# Improving ERS's Net Cash Income Forecasts using USDA Baseline Projections

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**Abstract**

USDA Economic Research Service's (ERS) farm income forecasts play an important role in decision making and planning across the agricultural sector, yet recent studies suggest that ERS's initial farm income forecasts are biased. This study examines the degree to which ERS's initial forecast of net cash income and its components can be improved using information from USDA's 10-year Agricultural Baseline Projections. We apply several forecast evaluation tools to a unique set of ERS forecasts, Baseline projections, and official estimates from 1997 through 2019. Our forecast encompassing tests show that Baseline provides important information for predicting livestock receipts, direct government payments, farm-related income, and cash expenses. Our findings are potentially useful for both ERS forecasters and a variety of farm income forecast users.



**Keywords:** farm income, forecast evaluation, forecast encompassing, USDA Baseline projections

**JEL Codes:** C53, Q14

## Introduction

The Federal government's primary statistical agencies are charged with "collecting, producing, and disseminating data that the public, businesses, and governments use to make informed decisions"(Office of Management and Budget, 2020). To this end, the United States Department of Agriculture's (USDA) Economic Research Service (ERS) is the Federal government's "primary source of statistical indicators that gauge the health of the farm sector, including farm income estimates and projections" (Office of Management and Budget, 2020, pp. 31). ERS produces annual estimates of sector-wide farm income as mandated by Congress and required by the US Office of Management and Budget (Kuethe & Morehart, 2012). These official estimates, however, are produced with a significant time lag, and as a result, ERS releases a series of forecasts to provide more timely information. Recent studies suggest that ERS's initial forecasts systematically under-predict realized farm incomes (Bora, Katchova, & Kuethe, 2021; Isengildina-Massa, Karali, Kuethe, & Katchova, 2020; Kuethe, Hubbs, & Sanders, 2018). This downward bias is important because ERS's farm income measures are among the most frequently cited USDA statistics (McGath et al., 2009). ERS's farm income forecasts are used by the farm equipment industry, agricultural lenders, and other farm-related industries to formulate business plans and by state and local governments to forecast personal and real property tax receipts (Dubman, McElroy, & Dodson, 1993). In addition, federal legislators use ERS farm income forecasts to determine the performance and direction of farm policy (Lucier, Chesley, & Ahearn, 1986).

This study examines the degree to which ERS's initial net cash income forecasts can be improved using information from USDA's Agricultural Baseline Projections. Agricultural Baseline provides long-term projections for the U.S. farm sector over the next 10 years, including projections of the global production and trade of agricultural commodities and aggregate U.S. farm income. Similar to ERS's initial farm income forecasts, Agricultural Baseline is released in February and includes projections for current year net cash income and its components. The USDA stresses that Baseline is "not intended to be a forecast of what the future will be" (USDA Office of the Chief Economist, 2020, pp. 1). Instead, Baseline offers a "conditional, long-run scenario about what would be expected to happen under a continuation of current farm legislation and other specific assumptions" (USDA Office of the Chief Economist, 2020, pp. iii). The specific assumptions include normal weather and no domestic or external shocks that would affect global agricultural supply and demand, as well as defined macroeconomic conditions, trade policies, and productivity growth rates.[1]

Despite Baseline projections' limited purpose, they may provide useful information for ERS's

[1]Although USDA draws a distinction between "projections" and "forecasts," we use the terms interchangeably when considering the short-term predictions of current conditions. Some studies, alternatively, label current-year projections "nowcasts."

initial farm income forecasts. Baseline projections are produced by the USDA's Interagency Agricultural Projections Committee, which consists of experts from 10 USDA agencies and offices, including ERS (USDA Office of the Chief Economist, 2020). Thus, Baseline projections draw information from a diverse set of experts. In addition, ERS's farm income forecasts are constructed from statistical models using thousands of equations and hundreds of data series (McGath et al., 2009). Baseline projections, by contrast, reflect a composite of model results and judgement-based analysis.[2] A growing body of literature suggests that subjective forecasts of economic variables derived from aggregate opinions of experts may outperform traditional empirical forecasts (Faust & Wright, 2013).

We evaluate the degree to which USDA's Agricultural Baseline Projections can be used to improve ERS's initial net cash income forecasts in three steps. First, we compare the relative accuracy of ERS forecast and Baseline projections of realized estimates of net cash income and its components from 1997 through 2019 (23 years). Components include crop receipts, livestock receipts, farm-related income, direct government payments, and cash expenses. For each component, we examine whether ERS or Baseline offers more accurate projections, using statistical tests developed by Diebold and Mariano (1995) and D. Harvey, Leybourne, and Newbold (1997). We also examine the system-wide accuracy across the vector of projections for both ERS and Baseline, following T. M. Sinclair, Stekler, and Carnow (2015) and Isengildina-Massa et al. (2020).

Second, we examine the degree to which Baseline farm income projections exhibit systematic bias. Isengildina-Massa et al. (2020) previously identified a systematic downward bias in ERS's initial forecasts of bottom-line net cash income, crop receipts, livestock receipts, and cash expenses. This finding was confirmed by Bora et al. (2021), who suggest that the bias is the result of asymmetric cost of over-predicting, relative to under-predicting, aggregate farm income. Following Isengildina-Massa et al. (2020), we formally test for bias in the Baseline projections on a series-by-series basis, as well as across the vector of projections, using a procedure developed by Holden and Peel (1990).

Finally, we test the degree to which Baseline may provide additional information to ERS's initial forecasts of net cash income and its components. Specifically, we test whether an optimal forecast can be constructed from a weighted combination of ERS and Baseline projections or whether ERS "encompasses" all of the relevant information in the Baseline projections, following D. I. Harvey, Leybourne, and Newbold (1998). We apply encompassing tests on both a series-by-series basis and across the vector of projections, following Clements and Hendry (1998).

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[2] https://www.ers.usda.gov/topics/farm-economy/agricultural-baseline/questions-answers/ (Accessed: 1 November 2020)

forecasts of net cash income and its components. Specifically, we test whether an optimal forecast can be constructed from a weighted combination of ERS and Baseline projections or whether ERS "encompasses" all of the relevant information in the Baseline projections, following D. I. Harvey et al. (1998). We apply encompassing tests on both a series-by-series basis and across the vector of projections, following Clements and Hendry (1998).

Our analysis yields a number of important findings. First, system-wide accuracy measures suggest that ERS forecasts are compositionally consistent with realized official estimates, yet Baseline projections are not. Thus, only ERS forecasts are suitable for decision making (T. M. Sinclair et al., 2015). However, on a series-by-series basis, we find robust evidence that Baseline projections of government payments are more accurate than those of ERS. We also find less robust evidence that ERS projections of bottom-line net cash income, crop receipts, and livestock receipts are more accurate than those of Baseline. Second, we find that, from 1997 to 2019, ERS and Baseline projections exhibited similar patterns of bias. Consistent with previous studies of ERS net cash income, we find that Baseline projections of bottom-line net cash income and livestock receipts are biased downwards. Finally, we find that ERS initial projections of net cash income and its components can be improved by including information from Baseline. Specifically, the optimal system-wide projection is obtained by using ERS forecasts for bottom-line net cash income and crop receipts and Baseline projections for government payments and farm-related income. The optimal projection of cash expenses and livestock receipts can be obtained using either ERS or Baseline. Our findings may be useful to both ERS forecasters and variety of ERS forecast users, including policymakers, lenders, and farm sector business leaders.

