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Joint Evaluation of the System of USDA’s Farm Income Forecasts

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Abstract

This study evaluates a system of USDA's Net Cash Income forecasts, released as part of the farm sector's income statement, which includes crop receipts, livestock receipts, government payments, farm-related income, and expenses over 1986-2017. We examine these forecasts jointly for bias, accuracy, efficiency, and compositional consistency. Our findings demonstrate that underestimation in early Net Cash Income forecasts stems from underestimation in crop and livestock receipts as well as expenses forecasts. While most components except government payments contribute to the improvement in 12-month ahead forecasts, improvements in 9-month out forecasts are mostly due to crop receipts and expenses forecasts, and government payment forecasts were a main source of improvement in 6-month ahead forecasts. Despite the observed biases and inefficiencies, these forecasts are compositionally consistent with the actual outcomes and represent realistic projections of the farm sector accounts.

Key words: accuracy tests, bias tests, efficiency tests, fixed-event forecast evaluation, multivariate forecast evaluation, net cash income forecasts, joint forecasts

JEL codes: E37, Q11, Q14

Joint Evaluation of the System of USDA's Farm Income Forecasts

USDA's farm income estimates are the official measures of the farm sector's contributions to the national economy and play an important role in the development of agricultural policy (Schnepf 2019). These forecasts have been released by USDA since 1910 and serve as one of the main indicators of the economic well-being of the farm sector. They are widely used by policymakers and media sources to help understand developments in the agricultural economy and by lenders and other agricultural sector stakeholders seeking to understand the magnitude and drivers of farm sector well-being. Farm income forecasts are also used to inform policies on trade assistance, crop insurance, and other policies designed to offset declining revenues and boost farm incomes. Therefore, these forecasts are often used by the farm equipment industry, farm banks, and other farm-related industries to formulate business plans and account for such policies. Furthermore, state and local governments use USDA farm income forecasts for forecasting personal and real property tax receipts. Thus, the interest in USDA's farm income forecasts spans across and beyond the farming community (Dubman, McElroy, and Dodson 1993).

Net farm income is one of the most frequently cited USDA statistics with the estimates providing a retrospective view of farmers' income and financial status (McGath et al. 2009). Lucier, Chesley, and Ahearn (1986) state that while net income forecasts are still used to measure the economic well-being of the farming sector as originally intended, they are also used by federal legislators to determine performance and direction of farm policies. Kuethe, Hubbs, and Sanders (2018) argue that net farm income forecasts are used extensively by all participants in the legislative process to alert lawmakers to changing economic conditions for farmers and ranchers. The Congressional Research Service provides an annual report prepared for members

and committees of the Congress that includes the USDA farm income forecast and an agricultural trade outlook to inform policy makers (Schnepf 2019). There are numerous instances where the farm income forecasts and estimates have been used to justify changes in farm policies or continuing an existing policy, particularly during Farm Bill discussions. Furthermore, these forecasts serve as an input in various USDA models as well as U.S. GDP estimates (McGath et al. 2009). Given the important role of these forecasts, it is imperative to ensure that they are accurate and reliable.

However, despite their prominent role in the agricultural sector, very little research has been devoted to evaluating farm income forecasts. In fact, most of the previous USDA forecast evaluation literature focused on price and production forecasts (e.g., Sanders and Manfredo 2002, 2003; Isengildina, Irwin, and Good 2006, 2013). Because these price and production forecasts often serve as inputs for farm income forecasts (McGath et al. 2009), it is likely that any deficiencies detected in production and price forecasting literature may be carried over into farm income forecasts. A recent study by Kuethe, Hubbs, and Sanders (2018) provides a detailed analysis of bottom line net farm income forecasts. One of their main findings suggests that there is a downward bias in the initial forecast released in February, 18 months before the official estimate is released in August of the following year. They also find that the updated forecasts, released 12 to 6 months before the official estimate, are inefficient as these forecasts tend to overreact to new information. However, their study is focused on the forecasts of total net farm income and does not evaluate the accuracy of its components that are released at the same time.

Data availability for the components of the farm income forecasts over an extended period of time is a major challenge for this type of analysis. Our study uses a new dataset that

includes cash components of farm income that form net cash income forecasts¹ over 1986-2017. Specifically, the components of the net cash income (NCI) include crop receipts, animal and animal product receipts, cash farm-related income, total direct government payments, and cash expenses. To the best of our knowledge, the accuracy and efficiency of these components of farm income accounts, as well as their contribution to the NCI forecast accuracy, has not been evaluated in previous studies. Furthermore, previous literature provides little guidance on evaluation of joint forecasts (such as net cash income forecasts and their components), as most of the forecast evaluation methodology (e.g., Nordhaus 1987; Holden and Peel 1990; Patton and Timmermann 2007) has been developed for single forecast applications, such as the net farm income analyzed by Kuethe, Hubbs, and Sanders (2018).

Only a few recent studies of the macroeconomic forecasts attempted multivariate evaluation of joint forecasts. Caunedo et al. (2013) jointly tested the rationality of the Federal Reserve's forecasts of inflation, unemployment, and output growth using the methodology developed by Komunjer and Owyang (2012). Their approach is based on deriving the weights for a multivariate utility function using forecast errors. Sinclair, Stekler, and Carnow (2015) developed an alternative approach that is based on comparison of vectors of related forecasts. The rationale behind this approach is whether several forecasts may be substituted for one another or used in place of actual data for policy decisions in real time. We believe that this approach is most suitable for net cash farm income forecast evaluation.

¹ Net cash income is a less comprehensive measure of farm income as it does not include non-cash items, such as the value of inventory adjustments.

Given the limitations of the previous literature, the goal of this study is to evaluate the accuracy of NCI forecasts and its components taking into account the joint nature of these forecasts. The evaluation of NCI forecasts and its components in this study focuses on three optimality conditions: bias, improvement, and efficiency. The multivariate approach considers the joint nature of the forecasts of the NCI components and provides insights into the combined accuracy of these forecasts. This characteristic is particularly relevant for forecasts used for policy analysis, such as NCI forecasts. Our findings indicate that, similar to net farm income forecasts, net cash income forecasts are biased downward at longer forecast horizons. In contrast to previous studies, our study is able to uncover sources of bias in NCI forecasts due to individual components and reveal their relative contribution to NCI forecast errors at various forecast horizons. Furthermore, we are able to demonstrate that the accuracy of NCI forecasts significantly improves between 18- and 12- month ahead forecasts and to identify the contribution of various component forecasts to this improvement. Finally, our findings show that despite the biases and inefficiencies detected in this study, NCI forecasting systems at all forecast horizons are compositionally consistent² with the official estimates which makes them suitable for decision making.

Farm Income and Wealth Forecasts

USDA's Economic Research Service (ERS) agency releases U.S. farm sector income and wealth statistics data which include historical U.S.- and state-level farm income and wealth estimates, as

² Compositional consistency is determined based on the difference between the vector of the forecasts and the vector of the official estimates.

well as U.S.-level forecasts for the current calendar year. These forecasts are released within an income statement that follows an accounting equation:

$$(1) \text{ Net cash income} = (\text{Crop receipts} + \text{Livestock receipts} + \text{Cash farm-related income} + \text{Total direct government payments}) - \text{Cash expenses} = \text{Gross cash income} - \text{Cash expenses}.$$

McGath et al. (2009) describe the economic models underlying each component and the aggregate net cash income forecasts used by USDA since 1986.³ USDA uses a bottom-up approach that starts with the forecasts of total cash receipts, including crop (CR) and livestock (LR) receipts. These cash receipts include revenues from sales in the open market and Commodity Credit Corporation (CCC) placements. The value of CCC placements is determined using the volume data obtained from CCC and the loan rates. The value of open market sales is determined using quantity sold in open market (i.e., total production – farm use – CCC placements), disaggregated into monthly sales based on historical patterns multiplied by monthly price forecasts obtained from ERS analysts. Farm-related income (FRI) includes cash income generated from a farm's resource base other than sale of farm commodities and may include forest products sold, rental value of farm dwellings, machine hire and customwork, total commodity insurance indemnities, and net cash rent received by operator landlords. Government payments (GP) include conservation payments, fixed payments, payments that are a function of

³ Note that several major changes to NCI forecasting and estimation procedures have been implemented in 2014.

crop prices and other program payments.⁴ The combination of all these various sources of income results in an estimate of gross cash income (GCI).

