Assessing the Accuracy of USDA's Farm Income Forecasts: The Impact of ARMS

by

Todd H. Kuethe, Todd Hubbs, and Dwight R. Sanders

Suggested citation format:

Kuethe, T. H., T. Hubbs, and D. R. Sanders. 2017. "Assessing the Accuracy of USDA's Farm Income Forecasts: The Impact of ARMS." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. [http://www.farmdoc.illinois.edu/nccc134].

Assessing the Accuracy of USDA's Farm Income Forecasts:
The Impact of ARMS

by

Todd H. Kuethe, Todd Hubbs, and Dwight R. Sanders*

Paper presented at the NCCC-134 Conference on Applied Commodity Price
Analysis, Forecasting, and Market Risk Management
St. Louis, Missouri, April 24-25, 2017

---

*Todd H. Kuethe and Todd Hubbs are Clinical Assistant Professors in the Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. Dwight R. Sanders is a Professor, Department of Agribusiness Economics, Southern Illinois University Carbondale.

Assessing the Accuracy of USDA's Farm Income Forecasts: The Impact of ARMS

Practitioner's Abstract

The USDA's forecasts for net farm income are important inputs for businesses, legislators, economists, and other policy-makers. While the USDA has been providing forecasts for net farm income for over 50 years, they have not been rigorously analyzed in regards to bias and efficiency. Here, the USDA's net farm income forecasts from 1975-2015 are evaluated along a number of dimensions. The results show that the USDA's initial forecasts for net farm income are downward bias. This bias is corrected as the forecasts evolve through the year. Moreover, upward revisions tend to lead to negative forecast errors or overestimates. Consistent with that finding, there is a tendency for reversals in the forecasts. That is, upward revisions tend to be corrected in subsequent revisions. Despite these inefficiencies, the forecasts provide remarkably good directional guidance by predicting growth or contraction correctly over 80% of the time. There was no evidence that forecast accuracy improved through time or with the availability of ARMS data.

Key words: farm income, forecast evaluation, Agricultural Resource Management Survey

Introduction

> "U.S. farm incomes will hit their lowest point this year since 2009, a U.S. Department of Agriculture forecast showed on Tuesday, deepening pain in the Farm Belt amid a multiyear downdraft in commodity prices." (*Wall Street Journal*, August, 2016).

As evidenced by the above quote from the *Wall Street Journal*, the status of U.S. farm incomes can make financial headlines. Indeed, shifts in the U.S. Department of Agriculture's (USDA) farm income estimates have important ramifications for producers, rural economies, agribusinesses, and creditors. It is not unusual for large input suppliers—such as John Deere Company or Monsanto—to see earnings estimates adjusted based on farm income estimates (Cancino, 2014). Despite the clear importance of USDA farm income projections, these forecasts have not been widely evaluated. The goal of this research is to provide the background and history behind the USDA's farm income forecasts. Then, the forecasts will be evaluated in terms of accuracy, rationality, and improvement through time.

The USDA has a long tradition of providing forecasts of net farm income. The original intent of the forecasts were to provide indications of the financial strength of the nation's farm sector ahead of the annual net farm income estimates first published in 1910. In early years, the forecasts were issued sporadically or in conjunction with major outlook meetings. In more recent years, a consistent release pattern of February, August, and November has been followed. The USDA provides limited documentation of the forecasting process (see Dubman, et al., 1993; McGath, et al., 2009). So, while it is not exactly known how some of the very early forecasts were compiled, we do know that major overhauls occurred after the implementation of the Agricultural Resource Management Survey (ARMS) in 1996 (Kuethe and Morehart, 2012). ARMS is the annual survey of farm and ranch operators conducted by USDA to obtain information about the status of farmers' finances, resource use, and household economic wellbeing. Prior USDA surveys failed to reflect information on farm sales, inventories, assets, and liabilities (Kuethe and Morehart, 2012). The data collected by ARMS is expected to provide the USDA with better capabilities in terms of forecasting U.S. farm income.

A key aspect of this research is to provide an assessment of whether or not USDA forecasts improved with the availability of these important data. USDA forecasts for farm income have clear importance to policy-makers, program administrators, and agribusinesses. For these decision-makers it is important that they have accurate and efficient forecasts. The goal of this research is to evaluate the USDA forecasts for net farm income to better understand how they have performed through time.

Data

Net farm income is measured in nominal dollars (billions). As shown in Figure 1, net farm income (logarithmic scale) was essentially flat from 1975 through 1984 with an annual growth rate of -0.49% per year. After passage of the 1985 Farm Bill, incomes started to increase—tied to federal payments—and have shown a more-or-less steady annual growth rate of 3.66% since that time.

A shown in Figure 2, net farm income includes calculations of cash income from crops, livestock, federal payments, and other farm income less cash expenses and inventory adjustments. So, net farm income has a number of moving parts. For instance, the largest source of receipts in 2017 are forecast to be cattle and calves ($63.0 billion), corn ($46.3 billion), soybeans ($39.4 billion), dairy ($38.9) and broilers ($26.9). Clearly, forecasting these revenues are a complex interaction of price and quantity. On the expense side, market prices for feed ($57.9 billion), fuel ($12.9), fertilizer ($19.3) and seed ($20.2) create considerable variation from year-to-year. Therefore, forecasting net farm income is an onerous task.

A consistent set of net farm income forecasts and realized values are available from 1975-2015 (41 time series observations). The forecasts are issued in February, August, and November of the same year for which income is being forecast (reference year, t). Another forecast is made again in the February following the reference year (t+1) and the actual or realized value is the estimate provided in August following the reference year. For example, the 2015 net farm income is first forecasted in February of 2015. That is followed by forecasts in August of 2015, November of 2015, and February of 2016. Then, the estimate released in August of 2016 serves as the final or realized value for empirical purposes.

