An Evaluation of Congressional Budget Office's Baseline Projections of USDA Mandatory Farm and Nutrition Programs

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Abstract

The Congressional Budget Office (CBO) projections of USDA's mandatory farm and nutrition program outlays play a vital role in shaping agricultural policy and in agricultural policy debates. However, these projections have not been rigorously evaluated. Using CBO projections and observed outcomes from 1985 through 2020, we examine the degree to which projections of farm, supplemental nutrition assistance, and child nutrition program outlays are unbiased, efficient, and informative. We find that projections for farm program and child nutrition program outlays are unbiased. Supplemental nutrition assistance program outlays are unbiased at short horizons but are downward biased beyond a three-year horizon. We find that all three series of projections are inefficient. The projections for supplemental nutrition assistance program and child nutrition program outlays are informative up to a five-year projection horizon, but the farm program outlay projections are informative for only a one-year horizon. Disaggregated farm program outlay projections since 2008 further suggest that the un-informativeness principally stems from conservation program projections. The findings may provide valuable insights for CBO to improve future projections and for projection *users*, including policymakers, to adjust expectations and future Farm Bill discussions.

Keywords: *CBO baseline, USDA farm and nutrition programs, forecast evaluation, Farm Bill*

1 Introduction

The Congressional Budget Office's (CBO) baseline projections for United States Department of Agriculture (USDA) mandatory farm and nutrition programs serve as the foundation for writing a new Farm Bill and analyzing funding availability (Monke, 2013). By mandate, CBO provides Congress with budget projections and projections of macroeconomic indicators, as well as spending for mandatory programs for the next ten years.[1] The Farm Bill is an omnibus, multi-year[2] law which addresses food and agricultural issues through a variety of programs (Johnson and Monke, 2019). Farm Bill programs have provided the majority of direct payments to farmers since the mid-nineties (Rosch 2021; ERS 2022). Over the years, direct government payments make up a significant portion of farm income and exploded since 2019, with a record high of $45 billion in 2020, nearly 40% of total farm income (Rosch 2021; ERS 2022). Likewise, the government's food and nutrition assistance programs reached a record high of $182.5 Billion in 2021, with average monthly participation of more than 47 million people (Jones, Toossi, and Hodges, 2022).

As the economic conditions fluctuate, policymakers need accurate long-run projections for planning. CBO's projections often serve a starting point for policy discussions and for comparing alternative policy scenarios. As Douglas and Raudla (2019) argued, members of Congress rely on CBO's projections to analyze the fiscal condition of the government and set agendas for policy debates. Douglas and Raudla (2019) argue that lawmakers on the Senate and House budget committees benefit from information on the accuracy of CBO projections (CBO 2020). Likewise, lawmakers on the Senate and House agricultural committees may benefit from information on the accuracy and informational value of CBO projections of USDA mandatory nutrition and farm program spending.

Despite their importance to food and agricultural policy, however, CBO's spending projections of USDA mandatory programs have not been rigorously evaluated. A majority of CBO's forecast evaluation studies focused on evaluating macroeconomic projections, such as gross domestic product, inflation, and unemployment, as well as budgetary projections, such as revenues and deficits (Huntley and Miller 2009; Ericsson and Martinez 2019; Arai 2020). These projections are important because they serve as a benchmark for evaluating the effects of proposed legislation, comparing alternative policies, and establishing a starting point for budget

[1] Before 1995, CBO projection horizon was five years.
[2] Typically for five years

resolution (Heniff 2012; Monke 2013; CBO 2018). According to CBO (2021), “the baseline projections reflect the CBO’s assessment of how the budget and the economy would evolve under existing laws and are not intended to predict budgetary or economic outcomes.” CBO (2018) highlights that baseline projections provide a neutral benchmark for deciding whether proposed legislation is subject to various budget enforcement procedures. In a recent media report, Summers (2016) states “CBO is an American national treasure. Without the impartial objectivity it brings to the budget process, our country would make much worse policy.” Arai (2020) argued that, as a non-partisan organization, CBO’s analysis of macroeconomic and budgetary projections is considered a benchmark in research and policy discussions.

Previous forecast evaluation studies, including CBO’s own studies, provide evidence of the mixed performance of CBO’s forecasts in terms of accuracy, unbiasedness, and efficiency (Kamlet, Mowery, and Su 1987; Kliesen and Thornton 2001; 2012; CBO 2017; 2020; Arai 2020). Some studies show that CBO outperforms other government forecasts and simple time series models, but a few studies indicate that CBO performs relatively poor compared to a random walk projection (Ericsson and Martinez, 2019). Kamlet, Mowery, and Su (1987) show that the CBO's long-term projections of macroeconomic indicators are as good as or better than the executive branch's projections. Consistent with this finding, Frendreis and Tatalovich (2000) find that the CBO’s short-term (yearly) forecasts of inflation, unemployment, and GDP are the most accurate in comparison to the forecasts of the Federal Reserve Board and the administration. Huntley and Miller (2009) indicate that CBO’s forecasts for nominal budget variables are at least as good as, or better than a vector autoregressive model. Kliesen and Thornton (2001, 2012), on the other hand, questioned the CBO's projections because they found no strong evidence of improvements in the CBO's deficit and debt projections when compared to a simple random walk. The authors do not find significant improvements in CBO's budget projection performance over time, arguing that if past behavior predicts future behavior, CBO's deficit projection errors would be higher. Belongia (1988) also indicates that CBO projections for inflation and unemployment are unbiased, but private sector forecasts are relatively more accurate than CBO forecasts. Arai (2020) demonstrates that the CBO's projections of fiscal and macroeconomic indicators are inefficient.

Recently, CBO’s baseline for USDA mandatory programs have been documented in extension and outreach related to farm and agricultural policy discussions. For example, Coppess et al. (2017) and Coppess et al. (2018) review the CBO spending projections for the 2018 Farm

Bill and argue that the CBO baseline tends to generate political debates which may influence the reauthorization of the 2018 Farm Bill. In addition, CBO regularly publishes accuracy measures of revenues, deficits, and outlays in reports such as "The accuracy of CBO's Budget Projections for Fiscal Year 2020"[3] and "An evaluation of CBO's Past Outlay Projections 2017".[4] CBO analyzes budget-year projections and sixth-year projections and indicates that mandatory spending outlays (excluding legislative changes) are over-estimated since 1992 (CBO 2017). They also show that the CBO's projections of mandatory spending are more accurate in comparison with the projections of the administration. While such evaluations provide a measure of accuracy and direction of over or underestimation of aggregate spending categories, a comprehensive evaluation would also examine the bias, efficiency, and informational value across projection horizons and across program levels.

In this study, we examine three important series of CBO's baseline outlays projections: 1) USDA farm program outlays including commodity programs, conservation programs, and federal crop insurance programs; 2) outlays for the supplemental nutrition assistance program (SNAP, formerly known as food stamps); and 3) outlays for the child nutrition program. These programs are the primary components of the Farm Bill.[5] The programs we evaluate in this study account for approximately 99% of anticipated current (2018) Farm Bill spending, which are: title I commodity programs (7%), title II conservation programs (7%), title IV nutrition (76%), and title XI crop insurance programs (9%) (Johnson and Monke, 2019). In this study, our objectives are to examine the degree to which the CBO's outlay projections for USDA mandatory programs are unbiased, efficient, and informative.

Recently, Bora, Katchova, and Kuethe (2022) evaluate USDA and Food and Policy Research Institute (FAPRI) baseline projections using various forecast evaluation tools. Their study focuses on evaluating farm income and acreage, production, yield, and price of major farm commodities, which are important for long-term planning and business investment decisions. Following Bora, Katchova, and Kuethe (2022), we similarly evaluate CBO's baseline projections of USDA mandatory farm and nutrition programs, which provide useful information for policymakers to debate agricultural policy and resource allocation decisions. First, we assess the accuracy of each projection component using traditional accuracy measures: mean absolute

[3] The Accuracy of CBO's Budget Projections for Fiscal Year 2020
[4] An Evaluation of CBO's Past Outlay Projections
[5] Child nutrition programs are authorized outside the Farm Bill, under the jurisdiction of the Senate Agriculture Committee (Monke 2013).

percent error (MAPE) and root mean square percent error (RMSPE). Second, we examine the degree to which CBO projections systematically deviate from realized outcomes (bias) and the degree to which CBO projection revisions incorporate all available information (efficiency). Third, we test the informational value of each projection horizon, following Breitung and Knüppel (2021). The test of informativeness provides empirical evidence of the longest horizon for which CBO projections provide meaningful information.