Net farm expenses (EXP) are production expenses related to inputs purchased for use in the production of commodities, including farm origin inputs (feed, livestock and poultry purchased, seed), manufactured inputs (fertilizer and lime, fuels and oils, electricity, pesticides), interest charges (short-term interest, real estate interest), other operating expenses (e.g. repair and maintenance, labor, machine hire and customwork), and overhead expenses (capital consumption, property taxes, net rent to non-operators). Expenses data are mainly based on information reported by farmers on Agricultural Resource Management Survey (ARMS) and the latest Census of Agriculture. ERS generates forecasts of production expenses by moving a base year estimate by the changes in the price and quantity indicators. Forecasts of prices paid indexes are used as the price indicators and they follow the prices paid indexes published by the National Agricultural Statistics Service (NASS). Finally, the difference between gross cash income forecast and cash expenses forecast results in the forecast of net cash income.

The first U.S. forecast for each calendar year t is released in February of that year, subsequently revised in August and November of year t , and in February of the following year $t+1$, followed by an official estimate in August of year $t+1$. Thus, every calendar year estimate is associated with four forecasts released 18 (February), 12 (August), 9 (November), and 6 (February) months ahead of the official estimate. Since the terminal event, the calendar year estimate, is the same across all these forecasts, they are considered fixed-event forecasts. Thus,

⁴ See USDA-ERS (<https://www.ers.usda.gov/topics/farm-economy/farm-sector-income-finances/farm-sector-income-forecast/>) for details.

the final estimate for component j for year t is denoted as $F_{\tau,t}^j$ and the h -period ahead forecasts are $F_{\tau-h,t}^j$ for $h = \{6, 9, 12, 18\}$ and $j = \{NCI, CR, LR, FRI, GP, EXP\}$, where τ represents the release time of the official estimate—August of year $t+1$. Figure 1 demonstrates this forecasting cycle and illustrates that when the first forecast for year t is made in February, an estimate for the previous year $t-1$ is not yet finalized. It is also important to note that the official estimate released in August of year $t+1$ is sometimes revised later as input data are updated by various USDA agencies.⁵ However, these revisions do not follow a regular pattern and are not included in this analysis. Therefore, the official estimates released in August, $F_{\tau,t}^j$, are treated as final estimates for the purposes of this study.

Various government publications, such as World Agricultural Supply and Demand Estimates (WASDE), Crop Production reports, and Cattle on Feed reports provide information used for farm income and wealth forecasts. However, most of these reports are not available when 18-month ahead forecasts are released and forecast providers have to rely on unpublished estimates from USDA commodity analysts.

⁵ This is especially true for cash receipts data which are based partially on NASS estimates. These estimates can be updated several times after their initial release and are not considered as “final” until the NASS “final estimates” are released based on the most current Census of Agriculture.

Data and Descriptive Statistics

Our study examines the USDA's forecasts of NCI and its main components, including CR, LR, FRI,⁶ GP, and EXP over 1986 through 2017. All data are obtained from USDA-ERS archives.

To facilitate comparisons across different forecast categories, we define forecasts in natural logarithm form as $f_{\tau-h,t}^j = \ln F_{\tau-h,t}^j$ and $f_{\tau,t}^j = \ln F_{\tau,t}^j$. Forecast revisions are computed as the

percentage difference between the current and the previous forecast: $r_{\tau-h\{i\},t}^j = 100 \times$

$(f_{\tau-h\{i\},t}^j - f_{\tau-h\{i+1\},t}^j)$, where $i = 1, 2, 3, 4$ denotes the first four elements of $h = \{0, 6, 9, 12,$

18}. Forecast errors are defined as the percentage difference between the official estimate

released in August following the reference year and the current forecast: $e_{\tau-h,t}^j =$

$100 \times (f_{\tau,t}^j - f_{\tau-h,t}^j)$, $h = \{6, 9, 12, 18\}$.

Table 1 shows descriptive statistics for both unit and log forecasts, forecast errors, and revisions. This table demonstrates that cash expenses is the largest component of NCI included in this analysis with average annual expenses of over \$198 billion. Crop and livestock receipts are the largest components of the GCI with average annual values of \$127 and \$118 billion, respectively. The other two components of GCI, government payments and farm-related income, are almost 10 times smaller in size with average annual values of \$13 billion and \$16 billion, respectively. Percent errors measure the difference between the forecasted value and the official estimate relative to the size of the category, thus a \$5.3 billion error for 18-month ahead crop receipt forecasts is 4.7% of its category while a \$0.78 billion error for 18-month ahead

⁶ Missing observations for *FRI* (prior to November 2013) were imputed from an accounting equation where $FRI = NCI + EXP - CR - LR - GP$.

government payment forecasts amounts to 6.7%. Errors in farm related income are the most variable among the forecasts included in this study.

Because the NCI forecasts are generated through an accounting equation, errors in NCI forecasts can be traced down to errors in its respective components. Thus, for each forecast horizon, NCI is an aggregate of errors in its components and the relative contribution of each component is estimated using the following ordinary least squares (OLS) regression:

$$(2) \quad e_{\tau-h,t}^{NCI} = \gamma_{0,\tau-h} + \gamma_{1,\tau-h} e_{\tau-h,t}^{CR} + \gamma_{2,\tau-h} e_{\tau-h,t}^{LR} + \gamma_{3,\tau-h} e_{\tau-h,t}^{GP} + \gamma_{4,\tau-h} e_{\tau-h,t}^{FRI} + \gamma_{5,\tau-h} e_{\tau-h,t}^{EXP} + u_{\tau-h,t}^j, \quad h = \{6, 9, 12, 18\}.$$

The results of this analysis shown in table 2 demonstrate that while errors in all components significantly contribute to NCI errors, the magnitude of their contribution differs considerably. The largest driver of NCI errors appears to be the expenses component with estimated coefficients suggesting that a 1% error in EXP leads to about -2.5% error in NCI at all forecast horizons. Crop and livestock receipt errors have a similar impact on NCI accuracy with 1% error in these components leading to about 1.5% error in NCI. The impact of these errors appears to grow across forecasting horizon, from 1.36 at h=18 to 1.7 at h=6 for crop receipts and from 1.5 at h=18 to 1.8 at h=6 for livestock receipts. GP and FRI errors tend to have the smallest impact with a 1% error in these components leading to about 0.1% to 0.2% increase in NCI error. The signs of the estimated coefficients demonstrate the offsetting between errors in revenue and expense components as shown for h=18 in figure 2. This figure shows that as long as errors in GCI (the sum of revenue components) and expense components are made in the same direction (e.g. overestimation), they would tend to cancel out through the accounting equation (where expenses are subtracted from GCI) resulting in smaller NCI errors. On the other hand, errors of

the components of GCI (which are summed to calculate GCI) should be negatively correlated to cancel out.

Figure 3 shows changes in average errors of various forecast categories across the forecasting horizon illustrating potential biases in these forecasts. For unbiased forecasts, positive errors should be offset by negative errors resulting in zero average errors. Figure 3 shows that 18-month ahead NCI errors are about 11% on average and remain positive across the forecasting cycle (suggesting underestimation). Similar patterns but on a smaller scale (4% at $h=18$) are observed for CR forecasts. EXP and LR errors are closest to zero suggesting a lack of bias in these forecasts. On the other hand, FRI forecasts tend to have large positive errors (suggesting underestimation) in both the beginning and the end of the forecasting cycle. GP forecast errors tend to average 6.66% at $h=18$ and -4.57% at $h=9$, indicating underestimation in long-term and overestimation in shorter-term forecasts. Our study examines whether these systematic errors are statistically significant.

Forecast revisions are another specific characteristic of fixed-event forecasts that show how forecasts evolve during the forecasting cycle. The sum of all forecast revisions is equivalent to forecast error. For example, for 6-month ahead forecasts, the revision is equal to the forecast error; but for 12-month ahead forecasts, forecast error is equal to the sum of two revisions (between 12 and 6 months and between 6 and 0 months). Figure 4 shows that, on average, the first revision between 18- and 12-month horizons appears to be positive for all categories, followed by another smaller positive revision in 9-month ahead forecasts (which is consistent with the pattern for underestimation observed with forecast errors in figure 3), and forecasts revisions for some categories become negative only at 6-month horizon. These patterns in forecast revisions are further analyzed later in this study within the forecast efficiency tests.