The farm income forecasts represent a fixed event forecast where a number of forecasts are made for the same value prior to its realization. In this respect, they can be treated much like a USDA forecast for crop production (see Isengildina, Irwin, and Good, 2013) or livestock production (see Bailey and Brorsen, 1998). The forecasted values of net farm income are compared to the official published estimates that are released in August following the reference year (with minor additional revisions again following the Census of Agriculture)

In the following analysis, forecast errors in year t forecast period i ($e_{i,t}$) will be defined as the $e_{i,t}=A_t - F_{i,t}$ where $F_{i,t}$ is the forecast made in month i for year t and A_t is the realized or actual farm income in year t. The forecast period i is simply indexed to the four months when forecasts are made in February (4), August (3), and November (2) of the reference year followed by the last forecast again in February (1) of the following year. A naïve, no-change forecast, will also be used as a standard of comparison with the $F_{i,t} = A_{t-1}$. Since the time series of farm income is non-stationary, the series is converted to natural logarithms and errors represent percentage errors.

One confounding aspect of the data set up is the inherent lag in knowing the "final" value for net farm income. For example the 2015 net farm income was forecast in February, August, and November of 2015 and again in February 2016. However, the actual final estimate was not published until August of 2016. This timeline is illustrated in Figure 3. In this timeline, the USDA is making the February forecasts for year 2 ($F_{4,2}$) without the benefit of actually knowing their performance in the prior year (A_1). In contrast, when they make their August forecast ($F_{3,2}$), they do have the actual for the prior year (A_1). In the following analysis, we are careful to only use information actually available to the forecasters. For example, when evaluating the February forecast of the reference year (February, t) the known value for the prior year is the value released in the same report (February, t+1). It is not until the August and November projections do the forecasters know the final value for the prior year.

Methods and Results

The USDA farm income forecasts will be evaluated along a number of dimensions, including forecast accuracy, efficiency, and rationality (non-smoothing) in a fixed-event framework (Bakhshi, Kapetanious, and Yates, 2005; Isengildina, Irwin, and Good, 2013). Special attention will be given to whether or not forecast accuracy improved since the implementation of ARMS. If the farm income forecasts have indeed improved, then this provides an indication of the information validity contained in the survey.

Accuracy Measures

Traditional measures of forecast error are presented in Table 1. The first two columns contain the naïve (no change) forecasts as for comparison. The first row shows the average error (bias) for each forecast month. Notably, there is a fairly consistent downward bias across all of the forecasts. The February forecast during the reference year (February, t) consistently underestimates net farm income by 8.67% that is statistically different from zero (p-value=0.0029). The bias in February is graphically clear when plotting the forecast errors in Figure 4. The other forecast horizons also show a downward bias with the November forecast in the reference year (November, t) a marginally significant 4.37%.

The accuracy measures reported are the root mean squared error (RMSE), mean absolute error (MAE), and Theil's U. As expected, the USDA forecasts become more accurate as the forecast horizon shortens. Harvey, Leybourne, and Newbold (1997) suggest differences in accuracy measures should be tested with their modified version of the Diebold-Mariano test (1995). Given two time series of forecast errors (e_{1t},e_{2t}), and a specified loss function g(e), the null hypothesis of equal expected forecast performance using the modified Diebold-Mariano (MDM) test is $E[g(e_{1t})-g(e_{2t})] = 0$. Specifically, the MDM test is based on the sample mean of dt, where $dt=g(e_{1t})-g(e_{2t})$, with the test statistic having a t-distribution.

The t-statistics from the MDM test are presented below the RMSE and MAE. Specifically, each forecast is compared to their appropriate naïve counterpart. For instance, the February forecast is compared to the naïve alternative of just using the prior year's February as the forecast. In this case, the null hypothesis of equal RMSE and MAE can be rejected at near the 5% significance levels (p-value = 0.0554 and 0.0.0442). In contrast, both the August forecasts do provide statistically significant smaller forecast errors than their naïve benchmark for the prior year's actual. The November forecasts produce a RMSE and MAE that are smaller than those of the naïve forecasts but they are not statistically different at the 5% level. The forecasts made in February following the reference year (February, t+1) produce statistically smaller RMSE and MAE than the naïve alterative (p-values < 0.01).

Theil's U relies on squared forecast errors, but normalizes the forecast errors by the volatility of the underlying series. Thus, Theil's U provides some basis of comparison across the three horizons. Theil's U has a lower bound of zero for perfect forecasts, and it takes a value of unity for naïve "no-change" forecasts (Leuthold, 1975). Looking across the markets, Theil's U indicates that the most improvement over a "no-change" forecast naturally occurs in February following the reference year (February, t+1) where there is a 49% (1.00-0.51) improvement over the naïve forecast.

Overall, the accuracy measures indicate that the net farm income forecasts are generally informative and rational. That is, they tend to provide more information than a naïve no change forecast and that information improves as the horizon shortens. That is, the forecast errors get smaller through the year.

Efficiency

To further explore the optimality conditions of these forecasts, tests for forecast efficiency are also conducted. Forecasts are weakly efficient if e_t is orthogonal to both the forecast, as well as prior forecast errors (Nordhaus, 1987). In fixed-event forecasts, this can be tested in the regression framework proposed by Bakhshi, Kapetanious, and Yates (2005).

