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Evaluating USDA's Baseline Projections

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Abstract

Agricultural baselines play an important role in shaping agricultural policy, yet there are few studies evaluating these projections. This study evaluates the accuracy and informativeness of two widely used baselines for the US farm sector published by the United States Department of Agriculture (USDA) and the Food and Agricultural Policy Research Institute (FAPRI). First, we examine the average percent errors of the projections and perform tests of bias. Second, we use a novel testing framework based on the encompassing principle to test the predictive content of the projections for each horizon (year), determining the longest informative projection horizon. Third, we compare the USDA and FAPRI baseline projections using a multi-horizon framework that considers all projection horizons together. We find that prediction error and bias increase with the horizon's length. The predictive content of the baselines projections for most variables diminishes after 4-5 years from the current year. The multi-horizon comparison suggests that neither the USDA nor the FAPRI projection has uniform or average superior predictive ability over the other projection. Our findings are useful for the agencies producing these baselines, and policymakers, agricultural businesses, and other stakeholders who use them.

Keywords: farm income, commodity projections, forecast evaluation, forecast encompassing, path forecasts, baseline projections, USDA, FAPRI

JEL Codes: C53, Q14

1 Introduction

The availability of long-term market information plays a vital role in many policy decisions by governments and investment decisions by business entities. The federal government's statistical agencies such as the United States Department of Agriculture's (USDA) Economic Research Service (ERS) are tasked with collecting, producing, and disseminating data that the public, businesses, and governments use to make informed decisions(Office of Management and Budget, 2020). As per this mandate, ERS leads ten statistical agencies within USDA to produce agricultural baseline projections in February each year, providing information about forces influencing agricultural markets for the next decade. The baselines facilitate comparing alternative policies by providing a conditional scenario based on specific macroeconomic, weather, policy, and trade assumptions. Another source of baseline projections is the Food and Agricultural Policy Research Institute (FAPRI), which also publishes ten-year projections of key agricultural variables every year. Over the years, the baseline projections have been used for various policy purposes, including estimating farm program costs and preparing the President's budget. Despite their growing role in shaping agricultural policy, the baselines have not been rigorously evaluated in the literature. In this study, we evaluate the accuracy and informativeness of USDA and FAPRI baselines using novel econometric techniques.

Our study focuses on two main series of projections which are released as part of USDA and FAPRI baseline reports: 1) the projections of bottom-line net cash income and its components, and 2) the projections of harvested acres, farm price, and yield of three major commodities (corn, soybeans, and wheat). We evaluate the projections in three steps. We first examine the accuracy of both USDA and FAPRI projections using standard measures of accuracy such as mean absolute percent error (MAPE) and root mean square percent error (RMSPE). We investigate whether each projection exhibits systematic bias, using a procedure developed by Holden and Peel (1990). Previous studies have identified a systematic downward bias in USDA's initial forecasts of bottom-line net cash income, crop receipts, livestock receipts, and cash expenses (Isengildina-Massa, Karali, Kuethe, & Katchova, 2020). This finding was confirmed by Bora, Katchova, and Kuethe (2021), who suggest that the bias may be attributed to an asymmetric loss of the forecasters. Since many USDA forecasts are used as an input for the beginning conditions for the USDA baseline models, baselines might also show a similar tendency to under-predict systematically many of these variables.

Second, we address the question of whether the baseline projections contain any useful information beyond a certain year into the future. Such inquiry can have important implications for how these projections are used by policymakers and market participants. In particular, the current baseline reports projections up to ten years which is of limited use for applications such as climate policy analysis. Such studies usually require projections for longer horizons. There might be a suggestion that the baseline projections may need to be stretched to facilitate such applications. However, if the projections do not stay informative beyond a certain number of years, stretching the projection horizon further will be unwarranted. We apply a recent encompassing approach to test the null hypothesis that the projections become uninformative beyond a certain forecast horizon (Breitung & Knüppel, 2021).

Finally, we compare the USDA and FAPRI models for superior predictive ability over the other model using a novel testing framework that takes into account the loss differential of the models across all projection horizons (Quaedvlieg, 2021), as opposed to the traditional single horizon tests (Diebold & Mariano, 1995; Harvey, Leybourne, & Newbold, 1997). As the full ten-year path of the baseline projections are used in policy analysis, analyzing all horizons jointly is more appropriate in this case. This approach also avoids any contradictions that may arise from testing for individual horizons, as one model might perform better than the other model at some horizons, while performing worse at the remaining horizons.

Our analysis yields a number of important findings. The accuracy measures show that, for most variables, the percent errors of the projections increase with the horizon, except for crop yields. Soybean harvested acres are consistently under-predicted while wheat harvested acres are consistently over-predicted at all horizons. Net cash income, crop receipts, livestock receipts, and cash expenses are biased downward, consistent with previously reported bias in ERS's farm income forecasts for the one year horizon, but the magnitude of bias increases with the projection horizon. Our tests of predictive content show that for most variables the projections stay informative up to 4-5 years, and start diminishing after that. Finally, our tests of multi-horizon comparison suggest that the USDA and FAPRI models do not outperform one another when the entire projection path is taken into account. The FAPRI model performs better at a shorter horizon which we believe is due to the fact that the FAPRI projections use the most recent information available to them as the FAPRI baseline report is released about a month later than the USDA's report. The findings have important implications for the models and processes used to produce the baselines by the agencies, and also for the users of these reports.

The remainder of the paper is organized as follows. The next section provides a detailed description of the agricultural baselines published by USDA and FAPRI. We present a survey of relevant literature in the third section. The fourth section summarizes our data. We then describe our empirical methods in the fifth section, followed by a discussion of the results. Finally, we present our concluding remarks.

2 Agricultural Baseline Projections

A baseline provides projections of key economic variables in the medium and long term (also called horizons), subject to specific assumptions. Various government agencies, international organizations, and private organizations produce such projections to help formulate policy and long-term planning. The agricultural baselines published by the USDA and FAPRI are the primary sources of long-run agricultural baseline projections for the US. Produced annually by the two agencies, the baselines describe several aspects of agricultural markets: commodity prices and production, global agricultural trade, and farm income. It is worth noting that the Organisation for Economic Co-operation and Development (OECD) also releases a ten-year global baseline agricultural outlook report in collaboration with the Food and Agricultural Organization (FAO). This report also contains some US agricultural indicators such as market conditions and consumption projections for key commodities as part of its regional brief on North America (OECD & Food and Agriculture Organization of the United Nations, 2020). In addition, the Congressional Budget Office (CBO) also produces baseline projections for several federal mandatory farm programs such as price loss coverage (PLC), agricultural risk coverage (ARC), crop insurance, disaster assistance, and conservation programs. Some agricultural indicators on prices, acreages, and yields of key commodities are available as part of these projections. However, in our study, we focus on USDA and FAPRI baselines as they offer the most comprehensive coverage of US agricultural indicators for the next ten years.

Baseline projections are produced by the USDA Interagency Agricultural Projections Committee, comprising experts from 10 USDA agencies and offices [1].The USDA releases its baseline in February each year. The USDA stresses that the baseline projections are "not intended to be a forecast of what the future will be" (USDA Office of the Chief Economist, 2020, pp. 1). Instead, the USDA baseline offers a "conditional, long-run scenario about what would be expected to happen under a continuation of current farm legislation and other specific assumptions" (USDA Office of the Chief Economist, 2020, pp. iii). The specific assumptions include normal weather and no domestic or external shocks that would affect global agricultural supply and demand, as well as defined macroeconomic conditions, trade policies, and productivity growth rates. [2] USDA's baseline projections reflect a composite of model results and judgment-based analysis.[3]. The projections are designed to provide "a neutral reference scenario that can serve as a point of departure for a discussion of alternative farm sector outcomes that could result under different domestic or international conditions" (USDA Office of the Chief Economist, 2020, pp. 1). The Baseline projection process begins the preceding August and September when domestic and international macroeconomic assumptions are developed. In October, the committee prepares detailed commodity projections for foreign countries. In November, the committee prepares core domestic analysis for program commodities. In December, projections for livestock and other non-program commodities are finalized. In January, ERS economists prepare the sector-wide projections for farm income and agricultural trade before publication in February. Hjort, Boussios, Seeley, and Hansen (2018) provides a detailed description of the USDA baseline model and various processes followed during the preparation of the baseline report.

FAPRI was established in July 1984 as a joint institute between the Center for National Food and Agricultural Policy (CNFAP), Department of Agricultural Economics at the University of Missouri, and the Centre for Trade and Agricultural Policy (CTAP), Department of Economics at Iowa State University with funding approved by the US Congress. FAPRI has been producing 10-year baselines for the US agricultural sector every year. Over the years, the FAPRI baseline procedures have evolved to include five main steps, as outlined in Meyers, Westhoff, Fabiosa, and Hayes (2010). The first step involves updating models, data, and assumptions to include November World Agricultural Supply and Demand Estimates (WASDE) and the latest macro-economic projections. The next step involves one week of deliberation among analysts in late November to produce a preliminary baseline. A peer review takes place involving analysts from government and international agencies, agribusinesses, and other universities in the third step. Then, in mid-January, FAPRI analysts revise the preliminary baseline based on comments received during the peer review and update the WASDE and macroeconomic projections. Finally, after the baseline is completed and US Congress briefing, the FAPRI baseline is released to the public. Overall, "the FAPRI approach" of producing the baseline focuses on developing good models while underlining their use by skilled analysts (Meyers & Westhoff, 2010).