Our study provides a number of important findings. First, our results indicate that both MAPE and RMSPE increases as projection horizon lengthens, a necessary condition of forecast rationality. Second, Farm programs and child nutrition programs outlays are unbiased but inefficient. SNAP outlays, on the other hand, are inefficient and exhibit downward bias beyond three years. Third, SNAP and child nutrition outlays are informative up to five years while farm program outlays are only informative for one year. Fourth, among the farm program components, crop insurance outlays are informative for all five years. Commodity program outlays are informative up to one year, and conservation program outlays are not informative at any horizon.

To the best of our knowledge, this is the first study to provide an in-depth evaluation of CBO's projections for USDA mandatory programs. Documentation of the CBO projection of USDA mandatory programs may serve as a starting point to analyze different components of each program. Our findings provide information which may be useful for policymakers, policy analysts, state agencies, and advocacy groups. For example, the direction of over-prediction or under-prediction and the test of informativeness may provide valuable insights for discussions on a continuation of existing programs and analyzing alternative policies. Our findings may also aid in the improvement of current models and methods used by CBO to produce USDA mandatory program outlay projections.

The rest of the paper is organized as follows. Section 2 outlines CBO's baseline projection process. Section 3 summarizes our data set and empirical approach for evaluating CBO projections. Section 4 summarizes our results, and Section 5 provides concluding remarks.

2 The CBO baseline projection process

The Congressional Budget Act of 1974 established the CBO to provide objective and nonpartisan information to support budgetary matters and to help Congress in making sound economic policy (CBO 2021). The primary responsibility of the CBO is to assist the House and Senate Committees with the matters under their jurisdiction. By mandate, CBO produces baseline projections of revenue and outlays under the assumptions that current laws would generally remain unchanged for the ensuing ten years (CBO 2017; CBO 2018). CBO (2018) describes how the baseline projections are prepared.[6] CBO analysts begin producing baseline projections by analyzing the previous year's realized values. They review the accuracy of previous projections, adjust/explain any noticeable unusual patterns, and ensure compliance with current law. Analysts then update their information sets and economic forecasts,[7] including sectoral information required to produce baseline projections. The diversity of mandatory programs requires analysts to compile and analyze a wide range of datasets through multiple sources. CBO’s Panel of Economic Advisors, which consist experts from diverse fields offer assistance in multiple sectors for producing baseline projection. Analysts also consider the effects of previous legislation on the related programs. CBO baseline is a combination of model outputs and judgment-based analysis. CBO uses information from diverse sources including expertise from several agencies of the federal government, such as: Office of the Management of Budget, Department of Revenue, executive branch agencies’ budget and program offices, Joint committee on Taxation, Government Accountability Office, and Congressional Research Service. Projections are reviewed and discussed among experts from different sectors and disciplines, such as those from government offices, the private sector, universities, and other think tanks. There are several rounds of external and internal reviews to ensure baseline estimates are as accurate as possible. CBO analysts assess potential factors affecting the projections, analyze and explain any atypical patterns, and ensure that CBO’s estimates reflect the middle range of expected outcomes. Finally, after many review meetings to ensure overall reasonableness and analytical soundness, CBO publishes “The Budget and Economic Outlook”[8] which is available online usually in January of each year. CBO also publishes detailed baseline projections for selected programs, such as USDA mandatory farm, SNAP, and child nutrition programs.

3 Data and Methods

3.1 Data

Our dataset consists of three series of CBO baseline projection outlays related to farm and nutritional programs: SNAP, child nutrition, and farm programs. Over the years, CBO publishes farm program outlays under different names, for example, farm price supports

[6] See detail in: How CBO Prepares Baseline Budget Projections | Congressional Budget Office
[7] To assist economic and budgetary decisions, CBO produces economic forecasts twice a year.
[8] For example: The Budget and Economic Outlook: 2021 to 2031 (cbo.gov)

programs, farm price and income support programs, commodity credit corporation programs, and agricultural programs. We compile data from the "Budget and Economic Outlook" report, which is published by CBO every year and available online. CBO typically updates projections in the Spring and Summer. For each year, we use updated projections if available. CBO projections were initially produced for five year horizons but extended projections to ten year horizon starting in 1996. Similar to the five-year Farm Bill cycle, our study is limited to five-year projection horizons from 1985 to 2020.

Our dataset spans 1985 through 2020. For the year t $(\mathrm{t} = 1, \dots \dots \dots, \mathrm{T})$, we denote the actual value as $\mathrm{Y_t}$. CBO projection for future year $\mathrm{t + h}$, made in year t, is denoted by $\hat{\mathrm{Y}}_{\mathrm{t+h|t}}$. The value of h ranges from 0 to 5. Where, $\mathrm{h} = 0$ denotes the projection for the current year t and $\mathrm{h} = 5$ denotes projection for year $\mathrm{t} + 5$. For example, 2020 baseline report contains projections for 2020 $(h = 0)$ through 2025$(h = 5)$. Thus, for the shortest projection horizon, $\mathrm{h} = 0$, our dataset consists of 36 yearly observations (T =36, 1985 through 2020). At the remaining projection horizons, we lose one observation. For example, our sample size (T) for $\mathrm{h} = 5$ is 31 because 5-year ahead projections and realized outcomes are available from 1990 through 2020.

Figures 1-3 show the projected (dotted line) and realized values (solid line) of SNAP, child nutrition, and farm program outlays from 1997 through 2020. As stated earlier, SNAP is the largest component of Farm Bill. The average monthly participation exceeds 41.5 million with total spending $113.8 billion in 2021 (Jones, Toossi, and Hodges, 2022). SNAP and Child Nutrition outlays show increasing trends over the years. Figure 1 shows a sharp increase in SNAP outlays around the period of 2008 financial crisis, a decline after 2012, and a subsequent rise during the COVID-19 pandemic. Further, SNAP projections generally underpredict realized values, except some period of mid-nineties and 2015 through 2019. Figure 2 shows a relatively steady increase in observed child nutrition outlays and off-setting periods of over- and under-prediction. Farm program outlays, however, fluctuate considerably over the observation period (Figure 3). Again, the projections appear to display off-setting periods of over- and under-prediction. In our empirical analysis, we use log transformations for both realized values and projections to control for changing forecast levels over time following Iselgildina-Massa et al. (2021) and Bora, Katchova, and Kuethe (2022).

