Domestic Sugar Production Revisions (Percent): FYs 1993/94- 2022/23

Revision Month	Mean	Mean Abs. Value	Std. Dev.	Min	Max	Range	Bias Test t-Stat
June	-0.05	0.30	0.82	-2.44	3.15	5.59	-0.31
July	0.04	1.02	1.42	-3.63	2.84	6.47	0.16
August	0.55	1.54	1.88	-3.23	4.49	7.72	1.60
September	0.00	1.06	1.43	-3.52	2.91	6.43	0.02
October	0.09	0.74	1.33	-5.27	2.67	7.94	0.35
November	-0.81	1.52	2.04	-6.43	3.35	9.78	-2.14*
December	0.28	1.28	1.72	-3.93	4.52	8.46	0.89
January	0.14	1.02	1.25	-1.51	2.55	4.06	0.62
February	0.06	0.66	0.93	-1.24	1.85	3.09	0.33
March	-0.26	0.64	0.86	-2.91	1.28	4.19	-1.64
April	-0.34	0.59	0.72	-1.98	1.61	3.59	-2.57*
May	-0.10	0.67	0.93	-1.92	2.59	4.51	-0.61
2^{nd} June	-0.07	0.35	0.54	-1.76	0.84	2.60	-0.73
2^{nd} July	-0.13	0.30	0.51	-1.46	1.22	2.68	-1.41
2^{nd} August	0.12	0.32	0.47	-0.72	1.33	2.05	1.45
2^{nd} September	-0.02	0.30	0.48	-1.27	1.24	2.52	-0.26
2^{nd} October	0.01	0.47	0.70	-1.55	1.72	3.27	0.06
2^{nd} November	0.12	0.53	0.64	-1.64	1.19	2.83	0.98

Note: The forecasting revision cycle includes 18 months; therefore, second June refers to the second June in the forecasting revision cycle and so forth. N=30. *$P < 0.05$, **$P < 0.01$ ***$P<0.001$.

Table 5. Adjacent Month Descriptive Statistics and Test of Bias for Domestic Sugar Consumption Revisions (Percent): FYs 1993/94 – 2022/23

Revision Month	Mean	Mean Abs. Value	Std. Dev.	Min	Max	Range	Bias Test t-Stat
June	-0.09	0.16	0.46	-2.05	1.03	3.08	-1.02
July	0.14	0.19	0.42	-0.80	1.68	2.48	1.83
August	0.03	0.26	0.63	-1.22	1.96	3.18	0.30
September	0.07	0.22	0.59	-1.53	2.59	4.12	0.65
October	0.13	0.26	0.46	-0.76	1.58	2.34	1.49
November	-0.20	0.42	0.74	-2.61	1.00	3.61	-1.47
December	0.07	0.16	0.40	-0.95	1.43	2.39	0.91
January	-0.01	0.01	0.03	-0.15	0.00	0.15	-1.00
February	-0.27	0.36	0.69	-2.25	1.14	3.40	-2.14*
March	0.19	0.37	0.61	-1.02	1.90	2.92	1.70
April	-0.05	0.19	0.41	-1.50	0.87	2.37	-0.68
May	0.17	0.49	0.74	-1.44	1.77	3.21	1.27
2nd June	0.13	0.26	0.68	-0.92	3.00	3.92	1.04
2nd July	0.22	0.31	0.51	-0.59	1.70	2.29	2.41*
2nd August	0.02	0.31	0.54	-1.11	1.15	2.26	0.20
2nd September	0.00	0.34	0.54	-1.20	1.13	2.33	-0.00
2nd October	0.02	0.34	0.54	-1.05	1.51	2.56	0.17
2nd November	0.02	0.74	1.09	-2.41	2.81	5.23	0.08

Note: The forecasting revision cycle includes 18 months; therefore, second June refers to the second June in the forecasting revision cycle and so forth. N=30. *$P < 0.05$, **$P < 0.01$ ***$P<0.001$.