3 Literature review

3.1 Literature on agricultural baselines

Despite their importance in shaping agricultural policy, US agricultural baseline projections have not been rigorously evaluated in the literature. Irwin and Good (2015) examine USDA baseline projections of corn, soybeans, and wheat prices and show that the baseline tends to project a steady-state and leads to high projection errors making them unsuitable for Farm Bill program choice decisions. In a recent paper, Kuethe, Bora, and Katchova (2021) show that the short-term, one year projections of net cash income and its components released as part of the USDA baseline report in February help improve ERS's farm income forecasts released in the same month. Especially, baseline projections of government payments and farm-related income can add extra information to USDA forecasts. While this study underlines the potential of baselines as another source of information, it does not examine the complete baseline projections for all horizons (ten years). Boussios, Skorbiansky, and MacLachlan (2021) examines the baseline projections for harvested areas of corn, soybeans, and wheat and find that the baseline consistently under-estimate corn harvested area and over-estimate wheat harvested area.

One application of the USDA baseline to evaluate a policy question is the feasibility study conducted for the Upper-Mississipi River-Illinois Waterway by the US Army Corps of Engineers (Transportation Research Board and National Research Council, 2001). One study used USDA baseline projections of production and use for corn and soybeans to project traffic flows from the Midwest to the port of New Orleans for export. Since the baseline only provides ten years of projections, the study extrapolates the baselines further to 50 years to assess the long-term feasibility of the project. The use of the baselines for this purpose, and particularly the long-term extrapolation, has drawn criticisms that pointed out limitations of baseline projections for use as forecasts. Nevertheless, this example shows the importance of long-run projections of agricultural commodities. It also shows that some applications may need to extend the projection horizon of the baseline beyond the existing ten years.

3.2 Literature on forecast informativeness

One of the early measures of predictive content of a forecast is the Theil's inequality coefficient (Theil's U statistic), showing whether the forecast is more informative than a naive benchmark (Theil, 1958). Building on this idea, Mincer and Zarnowitz (1969) showed that regression of actual values on their forecasts can be used to test for informativeness. Theil's U is related to the R^2 of a Mincer-Zarnowitz regression where the unconditional mean is the naive benchmark. Nelson (1976) interpreted the R^2 of the autoregressive moving average (ARMA) time series model as a measure of the relative predictability of a time series given its past history. Granger and Newbold (1986) proposed a similar measure of the forecastability of a covariance stationary series under squared-error loss based on the regression R^2. Diebold and Kilian (2001) proposed a generalized measure of predictability based on the ratio of the expected loss of a short-run forecast to the expected loss of a long-run forecast, which allows for general loss functions, univariate or multivariate information sets, and covariance stationary or difference stationary processes.

For multi-horizon forecasts or projections such as GDP growth or agricultural baselines, the horizon up to which they stay informative is a critical question. Galbraith (2003) terms the maximum informative forecast horizon as the *content horizon* of the forecasts. They define a forecast content function for each horizon and apply it to forecasts of GDP growth and inflation for the US and Canada. Galbraith and Tkacz (2007) apply the same concept to a series of macroeconomic variables and report a wide range of content horizons between a couple of months and several years, partly due to different data transformations. Isiklar and Lahiri (2007) use both Theil's U statistic and Diebold and Kilian (2001) measure to examine monthly GDP forecasts from Consensus Economics for 18 developed countries and find that the forecasts start becoming informative at a 14-month horizon. However, most of these approaches rely on choosing an uninformative framework against which to compare the forecasts. We use an alternative method proposed recently by Breitung and Knüppel (2021) that directly compares the mean-squared forecast error to the unconditional variance of the forecasted variable.

3.3 Literature on multi-horizon comparison of models

When comparing two competing projections for their relative accuracy, the commonly used tests are the Diebold-Mariano (DM) tests (Diebold & Mariano, 1995). The DM tests examine the expected loss differential between two projection series according to a loss function. The test is based on the sample mean of the loss differential which follows a normal distribution. Harvey et al. (1997) improve the small sample properties of the DM test statistic by introducing a bias correction and testing with a modified student t, rather than standard normal, distribution. However, the DM tests can compare one series at a time. For multi-horizon projections such as the baseline, this might give rise to contradictory results, as we might find USDA is better at predicting at some horizons while FAPRI is better at predicting at other horizons. Moreover, the policymaker may be interested in the path followed by the farm sector along the projection horizons, rather than an individual horizon. Therefore, it may be argued that testing for accuracy should be carried out along the entire projection path, rather than at a single horizon.

While comparing multi-horizon forecasts, Capistrán (2006) shows that a DM test using a multivariate loss function performs better than the simple method of using an average of the square of the forecast errors over the horizons. Patton and Timmermann (2012) propose an optimality test based on a regression of the actual values of the forecasted variable on its long-horizon forecasts and subsequent revisions. Jordà and Marcellino (2010) terms multi-step forecasts as *path forecasts*, and show how to construct simultaneous confidence regions for the forecast path. Òscar Jordà, Knüppel, and Marcellino (2013) discuss how to construct confidence regions of path forecasts when the model generating the forecasts in unavailable or unknown. Another recent work by Martinez (2020) develops a joint test of equal path forecast accuracy using the GFSEM concept of Clements and Hendry (1998).

We use the tests of multi-horizon superior predictive ability proposed by Quaedvlieg (2021) which jointly consider all horizons of the entire projection path. Similar to the framework in Giacomini and White (2006), they test for finite-sample multi-horizon predictive ability using estimated values of parameters. They introduce the concept of superior predictive ability (SPA) which can be used for pairwise comparison of multi-horizon forecasts, and also allows for multi-horizon comparison of more than two models. Quaedvlieg (2021) provides two alternative definitions of multi-horizon predictive ability. Uniform multi-horizon superior predictive ability (uSPA) is defined as the case where a model has lower loss at each horizon compared to the other model. A relaxed version of the concept is the average multi-horizon superior predictive ability (aSPA), which allows poor performance at some horizons to be compensated by superior performance at other horizons in terms of loss functions. They construct test statistic for both uSPA and aSPA using bootstrap techniques. When considered for a single horizon, both of these tests reduce to the standard DM test. We apply both multi-horizon forecast comparison tests to compare the USDA and FAPRI agricultural baseline models. Our results suggest that neither possesses superior predictive ability over the other model.

4 Data

Our dataset consists of USDA and FAPRI agricultural baseline projections from 1997 to 2020. The FAPRI baseline reports are available for a few additional years before 1997, but for comparison with USDA, we limit our period to 1997-2020. Both agencies release their baseline reports at the beginning of the year. The baseline reports typically include estimates of the previous year(s) and projections for the next ten years. For example, the February 2020 USDA report contains realized estimates for the year 2018, provisional estimates for the year 2019, and projections for 2020-2029. For some aggregate indicators such as farm income, the baselines report calendar year values, while for commodities, they report marketing year values.

In this study, we examine two main series of projections in the baseline reports. First, we examine the projections of bottom-line net cash income and its components: crop receipts, livestock receipts, direct government payments, farm-related cash income, and cash expenses. Net cash income is a sector-wide measure of the amount of cash earnings generated by farm businesses available to meet a variety of obligations, such as debt payments (McGath et al., 2009). It is defined as gross cash income less cash expenses. Gross cash income includes both crop and livestock cash receipts, direct government payments, and farm-related income. Direct government payments are limited to funds paid directly to farmers and ranchers by the Federal Government to support farm incomes, conserve resources, or compensate for natural disasters (McGath et al., 2009). Farm-related income includes machine hire and custom work, forest products, and other income from farm output and sales. Net cash income is calculated from its components using a bottom-up approach as per the accounting equation:

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

Second, we analyze the projections of harvested acres, farm price, and yield for three commodities: corn, soybeans, and wheat. Together, these field crops constitute a significant share of the area under cultivation in the US. The projections are averages for the marketing years, which differ by crop. The marketing year for corn begins on September 1 and comprises four quarters. For example, the marketing year 2020/21 for corn and soybeans starts on September 1, 2020, and ends on August 31, 2021. The 2020/21 marketing year for wheat begins on June 1, 2020 and ends on May 31, 2021. It is important to note that the estimates for 2020 are still provisional as the marketing years for various crops are yet to conclude and the farm income estimate for 2020 will be finalized in August 2021.

We compile our dataset from multiple online sources. The Albert R. Mann Library at Cornell University maintains an electronic record of archived USDA baseline projections since 1997 [4]. The majority of FAPRI baseline reports were taken from the FAPRI website[5]. For some early years, the baseline reports are available at Iowa State University Digital Repository [6]. The realized estimates for farm income indicators are taken from ERS's website [7]. As mentioned in the previous discussion, the baseline reports also publish the realized values for two years before the release year. However, the realized estimates published in the baseline report are subject to periodic revisions, as new information is released by various USDA agencies, such as the quinquennial Census of Agriculture. Moreover, since both USDA and FAPRI baseline reports release the realized estimates, we choose neither of the realized estimates from these reports, and instead use the most up-to-date information available at the ERS's website. Similarly, realized values for harvested acres, farm price, and yield of corn, soybeans, and wheat are obtained from the NASS Quickstats API (USDA National Agricultural Statistics Service, 2021).

For each reference year (calendar or marketing year), we define Y_t as the realized value for year t for farm income and harvested acres, farm price, and yield for corn, soybeans, and wheat. We use the log transformations of the realized values: $y_t = \ln(Y_t)$ to eliminate the impact of changing forecast levels, following Isengildina-Massa et al. (2020). We define $\hat{Y}^i_{t+h|t}$ to be the projection made in year t for the year $t+h$ by the agencies $i = \{USDA, FAPRI\}$, and again we use natural logarithms of the variables for our analysis: $\hat{y}^i_{t+h|t} = \ln(\hat{Y}^i_{t+h|t})$. The projection horizon h can take values between $h = 0$ for the projection made for the same reference year t and $h = 9$ for projections made for year $t + 9$. The projections made for the report year has $h = 0$, and can be termed as a *nowcast*. We will use boldface when representing a vector of projections where applicable. In Figure 1, we plot the baseline projections of net cash income and average farm prices of corn for the USDA and FAPRI reports between 1997 and 2021. As can be seen in the figure, the baseline projections are usually smoothed, particularly over longer horizons, and often miss the mark in presence of shocks to the market.