Figure 1: SNAP actual outlays and projected values, 1985-2027

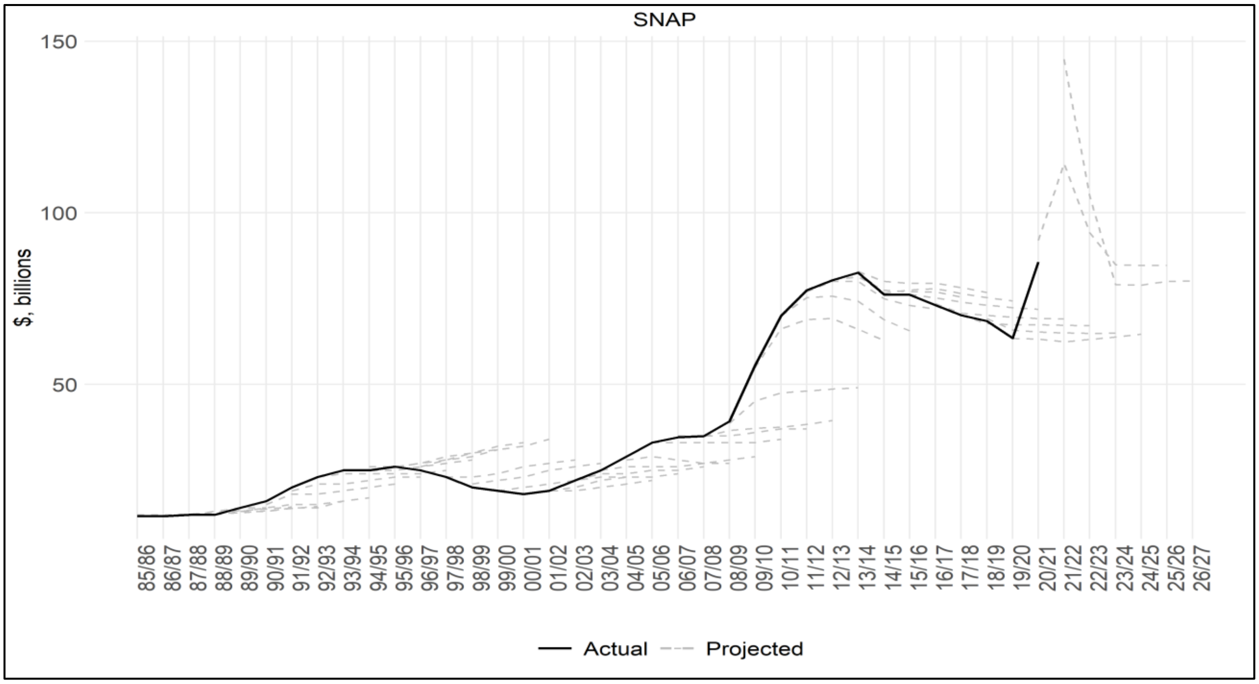


Figure 2: Child nutrition actual outlays and projected values, 1985-2027

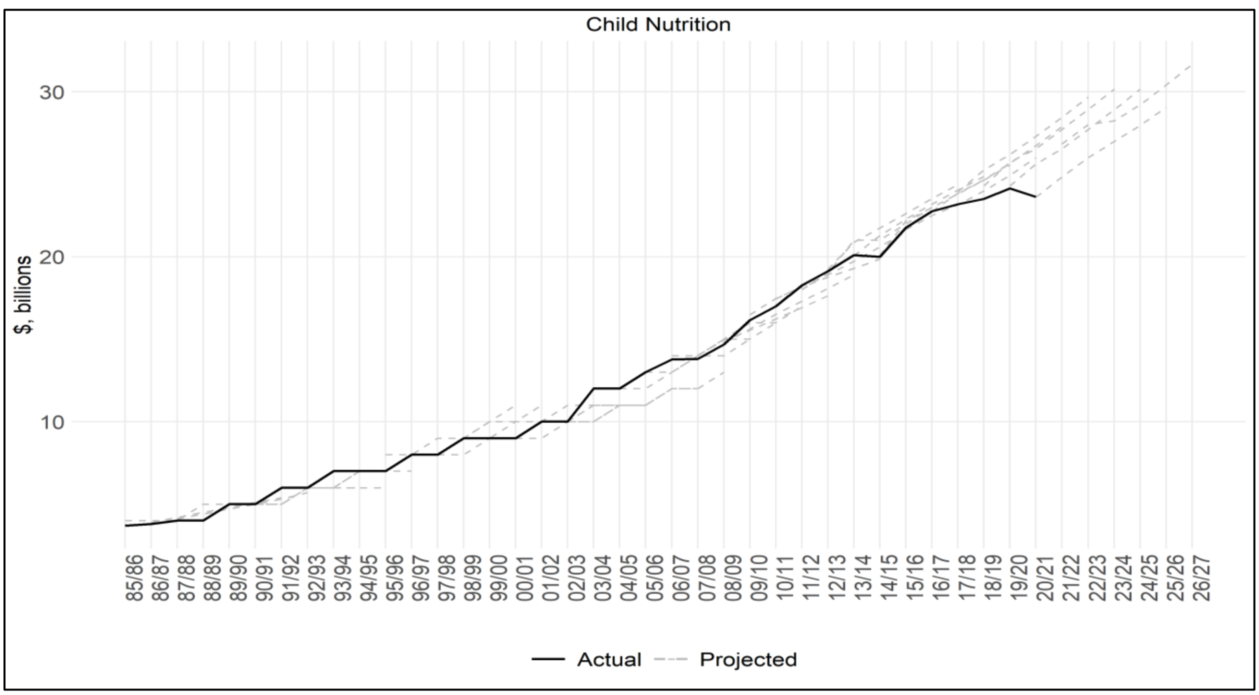
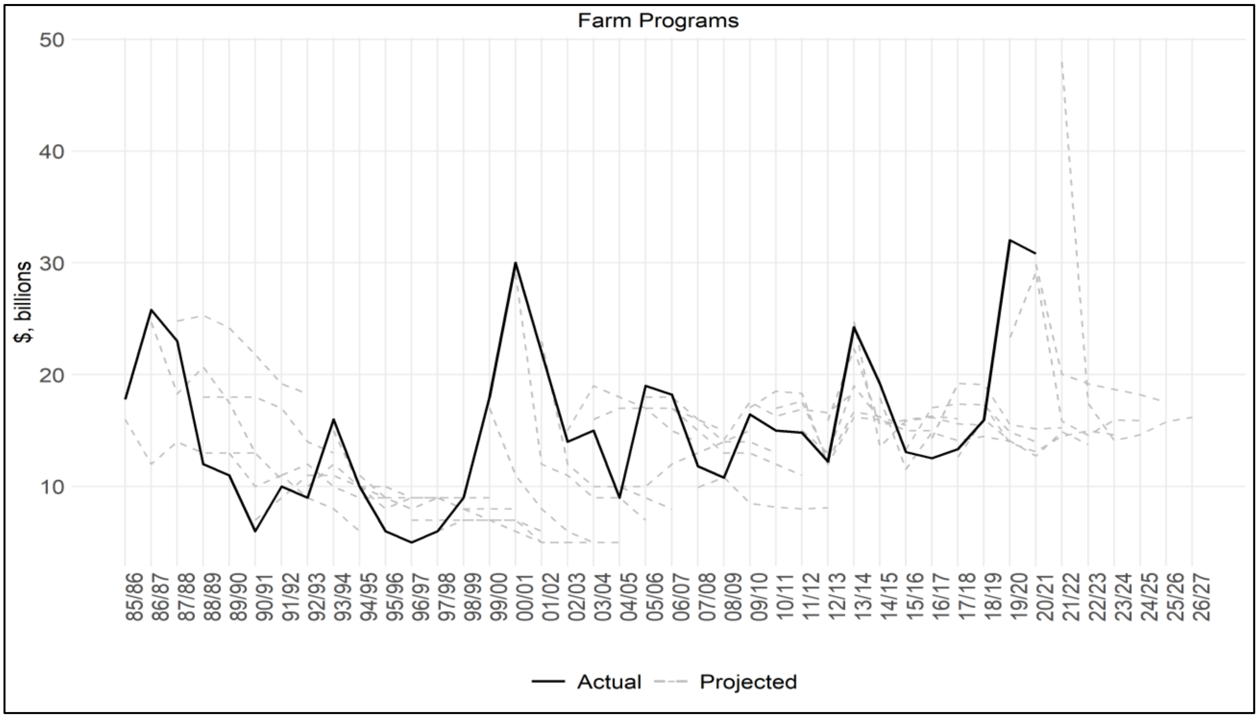


Figure 3: Farm program actual outlays and projected values, 1985-2027



3.2 Methods

As stated earlier, we evaluate CBO projections in three steps following Bora, Katchova, and Kuethe (2022). First, we analyze the accuracy of each series of projections at each horizon. Second, we test the bias and efficiency of each series of projections. Third, we identify the longest horizon at which each projection provides meaningful information.

3.2.1 Measure of accuracy

We use two common measures of the accuracy of each projection series: mean absolute percent error (MAPE) and root mean squared percent error (RMSPE). MAPE measures the average absolute error over the projection period. On the other hand, RMSPE measures the average squared errors which penalizes large prediction errors. A smaller value of MAPE and RMSPE would be preferable (indicate more accuracy). The projection error at each horizon is defined $e_{t+h|t} = \frac{\mathrm{Y_{t+h}} - \mathrm{\hat{Y}_{t+h|t}}}{\mathrm{Y_{t+h}}} \times 100$. MAPE and RMSPE are calculated:

$$\mathrm{MAPE_h} = \frac{1}{\mathrm{T}} \sum\nolimits_{\mathrm{t}} |\mathrm{e_{t+h|t}}| \tag{1}$$

and

$$\mathrm{RMSPE_h} = \sqrt{\frac{1}{\mathrm{T}} \sum\nolimits_{\mathrm{t}} (\mathrm{e_{t+h|t}})^2}. \tag{2}$$

Forecast rationality suggests that the projection error should be a weakly increasing function of the projection horizon (Patton and Timmermann, 2012). As a result, both MAPE and RMSPE are expected to increase as h increases.

