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Evaluating the USDA's Net Farm Income Forecast

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The USDA produces four forecasts of net farm income for each year; these forecasts are closely monitored by decision makers across the agricultural sector. However, little is known about the performance of these forecasts. Traditional forecast evaluation tests suggest that between 1975 and 2016, the long-horizon forecasts systematically under-predicted realized values. In addition, the shorter-horizon forecast revisions overreact to new information. The findings suggest that forecast users should adjust their expectations and that the USDA may want to consider other forecast approaches to supplement current procedures.

Key words: fixed-event forecasts, forecast evaluation, net farm income

Introduction

Net farm income is the U.S. government's official measure of farming's contribution to the national economy and one of the United States Department of Agriculture's (USDA) most cited statistics (McGath et al., 2009). The USDA has produced annual estimates of net farm income since 1910 (Lucier, Chesley, and Ahearn, 1986). The estimation process is a large undertaking, and, as a result, USDA official estimates are released following a significant time lag. To provide more timely information on farm-sector profitability, the USDA produces a series of forecasts of annual net farm income. The forecast is first released in February, then revised multiple times during the calendar year to reflect changes in information on aggregate production and prices. Schnepf (2016) describes this series of forecasts as "the single most watched indicator of farm sector well-being" (p. 1). The USDA's net farm income forecasts are frequently cited in farm policy discussions and closely monitored by farm input and machinery suppliers, agricultural lenders, and other farm-related industries (Dubman, McElory, and Dodson, 1993). The forecasts are also an important input in numerous USDA statistical models as well as the U.S. Department of Commerce's estimation of U.S. gross domestic product (McGath et al., 2009).

Despite their prominent role in the agricultural sector, the USDA's forecasts of net farm income have not been rigorously evaluated. This is surprising given the volume of research dedicated to evaluating other USDA forecasts, such as farm product prices (Sanders and Manfredo, 2003), crop production (Isengildina, Irwin, and Good, 2006, 2013; Isengildina-Massa, MacDonald, and Xie, 2012), livestock production (Bailey and Brorsen, 1998; Sanders and Manfredo, 2002), and grain stocks (Xiao, Hart, and Lence, 2017). While the existing literature documents the deficiencies of these forecasts, the USDA's net farm income forecasts are derived from hundreds of such projections, warranting a rigorous evaluation. This study examines the degree to which the USDA's net farm income forecasts satisfy the conditions of forecast optimality.

We contribute to the existing knowledge base in two important ways. First, by combining information from archived briefing materials, we construct the first systematic record of USDA net

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farm income forecasts from 1975 through 2016. We assemble a comprehensive archive of forecast revisions and official net farm income estimates for a long and dynamic period of the U.S. farm economy. Second, we conduct a series of empirical forecast optimality tests. According to Diebold and Lopez (1996), an optimal forecast is both unbiased and efficient. A forecast is unbiased if it does not differ systematically from realized values and is efficient if it contains all information available at the time of the forecast. Forecast optimality tests indicate that the USDA's early forecasts consistently under-predict realized net farm incomes. That is, aggregate farm profitability tends to be higher than suggested by the initial forecasts. The tests also indicate that later revised forecasts are inefficient, overreacting to new information, and that the forecast revisions are serially correlated. These findings have important implications for forecast users, including policy makers, program administrators, agribusinesses, extension educators, and researchers. The empirical tests can be used to adjust the expectations of forecast users and point to a need for continued improvement in the USDA's forecast procedure.

USDA Net Farm Income Forecast

The USDA defines net farm income as "the residual net value added after accounting for payments to stakeholders" (McGath et al., 2009, p. 35). Similar to other systems of national accounts, net farm income is derived using a value-added accounting framework:

$$
\begin{aligned}
\textit{Net farm income} \quad = \quad & \textit{Value of production (crops and livestock)} \\
& - \quad \textit{Operating expenses} \\
& + \quad \textit{Direct government payments} \\
& - \quad \textit{Property taxes and fees} \\
& - \quad \textit{Capital consumption} \\
& - \quad \textit{Payments to stakeholders}.
\end{aligned} \tag{1}
$$

Net farm income includes both cash and noncash income and expenses, such as the value of home consumption, changes in inventories, capital replacement, and implicit rent and expenses related to the farm operator's dwelling that are not reflected in cash transactions during the calendar year.