Methodology

Our forecast evaluation approach accounts for both the joint and fixed event nature of USDA's farm income forecasts. Evaluation of fixed event forecasts typically focuses on systematic component in forecast errors (bias), improvement in accuracy across forecast horizons, and independence of revisions (efficiency). Thus, as we discussed in the previous section, for unbiased forecasts positive errors should be offset by negative errors resulting in an average that is not significantly different from zero. Forecast improvement implies that as more information about the target estimate becomes available across the forecasting cycle, forecast errors should become smaller. If all information is incorporated in the forecasts, one should not be able to predict future forecast changes (revisions); thus, future revisions should be uncorrelated with current revisions. Evaluation of joint forecasts has to consider interdependence across various forecast categories. Furthermore, we examine the compositional changes in the vector of forecasts.

Tests of Bias

The basic requirement for forecast optimality is that forecasts at each horizon lack systematic error, or bias. The Mincer and Zarnowitz (1969) equation is traditionally used to test the correlation between realized and forecasted values in a single variable framework. However, this correlation may be spurious if either series contains a unit root. To address this limitation, Holden and Peel (1990) proposed a modified approach by bringing both forecasts and realized values to the left side of the regression equation and evaluating whether there is a systematic component of forecast errors. We apply the Holden and Peel's approach but modify it to jointly

estimate the equations for all NCI components using a seemingly unrelated regression (SUR) method as:⁷

$$(3) \mathbf{e}_{\tau-h,t} = \boldsymbol{\alpha}_{0,\tau-h} + \mathbf{u}_{\tau-h,t}, \quad h = \{6, 9, 12, 18\},$$

where the vectors $\mathbf{e}_{\tau-h,t}$ and $\mathbf{u}_{\tau-h,t}$ contain, respectively, percent forecast errors and disturbance terms for each j , and the vector $\boldsymbol{\alpha}_{0,\tau-h}$ contains parameters to be estimated for each forecast category given by $\boldsymbol{\alpha}_{0,\tau-h} = (\alpha_{0,\tau-h}^{CR}, \alpha_{0,\tau-h}^{LR}, \alpha_{0,\tau-h}^{GP}, \alpha_{0,\tau-h}^{FRI}, \alpha_{0,\tau-h}^{EXP}, \alpha_{0,\tau-h}^{NCI})'$. Greene (2012) shows that the SUR estimator has efficiency gains over the OLS estimator when the error terms across the equations are contemporaneously correlated, and when the common regressors across equations are different by either including different regressors or having different numeric values of the regressors. In this multivariate setting, the null hypothesis for a test of bias is $H_0: \alpha_{0,\tau-h}^j = 0, \forall j$, which is tested individually for each equation using Benjamini-Hochberg (1995) q-values as described in Anderson (2008) to adjust p-values for multiple testing, as well as jointly for the entire system.

⁷ Sinclair, Stekler, and Carnow (2015) use a vector autoregressive (VAR) model to evaluate bias in the errors of joint rolling-event forecasts (where the final event is equidistant from the forecasts, i.e. one-quarter ahead forecasts). However, our focus here is on the bias in the errors associated with fixed-event forecasts (with multiple forecasts, $h=18, 12, 9$ and 6 , of the same final event), which makes an SUR system more appropriate than a VAR.

Improvements in Forecast Accuracy

Another requirement for fixed-event forecasts is that errors decrease (i.e., accuracy increases) across the forecasting cycle (Patton and Timmermann 2007). Changes in errors across the forecasting cycle are reflected in forecast revisions as:

$$(4) \quad e_{\tau-h\{i\},t}^j - e_{\tau-h\{i+1\},t}^j = 100 \times (f_{\tau,t}^j - f_{\tau-h\{i\},t}^j) - 100 \times (f_{\tau,t}^j - f_{\tau-h\{i+1\},t}^j) \\ = 100 \times (f_{\tau-h\{i+1\},t}^j - f_{\tau-h\{i\},t}^j) = -r_{\tau-h\{i\},t}^j,$$

where $i = 1, 2, 3, 4$ denotes the i^{th} element of $h = \{0, 6, 9, 12\}$.

Joint evaluation of whether forecast revisions are different from zero is conducted by estimating the following equation via SUR:

$$(5) \quad \mathbf{r}_{\tau-h,t} = \boldsymbol{\delta}_{0,\tau-h} + \mathbf{u}_{\tau-h,t}, \quad h = \{6, 9, 12\},$$

where the vectors $\mathbf{r}_{\tau-h,t}$ and $\mathbf{u}_{\tau-h,t}$ contain, respectively, percent forecast revisions and disturbance terms for each component j , and the vector $\boldsymbol{\delta}_{0,\tau-h}$ contains parameters to be estimated for each forecast category given by $\boldsymbol{\delta}_{0,\tau-h} =$

$(\delta_{0,\tau-h}^{CR}, \delta_{0,\tau-h}^{LR}, \delta_{0,\tau-h}^{GP}, \delta_{0,\tau-h}^{FRI}, \delta_{0,\tau-h}^{EXP}, \delta_{0,\tau-h}^{NCI})'$. In this multivariate setting, the null hypothesis for

this test is $H_0: \delta_{0,\tau-h}^j = 0, \forall j$, which is tested individually for each equation using Benjamini-Hochberg (1995) q-values as described in Anderson (2008) to adjust p-values for multiple testing, as well as jointly for the entire system.

Evaluation of Forecast Efficiency

Weak-form efficiency of fixed-event forecasts, described by Nordhaus (1987), implies that forecast revisions should be uncorrelated with past revisions. This condition is typically

examined in a single variable framework by regressing forecast revisions on previous revisions. For joint forecasts, these regressions can be estimated jointly for all forecasted categories in an SUR model for each forecast horizon:

$$(6) \quad \mathbf{r}_{\tau-h\{i\},t} = \boldsymbol{\beta}_{0,\tau-h\{i\}} + \boldsymbol{\beta}_{1,\tau-h\{i\}} \mathbf{r}_{\tau-h\{i+1\},t} + \mathbf{v}_{\tau-h\{i\},t}, \quad h = \{0, 6, 9\}, \quad i = 1, 2, 3,$$

where $\boldsymbol{\beta}_{0,\tau-h\{i\}} = (\beta_{0,\tau-h\{i\}}^{CR}, \beta_{0,\tau-h\{i\}}^{LR}, \beta_{0,\tau-h\{i\}}^{GP}, \beta_{0,\tau-h\{i\}}^{FRI}, \beta_{0,\tau-h\{i\}}^{EXP}, \beta_{0,\tau-h\{i\}}^{NCI})'$ and $\boldsymbol{\beta}_{1,\tau-h\{i\}} = (\beta_{1,\tau-h\{i\}}^{CR}, \beta_{1,\tau-h\{i\}}^{LR}, \beta_{1,\tau-h\{i\}}^{GP}, \beta_{1,\tau-h\{i\}}^{FRI}, \beta_{1,\tau-h\{i\}}^{EXP}, \beta_{1,\tau-h\{i\}}^{NCI})$. Due to additivity of forecast revisions, NCI equations include not only its own revisions, but also revisions of each component forecasts. Therefore, the coefficient vectors $\boldsymbol{\beta}_{0,\tau-h\{i\}}^{NCI}$ and $\boldsymbol{\beta}_{1,\tau-h\{i\}}^{NCI}$ include the intercept and slope estimates of each component in the NCI equation. The null hypothesis of efficiency is then given by $H_0: \beta_{0,\tau-h\{i\}}^j = 0, \beta_{1,\tau-h\{i\}}^j = 0, \forall j$.