3.2.2 Bias and efficiency tests

A series of projections is optimal if it is both unbiased and efficient (Diebold and Lopez, 1996). Projections are unbiased if they do not systematically deviate from realized values. A series of projections is efficient if it incorporates all of the forecaster's information set I_t. Under the given information set I_t, an optimal projection, $\hat{Y}^{*}_{t+h|t}$ minimizes the forecaster's loss function $L_t\left(Y_{t+h} - \hat{Y}_{t+h|t}\right)$ (Elliott and Timmermann, 2016):

$$\hat{Y}^{*}_{t+h|t} = \underset{F_{t+h|t}}{\operatorname{argmin}} E[L(Y_{t+h}, \hat{Y}_{t+h|t})|I_t] \tag{3}$$

Using the first order condition of the mean square error (MSE) loss function, we obtain the optimal condition;

$$\hat{Y}^{*}_{t+h|t} = E[Y_{t+h} | I_t] \tag{4}$$

which indicates that the optimal projection should equal the conditional mean.

To test whether each projection systematically differs from realized values, we regress the projection error on a constant term, following Holden and Peel (1990). The regression is specified:

$$e_{t+h|t} = \alpha_h + \varepsilon_{t+h} \tag{5}$$

where α_h is an unknown parameter to be estimated and ε_{t+h} is the regression residuals. Equation (5) is estimated separately for each projection horizon by ordinary least squares (OLS) with heteroskedasticity and autocorrelated (HAC) standard errors (Newey and West, 1987). The unbiasedness of projection is tested in null hypothesis $H_0{:}\alpha_h = 0$. A rejection of the null hypothesis suggests that the projections are biased. A statistically significant and positive α_h indicates that the projections under-predict realized values (downward bias), and a statistically significant and negative α_h indicates that the projections over-predict realized values (upward bias).

We also test the degree to which the projections satisfy the necessary conditions of forecast efficiency. Nordhaus (1987) demonstrates that forecast revisions are uncorrelated in efficient forecasts (weak efficiency). We test the efficiency of each series of projections following Patton and Timmermann (2012). The forecast efficiency test offers more power to detect internal consistency in path forecasts with multiple projection horizons. This test also provides more power to detect bias and inefficiency in small samples. We define forecast revision between t and $\mathrm{t+j}$ as, $\mathrm{r_{t+h|t,t+j} = ln\hat{Y}_{t+h|t+j} - ln\hat{Y}_{t+h|t}}$, where, j $(0 < \mathrm{j} < \mathrm{h})$. For example, for 2020 realized values, a 5-year ahead projection was available in 2015, a 4-year ahead projection was available in 2016, and a 1-year ahead projection was available in 2019 along with a nowcast (current year) in 2020. The first revision in 2016, the second revision in 2017, and finally the fifth revision in 2020. We regress the realized value to the longest horizon forecast and all intermediate revisions. The Patton and Timmermann (2012) test follow the regression:

$$\mathrm{lnY_{t+h}} = \alpha + \beta_1 \mathrm{ln\hat{Y}_{t+h|t}} + \sum_{\mathrm{k=1}}^{\mathrm{j}} \gamma_{\mathrm{k}}\, \mathrm{r_{t+h|t+k-1,t+k}} + \varepsilon_{\mathrm{t+h}} \tag{6}$$

where, j is the total number of revisions in the regression and k $(1, \ldots., \mathrm{j})$ is the index of forecast revisions. The joint null hypothesis of unbiasedness and efficiency is evaluated using the restriction. $\mathrm{H_0}: (\alpha, \beta_1, \gamma_1, \ldots \ldots, \gamma_{\mathrm{J}}) = (0,1,1, \ldots \ldots.,1)$.

Patton and Timmermann (2012), further indicate that regressing realized value on the full sequence of forecasts can provide a straightforward interpretation of forecast efficiency. As a robustness check, following Patton and Timmermann (2012), we regress realized values on a full sequence of forecasts:

$$\mathrm{lnY_{t+h}} = \alpha + \beta_0 \mathrm{ln\hat{Y}_{t+h|t}} + \sum_{\mathrm{j=1}}^{\mathrm{h}} \beta_{\mathrm{j}}\, \mathrm{ln\hat{Y}_{t+h|t+j}} + \varepsilon_{\mathrm{t+h}} \tag{7}$$

The joint null hypothesis of unbiasedness and efficiency is tested using the restriction: $\mathrm{H_0}: (\alpha, \beta_0) = (0,1) \wedge \beta_{\mathrm{j}} = 0$ for $\mathrm{j} = 1, \ldots, \mathrm{h}$. Where the parameter estimate of the most recent forecast is equal to one, and all other coefficients, including intercept, should be zero.

3.3 Informativeness test

CBO projections are multi-horizon forecasts or “path forecasts” (Jordà and Marcellino, 2010). Multi-horizon forecast evaluation identifies the maximum projection horizon (also called predictive content) up to which the projections are informative or provide useful information. The maximum informative projection horizon is also called “content horizon” (Galbraith, 2003). The content horizon of multi-horizon forecasts is important for long-term planning and policy.

We measure the content horizon of CBO projections using the empirical approach developed by Breitung and Knüppel (2021) and adopted by Bora, Kuethe, and Katchova (2022). This approach, instead of comparing the forecast to some uninformative benchmark (naïve forecast), directly compares the mean-squared forecast error to the unconditional variance of the target variable. Under the assumption of quadratic loss and given the information set I_t, at time t, the optimal projection is equal to the conditional expectation, $\mu_{h,t} = E(\ln\widehat{Y}_{t+h}|I_t)$. Let μ denote the unconditional mean, $\mu = E(\ln Y_t)$, we test the hypothesis:

$$H_0: E(\ln Y_{t+h} - \ln\widehat{Y}_{t+h|t})^2 \geq E(\ln Y_{t+h} - \mu)^2, \quad t \in \{1, \dots \dots, T\} \text{ and for } h > h^* \qquad (8)$$

Breitung and Knüppel (2021) call (8) the "no information hypothesis," which states that there exists a maximum projection horizon (h^*) beyond which actual value (Y_{t+h}) is unpredictable under the information set I_t. Breitung and Knüppel (2021) further indicate another test of informativeness in which conditional mean of the projection remains constant within the sample (9), and show that if the projection for Y_{t+h} is identical to the conditional mean $(\mu_{h,t})$ of the series, (8) is equivalent to (9).

$$H_0: E(\ln\widehat{Y}_{t+h}|I_t)^2 = \mu_{h,t} = \mu, \qquad t \in \{1, \dots \dots, T\} \text{ and for for } h > h^* \qquad (9)$$

Breitung and Knüppel (2021) refer to (9) as the "constant mean hypothesis." The constant mean hypothesis is less restrictive than the no information hypothesis because the projection is considered uninformative if and only if there is no correlation between realized value and projection.