The measurement of net farm income is a large and complicated undertaking. The various components are estimated individually at "the most disaggregated level feasible" (McGath et al., 2009, p. 3) and then combined into a sector-wide measure of farm financial well-being. For example, the value of production includes cash receipts for eight crops (cotton, feed crops, food grains, fruits and nuts, oil crops, tobacco, vegetables and melons, and all other crops) and four animal products (dairy products/milk, meat animals, miscellaneous livestock, and poultry and eggs). The USDA's net farm income estimation process involves more than a thousand equations and hundreds of data series (McGath et al., 2009). The various data series employed include commodity production and price information from the World Agricultural Supply and Demand Estimates (WASDE), farm accounting records from the Agricultural Resource Management Survey (ARMS), price indices produced by the National Agricultural Statistics Service (NASS), and many additional economic measures collected and processed by Economic Research Service (ERS) analysts.

Many of the data series employed in the net farm income calculations are produced with a time lag, and, as a result, official estimates are released in August following the reference year. Given that the official estimates provide a retrospective view of farm profitability, the USDA produces a series of more timely forecasts of net farm income for each year based on projections of the various components outlined in equation (1). The forecast is updated multiple times throughout the year to reflect updated information on production and prices.

Figure 1 shows the sequence of USDA net farm income forecasts. Each line represents a single reference year. The middle line represents calendar year t. The actual or realized value of net farm

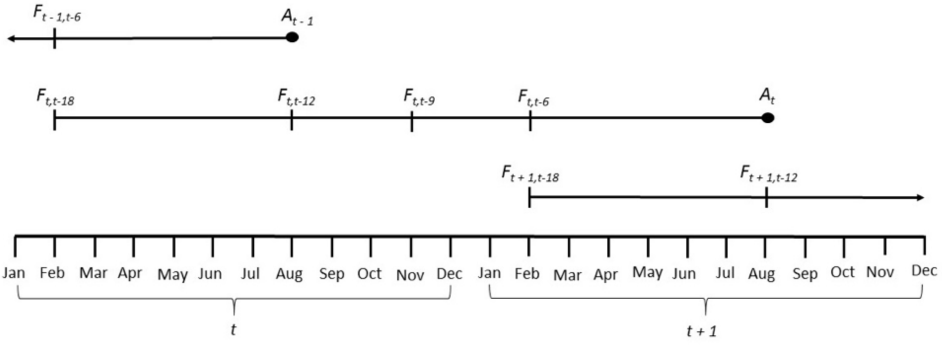

Figure 1. USDA Net Farm Income Forecast and Revision Process

Table 1. USDA 2015 Net Farm Income Forecast and Revision Process ($billion)

	Release Date				
Forecast Year	**February 2015**	**August 2015**	**November 2015**	**February 2016**	**August 2016**
2014	$F_{2014,t-6}$ $115.0	A_{2014} $127.0			
2015	$F_{2015,t-18}$ $89.4	$F_{2015,t-12}$ $100.3	$F_{2015,t-9}$ $93.0	$F_{2015,t-6}$ $93.0	A_{2015} $108.0
2016				$F_{2016,t-18}$ $90.9	$F_{2016,t-12}$ $100.4

income for year t, A_t, is released in August following the reference year. The USDA produces four forecasts of net farm income at set horizons $t - h$. Each forecast is represented by $F_{t,t-h}$, with the first subscript representing the reference year and the second subscript representing the number of months between the forecast and the publication of realized net farm income (i.e., the forecast horizon). The initial forecast for year t is released in February, 18 months prior to the release of the realized value. Thus, the initial forecast for year t is represented by $F_{t,t-18}$. The USDA releases a revised forecast in August, 12 months ahead of the release of the actual value, to reflect updated crop production estimates and cash receipts from the USDA's survey-based production and yield estimates. This forecast is labeled $F_{t,t-12}$. Another update is released in November, 9 months ahead of the official actual value, to reflect updated crop production and harvest information. This forecast is labeled $F_{t,t-9}$. The final revision is released in February following the reference year, 6 months prior to the official estimate. This forecast is labeled $F_{t,t-6}$.

In addition, several of the forecasts coincide with the release of forecasts in overlapping years. As shown in Figure 1, the initial forecast for each year t, $F_{t,t-18}$, coincides with the release of the final forecast for the previous year $t - 1$, $F_{t-1,t-6}$. In addition, the August forecast for year t, $F_{t,t-12}$, coincides with the release of the realized values of the previous year $t - 1$, A_{t-1}. Table 1 provides an example of the sequence of releases for year 2015.