First, forecast errors (e_t) must be orthogonal to forecast revisions (FR_t):

$$e_{i,t} = \alpha_1 + \beta_0 \, FR_{i,t} + \beta_1 \, FR_{i-1,t} + \beta_2 \, FR_{i-2,t} \ldots + \beta_n \, FR_{i-n,t} + \mu_{i,t}, \quad (1)$$

where, $e_{i,t}$ is the forecast error for year t made in forecast period i and $FR_{i,t}= F_{i,t}-F_{i-1,t}$ is the forecast revision made between period i-n and i. A rejection of the null hypothesis, $\alpha_1=0$, $\beta_n = 0$ for all n, would be evidence of inefficient use of information contained in past forecasts. Under the null hypothesis the forecast error is orthogonal to past revisions ($\beta_n=0$ for all n) and unbiased ($\alpha_1=0$). If $\beta\neq0$, then the direction of forecast revisions have an impact on the final forecast error. For example, if $\beta<0$, a large upward revision results in an overestimate or a negative forecast error.

Second, forecast revisions ($FR_{i,t}$) should be independent from prior revisions:

$$FR_{i,t} = \alpha_2 + \rho_1 \, FR_{i-1,t} + \rho_2 \, FR_{i-2,t} \ldots + \rho_n \, FR_{i-n,t} + \mu_{i,t}. \quad (2)$$

That is, under the null rationality hypothesis, α_2=0, ρ_n = 0 for all n, the forecast revisions unbiased (α_2=0) and are serially independent (ρ_n = 0). Forecast revisions should not be systematically different from zero (α_2=0) and should not be related to prior revisions (ρ_n = 0). If ρ_n >0, then the forecasts are smoothed—upward revisions are followed by upward revisions. If ρ_n <0, then the forecast revisions are corrected—upward revisions are followed by downward revisions.

Equations (1) and (2) are estimated using OLS with Newey-West standard errors to account for the autocorrelation generated by overlapping observations and heteroskedasticity related to declining forecast variance as the horizon shortens (Bakhshi, Kapetanious, and Yates, 2005). The null hypotheses are tested using an F-test on the stated parameter restrictions.

Equation (1) is estimated for each of the four forecast points, February, August, and November during reference year t and February following the reference year (February, t+1). The results are presented in Table 2. For the February, t forecast, the revisions is calculated as the change from the appropriate naïve forecast (prior year's forecast made during the same month).

The August and February (t+1) forecasts reject the null efficiency hypothesis at the 5% level (F-test) and the November model at the 10% level (p-value = 0.0878). An examination of the November model reveals the nature of the inefficiencies. In particular, downward bias documented in Table 1 shows up as a positive intercept term of 4.98% (p-value = 0.1141). Furthermore, upward revisions made in August and November itself results in negative forecast errors or overestimates. A 10% upward revision in net farm income from February to August is associated with that year's November forecast being 7.3% too high. Likewise, an upward revision from August to November of 10% generates a forecast that is 4.1% too high.

The pattern of a positive intercept (downward bias) and negative parameter estimates on revisions generally holds across the forecast horizons. This suggests some tendency for the USDA to be a bit too extreme in their forecast revisions: upward (downward) revisions lead to negative (positive) errors. Part of this tendency may stem from the finding that the first forecast of the year (February, t) is downward biased by 8.67% (see Table 1).

Equation (2) is also estimated for each of the four forecast points, February, August, November, and February, t+1. The results are shown in Table 3. For the February forecast of the reference year, the revision is again calculated as the change from the naïve forecast (prior year's estimated made in February). The null efficiency hypothesis is rejected for the August forecasts. However, it is not because the August forecast revision is related to the February revision (slope parameter is not statistically different from zero); instead, the August revision's constant term is a statistically significant 5.50% (p-value = 0.0006). This suggests that the change in net farm income forecasts consistently increase by 5.50% from February to August (holding the February revision constant). Indeed, the average revision in August from February is 5.0% and nearly 60% are positive. Given that the February forecast itself is downward biased by 8.67% (see Table 1), it makes some sense that revisions in August partly reverse the February bias.

The tendency to revise the forecast upward does not continue in November where the efficiency null is not rejected. However, the efficiency null is rejected marginally in February, t+1 (p-value

= 0.0684). For the February, t+1 revisions there is a notable constant increase of 2.60%, although it is not statistically different from zero. However, the February (t+1) revision is statistically related to the previous November revision with a slope coefficient of -0.45 (p-value = 0.0103). This is opposite of smoothing forecasts. Instead, if the November revision is 10% higher, then subsequent February (t+1) revision tends to be 4.5% lower or the November revision is roughly reverse by half.

The revision to the final published net farm income (from the February, t+1 forecast to the final August estimate) is also examined and efficiency is rejected (p-value=0.0476). In particular, there is a statistically significant 5.02% increase to the final estimate (p-value = 0.0401) as the downward bias in the forecasts are finally corrected (all else equal). There is also a tendency to again reverse revisions that occurred in August (p-value = 0.0361) and in the most recent February (t+1) forecast. In particular, a 10% downward revision in February (t+1) is reversed by 3.2% in the final estimate.

Overall, the efficiency tests suggest that the USDA's estimates for net farm income are generally not efficient. They do not smooth the forecasts. Instead, the forecasts show a notable upward bias in the initial February forecast that is corrected with consistent upward revisions in August and in the final estimate. There is also a tendency for revisions to be reversed in subsequent forecasts, all else equal. This represents a fairly complicated evolution of the forecasts through time.