The choice between hypotheses (8) and (9) depends on how the projections are created. Breitung and Knüppel (2021) present three potential scenarios of how the forecasts are generated. First, forecasts are generated based on individual expectations. Second, forecasts are created from survey expectations with a probability of contamination from noise. Third, forecasts are generated from empirical models. CBO's projections are a combination of empirical models and judgment-based analysis, similar to the second and third scenarios. Thus, both hypotheses (8) and (9) can be tested using the Mincer and Zarnowitz (1969) regression framework:

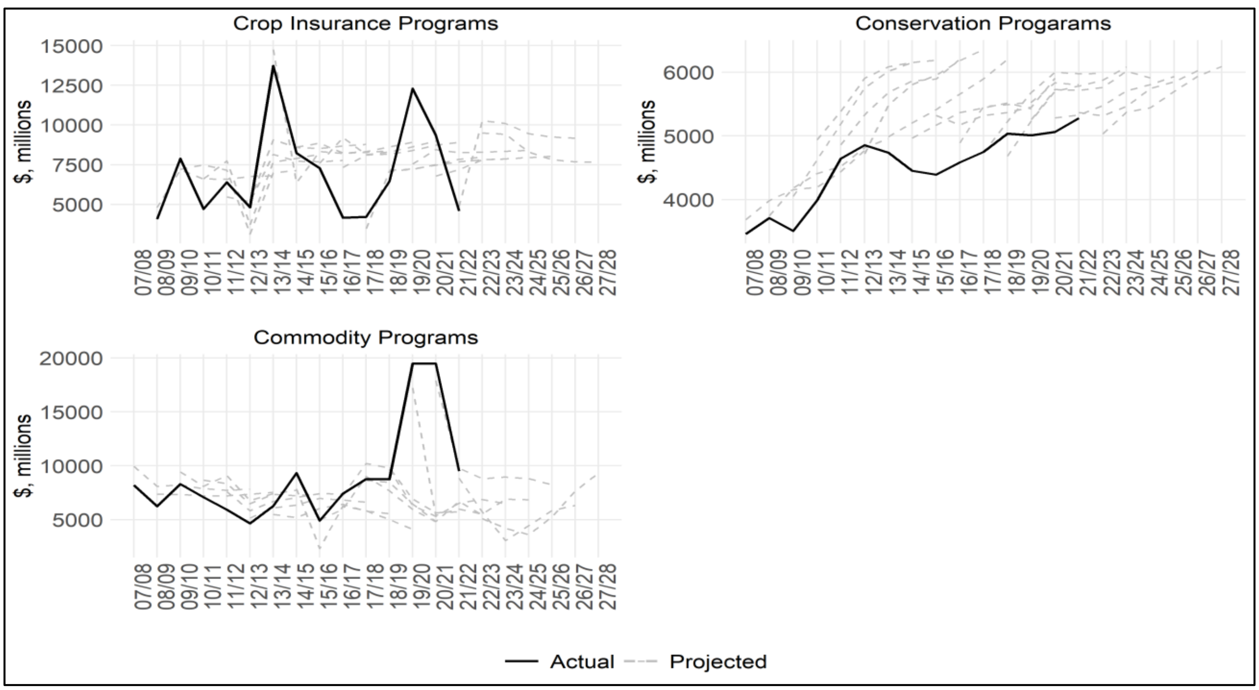
$$\ln Y_{t+h} = \gamma_h + \delta_h \ln\widehat{Y}_{t+h|t} + v_{t+h} \qquad (10)$$

If the projection is generated by a conditional mean of the projection and noise, Breitung and Knüppel, (2021) demonstrate that the no information hypothesis is equivalent to testing $H_0: \delta_h \leq 0.5$, and the constant mean hypothesis is equivalent to testing $H_0: \delta_h \leq 0$ in the Mincer and Zarnowitz (1969) regression framework (10). The maximum informative forecast horizon h^* is determined by testing the null hypothesis beginning from $h = 0$. Then, $h^* = h_{smallest} - 1$, where, $h_{smallest}$ is the smallest horizon for which we fail to reject the null hypothesis.

3.3.1 Disaggregated Farm Program Projections

Since 2008, CBO has published projections for disaggregated USDA farm programs outlays, including commodity, conservation, and crop insurance program outlays. Commodity programs include various commodity price and income supports programs. Conservation programs include different programs under Commodity Credit Corporation Conservation programs and Natural Resource Conservation programs. Crop insurance programs include various Federal Crop Insurance Corporation's programs. Figure 4 shows the projected (multiple dash lines) and realized values (solid lines) of disaggregated farm program outlays. As shown in Figure 4, both crop insurance and commodity program observed outlays fluctuate greatly during the observation period, but the projections appear to off-set periods of over- and under-prediction. Conservation program outlays, on the other hand, grow relatively consistently but at a pace slower than predicted by CBO projections.

Figure 4: Disaggregated farm Programs actual and projected outlays 2007-2027



The disaggregated farm program outlays may provide valuable information to CBO projection users on the accuracy and usefulness of CBO projections. However, the sample size for the disaggregated programs is small. For example, for $h = 0$, the sample size is 14, and for $h = 5$, the sample size is 9. As a result, the regression-based tests of bias, efficiency, and informativeness do not have sufficient statistical power. We, therefore, employ a non-parametric test to analyze the informational value of the disaggregated farm program projections. Following, McIntosh and Dorfman (1992) and Sanders and Manfredo (2003), we evaluate the baseline projections using the directional accuracy test developed by Henriksson and Merton (1981). The test uses conditional probabilities to test whether the projection has informational value or not.

The Henriksson and Merton (1981) test is constructed as follows. Let $\beta_t = 1$, if projection made at $t-1$ for t is such that $\widehat{Y}_t > Y_{t-1}$ and $\beta_t = 0$ if $\widehat{Y}_t \leq Y_{t-1}$. Then the conditional probabilities of correct prediction are: $P_1 = \text{Prob}\{\beta_t = 1 | Y_t > Y_{t-1}\}$ and $P_2 = \text{Prob}\{\beta_t = 0 | Y_t \leq Y_{t-1}\}$. P_1 and P_2 are conditional probabilities of a correct prediction of an upward revision and downward revision, respectively. The conditional probabilities of correct prediction (P_1 and P_2) depend only on whether Y_t is greater than or less than Y_{t-1}. A perfect directional forecast has P_1=1 and P_2=1 and $P_1+P_2 = 2$. Merton (1981) and McIntosh and Dorfman (1992) indicate that the null hypothesis of no information value is:

$$H_0: P_1+P_2=1 \tag{11}$$

The Henriksson and Merton (1981) test is asymptotically equivalent to the test of independence in a contingency table χ^2 statistic (Stekler and Schnader 1991; Cumby and Modest 1987; Pesaran and Timmermann 1994; Sanders and Manfredo 2003). The 2$\times$2 contingency table (see table 1) shows the forecasted direction change and actual direction change. The number of observations in each cell of the table is n. For example, $n_{11} = 1$ if $Y_t > Y_{t-1}$ and $\widehat{Y}_t > Y_{t-1}$, whereas $n_{22} = 1$ if $Y_t \leq Y_{t-1}$ and $\widehat{Y}_t \leq Y_{t-1}$. n_{11} and n_{22} represents the number of observations indicating perfect directional forecasting. In other words, $n_{12} = n_{21} = 0$ represent perfect directional forecasting.

Table 1: Contingency table to measure informational value

		Actual	
		$Y_t > Y_{t-1}$	$Y_t \leq Y_{t-1}$
Prediction	$\widehat{Y}_t > Y_{t-1}$	n_{11}	$n_{12}= N_2 - n_{22}$
	$\widehat{Y}_t \leq Y_{t-1}$	$n_{21}= N_1 - n_{11}$	n_{22}
	Total	N_1	N_2

4 Results

This section summarizes our empirical results for CBO outlay projections of SNAP, child nutrition and Farm programs. First, we evaluate CBO's initial projections, which is typically released in January. However, in most years, CBO releases updated projections in the Summer which incorporate new information, any significant macroeconomic developments, and changes in legislation. We assume that as new information becomes available, the updated projections may have more robust information sets than the initial projections. Our results demonstrate that updated projections are generally more accurate, unbiased (except for the longer horizons of SNAP), and more informative than initial projections[9]. Further, we also review the legislative history of the Farm Bill since 1985[10] to see potential usefulness of updated projections in Farm Bill debates. For example, the 1990 Farm Bill was considered under discussions in the House in March 1990. CBO released initial projections in January and updated them in July 1990. The legislative discussions/debate could have benefited from updated projections before the Farm Bill was approved in November 1990. Likewise, for the 2014 Farm Bill, CBO released updated projections in May 2013. The legislative discussions began in July 2013. The updated projections could have been offered as a reference or could have provided useful information in Farm Bill discussions prior to its approval in February 2014. Thus, given the potential useful implications of updated projections, our evaluation and discussions are based on updated projections.

4.1 SNAP outlay

Table 2 shows accuracy measures (MAPE and RMSPE) and our empirical tests results for SNAP outlays. Forecast rationality requires that forecast error variances are monotonically increasing as the forecast horizon increases (Patton and Timmermann 2012). Similarly, for path forecasts, forecast optimality requires predictions at shorter horizons must be at least as good as predictions at longer horizons (Patton and Timmermann 2012). Table 2 shows that SNAP projections meet these criteria as MAPE and RMSPE increase as the projection horizon increases.