[FIGURE 1 ABOUT HERE]

While our dataset spans the baseline projections between 1997 and 2020, the evaluation period T differs for each projection horizon. The evaluation period for 0 years ahead horizon projections ($h = 0$) starts in 1997, and runs through 2020, resulting in a sample size of $T = 24$ observations. We lose one year from our sample for each year increase in the projection horizon as. For example, for $h = 1$, the evaluation period is $t \in \{1998, 1999, \ldots, 2020\}$ and $T = 23$, as 1 year ahead projections are not available for $t = 1997$. Similarly, the sample size reduces to $T = 15$ observations for 9 years ahead projections ($h = 9$), the sample period for which runs from 2006 to 2020.

5 Methods

We evaluate the USDA and FAPRI agricultural baseline projections in three steps. First, we analyze the accuracy and bias of each of the projections. Second, we conduct tests for the predictive accuracy of the projections at different horizons and determine the maximum informative projection horizon for each variable (Breitung & Knüppel, 2021). Finally, we compare the USDA and FAPRI baseline models using multi-horizon tests developed by (Quaedvlieg, 2021).

5.1 Accuracy and Bias

We begin our investigation by examining the accuracy of the baseline projections. Accuracy is defined as the difference between realized and predicted values. For each variable, the percent prediction error at horizon h is defined as: $e^i_{t+h|t} = 100 \times (Y_{t+h} - \hat{Y}^i_{t+h|t})/Y_{t+h}$, where t is the reference year and $i = \{USDA, FAPRI\}$. We measure the relative accuracy of USDA and FAPRI projections of net cash income and its components using two common measures: mean absolute percent error (MAPE) and root mean squared percent error (RMSPE), which are defined as,

$$\text{MAPE}^i_h = \frac{1}{T}\sum_t |e^i_{t+h|t}| \tag{2}$$

$$\text{RMSPE}^i_h = \sqrt{\frac{1}{T}\sum_t (e^i_{t+h|t})^2} \tag{3}$$

MAPE is less sensitive to outliers, and therefore, is not affected by the occasional large prediction error. On the other hand, RMSPE measures the square root average of squared errors and places a larger weight on large prediction errors. Smaller MAPE or RMSPE values suggest more accurate projections.

The USDA or FAPRI projection would be unbiased if it does not consistently differ from its realized values. Following Isengildina-Massa et al. (2020), we test for bias in the USDA and FAPRI projections using the regression-based test of Holden and Peel (1990). For each series of projections from both agencies ($i = USDA, FAPRI$), we run the following regression for each $h = \{0, 1, \ldots 9\}$:

$$y_{t+h} - \hat{y}^i_{t+h|t} = \alpha^i_h + \varepsilon^i_{t+h}. \tag{4}$$

where α^i_h is an unknown constant to be estimated and ε^i_{t+h} is white noise. We test whether the baseline projection $i = USDA, FAPRI$ is unbiased at horizon h using the hypothesis $H_0 : \alpha^i_h = 0$. A positive and significant coefficient $\hat{\alpha}^i_h$ would suggest that the USDA or FAPRI projections systematically under-predict realized values, and a negative and significant coefficient $\hat{\alpha}^i_h$ would suggest that the projections systematically over-predict realized values. Equation (4) is estimated on a series-by-series basis for both USDA and FAPRI projections using ordinary least squares (OLS) with a HAC standard error (Newey & West, 1987).

5.2 Tests for Predictive Content

Our tests for predictive content of the USDA and FAPRI baseline projections are derived from Breitung and Knüppel (2021). The testing framework assumes that the realized values y_t are generated by a stationary and ergodic stochastic process. We further assume that the realized values y_t are generated by a linear process with constant variance, although this assumption may be relaxed in some conditions. The h-horizon projection based on information up to year t for projections $\{i = USDA, FAPRI\}$ is denoted by $\hat{y}^i_{t+h|t}$, where the forecast horizon $h \in \{0, 1, 2, \ldots 9\}$. Under quadratic loss, the optimal projection equals the conditional mean of the projection $\mu^i_{h,t} = E(\hat{y}^i_{t+h}|I_t)$, given the information set I_t available at reference year t.

The tests for the maximum informative prediction horizon compare the mean-squared prediction error of the projections to the variance of the realized values over the evaluation sample. In particular, we test the following hypothesis,

$$H_0 : E(y_{t+h} - \hat{y}_{t+h|t})^2 \geq E(y_{t+h} - \mu)^2, \text{ for } h > h^* \tag{5}$$

$$H_1 : E(y_{t+h} - \hat{y}_{t+h|t})^2 < E(y_{t+h} - \mu)^2 \tag{6}$$

where, $\mu = E(y_t)$ is the unconditional mean of the realized values. The null hypothesis states that there exists a maximum projection horizon h^* beyond which the realized values y_t would be unpredictable with respect to the information set I_t. We term the null hypothesis as *no information* hypothesis, against the alternative hypothesis which states that the projection remains informative as the mean-squared prediction error is lower than the variance of the realized values around their unconditional mean.

Another test of predictive content can be formulated based on the conditional mean of the projection being constant within the evaluation sample, or the *constant mean* hypothesis.

$$H_0 : E(\hat{y}^i_{t+h}|I_t) = \mu_{h,t} = \mu, \text{ for } h > h^* \tag{7}$$

This is a relaxed criteria than the *no infromation* hypothesis as it requires the projection to be uncorrelated with the realized value for it to be uninformative. If the projection $\hat{y}^i_{t+h}$ is identical to the conditional mean $\mu_{h,t}$ of the target variable, then the *no information* hypothesis is equivalent to the *constant mean* hypothesis (Breitung & Knüppel, 2021).

Breitung and Knüppel (2021) suggest considering three situations based on how the projections are generated. The first scenario refers to projections generated from the expectations of individuals, and the expectation is identical to some conditional mean. The second scenario involves projections generated from survey expectations which are also contaminated by noise (e.g. macro-economic forecasts of Consensus Economics). The third scenario refers to projections generated from models. The baseline projections are unique in the sense that they are generated based on models as well as expert opinions or expectations of individuals. Therefore, we consider the second and third scenarios. In both scenarios, the *no information* hypothesis and the *constant mean* hypothesis can be formulated in terms of testing coefficients in a Mincer-Zarnowitz regression.

Breitung and Knüppel (2021) show that if the baseline projection is generated by a conditional mean of the projection and noise (η_t), $\hat{y}^i_{t+h|t} = \mu_{h,t} + \eta^i_t$, the *no information* hypothesis is equivalent to testing the null hypothesis $\beta^i_h \leq 0.5$ in the regression,

$$y^i_{t+h} = \beta^i_{0,h} + \beta^i_h \hat{y}^i_{t+h|t} + \nu^i_{t+h} \tag{8}$$

Breitung and Knüppel (2021) further show that the *constant mean* hypothesis is equivalent to testing $\beta^i_h <= 0$ in the same regression, implying that the baseline projection is uncorrelated to the realized values. The tests of the parameters β^i_h can be performed using a heteroscedasticity and autocorrelation consistent (HAC) t-statistic constructed as,

$$\tau_a = \frac{1}{\hat{\omega}_a \sqrt{T}} \sum_t a_t \tag{9}$$

$$a_t = \left[y_{t+h} - \overline{y}^h - 0.5(\hat{y}_{t+h|t} - \overline{\hat{y}_h}) \right] (\hat{y}_{t+h|t} - \overline{\hat{y}_h}) \text{ for } H_0 : \beta_h = 0.5 \tag{10}$$

$$a_t = (y_{t+h} - \overline{y}^h)(\hat{y}_{t+h|t} - \overline{\hat{y}_h}) \text{ for } H_0 : \beta_h = 0 \tag{11}$$

where, $\hat{\omega}^2$ is a consistent estimator of the long-run variance of a_t. The LM-statistic has an asymptotic standard normal distribution.

While constructing the HAC t-statistic, we use the in-sample mean of the baseline projections. While alternative versions of the test use a recursive mean in place of the in-sample mean, they require more information prior to the evaluation period, which is not available in our case. To determine the maximum informative projection horizon h^*, we begin by testing the null hypothesis for the $h = 0$ horizon projection. If the null hypothesis is rejected, we test the $h = 1$ horizon projection, and so on. We stop when the null hypothesis is no longer rejected. The maximum informative projection horizon h^* is the penultimate horizon before the horizon for which null hypothesis is not rejected for the first time.

An advantage of the tests proposed by Breitung and Knüppel (2021) is that they do not require a naive benchmark, as they directly compare the mean-squared prediction error to the unconditional variance of the realized values. Another advantage is that when we apply the tests with in-sample mean, additional information prior to the evaluation period is not required, therefore these tests are suitable for our small sample size. The baseline projections share properties of both survey forecasts and model-based forecasts as they are a combination of model prediction and expert opinions. On the other hand, a limitation of these tests is that they can be sensitive to the transformations of the variables. In addition, the maximum information projection horizon is a conservative estimate and is subject to the process used to produce the projections. The maximum informative projection horizon could be longer if the projection process did not fully incorporate available information. Another limitation is that the tests at longer projection horizons may have less power due to smaller sample size.