The remainder of the paper is as follows. The next section provides a detailed description of ERS forecasts and USDA Agricultural Baseline Projections of net cash income and its components. The third section summarizes our data. Then, we describe our empirical methods in the fourth section. The fifth section presents our empirical findings, followed by concluding remarks.

## Net Cash Farm Income

USDA's net cash income is a sector-wide measure of the amount of cash earnings generated by farm businesses that are available to meet a variety of obligations, such as debt payments (McGath et al., 2009). It is defined as gross cash income less cash expenses. Gross cash income includes both crop and livestock cash receipts, direct government payments, and farm-related income. Direct government payments are limited to funds paid directly to farmers and ranchers by the Federal Government to support farm incomes, conserve resources, or compensate for natural disasters (McGath et al., 2009). Farm-related income include machine hire and custom work, forest products, and other income from farm output and sales. USDA's official estimates of net cash income, therefore, follow the accounting equation:

$$\begin{aligned} \text{Net cash income} =& (\text{Crop receipts} + \text{Livestock receipts} + \text{Cash farm-related income} \\ & + \text{Direct government payments}) - \text{Cash expenses}. \end{aligned} \tag{1}$$

Both ERS and USDA Agricultural Baseline produce projections for bottom-line net cash income and each of the components included in (1). The official estimates for each series are released in August, following the reference year, by ERS.

*ERS Forecasts*

Given that official estimates are released with a significant time lag, ERS provides a series of periodic forecasts of net cash income and its components to provide more timely information. In this study, we examine ERS's initial calendar year forecast, typically released in February, 18 months prior to official estimates. Previous studies show that ERS's initial forecasts consistently under-predict official estimates of bottom-line net cash income, crop receipts, livestock receipts, and cash expenses (Bora et al., 2021; Isengildina-Massa et al., 2020). It is important to note that ERS releases revised forecasts in August (12 month horizon), November (9 month horizon), and the following February (6 month horizon). The bias in the initial forecast diminishes throughout the revision process as the volume and quality of information increases (Bora et al., 2021; Isengildina-Massa et al., 2020; Kuethe et al., 2018). As Isengildina-Massa et al. (2020) notes, most of the reports and data employed in ERS's farm income forecasting models are not available when the initial forecast are constructed, and as a result, the 18-month-ahead forecasts primarily rely on unpublished estimates from ERS commodity analysts.

ERS uses a bottom-up forecasting approach, in which each component is forecast at the most granular level possible. McGath et al. (2009) describes the statistical models underlying each component forecast and the aggregate net cash income forecasts used by USDA since 1986. ERS implemented several major changes to net cash income forecasting and estimation procedures in 2014, the details of which are provided on the agency's website (Isengildina-Massa et al., 2020).[3]

*Baseline Projections*

USDA's Agricultural Baseline Projections are principally designed to model anticipated farm program costs over a 10-year horizon and are used to prepare the President's budget. Baseline projections are produced annually by the USDA Interagency Agricultural Projections Committee,

[3] https://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics/general-documentation/ (Accessed 1 November 2020)

comprised of experts from 10 USDA agencies and offices.[4] The projections are released in February by the committee and published by USDA Office of the Chief Economist (2020). The report also includes a detailed discussion of the assumptions that underlie the projections. The assumptions include a continuation of current farm legislation, no domestic or external shocks that would affect global agricultural supply and demand, and normal weather. The projections are designed to provide "a neutral reference scenario that can serve as a point of departure for a discussion of alternative farm-sector outcomes that could result under different domestic or international conditions" (USDA Office of the Chief Economist, 2020, pp. 1).

The Baseline projection process begins the preceding August and September, when domestic and international macroeconomic assumptions are developed. In October, the committee prepares detailed commodity projections for foreign countries. In November, the committee prepares core domestic analysis for program commodities. In December, projections for livestock and other non-program commodities are finalized. In January, ERS economists prepare the sector-wide projections for farm income and agricultural trade.

## Data

Our dataset consists of USDA Agricultural Baseline projections and ERS initial forecasts for bottom-line net cash income and its components: crop receipts, livestock receipts, direct government payments, farm-related cash income, and cash expenses. USDA baseline projections have been available to the public since 1996 (Baumel, 2001). An electronic record of archived Baseline projections since 1997 are maintained by the Albert R. Mann Library at Cornell University.[5] Archived ERS forecasts and realized official estimates from 1986 through 2017 were obtained from Isengildina-Massa et al. (2020). ERS forecasts and realized estimates since 2017 were obtained from the agency's website.[6] Consistent with prior studies, realized estimates are defined as the first official estimate released by ERS in August following the reference year (Bora et al., 2021; Isengildina-Massa et al., 2020; Kuethe et al., 2018). As these studies note, official estimates may be subject to periodic revision as new information is released by various USDA agencies, such as the quinquennial Census of Agriculture. In sum, our dataset of official estimates, Baseline projections, and ERS forecasts includes six series that each span 23 years from 1997

[4]World Agricultural Outlook Board (WAOB), Economic Research Service (ERS), Farm Production and Conservation Business Center, Foreign Agricultural Service (FAS), Agricultural Marketing Service (AMS), Office of the Chief Economist (OCE), Office of Budget and Program Analysis (OBPA), Risk Management Agency (RMA), Natural Resources Conservation Service (NRCS), National Institute of Food and Agriculture (NIFA)

[5]`https://usda.library.cornell.edu/concern/publications/qn59q396v?locale=en` (Accessed: 1 November 2020)

[6]`https://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics/data-files-us-and-state-level-farm-income-and-wealth-statistics/` (Accessed: 1 November 2020)

through 2019. The official estimates or actual values (solid line), ERS's initial forecasts (dotted line), and Baseline projections (dashed line) for each variable are plotted in Figure 1.

**[FIGURE 1 ABOUT HERE]**

For our empirical analysis, ERS forecasts and Baseline projections are expressed as percent changes from the previous year to avoid the impact of changing forecast levels over the study period, following Bora et al. (2021). For each reference year $t$, Agricultural Baseline publishes information for 12 years: ERS's most recent official estimate ($t-2$), ERS's November forecast for the preceding year ($t-1$), the Baseline projection of the current reference year $t$, and Baseline projections for the next 9 calendar years ($t+1, t+2, \ldots, t+9$). For example, USDA Office of the Chief Economist (2020) reported ERS's official estimates for 2018 (released August 2019), ERS's November forecasts for 2019 (released November 2019), and Baseline projections for 2020–2029.[7] As such, for both ERS and Baseline, the predicted percentage change is calculated as the current year projections relative to ERS's November forecast of the previous year, as published in the Baseline projections report. The percent change is calculated: $\boldsymbol{f}_{i,t} = 100 \times ln(\boldsymbol{F}_{i,t}/\boldsymbol{F}_{ERS,t-1})$, where $\boldsymbol{F}_{i,t}$ is the forecast/projection for $i = ERS, Baseline$ in reference year $t$ and $\boldsymbol{F}_{ERS,t-1}$ is the ERS forecast for year $t-1$ which was released in the November of the previous year and included in the Baseline report.[8]

To measure the accuracy of both ERS forecasts and Baseline projections, actual or realized official estimates are similarly transformed: $\boldsymbol{a}_t = 100 \times ln(\boldsymbol{A}_t/\boldsymbol{A}_{t-1})$, where $\boldsymbol{A}_t$ and $\boldsymbol{A}_{t-1}$ are ERS's official estimates for years $t$ and $t-1$, respectively. Percent forecast errors are thus calculated as the difference between the transformed official estimates and predicted changes: $\boldsymbol{e}_{i,t} = \boldsymbol{a}_t - \boldsymbol{f}_{i,t}$. As previously stated, actual or realized values $\boldsymbol{A}_t$ are defined as ERS's first official estimates of net cash income and its components, released in August following the reference year. Figure 2 plots the transformed official estimates $\boldsymbol{a}_t$ (solid line), ERS initial forecasts $\boldsymbol{f}_{ERS,t}$ (dotted line), and Baseline projections $\boldsymbol{f}_{Baseline,t}$ (dashed line) throughout our observation period, and Figure 3 similarly plots the forecast error for ERS initial forecasts $\boldsymbol{e}_{ERS,t}$ (solid line) and for Baseline projections $\boldsymbol{e}_{Baseline,t}$ (dotted line).