A forecast is optimal if it is both unbiased and efficient (Diebold and Lopez, 1996). Table 2 reports the results of the Holden and Peel (1990) bias test for CBO projections for SNAP

[9] CBO initial projection evaluation results are available from author upon request.
[10] legislative history of Farm Bill since 1985 is provided in appendix A.

outlays. Results indicate that SNAP outlays exhibit downward bias for horizons three through five. The magnitude of bias increases as horizon lengthens. For example, CBO projection underpredicts SNAP outlays by 8.6% for a three-year horizon and by 15.7% for a five-year horizon.

As previously described, an efficient forecast uses all information available at the time of the forecast, yet a forecaster's full information set may not be observed. A forecaster's information set, however, contains previous forecasts. Thus, a necessary condition of forecast rationality implies that forecast errors should be independent of forecast revisions, and the subsequent forecast revisions should be uncorrelated (Nordhaus 1987). We present the results of the Patton and Timmermann (2012) efficiency test for SNAP outlays estimated from equation (6) in table 2. Coefficient estimates close to one reflect an efficient projection. Results indicate that the coefficient estimates are close to one for the shorter projection horizons and decrease for the longer projection horizons. For example, the estimate for h=0 is 0.995, and the coefficient estimate decreases to 0.854 for h=5. Although the estimates for the shorter horizons are close to one, in the joint test, we reject the null hypothesis of efficiency indicating that SNAP outlay for all projection horizons are inefficient. All the revisions are positive which indicates that CBO projections are "smoothed" or revised too slowly. As a robustness check, we also regress actual values on the forecast as indicated in equation (7), as reported in table B in the appendix. Consistent with the findings in table 2, results indicate that SNAP outlays are inefficient.

We report the results of the Breitung and Knüppel (2021) informativeness tests in table 2. The parameters are estimated using Mincer and Zarnowitz (1969) regression framework as shown in equation (10). Coefficients estimates that are statistically indistinguishable from one indicate a one-to-one correspondence with realized value and projection. In general, our results indicate that the estimates are close to one for the short-term projection horizons and decrease for the long-term projection horizons. For example, the estimate decreases from 0.989 for the current year projection horizon (h=0) to 0.854 for the five years ahead projection (h=5). As discussed earlier, we compute the predictive content of the projection using no information and constant mean hypothesis. The maximum informative projection horizon is calculated by testing the null hypothesis starting from h=0, as shown in equation (10). When we fail to reject null hypotheses — $\mathrm{H_0}: \delta_\mathrm{h} \leq 0.5$ for the no information hypothesis and $\mathrm{H_0}: \delta_\mathrm{h} \leq 0$ for the constant mean hypothesis – the maximum informative projection horizon is $h^* = \mathrm{h_{smallest}} - 1$. Where $\mathrm{h_{smallest}}$

is the smallest horizon for which we fail to reject the null hypothesis. Our results indicate that SNAP are informative for all five horizons under both hypotheses.

Table 2: Accuracy, bias test, efficiency test, and informativeness test of SNAP outlay

	h=0	h=1	h=2	h=3	h=4	h=5
Accuracy						
MAPE	1.54	6.46	14.36	20.78	26.27	30.74
RMSPE	2.67	9.43	18.20	25.79	32.03	36.82
Bias: Holden and Peel (1990) test of bias[a]						
	0.000	0.019	0.054	0.086**	0.123***	0.157***
	(0.006)	(0.026)	(0.047)	(0.042)	(0.039)	(0.045)
Efficiency: Patton and Timmermann (2012) test of efficiency[b]						
	0.995**	1.034***	0.941***	0.869***	0.798***	0.854***
	(0.011)	(0.038)	(0.061)	(0.067)	(0.041)	(0.060)
Informativeness: Predictive content estimated in the Mincer and Zarnowitz (1969) regression[c]						
	0.989*** ###	1.011** ###	0.975* ###	0.941* ###	0.895*** ###	0.854*** ###
	(0.010)	(0.029)	(0.028)	(0.028)	(0.030)	(0.031)
$H_0: \delta_h \leq 0$; (constant mean hypothesis) Content horizon = 5						
$H_0: \delta_h \leq 0.5$; (no information hypothesis) Content horizon = 5						

***, **, and * denote 1%, 5%, and 10% significance levels, respectively. Figures in parenthesis are autocorrelation and heteroskedasticity consistent (HAC) standard errors
[a] Parameters are estimated from $e_{t+h|t} = \alpha_h + \varepsilon_{t+h}$. H_0: $(\alpha_h = 0)$.
[b] Parameters (β_1) are estimated from equation 6. H_0: $(\alpha, \beta_1, \gamma_1, \dots \dots, \gamma_j) = (0,1,1, \dots \dots .,1)$.
[c] Parameters (δ_h) are estimated from equation 10. ***,**, * denote 1%, 5%, and 10% significance levels, respectively for testing $H_0: \delta_h \leq 0$; while ###,##, and # denote 1%, 5%, and 10% significance levels, respectively for testing $H_0: \delta_h \leq 0.5$.

4.2 Child nutrition outlay

Table 3 similarly reports accuracy measures (MAPE and RMSPE) and empirical tests results for child nutrition outlays. Similar to SNAP outlays, both MAPE and RMSPE increase as the projection horizon increases for child nutrition outlays. This result is in consistent with the forecast rationality, as Patton and Timmermann (2012) indicate that rational forecast error increase with increase in projection horizon because forecaster is projecting ahead with relatively a smaller information set.

We report the results of Holden and Peel (1990) test of bias for child nutrition outlay in table 3. Contrary to SNAP outlay projection, result indicate that child nutrition outlay projection is unbiased for all the projection horizons. However, the results of efficiency test estimated from the Patton and Timmermann (2012) estimated from equation (6) indicate that child nutrition outlay projection evolved inefficiently for all projection horizons. Similar to SNAP outlays, for the robustness check, we also estimate efficiency test by regressing actual values on full sequence of forecast (equation 7) and results indicate that child nutrition outlays are evolved inefficiently for all projection horizons (see Appendix B).

Table 3 also reports the results of test of informativeness estimated from equation (10). Similar to SNAP outlays, results indicate that the estimates for the shorter projection horizon is close to one and decrease for the longer projection horizons. For example, the estimate decreases from 0.989 for the current year projection horizon (h=0) to 0.928 for the five years ahead projection (h=5). The content horizon estimated from Breitung and Knüppel (2021) empirical tests indicate that child nutrition outlay is informative for all five horizons under both hypotheses: constant mean hypothesis and no information hypothesis.

Table 3: Accuracy, bias test, efficiency test, and informativeness test of child nutrition outlay

	h=0	h=1	h=2	h=3	h=4	h=5
Accuracy						
MAPE	2.38	4.31	5.10	5.45	6.22	7.59
RMSPE	4.93	6.20	7.57	8.51	8.01	9.43
Bias: Holden and Peel (1990) test of bias[a]						
	0.000	0.009	0.006	0.011	0.024	0.042
	(0.009)	(0.014)	(0.017)	(0.019)	(0.024)	(0.025)
Efficiency: Patton and Timmermann (2012) test of efficiency[b]						
	0.938***	0.918***	0.934***	0.933**	0.942**	0.928***
	(0.017)	(0.022)	(0.023)	(0.023)	(0.025)	(0.022)
Informativeness: Predictive content estimated in the Mincer and Zarnowitz (1969) regression[c]						
	0.989***###	0.969***###	0.958***###	0.964***###	0.954**###	0.928***###
	(0.016)	(0.029)	(0.025)	(0.033)	(0.027)	(0.022)
$H_0: \delta_h \leq 0$; (constant mean hypothesis) Content horizon = 5						
$H_0: \delta_h \leq 0.5$; (no information hypothesis) Content horizon = 5						

***, **, and * denote 1%, 5%, and 10% significance levels, respectively. Figures in parenthesis are autocorrelation and heteroskedasticity consistent (HAC) standard errors

[a] Parameters are estimated from $e_{t+h|t} = \alpha_h + \varepsilon_{t+h}$. $H_0: (\alpha_h = 0)$.