Compositional Changes

Sinclair and Stekler (2013) developed a multivariate approach to evaluating accuracy of early GDP component estimates from the Bureau of Economic Analysis (BEA). Their methodology determined whether, for each quarter, the vector of the first vintage of BEA estimates of all the major GDP components was similar to a vector of a later vintage of BEA estimates of the same components. In order to determine whether the two sets of estimates are related, it is necessary to compare the difference between the two vectors. Sinclair and Stekler utilize the Mahalanobis measure for estimating the relationship between the two vectors. This measure, which is well established in the natural sciences, is a generalization of the Euclidean distance and allows for

interdependence of the vectors (Sinclair, Stekler, and Carnow 2015, p. 158).⁸ Thus, this approach combines the single accuracy measure for each component of the joint forecasts into a vector. Specifically, it focuses on the difference between the mean vectors of forecasts and outcomes while allowing for scale differences across different variables and a nonzero correlation between variables. The Mahalanobis distance is calculated as:

$$(7) \quad D^2 = (\bar{\mathbf{f}}_{\tau-h} - \bar{\mathbf{f}}_{\tau})' \mathbf{W} (\bar{\mathbf{f}}_{\tau-h} - \bar{\mathbf{f}}_{\tau}), \quad h = \{6, 9, 12, 18\},$$

where $\bar{\mathbf{f}}_{\tau-h}$ and $\bar{\mathbf{f}}_{\tau}$ are the mean vectors of forecasts and official estimates for each component across years. The matrix \mathbf{W} is the inverse of the pooled sample variance-covariance matrix. An F -statistic can be computed using this distance measure as:

$$(8) \quad F = \frac{(n-p-1)n_1n_2}{p(n-2)(n_1+n_2)} D^2,$$

with p and $n - p - 1$ degrees of freedom, where p is the number of samples in vector $\bar{\mathbf{f}}_{\tau}$, n_1 and n_2 are the number of variables in vectors $\bar{\mathbf{f}}_{\tau-h}$ and $\bar{\mathbf{f}}_{\tau}$, and $n = n_1 + n_2 - 2$. In our case, $p = 1$, $n_1 = n_2 = 6$, and $n = 10$. This measure is used to examine whether the Mahalanobis distance between a vector of NCI forecasts and their components and a vector of NCI official estimates is significantly different from zero. The rationale behind this test is that if a vector of forecasts is

⁸ The Mahalanobis distance test has also been used to evaluate GDP components forecasts by the Federal Reserve (Stekler, Sinclair, and Carnow 2015), to rank forecasters in a multivariate setting (Bauer et al. 2003; Eisenbeis, Waggoner, and Zha 2004; and Sinclair, Stekler, and Muller-Droge 2016), to evaluate path forecasts (Jordá and Marcellino 2010), and to measure multivariate forecast dispersion (Banerghansa and McCracken 2009).

similar to the vector of the outcomes, it can be substituted for the actual data for decision making. Thus, it is a more general measure of what constitutes a “good” overall forecast.

Results

Bias

The results for the test of bias reported in table 3 indicate that 18-month ahead NCI forecasts underestimate the final estimates by almost 11%. This finding is consistent with similar evidence found by Kuethe, Hubbs, and Sanders (2018) for bottom line net farm income forecasts over 1975-2016. Our analysis also reveals that the bias in 18-month ahead NCI forecasts is associated with underestimation of both crop and livestock receipts by about 4% and 3%, respectively, as well as underestimation of expenses by about 1.4%. While this bias disappears in shorter term livestock receipts and expenses forecasts, it tends to persist in crop receipts forecasts through all horizons, albeit declining to under 1% underestimation in 6-month ahead forecasts. The only other evidence of bias is associated with a 4.6% overestimation of government payments at the 9-month horizon. The direction of this bias is not surprising, as underestimation of receipts would lead to overestimation of government payments compensating for lower receipts, but the fact that this bias appears so late in the forecasting cycle (November of the forecasted calendar year) is unexpected. Due to significant underestimation of crop receipts, marginal evidence of underestimation of about 2.6% and 2.3% is detected in 9- and 6-month ahead NCI forecasts. Wald test results confirm these individual equation estimates. Additionally, joint significance test results indicate presence of bias in a system of 18-, 12-, and 9-month, but not 6-month ahead farm income forecasts.

Forecast Improvement

Our examination of improvement in forecast accuracy shown in table 4 demonstrates that there is a significant decrease in forecast errors between 18- and 12-month ahead forecasts. Thus, the initial error of about 11% in 18-month ahead NCI forecasts is reduced by almost 7% in 12-month ahead forecasts. Forecasts of all NCI components except GP become more accurate with reduction in errors of CR and LR forecasts by about 2%, errors in EXP forecasts by about 1% and reduction in FRI forecasts by about 8.5%. Significant improvements in accuracy between 12- and 9-month ahead forecasts are limited to CR and EXP forecasts with average decrease in error of about 1%. These improvements appear to cancel out in the accounting equation as the reduction in error of 9-month ahead NCI forecasts is not significantly different from zero. The only category that demonstrates improvement at the 6-month horizon is GP forecasts with about 3% decrease in forecast error, however this improvement is not statistically significant according to the Wald's Chi-squared statistic that considers multiple tests. On the other hand, the results of the joint significance tests indicate significant improvements in the entire system of forecasts at each horizon, 12-, 9-, and 6-month ahead forecasts. Note that the final changes in the forecasts between 6- and 0-month ahead are equivalent to the forecast error analysis displayed in table 3.

Forecast Efficiency

Tests of forecast efficiency shown in table 5 examine the degree to which these changes are random. Based on Nordhaus' (1987) definition, if forecasts are efficient, future revisions should not be predictable using current or past revisions, i.e. subsequent revisions should be uncorrelated. If revisions are positively correlated, the forecasts are considered "smoothed" or revisions are "too slow," and information is incorporated over several consecutive revisions. Negatively correlated revisions imply "jumpy" forecasts that are revised "too fast" and future

revisions tend to correct an “overreaction” to new information that took place in a previous revision. Furthermore, a significant constant would indicate systematic increases or decreases in the forecasts.

Table 5 shows a systematic component in CR revisions at $h=9$ and $h=0$, GP revisions at $h=6$, and EXP revisions at $h=9$. These revisions tend to correct the biases observed in these forecasts at the previous forecast horizons in table 3 (except expenses, where the bias is not statistically significant at $h=12$). Negative correlations indicating jumpiness are observed for CR revisions at $h=9$, and EXP and FRI revisions at $h=0$. These findings indicate that the previous revisions are likely too large and are corrected by these revisions in the opposite direction. Thus, a 1% increase in CR at $h=12$, would be followed by a 0.34% decrease in CR at $h=9$. An opposite pattern is observed in LR at $h=9$ and $h=6$ and in EXP at $h=6$ where revisions are positively correlated with previous revisions. This pattern suggests that the previous revisions are too small and are extended by these revisions in the same direction. Thus, a 1% increase in EXP at $h=9$ would be followed by a 0.37% increase at $h=6$. While the NCI forecasts pass the efficiency test with respect to their own and most other revisions, they appear to be negatively correlated with previous CR revisions at $h=9$, suggesting CR as a potential source of inefficiency in NCI forecasts. Finally, joint significance tests suggest that inefficiency is present in this forecasting system on all three forecast horizons considered here, $h=9$, $h=6$, and $h=0$.

Compositional Changes

Despite the evidence of biases and inefficiencies in the farm income forecasts, we need to determine whether forecasting system as a whole provides an overall view of the farm income that is consistent with the outcomes that actually occurred. The results of this analysis shown in table 6 apply the Mahalanobis distance measure to evaluate the component forecasts jointly. The

null hypothesis is that the forecasts accurately represent the farm income conditions, i.e. the distance between the vectors of forecasts and the official estimates is zero. Our findings show that we fail to reject the null hypothesis for both level and percent forecasts at all forecast horizons.⁹ Therefore, these forecasts are representative of the actual outcomes and could be used to obtain a realistic picture of the composition of the farm sector accounts. Specifically, the difference between the mean vector of forecasts, at each horizon, and the observed outcomes is sufficiently small. While the individual forecasts may contain bias or inefficiencies, the system of forecasts is compositionally consistent with the official estimate at each horizon.

Conclusions

This study seeks to evaluate USDA's net cash income forecasts and its components jointly as a system of fixed-event forecasts. While the forecasts of bottom line net farm income have been examined before, this is the first study to evaluate the forecasts of the components of farm income estimates that provide the building blocks for the total measures. A joint evaluation of the accuracy of the components and the total measures allows us to track down the sources of problems in the total measures to individual components in order to identify the opportunities for improving these forecasts by USDA forecast providers.