**[FIGURE 2 ABOUT HERE]**
**[FIGURE 3 ABOUT HERE]**

[7] Note: ERS's final forecast of 2019, released in February of 2020, was unavailable to the Baseline committee when the projections were assembled in January and February of 2020.

[8] Given that we limit our analysis to the initial ERS forecasts, the horizon $h$ is omitted from our notation, yet it is important to remember that the horizon for both ERS and Baseline is $h = 18$ months, from February to the following August.

## Methodology

As previously stated, we examine the degree to which USDA's Agricultural Baseline Projections can be used to improve ERS's initial net cash income forecasts in three steps. First, we empirically test whether Baseline projections provide more accurate predictions of realized net cash income and its components, relative to ERS's initial forecasts. Second, we examine the degree to which Baseline projections exhibit the same systematic biases previously identified in ERS's initial farm income forecasts (Bora et al., 2021; Isengildina-Massa et al., 2020). Third, we use forecast encompassing tests to examine the degree to which Baseline projections provide additional information to ERS's initial forecasts of net cash income and its components.

### *Accuracy*

Accuracy is defined as the difference between actual and predicted values. We measure the relative accuracy of ERS forecasts and Baseline projections of net cash income and its components using two common measures: mean absolute error (MAE) and root mean squared error (RMSE). For each variable, the forecast error is defined as the difference between actual and predicted percentage change $e_{i,t} = a_t - f_{i,t}$, where $i = ERS, Baseline$. MAE measures the average absolute forecast error over the period $t = 1, \dots, T$ and is defined:

$$\text{MAE}_i = \frac{1}{T} \sum_{t=1}^{T} |e_{i,t}|. \tag{2}$$

MAE is not sensitive to the occasional large forecast error. RMSE, on the other hand, measures the average squared forecast error over the observation period, which places a greater weight on large forecast errors. RMSE is defined:

$$\text{RMSE}_i = \sqrt{\frac{1}{T} \sum_{t=1}^{T} e_{i,t}^2}. \tag{3}$$

More accurate projections are, therefore, associated with smaller MAE or RMSE values.

Diebold and Mariano (1995) develop an empirical test of the difference in forecast accuracy among two competing projections. The test examines the difference in the expected loss of two forecast error series $\text{E}[g(e_{ERS,t}) - g(e_{Baseline,t})] = 0$, where $g(e_{i,t})$ is the forecaster's loss function. We consider two loss function specifications: a linear loss function based on the absolute error $|e_{i,t}|$ and a quadratic loss function based on the squared error $e_{i,t}^2$. The two loss functions closely mirror (2) and (3), respectively. The test is based on the sample mean of $d_t$, where $d_t = g(e_{ERS,t}) - g(e_{Baseline,t})$. We apply the so-called modified Diebold-Marianno test of

D. Harvey et al. (1997) that improves small sample properties of the test statistic by introducing a bias correction and testing with a modified student $t$, rather than standard normal, distribution. For each loss function, we examine one-sided $t$-tests. The lower one-sided $t$-test has an alternative hypothesis that the ERS forecast is *more* accurate than the Baseline projection, and the upper one-sided $t$-test has an alternative hypothesis that the ERS forecast is *less* accurate than the Baseline projection.

The modified Diebold-Marianno test, however, is limited to series-by-series comparisons between ERS and Baseline. Given that both ERS and Baseline generate a vector of projections, we also examine differences in accuracy system-wide. As Isengildina-Massa et al. (2020) argue, given that net cash income projections are based on the accounting equation (1), it is reasonable to assume that the individual series are not independent of one another. T. M. Sinclair et al. (2015) develop a test statistic of the difference between a vector of projections and the related vector of realized values that explicitly accounts for this interdependence. The difference between predicted and realized values is measured using the Mahalanobis distance, a generalization of Euclidean distance which allows for interdependence among the predicted series. The test evaluates whether the vector of predicted values are compositionally consistent with the vector of realized values or, in other words, whether the predicted values can be substituted for realized values for real-time decision making (Isengildina-Massa et al., 2020; T. M. Sinclair et al., 2015).

For the vector of projections $i = ERS, Baseline$, the Mahalanobis distance between the predicted and actual values is calculated:

$$D_i^2 = (\bar{\boldsymbol{f}}_i - \bar{\boldsymbol{a}})' \boldsymbol{W} (\bar{\boldsymbol{f}}_i - \bar{\boldsymbol{a}}) \tag{4}$$

where $\bar{\boldsymbol{f}}_i$ and $\bar{\boldsymbol{a}}$ are the mean vectors of ERS and Baseline projections and their actual values across the observation period, stacked over each component. The matrix $\boldsymbol{W}$ is the inverse of the pooled sample variance-covariance matrix. T. M. Sinclair et al. (2015) develop an $F$-statistic of the Mahalanobis distance between the predicted and actual vectors by weighting (4) as a function of the number of elements in each vector and the degrees of freedom. Following Isengildina-Massa et al. (2020), for the net cash income forecast, this yields $F_i = 3D_i^2$ for $i = ERS, Baseline$. The $F$-test therefore evaluates whether the Mahalanobis distance between the predicted vector of net cash income and its components and the actual vector is significantly different from zero. The Mahalanobis distance (4) has also been used to rank forecasts by Bauer, Eisenbeis, Waggoner, Zha, et al. (2003), Eisenbeis, Waggoner, and Zha (2004), and T. Sinclair, Stekler, and Muller-Droge (2016).

*Bias*

A forecast or projection is unbiased if it does not consistently differ from realized values. Previous studies identify a significant downward bias in ERS's initial forecasts of bottom-line net cash income, crop receipts, livestock receipts, and cash expenses (Bora et al., 2021; Isengildina-Massa et al., 2020). Thus, only two of the six series were previously shown to be unbiased predictors of realized values: farm-related income and direct government payments.

Following Isengildina-Massa et al. (2020), we formally test whether ERS forecasts or Baseline projections consistently differ from realized official estimates using the regression based test of Holden and Peel (1990). For each series, we regress the forecast errors $e_{i,t}$ ($i = ERS, Baseline$) on a constant:

$$e_{i,t} = \alpha_i + \varepsilon_{i,t}. \tag{5}$$

where $\alpha_i$ is an unknown constant to be estimated and $\varepsilon_{i,t}$ is a white noise regression error. Whether a projection is unbiased can be tested using the restriction $H_0 : \alpha_i = 0$. A positive and significant coefficient $\hat{\alpha}_i$ would suggest that the predicted series systematically under-predict realized values ($a_t > f_{i,t}$), and a negative and significant coefficient $\hat{\alpha}_i$ would suggest that the predicted series systematically over-predict realized values ($a_t < f_{i,t}$). Equation (5) is estimated on a series-by-series basis for both ERS and Baseline using ordinary least squares (OLS).