[b] Parameters (β_1) are estimated from equation 6. $H_0: (\alpha, \beta_1, \gamma_1, \dots \dots, \gamma_j) = (0,1,1, \dots \dots, 1)$.

[c] Parameters (δ_h) are estimated from equation 10. ***,**, * denote 1%, 5%, and 10% significance levels, respectively for testing $H_0: \delta_h \leq 0$; while ###,##, and # denote 1%, 5%, and 10% significance levels, respectively for testing $H_0: \delta_h \leq 0.5$.

4.3 Farm program outlay

Finally, Table 4 similarly reports accuracy measures and results of our empirical tests for farm program outlay projection. Results indicate that consistent with the forecast rationality, both MAPE and RMSPE increases for the short projection horizons but then remain relatively stable.

The results of Holden and Peel (1990) test of bias indicate that farm program outlay projection is weakly biased upward (at 10% significance level) for the current year projection (h=0) and then unbiased for the remaining horizons. Similar to SNAP and child nutrition outlay projections, the test of efficiency indicate that farm program outlay projection is evolved inefficiently for all projection horizons.

We also report the results of Breitung and Knüppel (2021) informativeness tests estimated in the Mincer and Zarnowitz (1969) regression framework (equation 10) for farm program outlay projection in table 4. Results indicate that we reject the null hypotheses — $H_0: \delta_h \leq 0.5$ for the no information hypothesis and $H_0: \delta_h \leq 0$ for the constant mean hypothesis — at the first horizon. Thus, farm program outlay is informative only for the one year horizon (h=1).

Table 4: Accuracy, bias test, efficiency test, and informativeness test of farm program outlay

	h=0	h=1	h=2	h=3	h=4	h=5
Accuracy						
MAPE	13.24	33.56	43.24	39.49	41.54	42.06
RMSPE	19.44	43.32	57.74	60.86	50.13	50.71
Bias: Holden and Peel (1990) test of bias[a]						
	-0.005*	0.027	0.072	0.128	0.181	0.247
	(0.031)	(0.085)	(0.125)	(0.152)	(0.169)	(0.178)
Efficiency: Patton and Timmermann (2012) test of efficiency[b]						
	1.178*	0.540**	0.169***	0.135***	0.092***	0.151***
	(0.135)	(0.392)	(0.388)	(0.299)	(0.264)	(0.218)
Informativeness: Predictive content estimated in the Mincer and Zarnowitz (1969) regression[c]						
	1.114***###	0.595***##	0.073	0.069	0.018	0.151***
	(0.073)	(0.238)	(0.346)	(0.315)	(0.253)	(0.218)
$H_0: \delta_h \leq 0$; (constant mean hypothesis) Content horizon = 1						
$H_0: \delta_h \leq 0.5$; (no information hypothesis) Content horizon = 1						

***, **, and * denote 1%, 5%, and 10% significance levels, respectively. Figures in parenthesis are autocorrelation and heteroskedasticity consistent (HAC) standard errors

[a] Parameters are estimated from $e_{t+h|t} = \alpha_h + \varepsilon_{t+h}$. $H_0: (\alpha_h = 0)$.

[b] Parameters (β_1) are estimated from equation 6. $H_0: (\alpha, \beta_1, \gamma_1, \dots \dots, \gamma_j) = (0,1,1, \dots \dots, 1)$.

[c] Parameters (δ_h) are estimated from equation 10. ***, **, * denote 1%, 5%, and 10% significance levels, respectively for testing $H_0: \delta_h \leq 0$; while ###, ##, and # denote 1%, 5%, and 10% significance levels, respectively for testing $H_0: \delta_h \leq 0.5$.

4.4 Disaggregated Farm Program Projections

Next, we examine the components of farm program outlays to gauge potential reasons for the short content horizon for aggregated farm program outlays projections. As discussed previously, CBO has published disaggregated farm program outlays since 2008. Due to the limited sample size of the disaggregated projections, we employ a non-parametric test of the directional accuracy of the disaggregated projections of crop insurance, conservation, and commodity program outlays.

First, we analyze the MAPE and RMSPE of the disaggregated farm program outlays projections across projection horizons, shown in table 5. The accuracy measures suggest that both MAPE and RMSPE increase as the forecast horizon increases. Among the three outlays of the farm programs, results indicate that conservation programs have the lowest MAPE and RMSPE, whereas crop insurance program outlays have the highest MAPE and RMSPE.

Table 5: MAPE and RMSPE of crop insurance, conservation, and commodity programs

Horizon	Crop Insurance		Conservation		Commodity	
	MAPE	RMSPE	MAPE	RMSPE	MAPE	RMSPE
h=0	21.36	29.02	8.24	10.76	12.71	14.92
h=1	37.52	51.26	12.91	13.78	30.67	37.82
h=2	37.68	47.99	16.64	17.70	27.23	36.66
h=3	38.19	49.91	17.74	20.64	32.85	38.86
h=4	41.73	55.18	19.71	23.59	40.62	45.52
h=5	41.66	54.73	22.49	26.69	41.41	49.25

We then use the Henriksson and Merton (1981) test to identify the predictive content of the components of the farm programs. The results of the Henriksson and Merton (1981) test for the informational value of projections of crop insurance, conservation, and commodity programs outlays are presented in table 6. We reject the null hypothesis of no informational value (equation 12) for all projection horizons for crop insurance outlays, which indicates that crop insurance program outlays have informational value for all five projection horizons. Further, results indicate that CBO correctly predicts directional changes in crop insurance program outlays over 80% of the time for all projection horizons. By contrast, we failed to reject the null hypothesis of no informational value for conservation program outlays, which suggests that conservation program outlays do not have informational value. Further, commodity programs have informational value for only the current year and at a one-year horizon.

In sum, our results indicate that the likely sources of un-informativeness for farm program outlays are potentially due to the projections of the conservation program and commodity program outlays. However, this finding is based on analysis of data since 2008, and a longer time series would potentially provide valuable information.

Table 6: Informational value of crop insurance, conservation, and commodity programs' outlay projections

Horizon	Crop Insurance			Conservation			Commodity		
	% Correct	χ^2- Statistics	$p-$ value	% Correct	χ^{2-} Statistics	$p-$ value	% Correct	χ^{2-} Statistics	$p-$ value
h=0	84.6	6.197	0.029	57.1	0.598	0.439	78.5	5.833	0.031
h=1	84.6	6.964	0.021	64.2	0.535	0.464	78.5	4.381	0.091
h=2	83.3	6.122	0.028	61.5	0.598	0.439	69.2	2.236	0.266
h=3	81.8	5.238	0.061	66.6	N/A	N/A	66.6	1.185	0.558
h=4	80.0	4.444	0.076	63.6	0.545	0.460	63.6	0.782	0.567
h=5	81.8	5.760	0.048	60.0	0.628	0.428	70.0	1.667	0.524

5 Discussion, Conclusions, and Policy Implications

CBO baseline projections provide the foundation for estimating farm program costs and debating future agricultural policy. While CBO macroeconomic and budgetary indicators have been examined previously, this study is the first to examine CBO projection of USDA mandatory farm and nutrition programs outlays. Our analysis examines projection accuracy, bias, efficiency, and the number of years for CBO projections of USDA mandatory programs are informative.

Using CBO projections and observed outcomes from 1985 through 2020, we demonstrate that, consistent with forecast rationality, the accuracy of CBO baseline projections of mandatory USDA programs decreases as the projection horizon increases for both MAPE and RMSPE. In other words, the error increases as projection horizon lengthens. This finding is consistent with the results of other projection evaluations. For example, Bora, Katchova, and Kuethe (2022) show that prediction error increases as horizon lengthens for most of the farm income and commodity projections of USDA and FAPRI baselines. Further, relative to SNAP and Child nutrition outlays discussed above, our results indicate that MAPE and RMSPE are higher for farm program outlay, which indicates that farm program outlay is relatively less accurate than SNAP and child nutrition outlays.