⁹ Through a Monte Carlo analysis, Hoffelder (2017) shows that Mahalanobis distance-based test statistics have a low probability of a type I error, but relatively high probability of a type II error in small samples.

Our findings demonstrate significant underestimation in these forecasts as a group at 18- to 9-month ahead horizons. Underestimation in 18-month ahead net cash income forecasts likely stems from underestimation in crop and livestock receipts as well as expenses forecasts. At shorter forecast horizons, crop receipts appear to remain the main source of underestimation in net cash income, while the bias becomes insignificant in other components. The forecasts of crop receipts are based on forecasted prices and quantities sold of the commodities and the distribution of these sales throughout the calendar year. USDA analysts should evaluate these forecasting procedures to identify the source of bias in the crop receipts forecasts that leads to underestimation of the net cash income forecasts.

Our findings reveal that forecast accuracy improves significantly at each forecast horizon with the largest improvement between 18- and 12-month ahead forecasts. Most components except government payments contribute to the significant improvement in the accuracy of 12-month ahead NCI forecasts. This finding is not surprising as better information from other USDA sources becomes available in time for the 12-month ahead forecasts, such as WASDE and initial Crop Production reports. Further improvement in crop receipt and expenses forecasts is observed at 9-month horizon due to better source data, but the government payment forecasts are not significantly improved until 6-month horizon. We believe that better communication with the USDA agencies responsible for administering government payment programs may help improve these forecasts earlier, and in the meantime, policy makers should consider government payments forecast accuracy during farm policy discussions.

Tests of efficiency in forecast revisions reveal significant correlations between consecutive revisions, indicating that new information is not incorporated into these forecasts efficiently. Specifically, 9- and 6-month ahead livestock receipt revisions and 6-month ahead

expenses revisions are positively correlated with previous revisions, suggesting that these forecasts are smoothed. On the other hand, negative correlation is detected between 9-month ahead and previous revisions of crop receipt forecasts and in the last expenses and farm-related income forecast revisions, indicating correction of information contained in the previous forecasts. Inefficiency in NCI forecasts is associated with crop receipts revisions at 9-month horizon and expenses revision at 6-month horizon.

Finally, the tests of compositional consistency, adopted from the macroeconomic literature, indicate that the farm income forecasting system as a whole is consistent with the conditions that actually occurred and therefore provided useful information for decision making. These tests combine individual accuracy measures in an attempt to make conclusions about the characteristics of the entire vector of forecasts as a whole. This method for evaluating joint forecasts can be applied to other forecasting systems, such as farm income balance sheet or WASDE forecasts as it allows for a better understanding of interaction of the components that comprise these forecasting systems and their contribution to its accuracy and efficiency.

Our results have implications for both USDA forecasters and the farm sector in general. To the extent that our results show a significant underestimation in the 18- to 9-month ahead forecasts, the USDA forecasters should consider changes to their forecast models and estimation procedures. On the other hand, farmers and other agricultural stakeholders can view these initial 18- to 9-month horizon forecasts as conservative projections when making their decisions, recognizing that the final estimates are typically higher.

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Table 1. Descriptive statistics for net cash income forecasts and their components, 1986-2017

Forecast Horizon	<i>h</i> =18	<i>h</i> =12	<i>h</i> =9	<i>h</i> =6	<i>h</i> =0	<i>h</i> =18	<i>h</i> =12	<i>h</i> =9	<i>h</i> =6	<i>h</i> =0
<i>Crop Receipts</i>										
	<i>Average</i>					<i>Standard Deviation</i>				
Forecast (Billion \$)	121.30	124.70	124.71	125.16	126.64	47.46	51.28	49.40	49.45	50.97
Forecast (Log)	4.73	4.75	4.75	4.76	4.77	0.38	0.40	0.39	0.39	0.39
Error (%)	3.96	1.91	1.40	0.97		5.18	3.57	3.08	2.23	
Revision (%)		2.08	0.63	0.43	0.97		4.27	3.04	1.95	2.23
<i>Livestock Receipts</i>										
Forecast (Billion \$)	114.64	117.80	117.98	118.42	118.38	36.83	39.50	38.17	38.33	38.45
Forecast (Log)	4.70	4.72	4.72	4.73	4.73	0.30	0.32	0.31	0.31	0.30
Error (%)	3.11	0.53	0.34	-0.03		6.90	2.78	1.89	1.56	
Revision (%)		2.03	0.23	0.38	-0.03		5.12	1.83	1.40	1.56
<i>Government Payments</i>										
Forecast (Billion \$)	11.91	12.82	13.26	12.88	12.69	4.02	4.60	4.44	4.46	4.44
Forecast (Log)	2.42	2.49	2.53	2.50	2.49	0.35	0.34	0.32	0.33	0.32
Error (%)	6.66	-0.85	-4.57	-1.36		26.32	17.73	10.71	7.11	
Revision (%)		5.76	3.33	-3.21	-1.36		25.51	14.14	8.01	7.11
<i>Farm-Related Income</i>										
Forecast (Billion \$)	15.42	16.75	16.26	15.68	16.07	9.51	10.06	9.38	9.38	9.30
Forecast (Log)	2.54	2.63	2.62	2.56	2.62	0.65	0.64	0.62	0.65	0.58
Error (%)	9.28	1.14	-0.01	5.27		34.30	35.98	34.09	39.41	
Revision (%)		8.45	0.57	-5.27	5.27		28.14	9.09	26.64	39.41
<i>Gross Cash Income</i>										
Forecast (Billion \$)	262.78	264.74	272.21	272.15	273.76	92.33	104.66	94.60	94.97	95.73
Forecast (Log)	5.51	5.49	5.55	5.55	5.56	0.34	0.44	0.34	0.34	0.34
Error (%)	4.16	6.16	0.58	0.60		4.22	27.86	2.29	2.07	
Revision (%)		-1.99	5.58	-0.03	0.60		26.50	27.52	1.37	2.07
<i>Expenses</i>										
Forecast (Billion \$)	195.56	198.32	199.09	198.66	198.44	73.21	75.09	73.31	73.09	72.59
Forecast (Log)	5.21	5.22	5.23	5.23	5.23	0.37	0.38	0.37	0.37	0.36
Error (%)	1.74	0.59	-0.18	0.00		4.69	3.78	2.66	2.57	
Revision (%)		1.18	0.74	-0.18	0.00		2.94	1.54	1.76	2.57
<i>Net Cash Income</i>										
Forecast (Billion \$)	67.22	72.61	73.11	73.48	75.32	20.99	25.99	23.50	24.21	25.32
Forecast (Log)	4.17	4.23	4.25	4.25	4.27	0.29	0.33	0.29	0.30	0.31
Error (%)	10.81	4.27	2.57	2.26		12.40	11.46	8.21	7.72	
Revision (%)		6.54	1.70	0.31	2.26		9.78	8.24	3.98	7.72

Note : Forecast (Billion \$) is the reported forecast amount: $F_{\tau-h}$. Forecast (Log) is the natural logarithm of the associated forecast: $f_{\tau-h}=\ln(F_{\tau-h})$. Forecast error is calculated as the percentage difference between the official estimate and the current forecast: $e_{\tau-h}=100\times(f_{\tau}-f_{\tau-h})$. Forecast revision is defined as the percentage difference between the current and previous forecast: $r_{\tau-h}=100\times(f_{\tau-h}-f_{\tau-(h+1)})$.