Data

While the USDA net farm income forecast is closely monitored by decision makers across the agricultural sector, the quality of the forecast has not been rigorously evaluated due to the lack of historic data. We construct the first comprehensive archive of USDA net farm income forecasts from 1975 through 2016 using two sources of information. The first is a series of USDA reports.

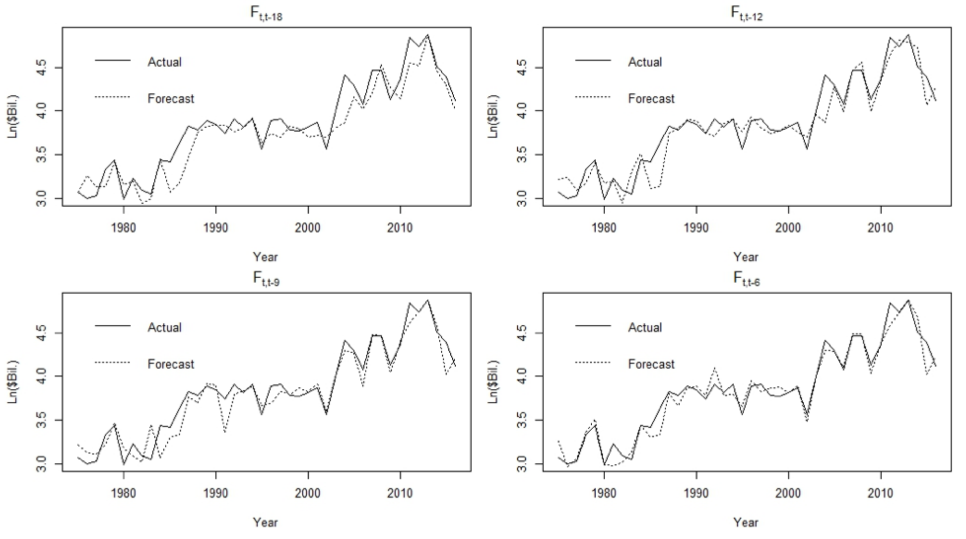

Figure 2. Net Farm Income Forecasts, 1975–2016

Between 1975 and 2002, the USDA Economic Research Service (ERS) published net farm income forecasts and estimates through the agency's monthly *Agricultural Outlook*. Archived issues of *Agricultural Outlook* are available electronically through the USDA Economics, Statistics and Market Information System (ESMIS) in conjunction with the Mann Library at Cornell University.[1] The USDA ceased publication of *Agricultural Outlook* in December 2002.

The second source of information is archived versions of the USDA website. Some time prior to ceasing publication of *Agricultural Outlook*, ERS began publishing net farm income forecasts through the agency's "Briefing Rooms" website, which provided detailed reports of the most recent forecast. However, when ERS revised the forecast, the previous forecast was replaced with the new projections, and the previous forecasts were not systematically archived. We obtained image capture versions of archived "Briefing Rooms" through the Internet Archive's Wayback Machine,[2] a freely available digital repository of websites published on the Internet (see Howell, 2006, for more detailed discussion of the archiving process). The Wayback Machine began archiving websites in 2000, so we were able to cross-validate the archived information with *Agricultural Outlook*between 2000 and 2002. The two sources provided identical information.

By combining information from these two sources, we construct a comprehensive record of USDA net farm income forecasts from 1975 through 2016. Our dataset contains 42 observations of realized net farm income, A_t. For each year, the dataset contains up to four forecasts. Net farm income is reported in billions of nominal dollars. For the purposes of our analysis, the series are expressed in natural logarithms so that forecast errors and revisions are stationary and can be interpreted as approximate percentage changes.

Figure 2 plots the natural logarithms of forecasted and realized net farm income between 1975 and 2016. Solid lines represent the actual or realized net farm income values A_t. Dotted lines represent the forecasted value for the given forecast horizon. The first panel plots the initial February forecast, $F_{t,t-18}$. The second panel plots the August forecast, $F_{t,t-12}$. The third panel plots the November forecast, $F_{t,t-9}$, and the fourth panel plots the final February forecast, $F_{t,t-6}$.

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[1] http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1503 (Accessed Jan. 23, 2018).
[2] https://archive.org/web/ (Accessed Jan. 23, 2018).