Directional Accuracy

For some decision-makers it may be sufficient to just know if net farm income will increase or decline. Certainly, this may be important when evaluating sales trends or possibly predicting increasing or decreasing outlays for farm programs.

McIntosh and Dorfman (1992) endorse the timing test proposed by Henriksson and Merton (1981) to qualitatively evaluate forecast performance. As demonstrated by Pesaran and Timmermann (1994), Henriksson and Merton's hypergeometric test is asymptotically equivalent to a chi-squared test for independence in a two-by-two contingency table (see Table 4). In Table 4, ΔF is the forecasted direction of change, ΔA is the actual direction of change, and n is the number of observations in each cell of the table. Perfect directional forecasting would be represented by $n_{21}=n_{12}=0$ or equivalently $n_{11}=N_1$ and $n_{22}=N_2$. Henriksson and Merton show that the null hypothesis of no timing ability is a test that the sum of the conditional probabilities of correct forecasts ($n_{11}/FN_1 + n_{22}/FN_2$) equals one and suggest a test based on the hypergeometric distribution of n_{22}. The test is equivalent to a test of independence in a two-by-two contingency table (Cumby and Modest) using a standard chi-squared test (Stekler and Schnader, 1991).

The definition of a forecasted increase or decrease clearly depends on the base period of comparison. For the August, November, and February (t+1) net farm income forecasts, the prior year's actual number is known and serves as the appropriate comparison. However, for the February forecast, the USDA forecasters do not yet know the prior year's final number. Instead, their forecast is presumably made relative to the prior year's forecast also made in February. So, for the February forecasted directional change the February estimate for the prior year serves as the base for both the predicted direction and actual direction.

The results of the Hendriksson-Merton test are shown in Table 5. The first row presents the percent of forecasts that correctly predicted if net farm income would increase or decrease. The second row shows the p-value for the chi-squared test of independence. The naïve forecast is simply that if net farm increased (decreased) in the prior year, it is predicted to increase (decrease) this year. This naïve approach is perversely inaccurate with only 35% of the directional changes correct which was statistically unlikely (p-value = 0.0551). The USDA forecasts performed much better with the February, August, November, and February (t+1) forecasts correctly predicting the directional change 78%, 83%, 85%, and 85% of the time, respectively. All of the forecast months have directional accuracy that is statistically significant at the 5% level. So, despite some of the inefficiencies documented in the prior section, the USDA does a remarkably good job of capturing expansion or contraction in net farm income.

Forecast Improvement

To test if the forecasts have improved over time, a method similar to that used by Bailey and Brorsen (1998) is incorporated. In this test, the absolute value of the forecast errors is regressed on a time trend and a dummy variable representing the availability of the ARMS data to the USDA forecasters.

$$\left| e_t \right| = \theta_1 + \theta_2 Trend_t + \theta_3 ARMS + \mu_t. \qquad (5)$$

If θ_2=0, then there is no systematic increase or decrease in the absolute value of the forecast error, $\left| e_t \right|$, over time. Rejection of this null hypothesis would suggest that forecasts either improved ($\theta_2 < 0$) or worsened ($\theta_2 > 0$) over time. The θ_3=0 null hypothesis is tested against the alternative that ARMS data lowered forecast errors ($\theta_3 < 0$) or potentially increased them ($\theta_2 > 0$) from 1997-forward (ARMS = 0 for years 1975-1996 and = 1 for years 1997-2015). The hypothesis are tested using a two-tailed t-test with results presented in Table 6.

There is no real evidence that forecast errors have changed through time. None of the estimated coefficients on the time trend or the ARMS dummy variable are statistically significant at the 5% level and there is no noticeable pattern across the parameter estimates.

It is possible that the information provide by ARMS is being masked by other changes that made overall forecasting more difficult after 1996 (such as the Freedom to Farm Act). One way to isolate the impact of ARMS is to focus on the relative improvement in the forecasts for which it is available. The ARMS data become available to forecasters when they are making their forecasts starting in August. Assuming all other informational advantages occur at the same time each year, then the availability of the ARMS data in 1997 might show up as a relative improvement in the August, November, and February (t+1) forecasts relative to the initial February forecast. That is, the ARMS data are not available in February during the USDA's first forecast. But, it is available to them in subsequent forecasts for the reference year. To test this possibility, equation (5) is estimated again but with the dependent variable the difference between the absolute errors for the February forecast ($e_{4,t}$) and subsequent forecasts ($e_{4-i,t}$).

$$|e_{4-i,t}| - |e_{4,t}| = \theta_1 + \theta_2 Trend_t + \theta_3 ARMS + \mu_t. \quad (6)$$

Equation (6) is estimated and presented in Table 7. The results are not overly convincing. For the relative performance of August versus February, none of the estimated coefficients are statistically different from zero at conventional levels. The November-February regression, the coefficient on the dummy variable does show a relative improvement of 17.53% for the November forecasts since the availability of ARMS data. The February, t+1 also shows a 18.44% relative improvement after 1996. However, this is offset by a positive time coefficient of 0.92% per year which would be a cumulative 17.5% decrease in advantage since the ARMS data were introduced. At best, this provides only modest evidence that ARMS data helping to improve the forecasts when they are available.

The lack of evidence for forecast improvement could simply be because the use of ARMS data coincides with a volatile time in the agricultural sector or it may, in fact, not really improve the forecasting ability of the agency.

A graphical analysis may provide some insights as to why these forecasts have not improved. The absolute percent error for the February, August, and November forecasts are plotted in Figures 5-7. Focusing on the August forecasts errors in Figure 6, there was a period of relative calm from 1988-2003 and a clumping of large errors in 1975-1987 and again from 2004-2015. Both of these intervals represent a tumultuous time in the both the U.S. economy in general and the farm economy in particular, so large errors may be expected during those periods. Indeed, in the later period, it is possible that errors might have been even larger were it not for the availability of the ARMS data.