Following Isengildina-Massa et al. (2020), we also test for bias across the vector of projections using the system of regression equations:

$$\boldsymbol{e}_{i,t} = \boldsymbol{\alpha}_i + \boldsymbol{\varepsilon}_{i,t}. \tag{5'}$$

where $\boldsymbol{e}_{i,t}$ is the vector of forecast errors for net cash income and its components for $i = ERS, Baseline$ at year $t$, and $\boldsymbol{\alpha}_i$ and $\boldsymbol{\varepsilon}_{i,t}$ are vector equivalents of the regression terms in (5). The vector of coefficients $\hat{\boldsymbol{\alpha}}_i$ is estimated using seemingly unrelated regression (SUR), and the system-wide bias is evaluated by a joint test of the restriction $\boldsymbol{\alpha}_i = 0$.

*Encompassing*

One set of projections encompasses another if it contains all of the relevant information of the competing projection. That is, the informational content of the preferred projection dominates the other. D. Harvey et al. (1997) develop a regression-based encompassing test. For our study, the regression is expressed:

$$e_{ERS,t} = \alpha + \lambda(e_{ERS,t} - e_{Baseline,t}) + \varepsilon_t. \tag{6}$$

where $e_{ERS,t}$ is the forecast errors of ERS's initial forecast, and $e_{Baseline,t}$ is the forecast error of Baseline projections. The parameters $\alpha$ and $\lambda$ are estimated by OLS, and $\varepsilon_t$ is a white noise regression error. The null hypothesis that ERS forecasts encompass the Baseline projections is evaluated by a two-tailed $t$-test of the restriction $\lambda = 0$. A failure to reject $\lambda = 0$ implies that ERS is preferred to baseline.

Alternatively, (6) can be viewed as a test of whether a composite forecast can be constructed from both ERS and Baseline that would yield a smaller expected squared forecast error. Under this interpretation, the estimated coefficient $\hat{\lambda}$ is the weight that should be placed on Baseline projections in the composite forecast. As a result, the hypothesis that Baseline encompasses ERS can be tested by a two-tailed $t$-test of the restriction $\lambda = 1$. A failure to reject $\lambda = 1$ suggests that Baseline projections are strictly preferred to ERS forecasts. In the optimal composite forecast, ERS is given the weight $(1 - \hat{\lambda})$. Thus, if we fail to reject both $\lambda = 0$ and $\lambda = 1$, the optimal composite forecast can be obtained using either ERS or Baseline. Finally, if we reject both $\lambda = 0$ and $\lambda = 1$, an optimal combined forecast is achieved by weighting Baseline by $\hat{\lambda}$ and ERS by $(1 - \hat{\lambda})$.

We estimate (6) by OLS on a series-by-series basis. In addition, we examine whether the vector of ERS forecasts encompass the vector of Baseline projections, following Clements and Hendry (1998). The system of equations is expressed:

$$\boldsymbol{e}_{ERS,t} = \boldsymbol{\alpha} + \boldsymbol{\lambda}(\boldsymbol{e}_{ERS,t} - \boldsymbol{e}_{Baseline,t}) + \boldsymbol{\varepsilon}_t \tag{6'}$$

where $\boldsymbol{e}_{ERS,t}$ and $\boldsymbol{e}_{Baseline,t}$ are vectors of stacked forecast error series for the components of the ERS forecasts and Baseline projections, respectively. The sets of coefficients $\hat{\boldsymbol{\alpha}}$ and $\hat{\boldsymbol{\lambda}}$ for each component are estimated using SUR. In a fashion similar to (6), forecast encompassing across the vector of projections is evaluated based on a joint test of the restriction $\boldsymbol{\lambda} = 0$ or $\boldsymbol{\lambda} = 1$.

## Results

The series-by-series accuracy measures for both ERS and Baseline are reported in table 1. Panel (a) includes the MAE loss for both ERS forecasts and Baseline projections, as well as the modified-Diebold-Mariano (MDM) test statistic based on the related linear loss function. The MAE measures suggest that, between 1997 and 2019, ERS yielded more accurate projections of crop receipts and livestock receipts, relative to Baseline. The MDM test suggests that ERS's better accuracy is statistically significant at a 10% level for crop receipts and at a 5% level for livestock receipts. The MDM tests suggest no statistical difference between ERS and Baseline projections for bottom-line net cash income, government payments, farm-related income and cash expenses. By contrast, the MDM tests under quadratic loss (panel (b)) do not find any series for which the differences in accuracy were statistically significant.

**[TABLE 1 ABOUT HERE]**

The differences in system-wide accuracy are reported in panel (c). The first column includes the average percent change in actual values from the previous year between 1997 and 2019, based on ERS's first official estimate. Columns two and three include the average percent changes based on ERS forecasts and Baseline projections, respectively. Panel (c) also reports the Mahalonobis distance measure of system-wide forecast accuracy of the vector of forecasts used in T. M. Sinclair et al. (2015) along with the associated $F$-statistics and $p$-values. The Mahalanobis distance $F$-tests suggest that ERS forecasts are compositionally consistent with actual values with a $p$-value of 0.107. Thus, ERS's forecasts can be substituted for actual data for decision making, consistent with Isengildina-Massa et al. (2020). However, the Baseline projections are not compositionally consistent at 5% level. Thus, Baseline projections cannot be substituted for realized values for real time decision making (T. M. Sinclair et al., 2015). Also, it is important to note that, following T. Sinclair et al. (2016), the ERS's vector of forecasts is more accurate than the Baseline vector of projections overall, as $D^2_{ERS} < D^2_{Baseline}$.

The average percent change in projections reported in table 1, panel (c), suggest that the Baseline projections may be biased, while the ERS's forecasts are unbiased. The formal bias tests of (5) and (5') are reported in table 2. The first two columns report the series-by-series coefficient estimates and Newey and West (1987) standard errors based on OLS estimation of (5), and the final two columns similarly report the coefficient estimates and Newey and West (1987) standard errors across the vector of projections using SUR of (5'). The OLS results suggest that both ERS and Baseline systematically under-predict realized bottom-line net cash income and government payments at a 5% significance level. In addition, ERS's initial forecasts under-predict cash expenses at a 5% significance level.

**[TABLE 2 ABOUT HERE]**

The SUR estimation, which controls for the interdependence of forecast errors across the series, finds more statistically significant evidence of bias in both ERS forecasts and Baseline projections. The results suggest that ERS under-predicts bottom-line net cash income at a 1% significance level, as well as livestock receipts, government payments, farm-related income, and cash expenses at a 10% significance level. In addition, the results suggest that Baseline under-predicts bottom-line net cash income at a 1% significance level, livestock receipts at a 1% significance level, and government payments and cash expenses at a 5% significance level. Thus, the primary difference between ERS forecasts and Baseline projections identified by the SUR results is that Baseline does not under-predict farm related income, but ERS does. The final row of table 2 reports the $F$-statistic value for the joint restriction of $\boldsymbol{\alpha}_i = 0$ for $i = ERS, Baseline$. The tests suggest that both ERS and Baseline projections are biased.