Forecast Evaluation

The USDA's net farm income forecasts are a sequence of multiple predictions of the same terminal event. In the forecast literature, this is referred to as a fixed-event forecast, and the existing literature provides a number of empirical tests for optimality of fixed-event forecasts. One implication of forecast optimality is that the forecast error should be a weakly increasing function of the forecast horizon (Patton and Timmermann, 2007). That is, if a forecast is unbiased and efficient, the forecast should become more accurate as the terminal event approaches. To test this property for the USDA's net farm income forecasts, we use two common measures of forecast accuracy: mean absolute error (MAE) and root mean squared error (RMSE). For each forecast horizon $t-h$, the forecast error is defined as $\ln A_t - \ln F_{t,t-h}$. Thus, the forecast errors represent approximate percentage errors. MAE measures the average absolute forecast error over the observation period $t = 1, \ldots, T$ and is defined as

$$\text{(2)} \qquad \text{MAE}_{t-h} : \frac{\sum_{t=1}^{T} \left| \ln A_t - \ln F_{t,t-h} \right|}{T}.$$

A forecast that minimizes MAE generates forecast errors that are close to 0, but MAE is not sensitive to occasional large forecast errors. In contrast, RMSE places a greater weight on larger forecast errors:

$$\text{(3)} \qquad \text{RMSE}_{t-h} : \sqrt{\frac{\sum_{t=1}^{T} (\ln A_t - \ln F_{t,t-h})^2}{T}}.$$

RMSE measures the average *squared* forecast error over the observation period $t = 1, \ldots, T$. A forecast that minimizes RMSE generates few forecast errors with large deviations from 0. Given that forecast error should be a weakly increasing function of the forecast horizon, we expect both MAE and RMSE to decline throughout the forecast sequence.

Further, forecast optimality requires that forecasts at each horizon be unbiased. The existing literature provides a number of empirical tests for forecast bias. Mincer and Zarnowitz (1969) developed an early test that examines the correlation between realized and forecasted values:

$$\text{(4)} \qquad \ln A_t = \alpha + \beta \ln F_{t,t-h} + \varepsilon_{t,t-h},$$

where $\ln A_t$ is the natural logarithm of realized value of net farm income and $\ln F_{t,t-h}$ is the natural logarithm of the forecast for year t at horizon $t-h$. An unbiased forecast is perfectly, positively correlated with the observed outcomes and does not exhibit a systematic deviation from realized values. Thus, the joint null hypothesis of unbiasedness is tested using the restriction $H_0 : (\alpha, \beta) = (0, 1)$. The correlation implied by the coefficient β in equation (4) may be spurious, however, if either series contains a unit root. As a result, Holden and Peel (1990) developed a preferred specification of equation (4) by constraining $\beta = 1$ and rearranging terms:

$$\text{(5)} \qquad \ln A_t - \ln F_{t,t-h} = \alpha + \varepsilon_{t,t-h}.$$

The Holden and Peel test is preferred because it does not require the forecast, $F_{t,t-h}$, to be uncorrelated with the residual term $\varepsilon_{t,h}$, and standard inference tests can be applied to equation (5), even if realized values are nonstationary. The null hypothesis of unbiasedness can be directly tested using the restriction $H_0 : \alpha = 0$. A positive and significant α suggests that forecasts systematically under-predict realized net farm income ($\ln F_{t,t-h} < \ln A_t$), and a negative and significant α suggests that forecasts systematically over-predict realized net farm income ($\ln F_{t,t-h} > \ln A_t$).

Forecast optimality also requires that the forecasts, at all horizons, be efficient, or contain all information available at the time $t-h$. It is difficult, however, to observe the forecaster's full information set. Given that previous forecasts are a known part of the forecaster's information set, Nordhaus (1987) provides two necessary (but not sufficient) conditions for forecast efficiency. First, the forecast *error* at time $t-h$ must be independent of all forecast revisions. Second, the forecast *revision* at any time must be independent of all previous forecast revisions. These propositions of weak-form efficiency can be tested empirically.

Nordhaus's (1987) first proposition can be tested using the regression equation

$$(6)\qquad (\ln A_t - \ln F_{t,t-h}) = \alpha + \beta(\ln F_{t,t-h} - \ln F_{t,t-(h+i)}) + \varepsilon_{t,t-h},$$

where $t-h$ is the horizon of the forecast being evaluated and $t-(h+i)$ is the horizon of the previous forecast, conducted i months prior to the forecast being evaluated. For example, a test of the August forecast examines the relationship between the August forecast error $(\ln A_t - \ln F_{t,t-12})$ and the change between the August and February forecasts $(\ln F_{t,t-12} - \ln F_{t,t-18})$. For a fixed-event forecast with several revisions, equation (6) can be easily generalized to include all prior revisions, as Nordhaus's proposition should hold across the entire forecast sequence. The joint null hypothesis of efficiency is $H_0 : (\alpha,\beta) = (0,0)$. Thus, if the forecast is efficient, then the forecast error will be random and independent of forecast revisions.