5.3 Multi-horizon Comparison Tests

When comparing two competing projections for their relative accuracy, the commonly used tests are Diebold-Mariano type of tests (Diebold & Mariano, 1995). We use the Diebold-Mariano test to examine the expected loss differential between the USDA and FAPRI projections according to a loss function. The test is based on the sample mean of the loss differential which follow a normal distribution. Harvey et al. (1997) improves the small sample properties of the Diebold-Mariano test statistic by introducing a bias correction and testing with a modified student t, rather than standard normal, distribution. However, the Diebold-Mariano tests can compare the USDA and FAPRI projections at each horizon. For multi-horizon projections such as the baseline, this might give rise to contradictory results, as we might find the USDA projection is better at some horizons while the FAPRI projection is better at other horizons. Moreover, entire projection path from horizons 0 through 9 might be of interest to policymakers. Therefore, testing for accuracy should be carried out along the entire projection path, rather than at a single horizon. We use the tests of multi-horizon superior predictive ability proposed by Quaedvlieg (2021) which jointly consider all horizons along the entire projection path.

To conduct multi-horizon comparison tests, we start by using a vectorized version of the previous notations, denoting the USDA and FAPRI projections $i \in \{USDA, FAPRI\}$ as, $\hat{\boldsymbol{y}}_t^i = [\hat{y}^i_{t|t-0}, \hat{y}^i_{t|t-1}, \ldots, \hat{y}^i_{t|t-9}]$, where $\hat{y}^i_{t|t-h}$ is $\{i = USDA, FAPRI\}$s projection of y_t based on the information set at time $t-h$. We are interested in comparing the USDA and FAPRI projections in terms of their loss differentials, following the approach in Diebold and Mariano (1995). We assume a general loss function $\boldsymbol{L}_t^i = L(\boldsymbol{y_t}, \hat{\boldsymbol{y}}_t^i)$ which maps the prediction errors into an 10-dimensional vector. For our analysis, we use mean squared error (MSE) and mean absolute error (MAE) loss function, however, these can be generalized to allow multivariate loss function. We calculate the loss differential for year t between the USDA and FAPRI projections as a 10-dimensional vector,

$$\boldsymbol{d}_t = \boldsymbol{L}_t^{USDA} - \boldsymbol{L}_t^{FAPRI} \tag{12}$$

The comparison of the USDA and FAPRI projections is based on the mean loss differential between them, $\boldsymbol{\mu} = \lim_{T\to\infty} \frac{1}{T}\sum_t E(\boldsymbol{d}_t)$. Traditional Diebold-Mariano tests for single horizons would compare the USDA and FAPRI projections by testing the null hypothesis that the mean loss differential at horizon h is zero ($H_{0,DM} : \mu_h = 0$) using a standard t-test:

$$t^h_{DM} = \frac{\sqrt{T}\bar{d}_h}{\hat{\omega_h}} \tag{13}$$

where, $\bar{d}_h = \frac{1}{T}\sum d^h_t$, and $\hat{\omega^2_h}$ is a HAC estimate of variance of d^h_t. However, this approach would require comparing the mean loss differential at each horizon separately, which often leads to contradictory results about which projection is superior to the other. Therefore, we use the concepts of uniform superior predictive ability (uSPA) and average superior predictive ability (aSPA) which combine loss differentials at different horizons, an approach proposed by Quaedvlieg (2021). The uSPA test would require the FAPRI projection to be uniformly superior than the USDA projection at every horizon.

$$\mu^{uSPA} = \min_h \mu_h \tag{14}$$

The uniform SPA test is given by the null hypothesis $H_{0,uSPA} : \mu^{uSPA} <= 0$, if the USDA projection has uniform superior predictive ability over the FAPRI projection against the alternative hypothesis $H_{a,uSPA} : \mu^{uSPA} > 0$, if the FAPRI projection has uSPA. In other words, the minimum loss differential between the USDA and FAPRI projections at each horizon h should be less than zero if the FAPRI projection is to be uniformly superior to the USDA projection. However, the uniform SPA is very strict criterion and therefore is not very realistic in practice. A relaxed version of the test is average SPA which is based on an weighted average of losses of all horizons, in other words, testing whether the FAPRI projection is on average superior to the USDA projection across all horizons. In mathematical terms,

$$\mu^{aSPA} = \boldsymbol{w}'\boldsymbol{\mu} = \sum_h w_h \mu_h \tag{15}$$

The aSPA allows losses at different horizons compensate for each other. For example, the FAPRI projection may perform worse at some horizons, but on average it may still be superior compared to the USDA projection. We test the null hypothesis $H_{0,aSPA} : \mu^{aSPA} <= 0$ (USDA projection has aSPA) against the alternative $H_{a,aSPA} : \mu^{aSPA} > 0$ (FAPRI projection has aSPA).

The choice of weights (w_h) is flexible. When performing the multi-horizon comparison tests, we use equal weights for each horizon h. We also conduct a second version of the aSPA test by weighing the loss differentials by the variance of the loss differential at the horizon that is being compared divided by the sum of variances across all horizons. The test statistic for the multi-horizon comparison tests are given by,

$$t_{uSPA} = \min_h \frac{\sqrt{T}\bar{d}_h}{\hat{\omega}_h} \tag{16}$$

$$t_{aSPA} = \frac{\sqrt{T}\bar{d}_h}{\hat{\zeta}_h} \tag{17}$$

We obtain estimates of variances $\hat{\omega}_h^2$ from the diagonal elements of covariance matrix of loss differential $\boldsymbol{d}$ calculated using an HAC-type estimator (Newey & West, 1987). Similarly, we get the estimates of variance $\hat{\zeta}_h^2$ for aSPA as the diagnonal elements of weighted covariance matrix of $\boldsymbol{d}$. The test-statistic for the uniform SPA is the minimum of Diebold-Mariano test statistic for all horizons. The average SPA test is simply an DM-test on average loss differential (Quaedvlieg, 2021). The critical values and p-values for the uSPA and aSPA tests are obtained using a moving block bootstrap (MBB) technique. By computing either of the test statistics on many MBB re-samples, we approximate the distribution of the original statistics under the null hypothesis. The critical values at α significance level are obtained by calculating the α percentile of the bootstrap distribution.

6 Results

6.1 Accuracy and Bias

[FIGURE 2 ABOUT HERE]

[FIGURE 3 ABOUT HERE]

In figure 2, we plot the MAPE and RMSPE of harvested acres, farm price, and yield of the three commodities for both FAPRI and USDA projections between 1997-2020 against the projection horizon h. For harvested acres and farm price of corn, soybeans, and wheat, both MAPE and RMSPE increase with the projection horizon for both the USDA and FAPRI projections. Crop yields, however, show an unusual pattern of projection errors as both MAPE and RMSPE are smaller, and they do not increase with the horizon h, and in the case of wheat yield, the errors decrease with h. This may be due to the fact that crop yield is expected to have an upward trend with only small deviations around this long-term trend, so projections errors remain low for all horizons. Figure 3 shows the projection errors for net cash income components. Both MAPE and RMSPE are increasing with the horizon

h for net cash income and its components. Interestingly, projection errors for net cash income, crop receipts, and livestock receipts are lower for the FAPRI baseline at shorter horizons, while USDA baseline projection errors are lower at longer horizons. For farm-related income, the FAPRI projection has lower errors for all horizons.

[TABLE 1 ABOUT HERE]

[TABLE 2 ABOUT HERE]

The tests of bias for both commodity and net cash income projections show a similar pattern as reported in previous studies of USDA forecasts. In tables 1 and 2, we report the estimates of bias $\hat{\alpha}_h^i$ for projections $i = USDA, FAPRI$ at horizon h from equation (4) along with HAC standard errors. As reported in Boussios et al. (2021), the USDA baselines consistently under-predict soybean harvested acres and over-predict wheat harvested acres. The magnitude of bias increases with the projection horizon h. Corn harvested acres do not show such bias. Farm prices of the three commodities do not show significant bias for shorter horizons, but they tend to be under-predicted for horizons larger than four years. Crop yield predictions do not show significant bias for any of the three commodities. Both FAPRI and USDA projections of net cash income, crop receipts, livestock receipts, and cash expenses are biased downward at a 5% significance level, and the magnitude of bias increases with the horizon. This finding is consistent with previous findings of downward bias in USDA net cash income forecasts which can be compared with projections at horizons $h = 0, 1$ (Isengildina-Massa et al., 2020; Kuethe et al., 2021). As the short-term, one year USDA forecasts are an input for short-term baseline projections, it is not surprising that baselines are also biased downward, and that the bias carries forward to longer horizons. USDA projections of government payments show downward bias at longer horizons, while FAPRI projections of government payments do not show bias. Farm-related income projections are biased at longer horizons for both FAPRI and USDA projections.

6.2 Tests of Predictive Content

[TABLE 3 ABOUT HERE]

[TABLE 4 ABOUT HERE]

[FIGURE 4 ABOUT HERE]

[FIGURE 5 ABOUT HERE]

In tables 3 and 4, we present estimates of $\hat{\beta}_h^i$ for the projections $i = USDA, FAPRI$ at horizon h from the Mincer-Zarnowitz regression shown in equation (8) along with the significance of the *no information* and *constant mean* tests. In traditional Mincer-Zarnowitz tests, the optimality condition is that the regression of the realized values on the projection values should have an intercept of zero and a coefficient on the projection values of 1. However, for our tests for predictive content, we test the null hypotheses $H_0 : \hat{\beta}_h^i <= 0.5$ for *no information* and $H_0 : \hat{\beta}_h^i <= 0$ for *constant mean*. As observed from tables 3 and 4, the estimates of $\hat{\beta}_h^i$ are closer to unity for shorter horizons, but decrease for longer horizons. For example, for the USDA projections of corn harvested acres the estimates of $\hat{\beta}_h^{USDA}$ decrease from 0.98 for the next year projection (horizon $h = 1$) to 0.07 for the ten years ahead projection ($h = 9$), showing a reduction in the predictive content of the USDA projections at longer horizons (table 3). Similarly, for the FAPRI projections of corn harvested acres the estimates of $\hat{\beta}_h^{FAPRI}$ decrease from 0.996 for horizon $h = 1$ to -0.044 for $h = 9$. (table 4). We further plot the p-values for the *no information* and *constant mean* tests for predictive content against the projection horizon h for the commodities and net cash income components in figures 4 and 5. The horizontal dashed line stands for significance at a 5% level. These figures miror and confirm the results in tables 3 and 4.