The encompassing tests of (6) and (6') are reported in table 3. The first two columns report the estimated coefficients and Newey and West (1987) standard errors of the series-by-series encompassing tests (6) by OLS. The final two columns report the estimated coefficients and Newey and West (1987) standard errors of the system-wide encompassing test (6') by SUR. Though the standard errors are generally lower using SUR than OLS, the significance of the coefficients is the same for both the OLS and SUR estimations. The null hypothesis $\boldsymbol{\alpha} = 0$ is rejected confirming the results of bias in table 2.

**[TABLE 3 ABOUT HERE]**

The null hypothesis $\lambda = 0$ is rejected at the 1% significance level for two series: government payments and farm-related income. As previously noted, $\hat{\lambda}$ represents the weight that should be placed on Baseline projections when constructing an optimal composite forecast using both ERS and Baseline. As a result, we also test the competing forecast $\lambda = 1$. For both government payments and farm-related income, we fail to reject $\lambda = 1$. Thus, Baseline projections for government payments and farm-related income are strictly preferred to ERS. The MDM tests for government payments under linear and quadratic loss (table 1) showed that Baseline projections were more accurate than ERS's forecasts though they barely missed being significant at a 10% level.

By contrast, we fail to reject $\lambda = 0$ for bottom-line net cash income, crop receipts, livestock receipts, and cash expenses. For bottom-line net cash income and crop receipts, the null hypothesis $\lambda = 1$ is rejected. Thus, ERS's forecasts of bottom-line net cash income and crop receipts are strictly preferred to those of Baseline. For livestock receipts and cash expenses, we fail to reject both $\lambda = 0$ and $\lambda = 1$. The encompassing test results therefore suggest that an optimal forecast can be constructed using either ERS or Baseline. As previously discussed, $\hat{\lambda}$ represents the weight that should be applied to Baseline and $(1 - \hat{\lambda})$ represents the weight that should be applied to ERS. In either case, we cannot conclude that either series should receive full or zero weight. The two predictions are indistinguishable.

The final rows of table 3 report the $F$-statistics for the joint restrictions $\boldsymbol{\lambda} = \mathbf{0}$ and $\boldsymbol{\lambda} = \mathbf{1}$ in (6'). The SUR results reject $\boldsymbol{\lambda} = \mathbf{1}$, which implies that ERS vector of forecasts contains information in addition to Baseline. This result is not surprising as ERS forecasters likely receive additional information for the February forecast that is not available to the Baseline committee when the net cash income projections are produced in December and January, such as the revised forecasts of the previous year. However, the SUR results also reject $\boldsymbol{\lambda} = \mathbf{0}$, which suggests that the Baseline vector of projections contains additional information that could be used to improve ERS forecasts. The information may be related to additional trade and commodity information of the Baseline committee or the relative balance of judgement and model-based information. Thus, our results suggest that both ERS forecasts and Baseline projections contain useful information for different components that are not fully encompassed in the other projection.

In sum, our results suggest that ERS's net cash income forecasts could be improved by incorporating information from USDA's Baseline Projections. Specifically, our encompassing test results suggest that Baseline projections for government payments and farm related income are strictly preferred to those of ERS. This finding has important implications for ERS's net cash income forecasts. While ERS's bottom-line net cash income forecasts receive the most attention, the agency uses a bottom-up forecasting approach because the information provided by the individual component forecasts is often valued by decision makers (McGath et al., 2009). It is important to note, however, that government payments and farm related income represent a modest share of overall net cash income (Isengildina-Massa et al., 2020). Thus, the improvement to the aggregate net cash income forecasts or the significance of these improvements may be minimal.

To examine the degree to which ERS's bottom-line net cash income forecasts can be improved based on our findings, we construct a composite forecast by substituting ERS's forecasts of government payments and farm related income with the preferred Baseline projections. The composite forecast is constructed using ERS's component forecasts of crop receipts, livestock receipts and cash expenses and Baseline's component projections of government payments and farm related income, following equation (1). Figure 4 plots the forecasts errors of this composite net cash income forecast, along with those of ERS and Baseline. As the figure suggests, the composite forecast is marginally more accurate than ERS's forecast of bottom-line net cash income. The RMSE of the composite net cash income forecast is 17.3, which is lower than the RMSE of either ERS or Baseline (17.8 and 18.6, table 1). Further, the composite forecast of net cash income is slightly less biased than either ERS or Baseline. Regression estimates of equation (5) on the composite forecast yield a coefficient estimate of $\hat{\alpha} = 8.133$, with a standard error of 3.26 and a $p$-value of 0.02. While the composite forecast is also biased downward, the degree of bias is less than those of either ERS or Baseline (see table 2).

**[FIGURE 4 ABOUT HERE]**

## Conclusion

ERS's net cash income forecasts are an important source of information on the "health of the farm sector" (Office of Management and Budget, 2020, pp. 31) for decision makers across the agricultural sector and beyond. ERS's system of farm sector financial accounts are among the USDA's most cited statistics (McGath et al., 2009). They are widely used by policymakers, agricultural businesses, and program administrators. However, recent studies suggest ERS's initial forecasts of bottom-line net cash income, and several of its components, systematically under-predict realized values (Bora et al., 2021; Isengildina-Massa et al., 2020).

Given the important role of ERS's net cash income forecasts, this study examines the degree to which ERS's initial net cash income forecasts can be improved using information of similar set of projections contained in USDA's Agricultural Baseline Projections. USDA's Agricultural Baseline includes 10-year projections of global production and trade of agricultural commodities and U.S. net cash income. The USDA asserts that Baseline is "not intended to be a forecast of what the future will be" (USDA Office of the Chief Economist, 2020, pp. 1), but its farm income projections closely mirror the structure of ERS's projections of current year net cash income and its components. Both ERS forecasts and Baseline projections are released in February. ERS's net cash income forecasts are principally derived from statistical models (McGath et al., 2009). However, Baseline uses a combination of both statistical models and the judgement of a broad panel of experts.

Using a unique combination of ERS forecasts, Baseline projections, and realized official USDA estimates from 1997 through 2019, we examine the relationship between ERS and Baseline using a number of forecast evaluation tools. The modified Diebold-Marianno test of D. Harvey et al. (1997) suggests that ERS forecasts of crop receipts and livestock receipts are more accurate than those of Baseline under MAE loss function. However, under the standard mean square error (quadratic) loss, the two sets of predictions are indistinguishable. The forecast bias test of Holden and Peel (1990) suggests that Baseline exhibits many of the same bias of ERS's forecasts documented in the existing literature (Bora et al., 2021; Isengildina-Massa et al., 2020), with the notable exception of farm-related income. Finally, forecast encompassing tests of D. I. Harvey et al. (1998) show that Baseline contains additional information that could be used to improve ERS's initial forecasts of net cash income and its components. Specifically, ERS may produce a better forecast by substituting Baseline's projections for its own forecasts of government payments and farm-related income.

Our findings, therefore, provide guidance for ERS forecasters to improve the documented bias in its initial forecasts of net cash income and its components. In addition, our findings provide important information for the various users of ERS's farm income forecasts. ERS's forecasts are designed to meet the needs of many decision makers who require timely information on the financial health of the farm sector, including policymakers, agribusiness leaders, and program administrators. Finally, our findings highlight an important aspect of USDA's Agricultural Baseline Projections that is frequently overlooked. The production of Agricultural Baseline Projections require significant USDA resources. Media attention and policy discussions typically focus on the long-run information provided by these 10-year projections. However, our analysis suggests that Baseline also provides important short-run information on current year conditions. The balance of empirical models and the judgment of a broad panel of experts employed by Baseline may also prove beneficial to other short-term USDA forecasts, such as those of commodity production and trade.