If the coefficients α and β in equation (6) are significantly different from 0, they can be interpreted in the context of the forecasting process. A positive and significant intercept term α indicates that, controlling for revisions, the forecast systematically under-predicts realized net farm income $(\ln F_{t,t-h} < \ln A_t)$. Similarly, a negative and significant intercept term indicates that, controlling for revisions, the forecast systematically over-predicts realized net farm income $(\ln F_{t,t-h} > \ln A_t)$. Since the forecast revision is known, a positive and significant β coefficient would be interpreted as an indication that all new information had not been fully incorporated into the forecast at horizon $t-h$. A positive and significant β coefficient has been interpreted as smoothing or forecast rigidity (Messina, Sinclair, and Stekler, 2015). A significant and negative β coefficient would be interpreted as an indication that the forecast had been over-adjusted based on new information.

The relationship between the β coefficient and the forecasting process can be observed by rearranging the terms of equation (6):

$$(6')\qquad \ln F_{t,t-h} = \frac{-\alpha}{(1+\beta)} + \frac{1}{(1+\beta)}\ln A_t + \frac{\beta}{(1+\beta)}\ln F_{t,t-(h+i)} + \varepsilon_{t,t-h}.$$

When $\alpha = \beta = 0$, the forecast at time $t-h$ is equal to the realized value, A_t. When $\beta > 0$, the prior forecast is given a positive weight, and when $\beta < 0$, the prior forecast is given a negative weight.

Nordhaus's (1987) second proposition can be tested using the regression equation

$$(7)\qquad (\ln F_{t,t-h} - \ln F_{t,t-(h+i)}) = \alpha + \beta(\ln F_{t,t-(h+i)} - \ln F_{t,t-(h+j)}) + \varepsilon_{t,t-h},\ i < j,$$

where $t-h$ is the horizon of the most recent forecast, $t-(h+i)$ is the horizon of the previous forecast, and $t-(h+j)$ is the forecast that preceded the forecast at $t-(h+i)$. For example, a test of the efficiency of the November net farm income forecast would examine the relationship between the change from the November to August forecasts $(\ln F_{t,t-9} - \ln F_{t,t-12})$ and the change from the August to February forecasts $(\ln F_{t,t-12} - \ln F_{t,t-18})$. When the fixed-event forecast contains several iterations, equation (7) can be generalized to include all prior revisions, as Nordhaus's second proposition should hold across the entire sequence. The joint null hypothesis of efficiency is $H_0 : (\alpha,\beta) = (0,0)$. A statistically significant intercept term α suggests that forecast revisions follow a systematic pattern. That is, forecasts tend to adjust up or down by similar amounts. A statistically significant β coefficient implies that the revisions are autocorrelated. That is, a rejection of the null hypothesis suggests that the revisions are predictable. As Nordhaus states, "If I could look at your

Table 2. Forecast Accuracy and Bias

	Initial ($F_{t,t-18}$)	August ($F_{t,t-12}$)	November ($F_{t,t-9}$)	February ($F_{t,t-6}$)
Accuracy measures				
Mean absolute error	0.140	0.125	0.111	0.084
Root mean square error	0.187	0.175	0.157	0.120
Holden and Peel (1990) bias test				
Estimate	0.085***	0.028	0.036	0.018
	(0.030)	(0.027)	(0.022)	(0.018)

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Numbers in parentheses are Newey and West (1987) standard errors.

most recent forecast and accurately say, 'Your next forecast will be 2% lower than today's,' then you can surely improve your forecast" (p. 673).