Summary and Conclusions

USDA net farm income forecasts are examined along a number fronts: accuracy, efficiency, directional accuracy, and changes through time. The results show that the forecasts rationally become more accurate as the forecast horizons shorten. The forecasts are generally do not meet the requirements for efficiency. In particular, the USDA net farm income forecasts are downward biased. Moreover, upward revisions tend to lead to negative forecast errors or overestimates. Consistent with that finding, there is a tendency for reversals in the forecasts. That is, upward revisions tend to be corrected in subsequent revisions. Despite these inefficiencies, the forecasts provide remarkably good directional guidance. The February forecast correctly indicates expansion or contraction in farm income 78% of the time and the November forecast is correct in 85% of the years.

The forecast errors showed no distinctive changes through time. That is, the forecast errors show no systematic tendency to get smaller through time. In some ways, this is amazing given the technological and computing improvements over the last 40 years. Despite the highly regarded ARMS data that was collected starting in 1996, it has not been accompanied by a noticeable reduction in forecast errors. Perhaps this should not be surprising given the volatile agricultural markets in the late 2000’s. Or, perhaps the forecasts would have been significantly worse were it not for the use of ARMS data during this time period. Importantly, this in no way is a commentary on the value of those data as they provide key inputs for many other important USDA decision-making processes.

This research is important along a number of fronts. First, the users of farm income forecasts need to understand the accuracy of those estimates. Practitioners use the forecasts to make important business decisions regarding farm credit conditions as well as equity valuations. Second, the agencies that produce the forecasts need feedback regarding the performance of the forecasts and how they be improved and the impact of such programs as ARMS. While this research did not find any vast improvement in the forecasting in recent years, that should not necessarily be surprising. Other researchers have documented that it is notoriously difficult to forecast farm product prices (Sanders and Manfredo, 2003) and farm input costs (Sanders, Manfredo, and Boris, 2008) and U.S. farm income calculations rely on thousands of such projections. As U.S. prices and output become increasing reliant on global markets, it may take large initiatives (like ARMS) just to maintain a steady forecasting performance.

References

Aadland, D. and D. Bailey. "Short-Run Supply Responses in the U.S. Beef-Cattle Industry." American Journal of Agricultural Economics. 83(2001):826-839.

Aaron, H.J. "Presidential Address—Seeing Through the Fog: Policymaking with Uncertain Forecasts." *Journal of Policy Analysis and Management*. 19(2000):193-206.

Bailey, D.V. and B.W. Brorsen. "Trends in the Accuracy of USDA Production Forecasts for Beef and Pork." *Journal of Agricultural and Resource Economics*. 23(1998):515-525.

Bakhshi, H., G. Kapetanios, and T. Yates. (2005) "Rational Expectations and Fixed-Event Forecasts: An Application to UK Inflation." *Empirical Economics* 30:539-553.

Brown, B.W. and S. Maital. "What do Economists Know? An Empirical Study of Experts' Expectations." *Econometrica*. 49(1981):491-504.

Cancino, A. "Deere Profit Falls, Cuts Forecast." Chicago Tribune. August 13, 2014. (Available at http://www.chicagotribune.com/business/chi-deere-earnings-20140813-story.html, last accessed on January 24, 2017).

Diebold, F.X. and R.S. Mariano. "Comparing Predictive Accuracy." *Journal of Business and Economic Statistics*. 13(1995):253-263.

Dubman, R., R. McElroy, and C. Dodson (1993) "Forecasting Farm Income: Documenting USDA's Forecast Model" Technical Bulletin #1825, USDA, Washington, DC.

Elam, E.W. and S.H. Holder. "An Evaluation of the Rice Outlook and Situation Price Forecasts." *Southern Journal of Agricultural Economics*. (1985): 155-161.

Granger, C.W.J. "Can We Improve the Perceived Quality of Economic Forecasts?" Journal of Applied Econometrics. 11(1996):455-473.

Granger, C.W.J. and P. Newbold. Forecasting Economic Time Series. Second Edition. New York: Academic Press, 1986.

Hamilton, J.D. Time Series Analysis. New Jersey: Princeton University Press, 1994.

Harvey, D., S. Leybourne, and P. Newbold. "Testing the Equality of Prediction Mean Squared Errors." *International Journal of Forecasting*. 13(1997): 281-291.

Henriksson, R.D. and R.C. Merton. "On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills." *Journal of Business*. 1981(54):513-533.

Isengildina, O., S.H. Irwin, and D.L. Good. (2013) "Do Big Crops Get Bigger and Small Crops Get Smaller? Further Evidence on Smoothing in U.S. Department of Agriculture Forecasts." *Journal of Agricultural and Applied Economics* 45: 95-107.

Kuethe, T.H. and M. Morehart "The Agricultural Resource Management Survey: An Information System for Production Agriculture." *Agricultural Finance Review* 72 (2): 191-200.

Leuthold, R.M. "On the Use of Theil's Inequality Coefficients." *American Journal of Agricultural Economics*. 57(1975):344-346.

McIntosh, C.S. and J.H. Dorfman. "Qualitative Forecast Evaluation: A Comparison of Two Performance Measures." *American Journal of Agricultural Economics*. 74(1992):209-214.