Table 2. Components of net cash income forecast errors, 1986-2017

Dependent variable: Forecast Error in <i>Net Cash Income</i>	<i>h</i> =18	<i>h</i> =12	<i>h</i> =9	<i>h</i> =6
Constant	2.605 *** (0.790)	0.544 * (0.306)	0.201 (0.299)	0.186 (0.201)
Forecast Error				
<i>Crop Receipts</i>	1.360 *** (0.132)	1.423 *** (0.092)	1.620 *** (0.132)	1.705 *** (0.109)
<i>Livestock Receipts</i>	1.545 *** (0.060)	1.584 *** (0.099)	1.597 *** (0.168)	1.823 *** (0.176)
<i>Government Payments</i>	0.160 *** (0.018)	0.206 *** (0.020)	0.192 *** (0.032)	0.151 *** (0.037)
<i>Farm-Related Income</i>	0.101 *** (0.019)	0.143 *** (0.005)	0.147 *** (0.007)	0.132 *** (0.003)
<i>Expenses</i>	-2.482 *** (0.161)	-2.378 *** (0.087)	-2.388 *** (0.196)	-2.519 *** (0.111)
R-Squared	0.96	0.98	0.97	0.97
N	31	30	32	32
Residual Diagnostics				
		Chi-squared / [p-values]		
Durbin's alternative autocorrelation test	0.277 [0.60]	3.232 * [0.07]	0.395 [0.53]	0.211 [0.65]
White's heteroskedasticity test	23.07 [0.29]	15.01 [0.78]	24.76 [0.21]	20.65 [0.42]
LM test for ARCH	2.546 [0.11]	0.714 [0.40]	3.017 * [0.08]	0.204 [0.65]

Note : Robust standard errors clustered by year are in parantheses. The null hypotheses for the residual diagnostics tests are no serial correlation for the Durbin's alternative autocorrelation test, constant variance for the White's heteroskedasticity test, and no autoregressive conditional heteroskedasticity (ARCH) effects for the Langrange multiplier (LM) test. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3. Evaluation of bias in net cash income forecasts and their components, 1986-2017

Dependent variable: Forecast Error	<i>h</i> =18	<i>h</i> =12	<i>h</i> =9	<i>h</i> =6	<i>h</i> =18	<i>h</i> =12	<i>h</i> =9	<i>h</i> =6
	Constant / (Standard error)				Wald Tests Chi-squared / [p-values]			
<i>Crop Receipts</i>	3.682 *** (0.886)	2.060 *** (0.634)	1.404 *** (0.537)	0.971 *** (0.388)	17.26 *** [0.00]	10.56 *** [0.01]	6.84 ** [0.03]	6.26 * [0.09]
<i>Livestock Receipts</i>	3.000 ** (1.234)	0.499 (0.507)	0.341 (0.328)	-0.034 (0.272)	5.91 ** [0.03]	0.97 [0.46]	1.08 [0.42]	0.02 [0.99]
<i>Government Payments</i>	7.100 (4.707)	-0.854 (3.182)	-4.566 *** (1.863)	-1.355 (1.237)	2.28 [0.13]	0.07 [0.86]	6.01 ** [0.03]	1.20 [0.48]
<i>Farm-Related Income</i>	9.277 (6.060)	1.143 (6.459)	-0.007 (5.931)	5.268 (6.857)	2.34 [0.13]	0.03 [0.86]	0.00 [1.00]	0.59 [0.62]
<i>Expenses</i>	1.404 * (0.769)	0.901 (0.615)	-0.179 (0.464)	0.004 (0.447)	3.33 * [0.10]	2.14 [0.25]	0.15 [0.82]	0.00 [0.99]
<i>Net Cash Income</i>	10.836 *** (2.227)	2.111 (1.401)	2.571 * (1.428)	2.258 * (1.343)	23.67 *** [0.00]	2.27 [0.25]	3.24 [0.13]	2.83 [0.33]
Joint significance					83.88 *** [0.00]	18.55 *** [0.01]	17.12 *** [0.01]	8.83 [0.18]
N					31	30	32	32

Note : Standard errors are in parentheses and Benjamini-Hochberg q-values (i.e., adjusted p-values for multiple testing) are in square brackets. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% level, respectively. The null hypothesis of Wald test is all coefficients within an equation are equal to zero; the null hypothesis of joint significance test is all coefficients across all equations are equal to zero.

Table 4. Changes in accuracy of net cash income forecasts and their components, 1986-2017

Dependent variable: Forecast Revision	<i>h</i> =12	<i>h</i> =9	<i>h</i> =6	<i>h</i> =12	<i>h</i> =9	<i>h</i> =6
	Constant / (Standard error)			Wald Tests Chi-squared / [p-values]		
<i>Crop Receipts</i>	2.087 *** (0.800)	0.914 ** (0.474)	0.433 (0.340)	6.81 ** [0.03]	3.71 [0.16]	1.62 [0.38]
<i>Livestock Receipts</i>	2.074 ** (0.964)	0.236 (0.333)	0.375 (0.244)	4.64 * [0.06]	0.50 [0.72]	2.36 [0.37]
<i>Government Payments</i>	6.318 (4.703)	3.328 (2.538)	-3.211 ** (1.394)	1.80 [0.18]	1.72 [0.38]	5.31 [0.13]
<i>Farm-Related Income</i>	8.451 * (5.134)	0.571 (1.632)	-5.275 (4.635)	2.71 [0.12]	0.12 [0.76]	1.30 [0.38]
<i>Expenses</i>	1.114 ** (0.542)	0.853 *** (0.255)	-0.183 (0.307)	4.22 * [0.06]	11.15 *** [0.01]	0.35 [0.65]
<i>Net Cash Income</i>	6.995 *** (1.848)	0.319 (1.044)	0.312 (0.693)	14.33 *** [0.00]	0.09 [0.76]	0.20 [0.65]
Joint significance				21.49 *** [0.00]	16.51 *** [0.01]	13.44 ** [0.04]
N				29	30	32

Note : Standard errors are in parentheses and Benjamini-Hochberg q-values (i.e., adjusted p-values for multiple testing) are in square brackets. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% level, respectively. The null hypothesis of Wald test is all coefficients within an equation are equal to zero; the null hypothesis of joint significance test is all coefficients across all equations are equal to zero.

Table 5. Examination of efficiency in revisions of net cash income forecasts and their components, 1986-2017

Dependent variable: Forecast Revision	<i>h</i> =9	<i>h</i> =6	<i>h</i> =0	<i>h</i> =9	<i>h</i> =6	<i>h</i> =0	<i>h</i> =9	<i>h</i> =6	<i>h</i> =0
	Constant / (Standard error)			Lagged Revision / (Standard error)			Wald Tests Chi-squared / [p-values]		
<i>Crop Receipts</i>	1.611 *** (0.475)	0.476 (0.356)	0.937 ** (0.396)	-0.344 *** (0.087)	-0.176 (0.115)	0.078 (0.198)	19.88 *** [0.00]	3.20 [0.24]	6.45 [0.12]
<i>Livestock Receipts</i>	-0.124 (0.327)	0.327 (0.239)	0.058 (0.276)	0.112 ** (0.052)	0.230 ** (0.113)	-0.244 (0.189)	4.86 [0.13]	6.69 * [0.07]	1.68 [0.45]
<i>Government Payments</i>	2.783 (2.669)	-3.297 ** (1.495)	-1.653 (1.324)	0.047 (0.092)	0.002 (0.099)	-0.093 (0.147)	1.66 [0.44]	5.09 [0.12]	1.60 [0.45]
<i>Farm-Related Income</i>	1.222 (1.734)	-4.233 (4.863)	1.194 (5.955)	-0.075 (0.054)	-0.267 (0.227)	-0.772 *** (0.222)	2.05 [0.43]	2.19 [0.34]	12.91 *** [0.01]
<i>Expenses</i>	0.751 *** (0.257)	-0.376 (0.303)	-0.078 (0.430)	0.002 (0.074)	0.371 *** (0.088)	-0.447 ** (0.225)	9.54 [0.03]	17.88 *** [0.00]	3.95 [0.28]
<i>Net Cash Income</i>	1.308 (1.034)	0.762 (0.603)	2.054 (1.291)	-0.028 (0.177)	-0.078 (0.196)	0.591 (0.796)	17.14 ** [0.03]	16.81 * [0.06]	8.30 [0.45]
CR				-0.554 * (0.333)	-0.249 (0.379)	-0.958 (1.247)			
LR				0.102 (0.319)	0.424 (0.384)	-1.807 (1.392)			
GP				0.018 (0.044)	0.036 (0.053)	-0.262 (0.206)			
FRI				0.007 (0.041)	-0.030 (0.047)	-0.117 (0.110)			
EXP				-0.084 (0.612)	-0.880 (0.559)	1.919 (2.044)			
Joint significance							44.17 *** [0.00]	42.29 *** [0.00]	32.99 *** [0.01]
N							29	30	32

Note : Standard errors are in parentheses and Benjamini-Hochberg q-values (i.e., adjusted p-values for multiple testing) are in square brackets. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% level, respectively. The null hypothesis of Wald test is all coefficients including the constant term within an equation are equal to zero; the null hypothesis of joint significance test is all coefficients including the constant term across all equations are equal to zero.