While the empirical tests of Holden and Peel (1990) and Nordhaus (1987) provide intuitive interpretation and are widely used in the literature, more recent studies suggest that the tests may have limited power in small samples. Patton and Timmermann (2012) develop similar empirical tests for fixed-event forecasts that have a greater power to detect forecast bias and inefficiency in finite samples. Building on the Mincer and Zarnowitz (1969) forecast bias test, Patton and Timmermann demonstrate that the observed values should be perfectly, positively correlated with the final forecast and uncorrelated with all previous forecast revisions. The test is based on the full sequence of forecasts and is expressed as

$$\ln A_t = \alpha + \sum_{i=0}^{H} \beta_i \ln F_{t,t-(h+i)} + \varepsilon_{t,t-h}, \tag{8}$$

where the forecasts are conducted at varying horizons $i = 0, \ldots, H$. The joint null hypothesis of unbiased long-run forecasts and optimal revisions is tested on the restriction $H_0 : (\alpha, \beta_0) = (0,1) \cap \beta_j = 0$ for $j = 1, \ldots, H$. For the USDA's net farm income forecast, this implies that the coefficient on the final forecast, $F_{t,t-6}$, is equal to 1 and that all other coefficients, including the intercept, are equal to 0.

Patton and Timmermann (2012) also recognize that the final values for many economic variables are unobserved, observed with measurement error, or subject to substantial revision. Thus, many macroeconomic forecasters have limited confidence in observed or actual values, A_t. The authors demonstrate that, in such a case, the final forecast can be treated as a proxy for the actual values, and the same conditions of equation (8) should hold. In our example, this suggests that in the regression equation

$$\ln F_{t,t-6} = \alpha + \sum_{i=1}^{H} \beta_i \ln F_{t,t-(h+i)} + \varepsilon_{t,t-h}, \tag{9}$$

the coefficient on the penultimate forecast, $F_{t,t-9}$, should be equal to 1 and all other coefficients, including the intercept, should be equal to 0. More formally, the joint null hypothesis is evaluated using the restriction $H_0 : (\alpha, \beta_1) = (0,1) \cap \beta_j = 0$ for $j = 2, \ldots, H$. A rejection of the null suggests that forecast process is not optimal.

Results

As previously stated, a forecast is optimal if it is both unbiased and efficient. One implication of forecast optimality is that the forecast error should decline as the terminal event approaches (Patton and Timmermann, 2007). The first two rows of Table 2 report the MAE and RMSE forecast accuracy measures for the USDA's net farm income forecast between 1975 and 2016 for each forecast horizon. Both measures suggest that the forecast errors decline throughout the forecast sequence; that is, the forecast becomes more accurate throughout the forecast sequence. For example, the mean absolute error declines from 14% at the longest horizon to 8% for the final forecast. This implies that forecasters benefit from the additional information included in the later forecasts, such as updated information on production and prices.

The bottom two rows of Table 2 report the coefficient estimates and standard errors of the Holden and Peel (1990) forecast bias test of equation (5). The coefficients were estimated using ordinary least squares (OLS) with Newey and West (1987) standard errors to account for the autocorrelation generated by overlapping observations and heteroskedasticity related to declining forecast variance as the horizon shortens (Bakhshi, Kapetanios, and Yates, 2005). The bias coefficient is statistically significant for only the initial forecast, $F_{t,t-18}$, released in February of the reference year. The bias coefficient implies that the initial forecast under-predicts net farm income by approximately 8.5%. Thus, the initial forecast is too low, as aggregate net farm income typically exceeds early projections. This tendency can also be observed in the top left panel of Figure 2. We fail to reject the null hypothesis for the remaining forecast horizons, which suggests that later forecasts are unbiased.

While the remaining forecasts are unbiased, the two tests developed by Nordhaus (1987) suggest that the later forecasts are inefficient. Table 3 reports the results of the OLS regression tests with Newey and West (1987) standard errors for equations (6) and (7). If a forecast is efficient, Nordhaus's first proposition suggests that the forecast errors should be independent of forecast revisions. As shown by the F-test reported at the bottom of the first three columns of Table 3, the joint null hypothesis of Nordhaus's first proposition for forecast efficiency is rejected for the August ($F_{t,t-12}$), November ($F_{t,t-9}$), and February ($F_{t,t-6}$) forecasts. The individual coefficient estimates for each of the three equations suggest the same pattern of forecast inefficiency. All but one of the slope coefficients are negative and statistically significant, suggesting that the forecasts over-react to new information (Messina, Sinclair, and Stekler, 2015). For example, a 10% upward revision between the initial and August forecasts ($F_{t,t-12} - F_{t,t-18}$) is associated with the August forecast being 5.7% too high. Even though the MAE and RMSE suggest that the forecast is improving throughout the process, the initial over-reaction of the August forecast has a lasting impact. A 10% upward revision between the initial and August forecasts also leads to the November forecast ($F_{t,t-9}$) being 5.1% too high and the February forecast ($F_{t,t-6}$) being 4.0% too high.