Finally, we calculate the maximum informative projection horizons h^* for both tests at a 5% significance level in table 5. The maximum informative projection horizon is calculated as the penultimate horizon after which the null hypothesis is not rejected for the first time. For example, using the *no information* hypothesis test, $h^* = 5$ for corn harvested acres projections by both USDA and FAPRI as *no information* test is significant at 5% level until $h = 5$. Similarly, using the *constant mean* hypothesis test, $h^* = 7$ for corn harvested acres projections by both USDA and FAPRI as no information test is significant at 5% level until $h = 7$. Because $\hat{\beta}_h^i$ are generally decreasing with the horizon h, and because the *no information* hypothesis tests for this parameter to be less than 0.5 versus the *constant mean* hypothesis tests for this parameter to be less than 0, this implyes that the *no information* hypothesis is not rejected at shorter horizons than the *constant mean* hypothesis. In other words, projections for the shortest horizons are both informative and do not have constant mean, then for the medium horizons they become uninformative, and for the longest horizons they also become constant mean.

For most variables, the informative content of the projections starts diminishing after 4-5 years from the current year, using the more conservative no information test results. The findings, however, do not suggest that the projections cannot be improved beyond the reported maximum horizon, as our test results are subject to the projection process. Our resuts only suggest that using improved models the projections may stay informative for a longer period.

6.3 Multi-horizon Comparison Tests

[FIGURE 6 ABOUT HERE]

[FIGURE 7 ABOUT HERE]

We first compare the FAPRI and USDA baselines using the modified Diebold-Mariano (MDM) test of Harvey et al. (1997) using a root mean square error in table 6. For this modified DM test, we perform a comparison between the USDA and FAPRI projections at each horizon separately. We then perform multi-horizon uniform SPA test to test whether the FAPRI model perform better than USDA in table 7. Then, we conduct two versions of the average SPA test. The first average SPA test assigns equal weights to each horizon while calculating loss differentials, and its results are presented in table 8. Table 9 presents results of average SPA test using weights based on variances of loss differentials of the horizons. The multi-horizon tests of uniform SPA and average SPA are performed for all horizons up to h. Thus, at the last horizon $h = 9$, we run the full version of the multi-horizon comparison test by including all horizons. We show the p-values of all the multi-horizon comparison tests and the MDM test in figures 6 and 7.

The multi-horizon comparison test results suggest that FAPRI model tend to do well in shorter horizons for net cash income and crop receipts, while it consistently does better than USDA in predicting farm related income at almost all horizons. For net cash income and crop receipts, the FAPRI model performs better at shorter horizons at $h <= 4$, while for farm-related income FAPRI model performs better for $h <= 9$. The p-values of all the four comparison tests for the commodities projections in figure 6 suggest that the FAPRI model doesn't outperform the USDA model for other variables, as we cannot reject the null hypothesis. One possible reason why the FAPRI model performs better at shorter horizons is that the FAPRI model uses the most recent forecasts available in November as inputs to their models, while the USDA uses forecasts available in October. Also, USDA releases their projections a couple of weeks earlier than FAPRI so they miss out on some of the additional available information, especially expert opinions. Since expert opinions mostly influence shorter horizons of the projections, the FAPRI model does better for some variables. Additionally, the three multi-horizon comparison tests yield similar results, and the findings are consistent with the results of single horizon MDM test.

7 Conclusion

Both USDA and FAPRI baseline projections play an important role in shaping agricultural policy in the US. The baseline projections provide a conditional scenario against which alternative policies can be evaluated. The baselines have been widely used by policymakers, agricultural businesses, and program administrators in recent years. Given the importance of the baselines in determining the long-term outlook of the farm economy, this study examines the accuracy and informativeness of both sets of baseline projections using a number of forecast evaluation techniques.

Both USDA and FAPRI agricultural baselines include 10-year projections of global production and trade of agricultural commodities and U.S. net cash income. USDA states that the baseline is "not intended to be a forecast of what the future will be" (USDA Office of the Chief Economist, 2020, pp. 1), and both USDA and FAPRI add that the baselines are not to be used as forecasts. Both sets of baselines are released after a series of deliberations by several agencies involved in the process and represent a combination of both statistical models and the judgment of a broad panel of experts.

Our measures of prediction error show that the projections become less accurate as the projection horizon increases, with crop yields being a notable exception. Our tests of bias suggest that the baselines show similar bias as USDA's short-term forecasts documented in the existing literature (Bora et al., 2021; Isengildina-Massa et al., 2020), and the magnitude of the bias increases as the projection horizon increases. This is not surprising given the fact that inputs for many baseline models come from USDA forecasts such as WASDE and farm income forecasts. Our tests of predictive content show that the information content of most of the projected variables starts to diminish after 4-5 years from the current year. The findings suggest that the projections may be improved using better models and processes. Our multi-horizon comparison tests suggest that neither the USDA nor the FAPRI baselines outperform one another. The FAPRI projection, however, performs better at shorter horizons, potentially due to the updated information available to the FAPRI projection process which follows the USDA report of the baselines projections by a few weeks.

Our findings provide valuable insights which may help improve the models and processes employed while producing the projections by each agency. Especially, our tests of informativeness might be useful for any future proposals to extend the baseline horizons. The balance of empirical models and the judgment of a broad panel of experts employed by the baseline may also prove beneficial to other short-term USDA forecasts, such as those of commodity production and trade. In addition, our findings provide important information for the various users of baseline projections.

Notes

[1]The 10 USDA agencies producing the baselines are World Agricultural Outlook Board (WAOB), Economic Research Service (ERS), Farm Production and Conservation Business Center, Foreign Agricultural Service (FAS), Agricultural Marketing Service (AMS), Office of the Chief Economist (OCE), Office of Budget and Program Analysis (OBPA), Risk Management Agency (RMA), Natural Resources Conservation Service (NRCS), National Institute of Food and Agriculture (NIFA)

[2] Throughout the paper, we will use the term "projection" and "prediction" interchangeably, while limiting the use of the term "forecast".

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

[4]USDA Agricultural Projections, `https://usda.library.cornell.edu/concern/publications/qn59q396v?locale=en` (Accessed: April 1, 2021)

[5] Food & Agricultural Policy Research Institute, `https://www.fapri.missouri.edu/publications/outlook/` (Accessed: April 1, 2021)

[6]Iowa State University Digital Repository, `https://lib.dr.iastate.edu/fapri_staffreports/` (Accessed: April 1, 2020)

[7]Farm Income and Wealth Statistics, `https://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics/data-files-us-and-state-level-farm-income-and-wealth-statistics/` (Accessed: April 1, 2021)

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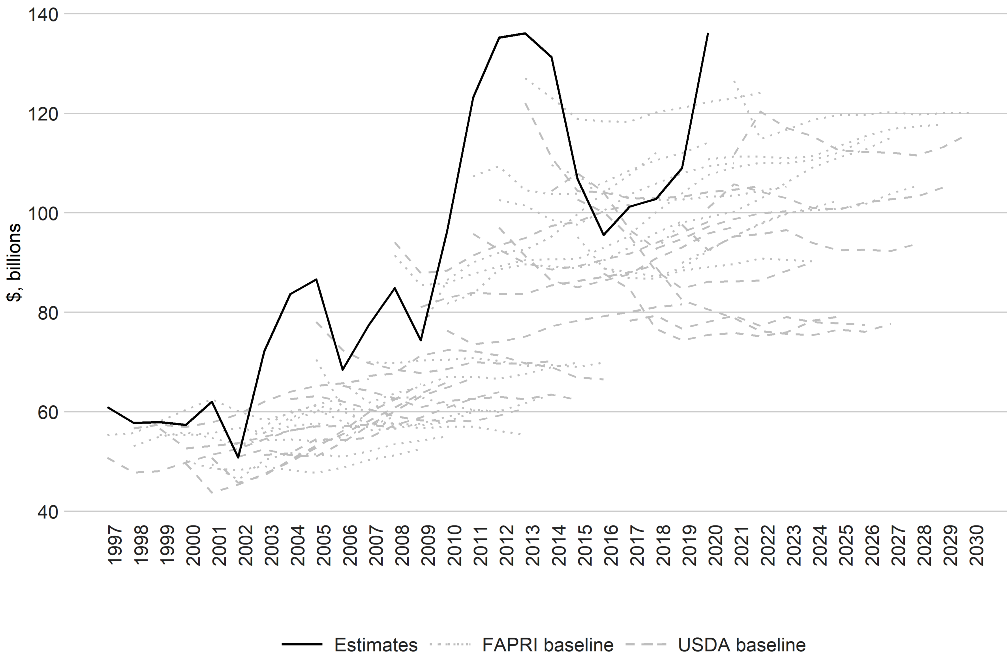
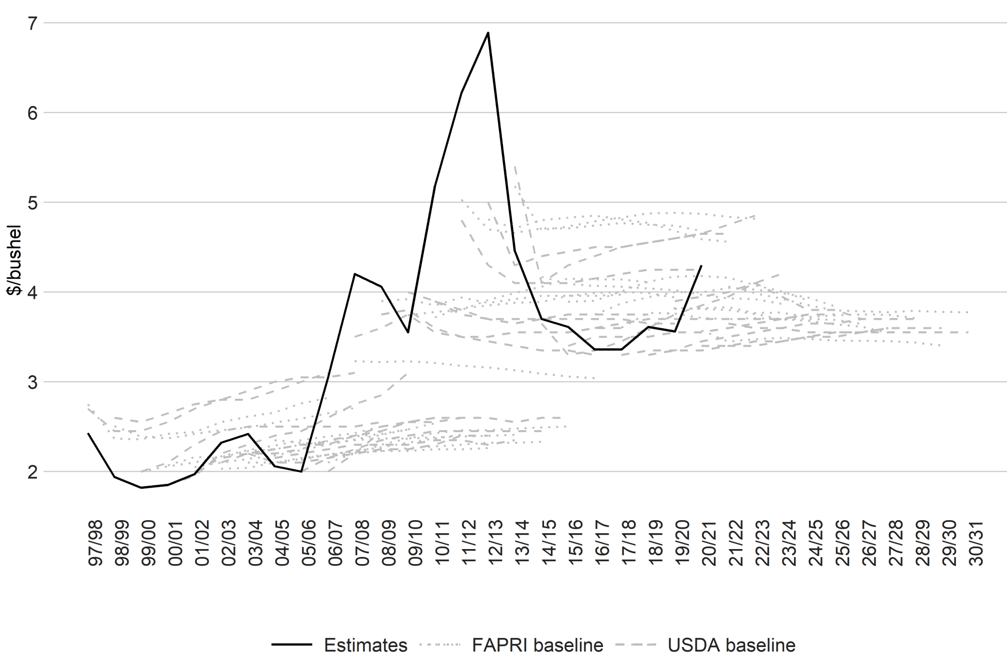