Table 6. Compositional consistency of net cash income forecasts, 1986-2017

	<i>h</i> =18	<i>h</i> =12	<i>h</i> =9	<i>h</i> =6	<i>h</i> =0
	Forecast (Billion \$)				
<i>Crop Receipts</i>	121.30	124.70	124.71	125.16	126.64
<i>Livestock Receipts</i>	114.64	117.80	117.98	118.42	118.38
<i>Government Payments</i>	11.91	12.82	13.26	12.88	12.69
<i>Farm-Related Income</i>	15.42	16.75	16.26	15.68	16.07
<i>Expenses</i>	195.56	198.32	199.09	198.66	198.44
<i>Net Cash Income</i>	67.22	72.61	73.11	73.48	75.32
<i>D</i>	0.055	0.012	0.008	0.008	
<i>D-squared</i>	0.003	0.000	0.000	0.000	
<i>F-statistic</i>	0.009	0.000	0.000	0.000	
<i>p-value</i>	0.926	0.984	0.989	0.989	
	Forecast (%)				
<i>Crop Receipts</i>	4.73	4.75	4.75	4.76	4.77
<i>Livestock Receipts</i>	4.70	4.72	4.72	4.73	4.73
<i>Government Payments</i>	2.42	2.49	2.53	2.50	2.49
<i>Farm-Related Income</i>	2.54	2.63	2.62	2.56	2.62
<i>Expenses</i>	5.21	5.22	5.23	5.23	5.23
<i>Net Cash Income</i>	4.17	4.23	4.25	4.25	4.27
<i>D</i>	0.052	0.011	0.002	0.012	
<i>D-squared</i>	0.003	0.000	0.000	0.000	
<i>F-statistic</i>	0.008	0.000	0.000	0.000	
<i>p-value</i>	0.930	0.985	0.998	0.983	

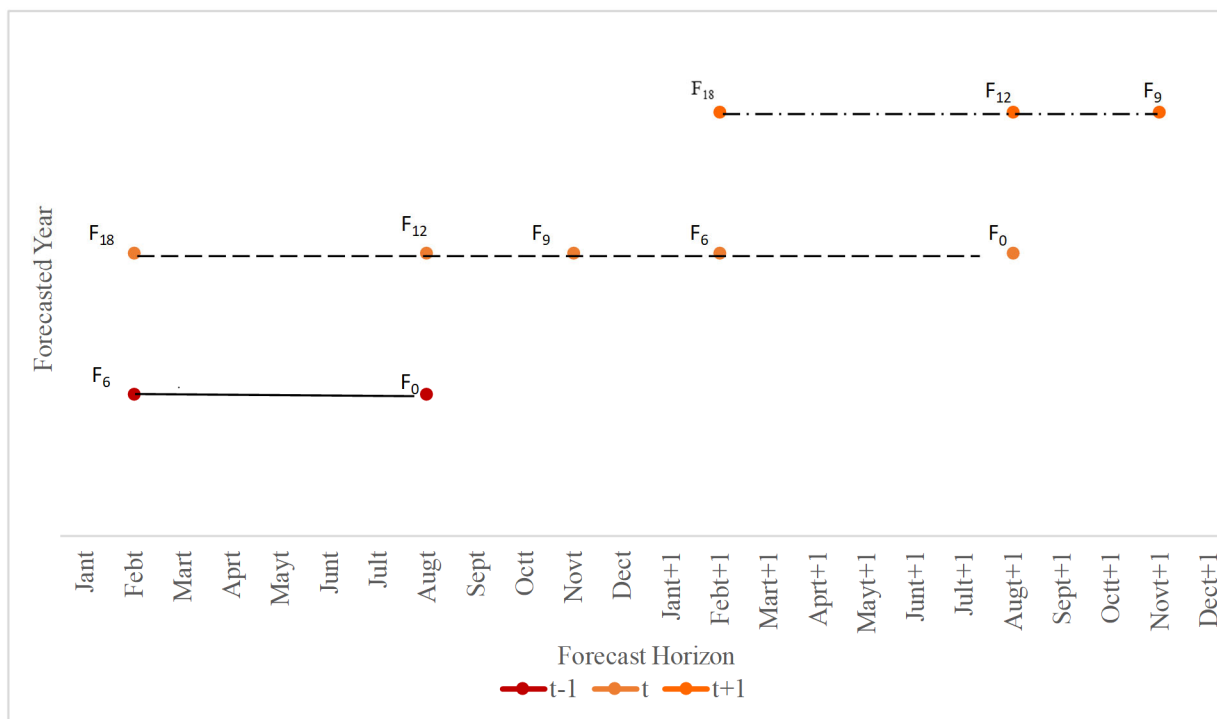


Figure 1. Forecasting cycle for net cash income forecasts

Note: F₁₈ is the forecast released 18 months ahead of the official estimate, F₁₂ is a 12-months ahead forecast, F₉ is a nine-months ahead forecast, F₆ is a six-months ahead forecast, F₀ is an official estimate.

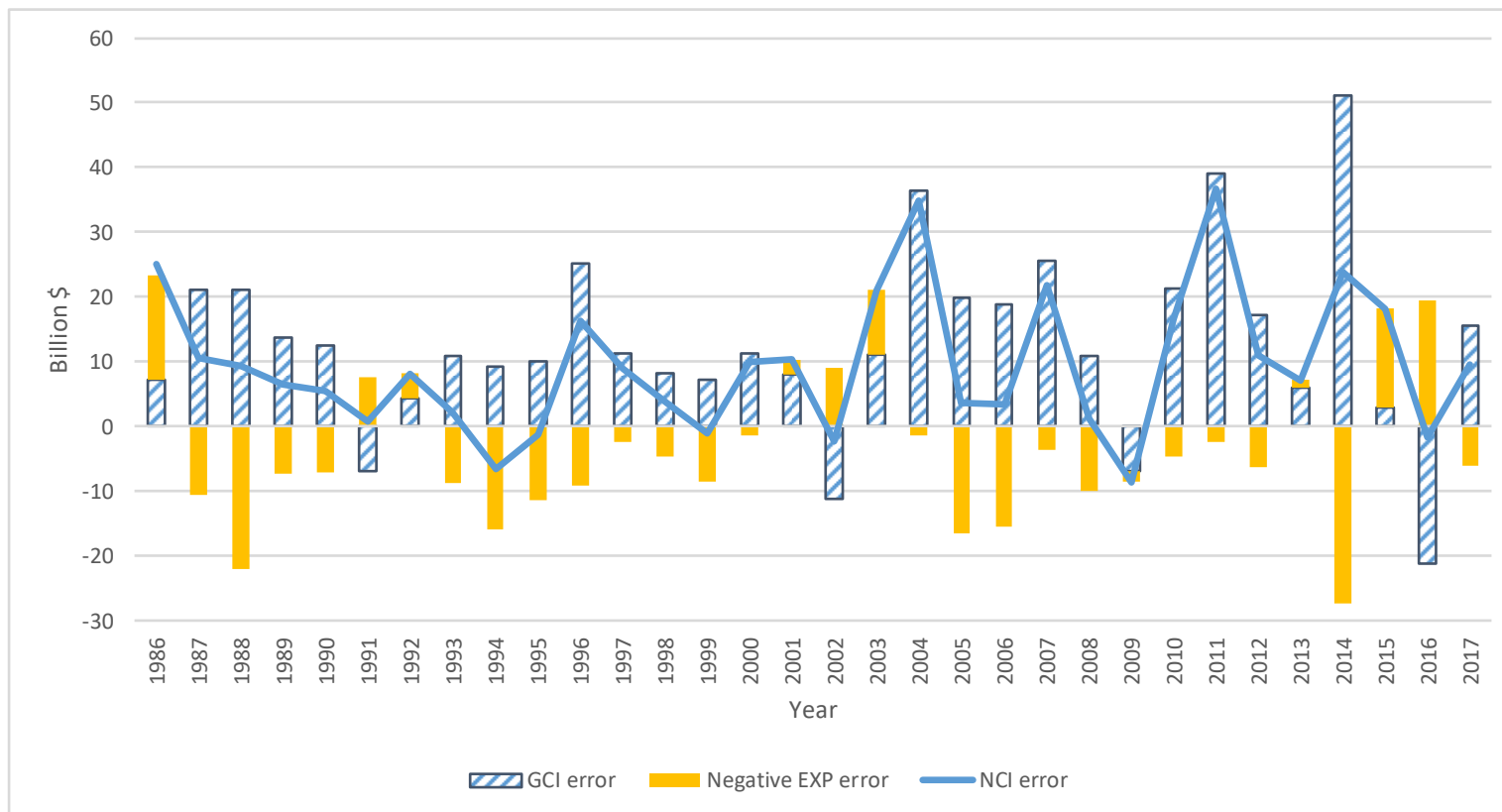


Figure 2. Additivity of gross cash income and expenses errors within net cash income forecast errors at h=18, 1986-2017