McGath, C., R. McElroy, R. Strickland, L. Traub, T. Covey, S.D. Short, J. Johnson, R. Green, M. Ali, and S. Vogel (2009) "Forecasting Farm Income: Documenting USDA's Forecast Model" Technical Bulletin #1924, USDA, Washington, DC.

Newman, J. "U.S. Farm Incomes to Hit the Lowest Level Since 2009." *Wall Street Journal* August 30, 2016.

Nordhaus, W.D. "Forecasting Efficiency: Concepts and Applications." *The Review of Economics and Statistics*. 69(1987):667-674.

Pesaran, M.H. and A.G. Timmermann. "A Generalization of the Non-Parametric Henriksson-Merton Test of Market Timing." *Economic Letters*. 44(1994): 1-7.

Pons, J. "The Rationality of Price Forecasts: A Directional Analysis." *Applied Financial Economics*. 11(2001):287-290.

Steckler, H.O. and M.H. Schnader. "Evaluating Predictions of Change: An Application to Inflation Forecasts." *Applied Financial Economics*. 1(1991):135-137.

Sanders, D.R. and M.R. Manfredo. "USDA Livestock Price Forecasts: A Comprehensive Evaluation." *Journal of Agricultural and Resource Economics*. 28(2003): 316-334.

Sanders, D.R. and M.R. Manfredo. "USDA Production Forecasts for Pork, Beef, and Broilers: An Evaluation," *Journal of Agricultural and Resource Economics*. 27(2002): 114-127.

Sanders, D.R., M.R. Manfredo, and K. Boris. "Accuracy and Efficiency in the U.S. Department of Energy's Short-term Supply Forecasts." *Energy Economics*. 30(2008):1192-1207.

Table 1. Accuracy Measures, Net Farm Income Forecasts, 1975-2015

	Naïve Prior February	Naïve Prior Actual	February, t	August, t	November, t	February, t+1
Bias	4.50	3.30	8.67	3.69	4.37	2.58
t-stat.	1.0958	0.8935	3.1843	1.3328	1.7909	1.3979
p-value	0.2799	0.3771	0.0029	0.1903	0.0811	0.1700
RMSE	26.0	23.3	19.1	17.7	15.8	11.8
p-value			0.0554	0.3074	0.2282	0.0044
MAE	21.0	18.6	14.4	12.4	11.1	8.1
p-value			0.0422	0.3065	0.0652	0.0005
Theil's U	1.00	1.00	0.73	0.76	0.68	0.51

Note, the p-values for RMSE and MAE are testing the null hypothesis that these accuracy measures are equal to those of the naïve forecasts. For the February forecast, the naïve standard is the prior February forecast and for the August and November forecasts the naïve comparison is the prior actual value.

Table 2. Test of Orthogonality between Forecast Errors and Revisions, 1975-2015

		----Forecast Error-----			
		February, t	August, t	November, t	February, t+1
	Constant	5.77	4.43	4.98	5.02
	p-value	0.1153	0.2059	0.1141	0.0401
-----Revision-----	February, t	-0.04	-0.07	0.00	0.02
	p-value	0.8105	0.6706	0.9875	0.8269
	August, t		-0.75	-0.73	-0.37
	p-value		0.0042	0.0216	0.0361
	November, t			-0.41	-0.06
	p-value			0.0930	0.6741
	February, t+1				-0.3166
	p-value				0.0402
	F-statistic	1.4206	3.3599	2.3584	2.8403
	p-value	0.2541	0.0289	0.0878	0.0386

Table 3. Test of Orthogonality between Forecast Revisions, 1975-2015

----Forecast Revision-----		----Forecast Revision-----			
		August, t	**November, t**	**February, t+1**	**Actual, t+1**
	Constant	5.50	-0.94	2.60	5.02
	p-value	0.0006	0.6982	0.2452	0.0401
	February, t	0.12	-0.12	0.05	0.02
	p-value	0.2537	0.5218	0.4332	0.8269
	August, t		-0.04	-0.19	-0.37
	p-value		0.7939	0.2424	0.0361
	November, t			-0.45	-0.06
	p-value			0.0103	0.6741
	February, t+1				-0.32
	p-value				0.0402
	F-statistic	6.9839	0.4642	2.3956	2.5184
	p-value	0.0026	0.7090	0.0684	0.0476

Table 4. Contingency Table to Forecast Market Direction

	Actual		
Forecast	$\Delta A>0$	$\Delta A\leq 0$	Subtotal
$\Delta F>0$	n_{11}	n_{12}	FN_1
$\Delta F\leq 0$	n_{21}	n_{22}	FN_2
Subtotal	N_1	N_2	N

Note: ΔF is the forecasted direction of change, ΔA is the actual direction of change, and $n_{i,j}$ is the number of observations in the i,j cell of the table.

Table 5. Hendriksson-Merton Test for Directional Accuracy, 1975-2015

		----Forecast Month-----			
	Naïve	**February, t**	**August, t**	**November, t**	**February, t+1**
% Correct	35%	78%	83%	85%	85%
p-value	0.0551	0.0002	0.0000	0.0000	0.0000

Table 6. Test for Changes through Time, 1975-2015

	Naïve	**February, t**	**August, t**	**November, t**	**February, t+1**
Constant	13.16	22.51	20.53	16.35	4.59
p-value	0.0356	0.0000	0.0004	0.0046	0.1648
Trend	0.36	-0.58	-0.34	0.04	0.33
p-value	0.4229	0.0970	0.3842	0.9111	0.1681
ARMS	-2.97	11.35	6.35	-6.18	-7.09
p-value	0.7739	0.1590	0.4871	0.5064	0.2059