(a) Net cash income realized values and baseline projections, 1997-2021



(b) Corn price realized values and baseline projections, 1997-2021

Figure 1: Net cash income and corn price realized values and baseline projections between 1997 and 2021

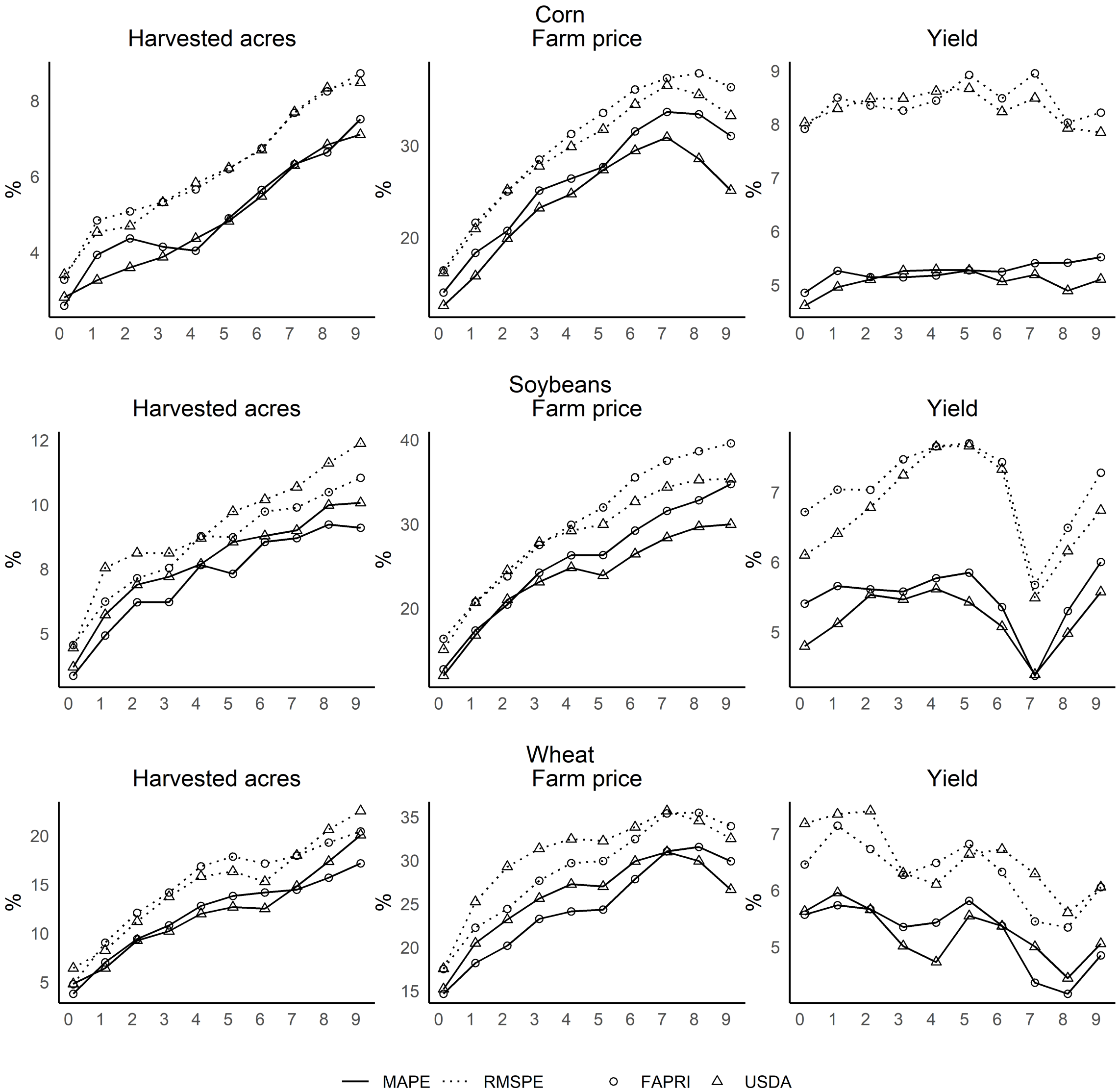


Figure 2: Mean absolute percent error (MAPE) and root mean square percent error (RMSPE) for baseline projections of corn, soybeans and wheat by projection horizon, 1997–2020

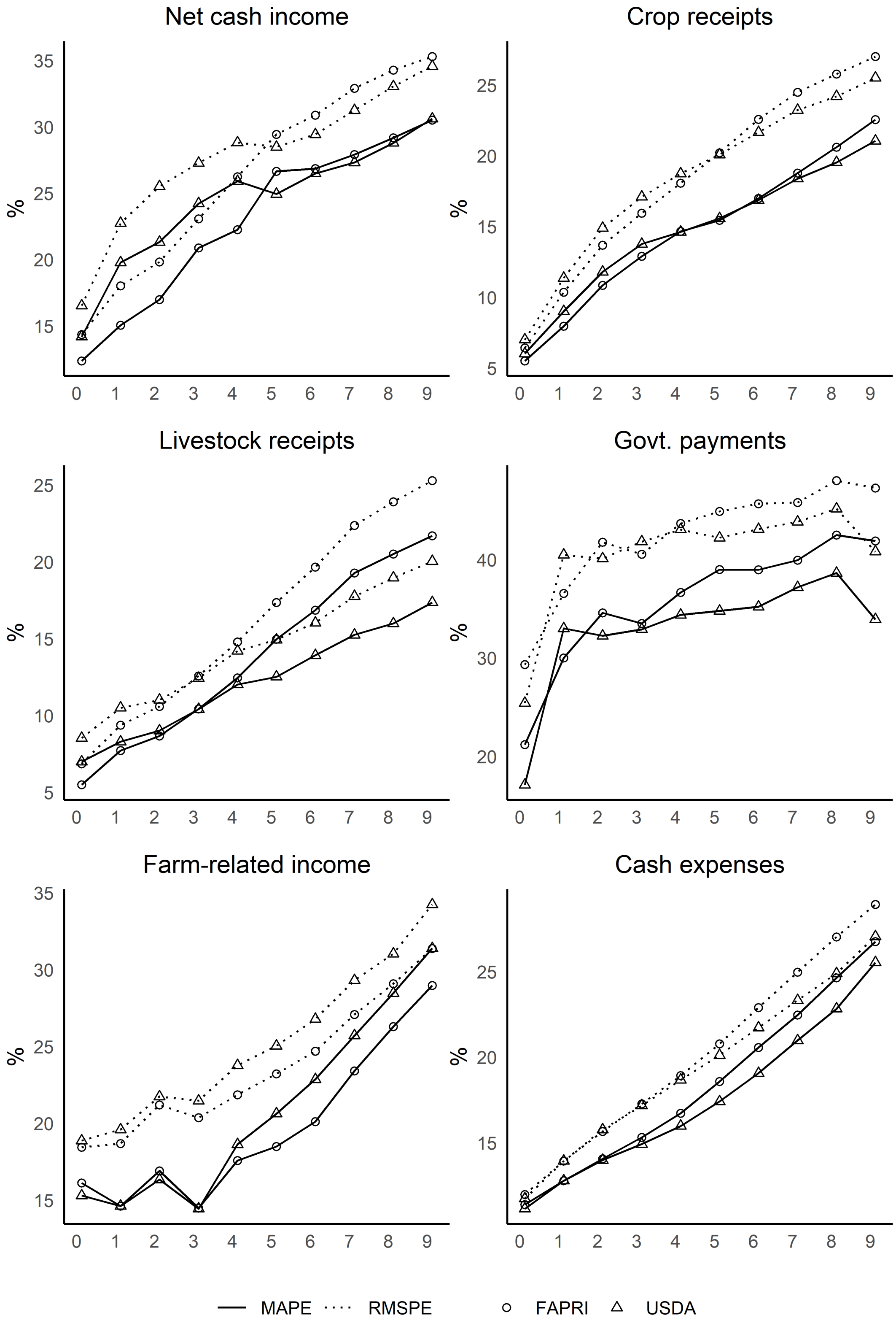


Figure 3: Mean absolute percent error (MAPE) and root mean square percent error (RMSPE) for baseline projections of net cash income and its components by projection horizon, 1997–2020