Note: GCI=Gross cash income, EXP=expenses, NCI=net cash income

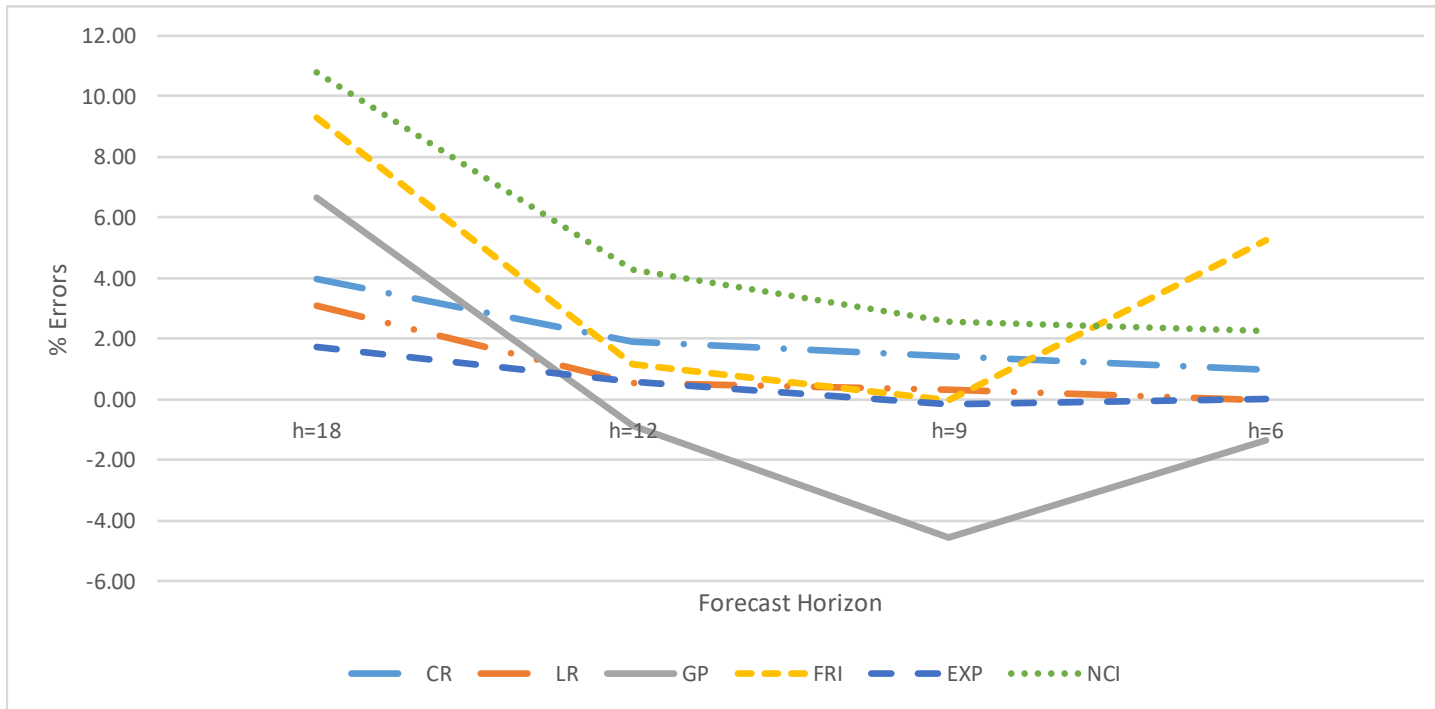


Figure 3. Changes in farm income forecast errors over the forecasting horizon

Note: The graph shows average errors at various forecast horizons for the following categories: CR=crop receipts, LR=livestock receipts, GP=government payments, FRI=farm related income, EXP=expenses, NCI=net cash income.

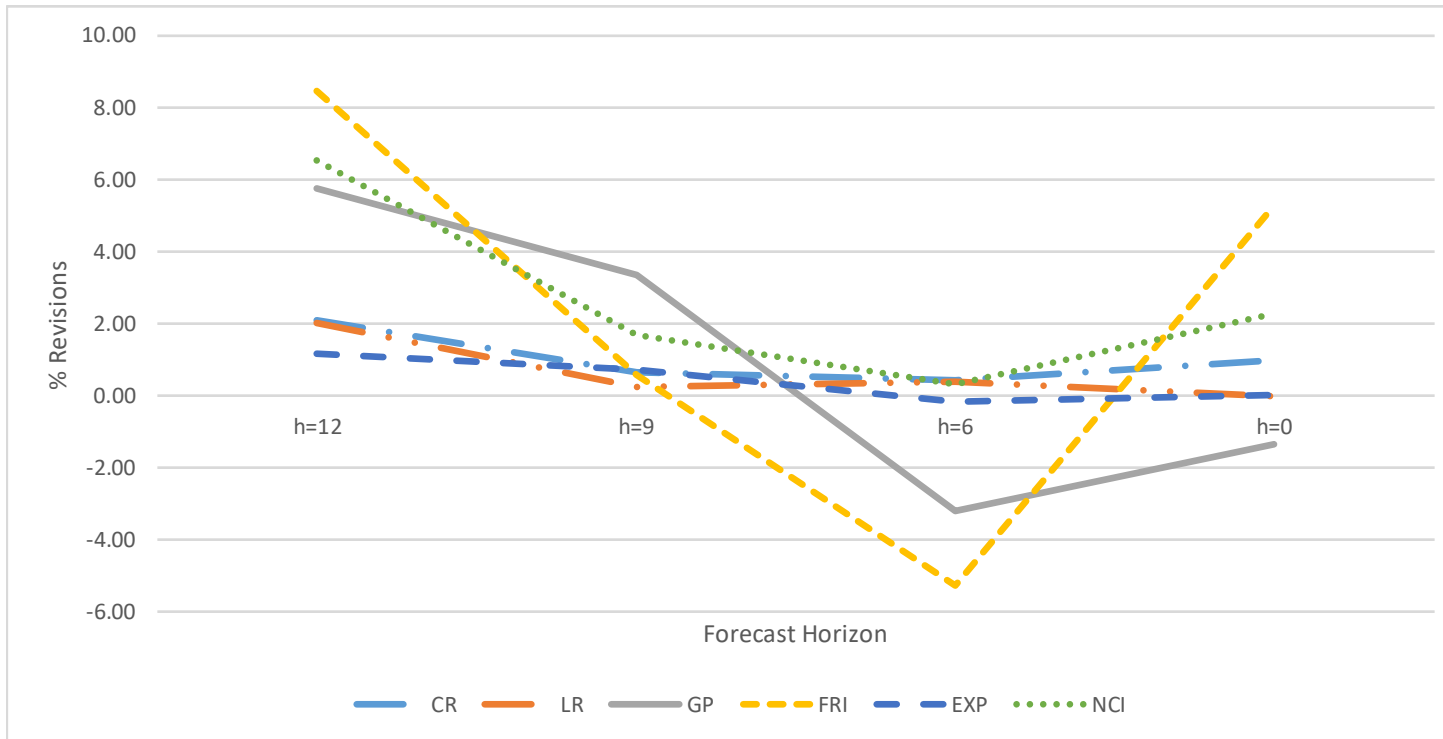


Figure 4. Changes in farm income forecast revisions over the forecasting horizon.

Note: The graph shows average revisions at various forecast horizons for the following categories: CR=crop receipts, LR=livestock receipts, GP=government payments, FRI=farm related income, EXP=expenses, NCI=net cash income.