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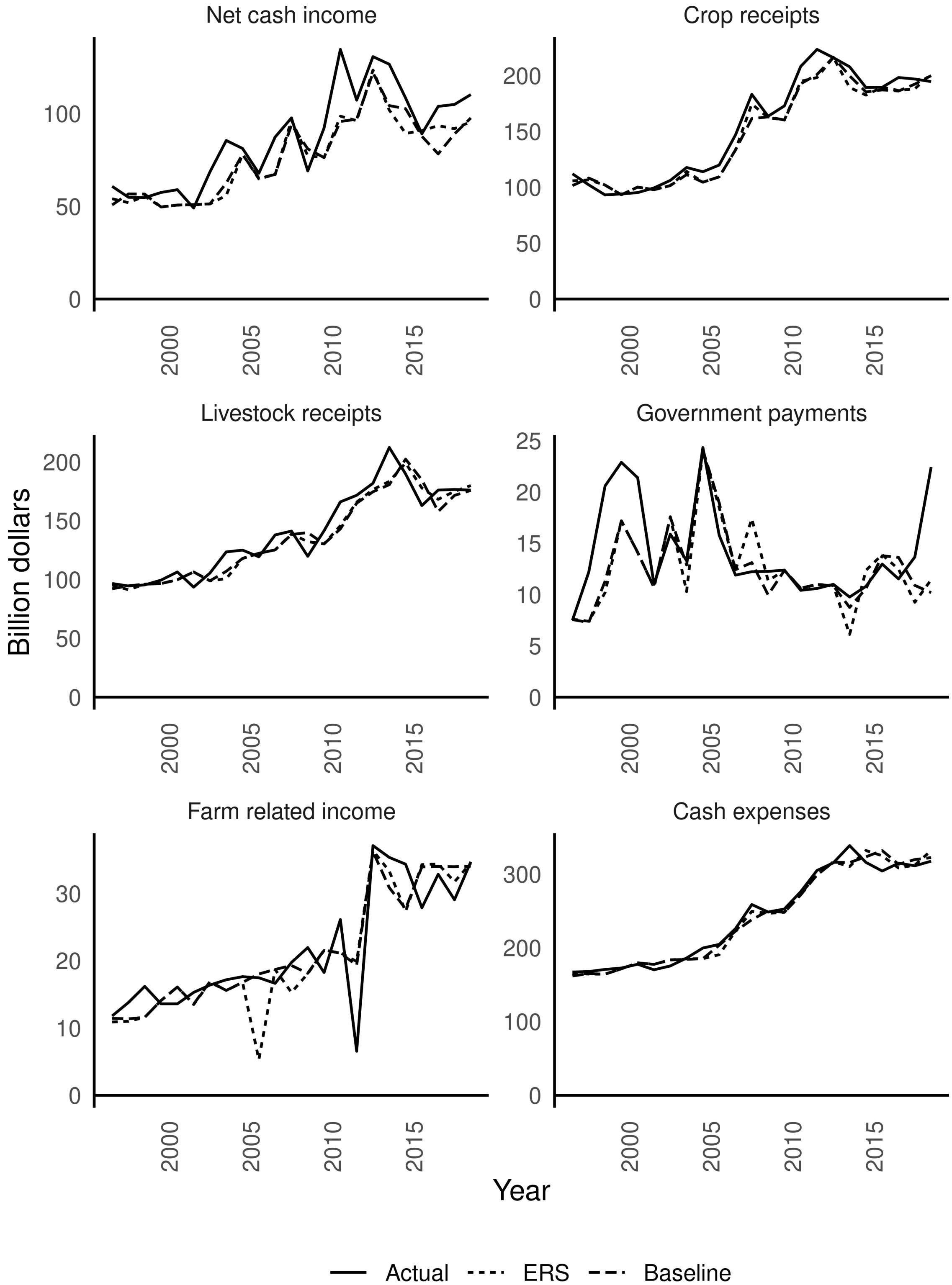


Figure 1: ERS forecasts and Baseline projections for net cash income and its components, in billions of dollars, 1997–2019

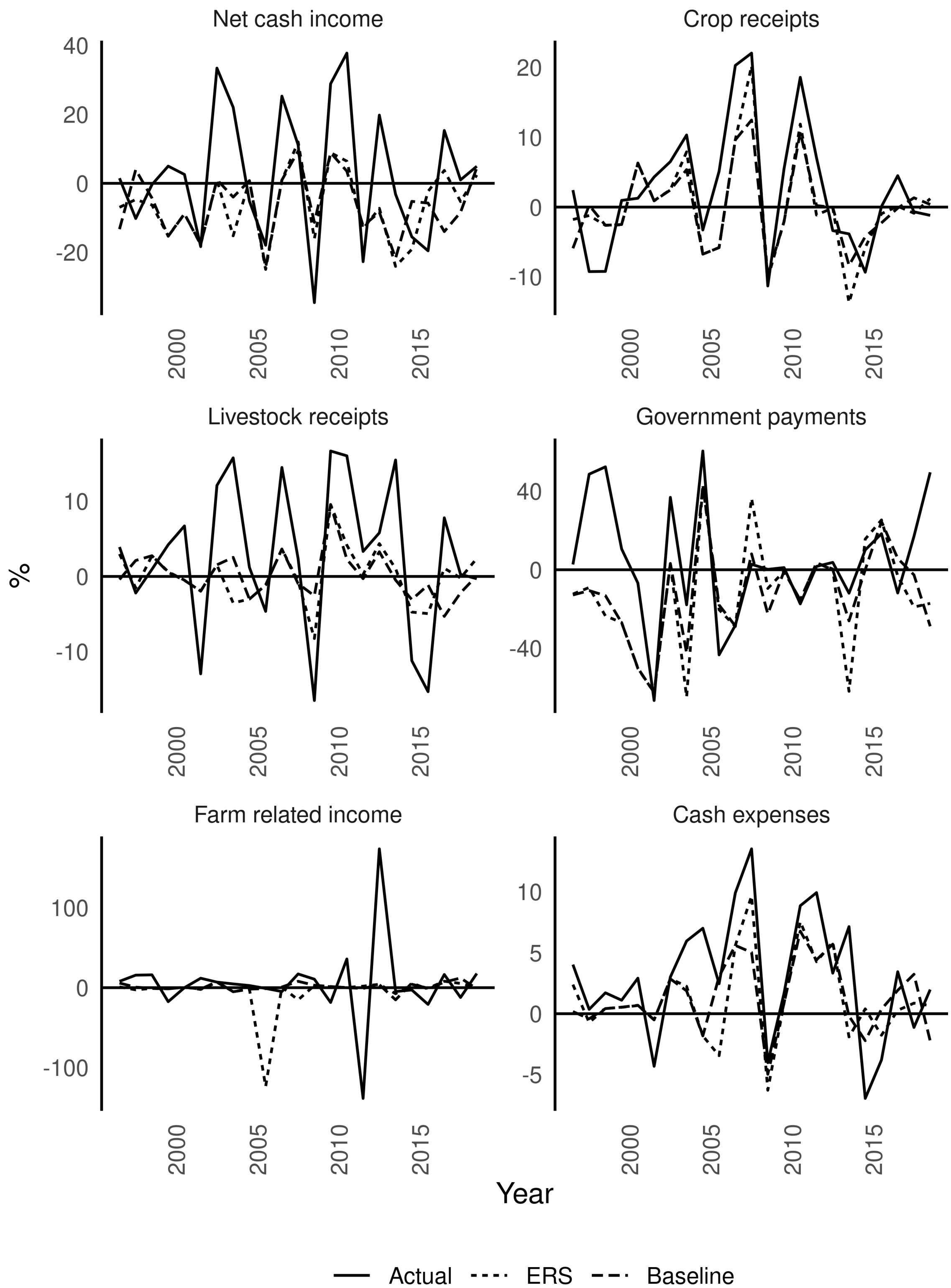


Figure 2: ERS forecasts and Baseline projections for net cash income and its components, percent, 1997–2019