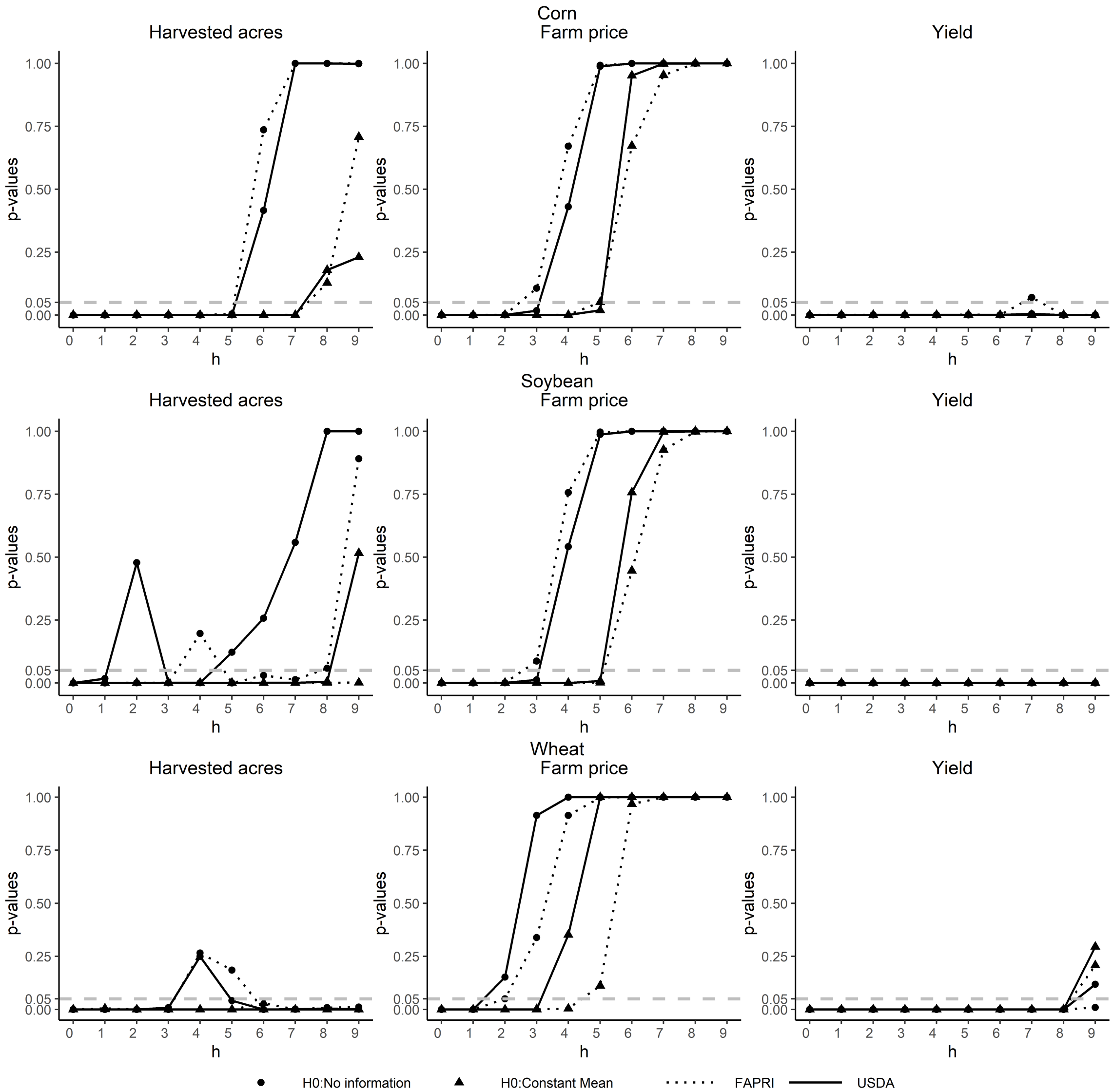


Figure 4: P-values for the tests of predictive content of the USDA and FAPRI commodity projections by horizon, 1997–2020

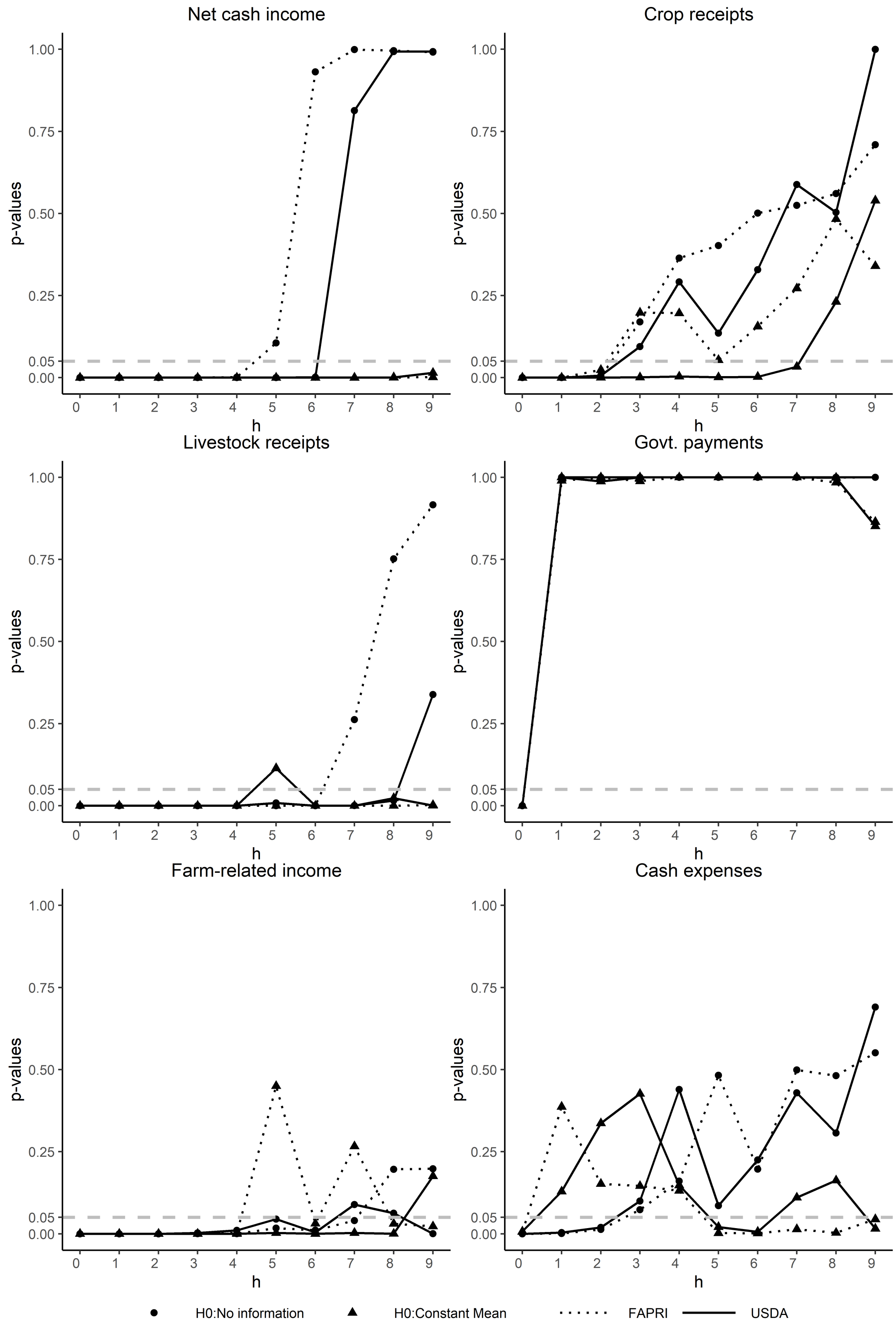


Figure 5: P-values for the tests of predictive content of the USDA and FAPRI farm income components projections by horizon, 1997–2020