Table 7. Test for Relative Changes through Time, 1975-2015

	August, t - February, t	**November, t - February, t**	**February, t+1 - February, t**
Constant	-1.99	-6.17	-17.93
p-value	0.6169	0.2644	0.0025
Trend	0.24	0.63	0.92
p-value	0.4174	0.1260	0.0299
ARMS	-5.01	-17.53	-18.44
p-value	0.4592	0.0660	0.0569

Figure 1. U.S. Net Farm Income, 1975-2015

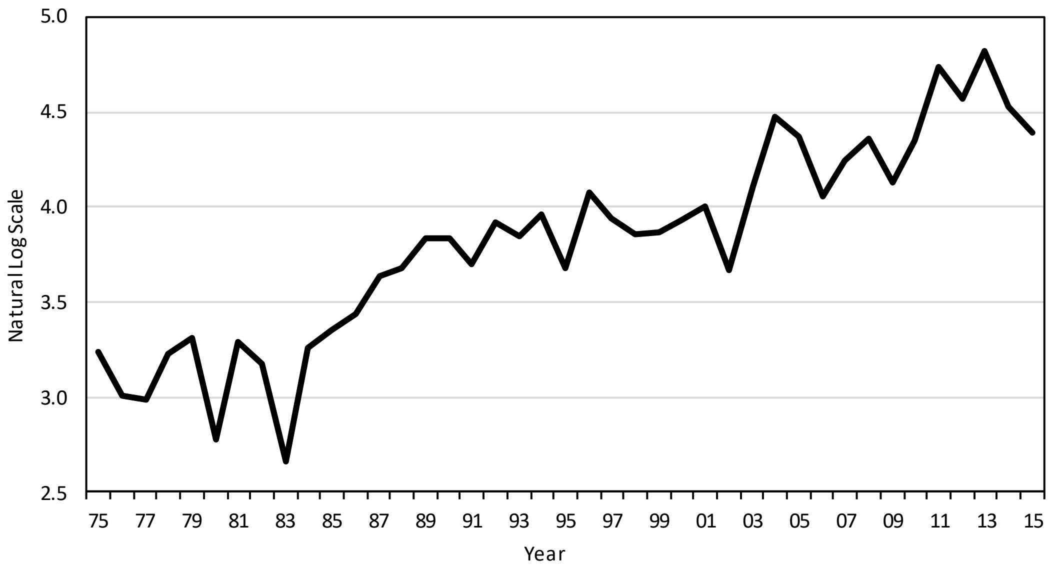

Figure 2. U.S. Net Farm Income Calculations, February 7, 2017

Cash income statement	($ billions)
a. Cash receipts	354.9
Crops 1/	186.7
Animals and products	168.2
b. Federal Government direct farm program payments 2/	12.5
c. Cash farm-related income 3/	34.4
d. Gross cash income (a+b+c)	401.8
e. Cash expenses 4/, 5/	308.3
f. Net cash income (d-e)	93.5
Farm income statement	
g. Gross cash income (a+b+c)	401.8
h. Nonmoney income 6/	19.9
i. Value of inventory adjustment	-9.3
j. Total gross income (g+h+i)	412.4
k. Total expenses	350.0
l. Net farm income (j-k)	62.3

Source: USDA, Economic Research Service, Farm Income and Wealth

1/ Includes CCC loans.

2/ Note: Government payments reflect payments made directly to all recipients in the farm sector, including landlords. The nonoperator landlords' share is offset by its inclusion in rental expenses paid to these landlords and thus is not reflected in net farm income or net cash income.

3/ Income from custom work, machine hire, recreational activities, forest product sales, and other farm sources.

4/ Excludes depreciation and perquisites to hired labor.

5/ Excludes farm household expenses.

6/ Value of home consumption of farm products plus the imputed rental value of operator and hired labor dwellings.