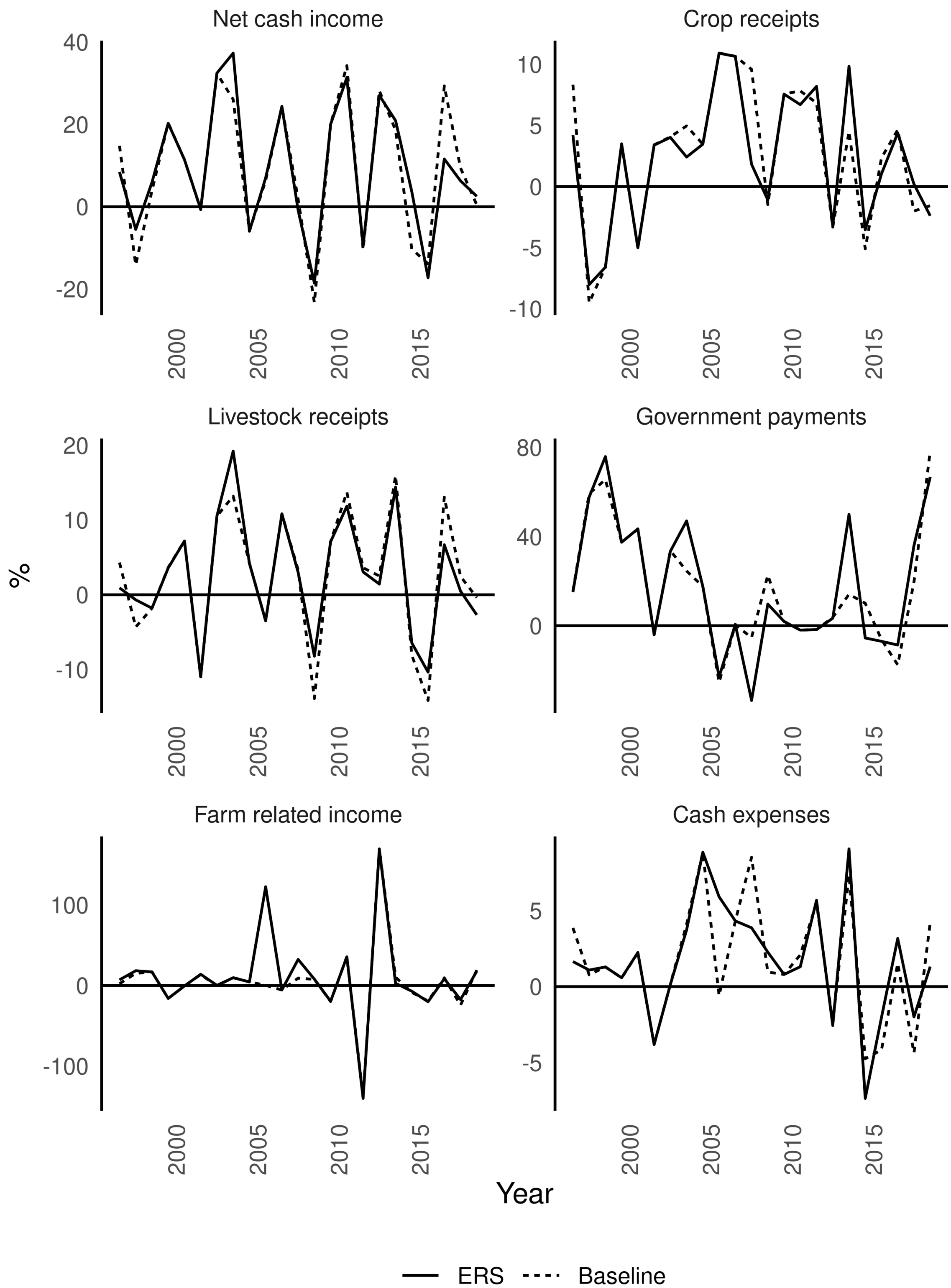


Figure 3: Forecast errors of ERS forecasts and Baseline projections for net cash income and its components, 1997–2019

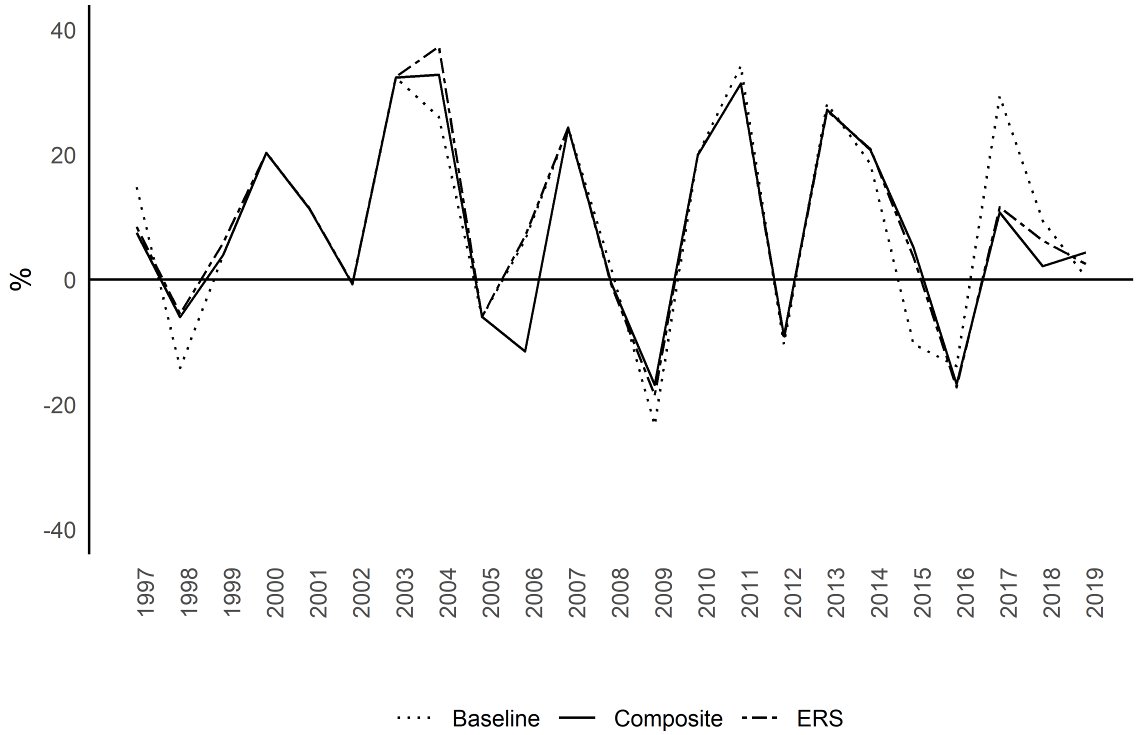


Figure 4: Forecast errors of composite forecasts of net cash income against ERS and baseline, 1997–2019