Table 6. Weak Form Efficiency Test Results: FYs 1993/94- 2022/23

Fiscal Year Forecast	Domestic Sugar Production		Domestic Sugar Consumption	
	Coefficient	t-Stat	Coefficient	t-Stat
1993/94	0.10	0.40	0.11	0.42
1994/95	0.52	2.37*	0.09	0.37
1995/96	0.10	0.41	0.04	0.15
1996/97	0.25	1.03	0.02	0.09
1997/98	0.39	1.55	0.01	0.04
1998/99	0.20	0.83	0.52	2.41*
1999/00	0.48	2.19*	0.28	0.84
2000/01	0.02	0.08	1.16	7.20***
2001/02	0.09	0.37	0.24	0.77
2002/03	0.00	0.00	-0.46	-1.30
2003/04	-0.29	-1.13	0.05	0.21
2004/05	0.24	1.00	0.36	1.10
2005/06	-0.08	-0.32	0.18	0.74
2006/07	0.04	0.17	0.00	0.00
2007/08	0.18	0.72	0.2	0.80
2008/09	-0.01	-0.04	-0.1	-0.29
2009/10	-0.14	-0.55	0.45	2.15*
2010/11	0.43	1.89	0.53	2.50*
2011/12	0.44	1.92	-0.29	-1.07
2012/13	0.31	1.21	-0.34	-1.02
2013/14	-0.48	-1.42	0.00	0.00
2014/15	-0.10	-0.43	-0.48	-2.18*
2015/16	-0.00	-0.02	0.04	0.18
2016/17	0.52	2.41*	0.04	0.13
2017/18	-0.04	-0.18	0.17	0.66
2018/19	0.12	0.42	0.40	1.54
2019/20	0.38	1.65	0.33	1.35
2020/21	0.37	1.60	0.09	0.28
2021/22	0.09	0.34	0.23	0.91
2022/23	-0.11	-0.53	0.17	0.67

The forecasting revision cycle includes 19 months; thus, there are 18 revisions and n=17 observations. Note three FYs did not have a monthly revision so n=14 in FYs 2018/19 and 2013/14, and n=15 in 2013. The regressions were conducted using equation (2). $^*P < 0.05$, $^{**}P < 0.01$ $^{***}P<0.001$.

Table 7. Mexican Production Weak Form Efficiency Test Results: FYs 2009/10- 2022/23

Fiscal Year Forecast	Coefficient	t-Stat
2009/10	0.48	2.21*
2010/11	0.00	0.01
2011/12	0.01	0.05
2012/13	0.28	1.14
2013/14	0.06	0.24
2014/15	0.04	0.15
2015/16	0.01	0.02
2016/17	0.05	0.20
2017/18	0.00	0.00
2018/19	0.24	1.09
2019/20	0.16	0.66
2020/21	0.24	0.97
2021/22	0.07	0.29
2022/23	-0.06	-0.24

Note: The forecasting revision cycle includes 19 months; thus, there are 18 revisions and n=17 observations. Note three FYs did not have a monthly revision so n=14 in FYs 2018/19 and 2013/14, and n=15 in 2012/13. The regressions were conducted using equation (2). **P* < 0.05, ***P* < 0.01 ****P*<0.001.

Table 8. Adjacent Month Weak Form Efficiency Test Results: FYs 1993/94- 2022/23

Dependent Variable	Independent Variable	Domestic Sugar Production Coefficient	t-Stat	Domestic Sugar Consumption Coefficient	t-Stat
July	June	0.08	0.25	0.00	0.00
August	July	0.13	0.49	0.13	0.47
September	August	0.01	0.07	0.42	2.69**
October	September	-0.05	-0.25	0.23	1.56
November	October	0.15	0.50	0.22	0.74
December	November	0.26	1.76	-0.05	-0.54
January	December	0.03	0.20	-0.02	-1.28
February	January	0.16	1.16	0.00	0.00
March	February	0.31	1.78	-0.17	-1.05
April	March	0.40	2.69**	0.13	1.08
May	April	0.33	1.60	0.39	1.15
2nd June	May	0.07	0.61	-0.20	-1.25
2nd July	2nd June	0.29	1.67	0.15	1.03
2nd August	2nd July	-0.38	-2.44*	0.21	1.22
2nd September	2nd August	0.11	0.61	-0.13	-0.69
2nd October	2nd September	0.09	0.34	0.27	1.42
2nd November	2nd October	0.24	1.38	0.29	0.77

Note: N=30. The regressions were conducted using equation (3). *$P < 0.05$, **$P < 0.01$ ***$P<0.001$.