We show that the projections of child nutrition and farm program outlays are unbiased (except farm program is weakly biased for nowcast). However, SNAP projection exhibit downward bias at longer horizons (beyond 3-year projection) and the magnitude of bias increases for the longer projection horizons (see table 2). One potential reason for the higher magnitude of downward bias for SNAP outlays for the longer projection horizons might be due to forecasters' optimism for future economic conditions. Further, FAPRI, recently began producing SNAP projection (Hoang and Westhoff, 2018), and once enough observations can be acquired, FAPRI and CBO baseline projections can compared or combined to produce optimal predictions in manner similar to Kuethe, et al. (2022).

Our results indicate that the revisions of CBO projections of SNAP, child nutrition, and farm program outlays are inefficient. Specifically, we find that the all of the revisions are positively correlated indicating that CBO projections have been "smoothed" or are being revised too slowly. This finding suggests that subsequent revisions of the CBO are not fully updated with the available information sets. There are competing explanations for the potential reasons for forecast inefficiency. For example, forecaster may have a reputational concern (Ehrbeck and Waldmann 1996), may have an asymmetric loss function (Elliot, Komunjer, and Timmermann 2005), may have a Bayesian learning process (Lahiri and Sheng 2008), may be limited by information rigidity (Coibion and Gorodnichenko 2012; Goyal and Adjemian 2022), or be influenced by macroeconomic assumptions used to generate projections (Arai, 2020).

The predictive content tests indicate that CBO projections of SNAP and child nutrition programs outlays remain informative up to five horizons, yet the projections for farm program outlays are only informative for current and one-year projections. However, farm program projections may stay informative beyond one-year horizon using improved forecasting methods or better information sets. We, further examine the potential sources of uninformativeness of farm program outlay using disaggregated data. Farm program outlays consists of multiple spending categories, such as conservation programs, crop insurance programs, and commodity programs, which might impact the informational value of farm program projection. Our findings suggest the likely sources of un-informativeness for farm program outlays are potentially due to the projections of the conservation program and commodity program outlays.

The programs we evaluate in this study account for 99% of anticipated current (2018) Farm Bill spending. The information on the accuracy and informativeness of CBO projections may serve as a reference to help policymakers to estimate farm and nutrition program costs. Accurate and informative baseline projections result in accurate estimates of mandatory program costs which are important to the farm economy and nutritional security given that Farm Bill programs have provided the majority of direct payments to farmers and the spending on food and nutrition assistance programs are increasing in recent years.

The information on accuracy, bias, and informativeness of CBO long-term projections at least for a 5-years horizon and at program levels may provide valuable insights for policymakers to adjust expectation in future Farm Bill discussions. For example, SNAP projection exhibits downward bias beyond a three-year horizon, suggesting that when debating SNAP policy and funding allocation, policymaker may adjust expectation in a way that SNAP spending will likely cost more in later Farm Bill years. As a result, supporters may lobby for more resources for SNAP than projected for the later Farm Bill period. Further, all of the revisions are positively correlated indicating that CBO projections have been “smoothed” or under-react to new information. Thus, all USDA program outlays would be expected to fluctuate more than implied by CBO projections. Likewise, policymakers can consider discounting the value of long-term farm program projection (beyond 1-year horizon) relatively more to current year projection especially for conservation and commodity programs.

One limitation of our study that should be considered is that we do not have sufficient historical record projections for USDA mandatory programs that allow us to examine the degree to which the bias, inefficiency, and informativeness remain steady over time, due to our small sample size. Further, our findings related to disaggregated projections are based on analysis of data since 2008 (disaggregated data are publicly available since 2008). Examining accuracy and informativeness using additional data may provide more meaningful insights.

Finally, our findings provide valuable insights that may aid in the improvement of CBO projections in the future. There are two potential sources of inefficiency in CBO projections a) behavioral or strategic smoothing reflected in modeling or judgement process or b) inefficiency due to data or informational problems. CBO forecasters may evaluate their model and/or update information to improve future projections. For example, Goyal and Adjemian (2022) show that data challenges, instead of empirical modelling practices are the most likely culprit for the inefficiency in USDA production forecasts. As stated earlier, to the best of our knowledge, this is the first study to examine the accuracy and informativeness of CBO agricultural spending projections. However, examining the degree to which various potential error sources (modeling process, economic forecasts, and legislative changes) affect CBO's outlay projections errors are important areas for future research.

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Appendix A: Legislative history of Farm Bill since 1985

Table A.1: Legislative History of Farm Bill since 1985

Year	Name	Legislative History	Passed
1985	Food Security Act of 1985	**Sep 20,26, Oct 1-3, 7,8,** considered and passed House **Oct 25,28-31, Nov 1, 18-22,** S.1714 considered in Senate **Nov 23,** H.R. 2100 considered and passed Senate amended, in lieu of S. 1714 **Dec 18,** House and Senate agreed to conference report	Dec 23, 1985
1990	Food, Agriculture, Conservation, and Trade Act of 1990	**Mar 6**, H.R. 4077, considered and passed House **Mar 14-15,22**, H.R. 3581 considered and passed House **July 19-20, 23-27,** S. 2830 considered and passed Senate **July 23-25,27, Aug 1,** H.R. 3950 considered and passed House **Aug 3,** S. 2830 considered and passed House, amended, in lieu of H.R. 3581, H.R. 3950, and H.R. 4077. **Oct 23,** House agreed to conference report **Oct 25,** Senate agreed to conference report	Nov 28, 1990
1996	Federal Agriculture Improvement and Reform Act of 1996	**Jan 31, Feb 1, 6-7,** considered and passed Senate, S. 1541 **Feb 28-29,** considered and passed House, H.R. 2854 **March 12,** considered and passed Senate, amended in lieu of S. **March 27,** Senate considered conference report **Mar 28,** Senate and House agreed to conference report	Apr 4, 1996
2002	Farm Security and Rural Investment Act of 2002	**Oct 3-5 (2001),** considered and passed House **Feb 13,** considered and passed Senate, amended in lieu of S.1731 **May 2,** House agreed to conference report Senate considered conference report **May 7-8,** Senate considered and agreed to conference report	May 13, 2002
2008	Food, Conservation, and Energy Act of 2008	**Jul 26-27 (2007),** considered and passed House **Nov 5-6,8,13-26, Dec 5,7,10-14 (2007)** considered and passed Senate, amended	May 22, 2008

		May 14, House agreed to conference report. Senate considered conference report **May 15**, Senate agreed to conference report **May 21**, Presidential veto message **May 21**, House overrode veto **May 22**, Senate overrode veto	
2014	Agricultural Act of 2014	**Jul 11 (2013)**, considered and passed House **Jul 18 (2013)**, considered and passed Senate, amended **Sep 28 (2013)**, House concurred in Senate amendment pursuant to H. Res. 361 **Oct 1(2013)**, Senate disagreed to House amendment **Jan 29**, House agreed to conference report **Jan 30; Feb 3-4,** Senate considered and agreed to conference report	Feb 7, 2014
2018	Agricultural Improvement Act of 2018	**May 16-18**, considered and failed House **Jun 21**, considered and passed House **Jun 27-28**, considered and passed Senate, amended **Dec 11**, Senate agreed to the conference report **Dec 12**, House agreed to the conference report	Dec 20, 2018

Source: History of the United States Farm Bill, Library of Congress. Available on History of the United States Farm Bill (loc.gov) (Retrieved on 8/25/2022).

Appendix B: Patton and Timmermann (2012) test using forecasts

Table B.1: Patton and Timmermann (2012) test

	h=0	h=1	h=2	h=3	h=4	h=5
Snap	0.892**	1.662***	1.736***	2.003***	2.142***	0.854***
	(0.049)	(0.129)	(0.216)	(0.402)	(0.312)	(0.031)
Child nutrition	0.478***	1.089***	0.196***	0.685**	0.582**	0.928***
	(0.127)	(0.196)	(0.188)	(0.165)	(0.188)	(0.022)
Farm program	1.145*	0.932**	0.095***	0.148***	-0.204***	0.151***
	(0.095)	(0.253)	(0.319)	(0.248)	(0.104)	(0.218)
Observations: 31; Joint test: $H_0: (\alpha, \beta_0) = (0,1) \wedge \beta_j = 0$ for $j = h_1 \ldots h_H$						

***,**, and * denote 1%, 5%, and 10% significance levels, respectively. Figures in parenthesis are autocorrelation and heteroskedasticity consistent (HAC) standard errors