Table 1: Forecast Accuracy

a) MDM Test for Mean Absolute Error (MAE) Loss Function

| | MAE | | MDM Test | | |
|---|---|---|---|---|---|
| | ERS | Baseline | MDM Statistic | p-value ($H_1$ :Baseline preferred) | p-value ($H_1$ :ERS preferred) |
| Net Cash Income | 14.301 | 15.664 | -1.223 | 0.883 | 0.117 |
| Crop Receipts | 4.883 | 5.536 | -1.361 | 0.906 | 0.094 |
| Livestock Receipts | 6.489 | 7.518 | -1.931 | 0.967 | 0.033 |
| Government Payments | 25.271 | 22.175 | 1.240 | 0.114 | 0.886 |
| Farm-related Income | 30.190 | 24.175 | 1.110 | 0.140 | 0.860 |
| Expenses | 3.255 | 3.349 | -0.225 | 0.588 | 0.412 |

b) MDM Test for Mean Square Error (MSE) Loss Function

| | RMSE | | MDM Test | | |
|---|---|---|---|---|---|
| | ERS | Baseline | MDM Statistic | p-value ($H_1$ :Baseline preferred) | p-value ($H_1$ :ERS preferred) |
| Net Cash Income | 17.799 | 18.641 | -0.637 | 0.735 | 0.265 |
| Crop Receipts | 5.756 | 6.221 | -0.943 | 0.822 | 0.178 |
| Livestock Receipts | 8.093 | 8.895 | -1.081 | 0.854 | 0.146 |
| Government Payments | 33.891 | 30.771 | 1.203 | 0.121 | 0.879 |
| Farm-related Income | 54.623 | 47.680 | 1.085 | 0.145 | 0.855 |
| Expenses | 4.103 | 4.155 | -0.116 | 0.546 | 0.454 |

c) System-Wide Forecast Accuracy

| | Average Forecasts (percent change) | | |
|---|---|---|---|
| | Actual | ERS | Baseline |
| Net Cash Income | 2.655 | -6.579 | -6.174 |
| Crop Receipts | 2.505 | 0.226 | -0.018 |
| Livestock Receipts | 2.778 | 0.172 | 0.229 |
| Government Payments | 4.884 | -12.952 | -11.875 |
| Farm-related Income | 5.038 | -5.414 | 1.073 |
| Expenses | 2.963 | 1.249 | 1.356 |
| Mahalanobis Distance, $D^2$ | | 1.096 | 1.862 |
| F-statistic | | 3.288 | 5.587 |
| p-value | | 0.107 | 0.046 |

Notes: 1) MDM tests are conducted for the MAE and MSE loss functions separately. The alternative hypothesis $H_1$ : *Baseline preferred* indicates the Baseline projection is more accurate than the ERS forecast. Similarly, the alternative hypothesis $H_1$ : *ERS preferred* indicates that the Baseline projection is less accurate than the ERS forecast. 2) Panel c) presents mean percent change for ERS forecasts and Baseline projections along with the actual values.

Table 2: Tests for Bias

| | OLS | | SUR | |
|---|---|---|---|---|
| | ERS | Baseline | ERS | Baseline |
| | $\hat{\alpha}_{ERS}$ | $\hat{\alpha}_{Baseline}$ | $\hat{\boldsymbol{\alpha}}_{ERS}$ | $\hat{\boldsymbol{\alpha}}_{Baseline}$ |
| Net Cash Income | $9.234^{**}$ | $8.829^{**}$ | $9.234^{***}$ | $8.829^{***}$ |
| | $(3.279)$ | $(3.446)$ | $(2.321)$ | $(1.711)$ |
| Crop Receipts | $2.279^{*}$ | $2.524^{*}$ | $2.279^{*}$ | $2.524$ |
| | $(1.154)$ | $(1.324)$ | $(1.354)$ | $(1.588)$ |
| Livestock Receipts | $2.606$ | $2.549$ | $2.606^{**}$ | $2.549^{***}$ |
| | $(1.656)$ | $(1.775)$ | $(1.172)$ | $(0.887)$ |
| Government Payments | $17.836^{**}$ | $16.759^{**}$ | $17.836^{**}$ | $16.759^{**}$ |
| | $(8.078)$ | $(7.522)$ | $(8.357)$ | $(7.556)$ |
| Farm-related Income | $10.452$ | $3.965$ | $10.452^{**}$ | $3.965$ |
| | $(7.604)$ | $(5.858)$ | $(5.165)$ | $(2.465)$ |
| Expenses | $1.714^{**}$ | $1.607^{*}$ | $1.714^{**}$ | $1.607^{**}$ |
| | $(0.770)$ | $(0.778)$ | $(0.809)$ | $(0.794)$ |
| F-statistic ($H_0 : \boldsymbol{\alpha}_{ERS} = \mathbf{0}$) | | | 6.086*** | |
| F-statistic ($H_0 : \boldsymbol{\alpha}_{Baseline} = \mathbf{0}$) | | | | 8.094*** |

Notes: *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Standard errors (in parentheses) are heteroskedasticity and autocorrelation consistent (Newey & West, 1987). The F-statistic corresponds to a joint test of all coefficients equal to zero.

Table 3: Forecast Encompassing Tests

| | OLS | | SUR | |
|---|---|---|---|---|
| | $\hat{\alpha}$ | $\hat{\lambda}$ | $\hat{\alpha}$ | $\hat{\lambda}$ |
| Net Cash Income | $9.247^{**}$ | $-0.032^{++}$ | $9.247^{***}$ | $-0.032^{++}$ |
| | (3.295) | (0.466) | (2.927) | (0.462) |
| Crop Receipts | $2.303^{*}$ | $0.1^{++}$ | $2.303^{*}$ | $0.1^{++}$ |
| | (1.230) | (0.355) | (1.245) | (0.355) |
| Livestock Receipts | 2.631 | -0.453 | $2.631^{*}$ | -0.453 |
| | (1.652) | (0.856) | (1.488) | (0.882) |
| Government Payments | $16.727^{**}$ | $1.03^{***}$ | $16.727^{**}$ | $1.03^{***}$ |
| | (6.564) | (0.317) | (6.894) | (0.316) |
| Farm-related Income | 4.084 | $0.982^{***}$ | 4.084 | $0.982^{***}$ |
| | (9.060) | (0.105) | (6.447) | (0.076) |
| Expenses | $1.67^{**}$ | 0.411 | $1.67^{**}$ | 0.411 |
| | (0.801) | (0.365) | (0.748) | (0.374) |
| F-statistic ($H_0 : \boldsymbol{\alpha} = \mathbf{0}$) | | | | 4.643*** |
| F-statistic ($H_0 : \boldsymbol{\lambda} = \mathbf{0}$) | | | | 29.588*** |
| F-statistic ($H_0 : \boldsymbol{\lambda} = \mathbf{1}$) | | | | 2.778++ |

Notes: *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively for testing the null hypotheses $H_0 : \alpha = 0$, and $H_0 : \lambda = 0$. Likewise, +, ++, and +++ denote statistical significance at 10%, 5%, and 1% respectively for testing the null hypothesis $H_0 : \lambda = 1$.