Figure 3. Timeline for Releasing Farm Income Data

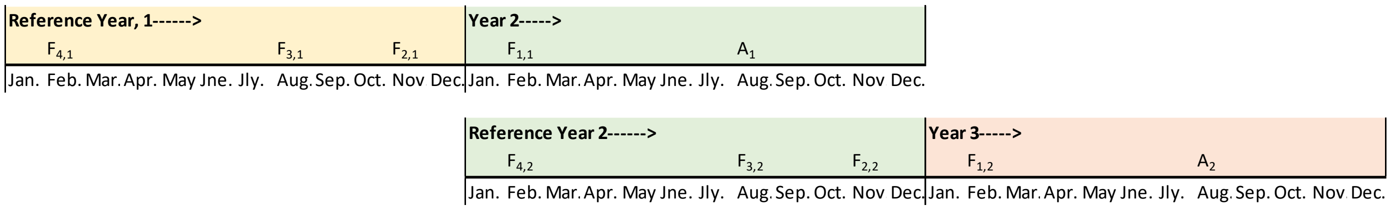

Figure 4. U.S. Net Farm Income Forecasts, February, Percent Errors, 1975-2015

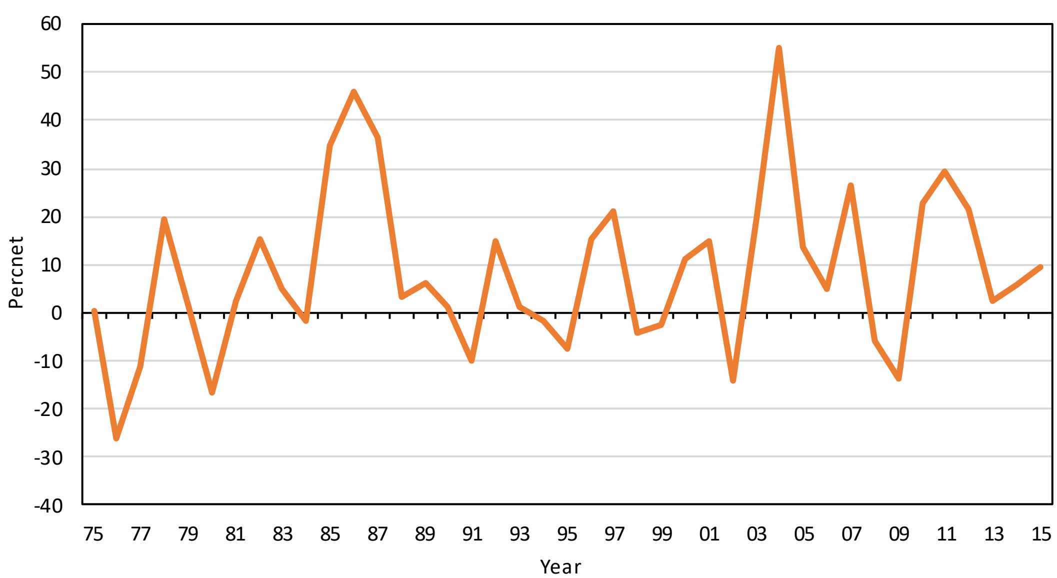

Figure 5. U.S. Net Farm Income Forecasts, February, Absolute Errors, 1975-2015

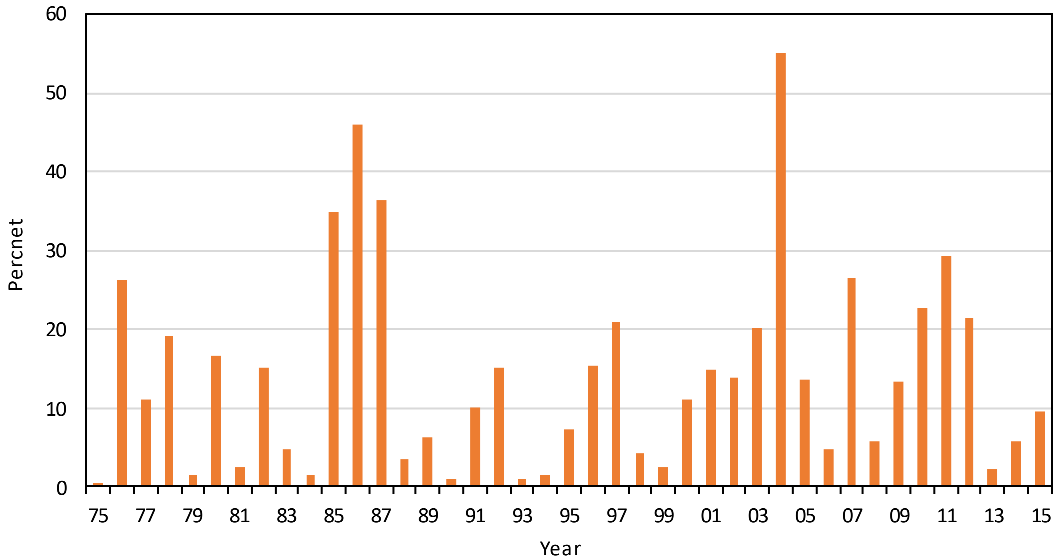

Figure 6. U.S. Net Farm Income Forecasts, August, Absolute Errors, 1975-2015

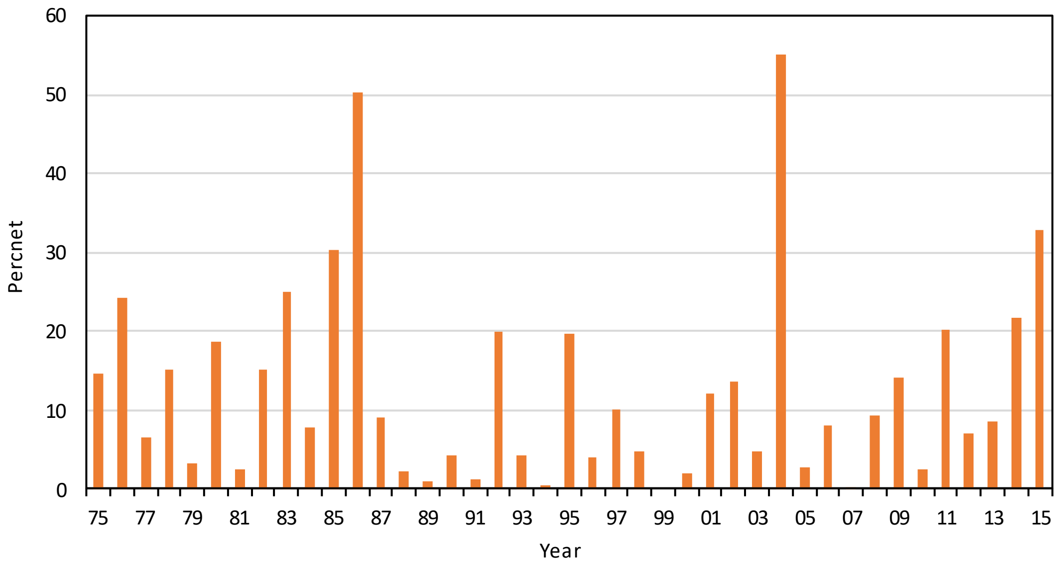

Figure 7. U.S. Net Farm Income Forecasts, November, Absolute Errors, 1975-2015