The finding that USDA net farm income forecast revisions tend to over-react to new information is somewhat surprising given the prior evidence that the USDA's production forecasts under-weight new information or are "smoothed" (Isengildina, Irwin, and Good, 2006, 2013; Isengildina-Massa, MacDonald, and Xie, 2012). The intercept coefficient is also statistically significant and positive for the August ($F_{t,t-12}$), November ($F_{t,t-9}$), and February ($F_{t,t-6}$) forecasts. This suggests that, when controlling for new information, the forecasts modestly under-predict net farm income by 0.06% in August, 0.06% in November, and 0.05% in February. Thus, despite the tendency to over-react to new information, the forecast appears to be conservative.

The final two columns of Table 3 report the results of the test of Nordhaus's (1987) second proposition that forecast revisions are independent. The joint F-test suggests that the November forecast ($F_{t,t-9}$) is efficient but that the final February forecast ($F_{t,t-6}$) is inefficient, although the test is marginally significant (≤ 0.10). Specifically, the change between the November and February forecasts ($F_{t,t-6}F_{t,t-9}$) is negatively correlated with the change between November and August forecasts ($F_{t,t-9}F_{t,t-12}$), or the final revisions tend to offset one another. For example, an upward 10% revision between November and August is associated with a 4.6% downward revision between February and November. This pattern may partially offset prior over-reactions but also signals that that forecasts could be improved.

Finally, more recent studies suggest that traditional tests of bias and efficiency may have limited power in small samples (Patton and Timmermann, 2012). As a result, we also apply the two tests by Patton and Timmermann, which are more powerful in finite samples. The results are reported in

Table 3. Nordhaus (1987) Forecast Efficiency Tests

Panel A. Dependent Variable: Forecast Errors

	August ($F_{t,t-12}$)	**November** ($F_{t,t-9}$)	**February** ($F_{t,t-6}$)
Intercept	0.061*	0.063**	0.046**
	(0.032)	(0.026)	(0.022)
August revision	−0.568***	−0.515*	−0.404**
($F_{t,t-12} - F_{t,t-18}$)	(0.157)	(0.172)	(0.167)
November revision		−0.376**	−0.067
($F_{t,t-9} - F_{t,t-12}$)		(0.198)	(0.141)
February revision			−0.327**
($F_{t,t-6} - F_{t,t-9}$)			(0.140)
R^2	0.179	0.296	0.263
Joint test: $H_0 : (\alpha, \beta) = (0,0)$			
F-test	6.583***	4.290	3.477**
Degrees of freedom	2	3	4

Panel B. Dependent Variable: Forecast Revisions

	November ($F_{t,t-12}$)	**February** ($F_{t,t-9}$)
Intercept	−0.003	0.024
	(0.024)	(0.021)
August revision	−0.086	−0.165
($F_{t,t-12} - F_{t,t-18}$)	(0.134)	(0.135)
November revision		−0.460**
($F_{t,t-9} - F_{t,t-12}$)		(0.178)
February revision		
($F_{t,t-6} - F_{t,t-9}$)		
R^2	0.006	0.263
Joint test: $H_0 : (\alpha, \beta) = (0,0)$		
F-test	0.459	2.376*
Degrees of freedom	2	3

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Numbers in parentheses are Newey and West (1987) standard errors.

Table 4. Both test statistics reject the joint null hypothesis, which suggests that the long-run forecasts are biased and the revisions are not optimal. These findings are consistent with the Holden and Peel (1990) and Nordhaus (1987) tests but provide more robust evidence of bias and inefficiency.

Discussion and Conclusions

Net farm income is the U.S. government's official measure of farming's contribution to the national economy and one of the U.S. Department of Agriculture's (USDA) most cited statistics (McGath et al., 2009). The USDA's net farm income forecasts are closely monitored by policy makers, program administrators, and agribusinesses, which use them to make plans and projections. Despite their prominent role in the agricultural sector, the USDA's forecasts of net farm income have received

Table 4. Patton and Timmermann (2012) Test

	Dependent Variable: Actual (A_t)		Dependent Variable: February Forecast ($F_{t,t-6}$)	
	Expected Value	**Estimate**	**Expected Value**	**Estimate**
Intercept	0	−0.040	0	−0.078
		(0.175)		(0.146)
February forecast	1	0.662**		
$F_{t,t-6}$		(0.146)		
November forecast	0	0.276**	1	0.551**
$F_{t,t-9}$		(0.110)		(0.183)
August forecast	0	−0.343*	0	0.284*
$F_{t,t-12}$		(0.203)		(0.167)
Initial forecast	0	0.428**	0	0.192
$F_{t,t-18}$		(0.170)		(0.156)
R^2		0.960		0.948
Joint test: $H_0 : (\alpha, \beta_1) = (0, 1) \cap \beta_j = 0$				
F-test		2.668**		2.384*
Degrees of freedom		5		4

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Numbers in parentheses are Newey and West (1987) standard errors.

very limited empirical analysis. We apply a suite of forecast bias and efficiency tests to the USDA's net farm income forecasts from 1975 through 2016.

The analysis provides a number of important insights about the USDA's sequence of net farm income forecasts. First, the initial forecast, released in February, 18 months before the official estimates, is downward biased. Second, the updated forecasts, released 12 to 6 months before the official estimates, are inefficient. Specifically, the results imply that the USDA forecasters over-react to new information. Finally, we show that the findings of downward bias in long-horizon forecasts and inefficiencies in forecast revisions are robust to finite sample size (Patton and Timmermann, 2012).

As highlighted by Schnepf (2016), the net farm income forecasts play a particularly important role in the development of agricultural policy, and the bias and inefficiency of the USDA's net farm income forecasts can, therefore, impact the broader agricultural sector. For example, the 2014 Farm Bill (the Agricultural Act of 2014) passed the House of Representatives on January 29, 2014, and the Senate on February 4, 2014. The President signed the measure into law on February 7, 2014 (Chite, 2014). In January and February 2014, the most recent information on farm sector financial well-being was from the November 2013 forecast of 2014 net farm income, at $108.2 billion. However, the official estimate of 2014 net farm income, released in August 2015, was $127 billion. Thus, consistent with the pattern implied by the empirical tests, the real-time forecast of net farm income at the time the legislation was adopted was $18.8 billion, or 17.4%, below the official estimates. That is, the forecasts suggested that the farm sector was in worse financial shape than it was in actuality, which may have had some influence on the shape of farm policy.

The change in farm income information may also alter the interpretation of the policy decisions surrounding the 2014 Farm Bill *ex post*. As highlighted by Croushore and Stark (2001), policy makers are forced to make choices based on information available at the time, yet changes in aggregate economic data can distort the interpretation of these decisions. As a result, policy analysis can be improved by examining changes as they relate to real-time economic data.

The estimates of historical bias and inefficiency can be used to adjust or discount the USDA's net farm income forecasts. As shown empirically by Arai (2014), fixed-event forecasts can be weighted by the coefficient estimates of forecast evaluation tests to provide more accurate predictions. Thus, given the documented downward bias in the USDA's net farm income forecast, forecast users should consider increasing the value of real-time forecasts. Also, as forecasts are revised throughout the forecast horizon, forecast users should temper the implied change between forecasts.

This study also provides a number of avenues for future research. Our analysis is limited to the forecasts of "bottom-line" net farm income; future research could examine the optimality of the various component forecasts, such as the value of production or capital consumption. Dubman, McElory, and Dodson (1993) examine the accuracy of bottom-line net farm income, as well as a number of component forecasts, between 1985 and 1993. Their analysis suggests that forecast errors over that period were greatest for value of inventory adjustment (115% average forecast error), but the forecasts for receipts and cash expenses were much more accurate (3%–4% average forecast error). Obviously, the agricultural sector has changed in a number of ways since their observation period, and the USDA has also changed its net farm income forecast procedure (McGath et al., 2009). Thus, a further examination of the bias and efficiency of the forecast components is warranted.

Finally, our finding that the USDA's net farm income forecast is biased and inefficient suggests the need for continued improvement in the forecast methodology. Currently, the USDA uses a traditional "bottom-up" forecasting approach in which each component of the forecast is predicted individually. An accounting equation is then used to generate sector-wide projections of bottom-line net farm income (McGath et al., 2009). Going forward, the USDA may want to consider alternative procedures to generate "top-down" or direct forecasts of aggregate net farm income to supplement existing methods.

The goal of this research was to evaluate the efficacy of the USDA net farm income forecasts. While the results show that these forecasts are biased and evolve inefficiently, we hesitate to be overly critical given the enormity of the task. In particular, the USDA's forecasting methods, procedures, and personnel change over time. The USDA should be aware of their historical performance and consider cross-checks on their bottom-up forecasting approach. Likewise, forecast users will want to be aware of the statistical biases in the forecasts. Collectively, this may help to improve decision making within the agricultural sector.

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