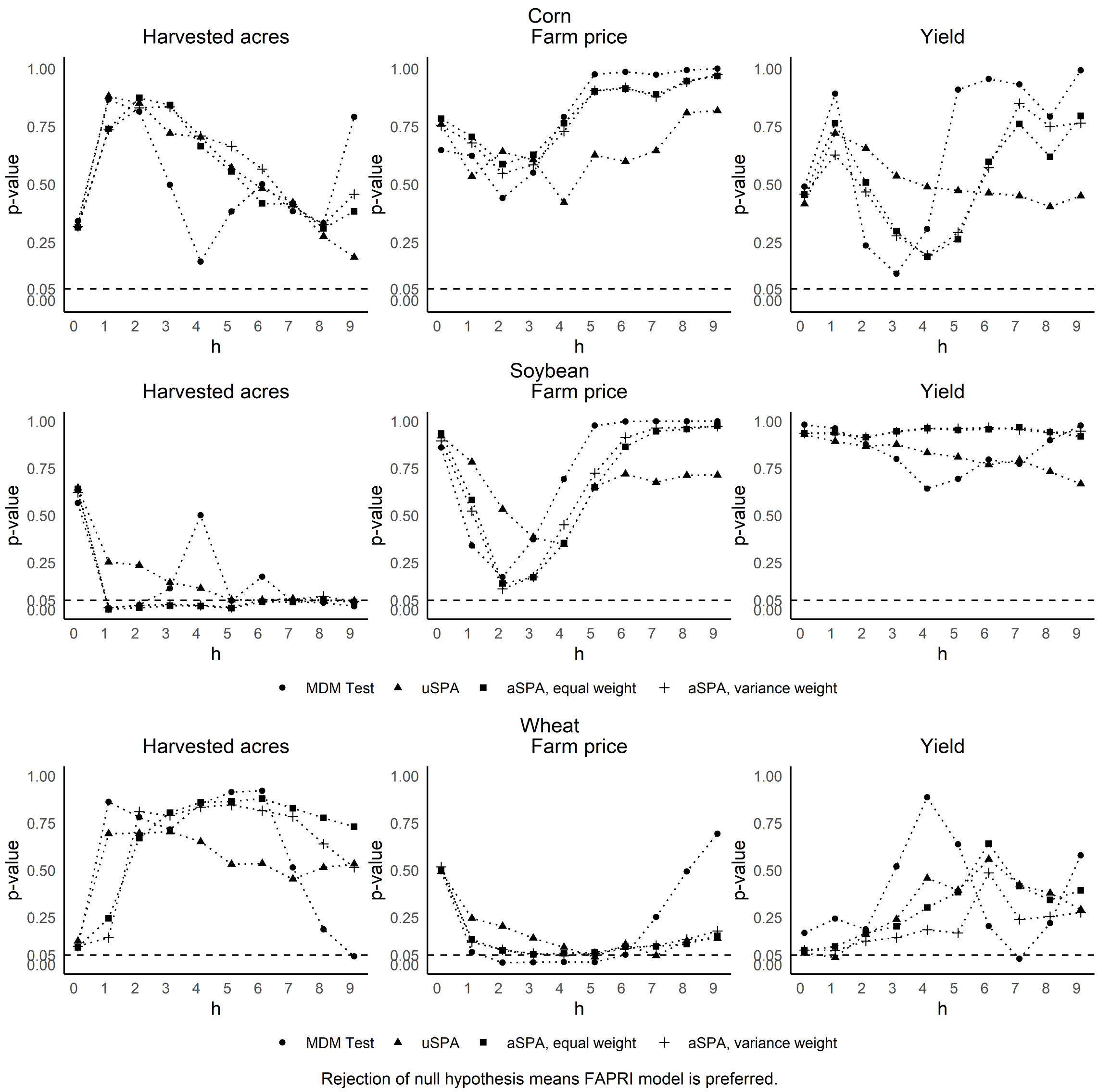


Figure 6: Multi-horizon comparison tests of USDA and FAPRI commodity projections by horizon, 1997–2020

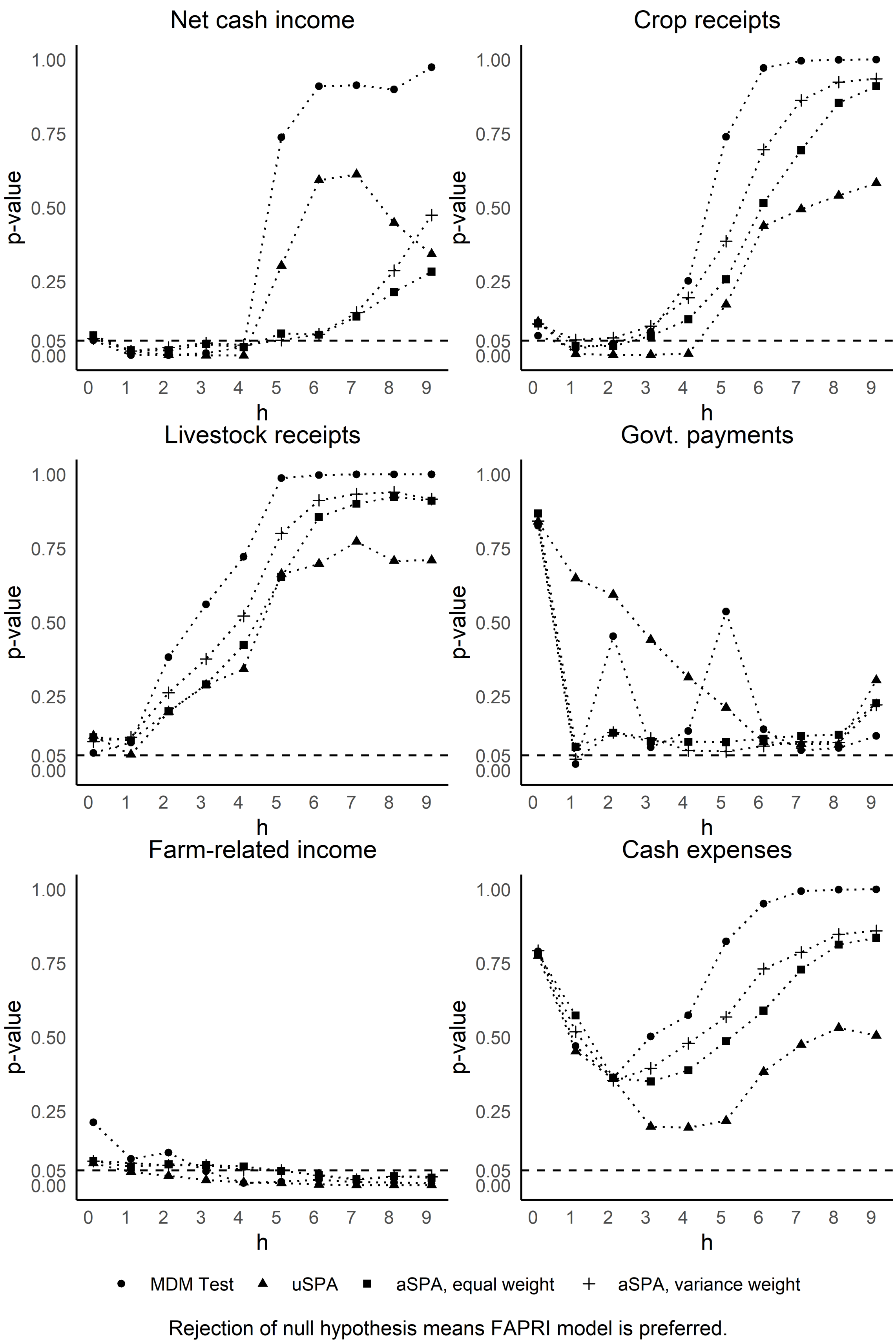


Figure 7: Multi-horizon comparison tests of USDA and FAPRI net cash income projections by horizon, 1997–2020

Table 1: Estimates of bias in USDA baseline projections, 1997–2020

	Projection horizon									
	h=0	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9
Corn										
Harvested acres	−0.009	−0.001	0.008	0.011	0.015	0.022	0.028	0.035	0.044	0.054
	(0.007)	(0.009)	(0.012)	(0.014)	(0.018)	(0.021)	(0.025)	(0.027)	(0.030)	(0.031)
Farm price	0.047	0.078	0.093	0.111	0.133*	0.158**	0.178	0.204*	0.258**	0.319**
	(0.039)	(0.069)	(0.096)	(0.082)	(0.071)	(0.067)	(0.103)	(0.100)	(0.099)	(0.133)
Yield	−0.010	−0.008	−0.007	−0.006	−0.006	−0.005	0.001	0.002	−0.003	−0.002
	(0.018)	(0.020)	(0.021)	(0.022)	(0.023)	(0.023)	(0.024)	(0.024)	(0.022)	(0.023)
Soybeans										
Harvested acres	0.007	0.028*	0.040**	0.055***	0.064***	0.071***	0.078***	0.085**	0.089**	0.098**
	(0.009)	(0.016)	(0.019)	(0.018)	(0.019)	(0.020)	(0.025)	(0.030)	(0.033)	(0.034)
Farm price	0.106***	0.135*	0.148	0.165	0.185***	0.214***	0.238**	0.253***	0.304***	0.362***
	(0.036)	(0.066)	(0.092)	(0.098)	(0.061)	(0.061)	(0.098)	(0.070)	(0.079)	(0.079)
Yield	−0.003	−0.003	−0.002	0.001	0.004	0.004	0.008	0.018	0.017	0.015
	(0.014)	(0.016)	(0.020)	(0.021)	(0.022)	(0.024)	(0.024)	(0.022)	(0.026)	(0.032)
Wheat										
Harvested acres	−0.040***	−0.046**	−0.056*	−0.072*	−0.090**	−0.102**	−0.112***	−0.134***	−0.156***	−0.179***
	(0.008)	(0.016)	(0.028)	(0.034)	(0.039)	(0.036)	(0.031)	(0.032)	(0.030)	(0.027)
Farm price	0.058	0.102	0.126	0.145*	0.165*	0.182**	0.189**	0.205	0.239*	0.278*
	(0.047)	(0.088)	(0.101)	(0.081)	(0.095)	(0.070)	(0.084)	(0.117)	(0.113)	(0.138)
Yield	0.019	0.018	0.016	0.015	0.015	0.016	0.027	0.025	0.026*	0.028*
	(0.015)	(0.017)	(0.015)	(0.014)	(0.013)	(0.015)	(0.017)	(0.015)	(0.014)	(0.015)
Farm income										
Net cash income	0.141***	0.204***	0.248***	0.278***	0.296***	0.300***	0.325***	0.343***	0.361***	0.393***
	(0.027)	(0.043)	(0.048)	(0.040)	(0.055)	(0.060)	(0.067)	(0.079)	(0.094)	(0.078)
Crop receipts	0.039**	0.064	0.085	0.100***	0.117***	0.138***	0.156***	0.176***	0.203***	0.254***
	(0.019)	(0.042)	(0.052)	(0.032)	(0.011)	(0.010)	(0.022)	(0.035)	(0.029)	(0.056)
Livestock receipts	0.023	0.043*	0.060**	0.072**	0.085*	0.096*	0.122**	0.147**	0.164**	0.190***
	(0.018)	(0.023)	(0.028)	(0.032)	(0.044)	(0.049)	(0.052)	(0.053)	(0.056)	(0.057)
Govt. payments	0.165	0.298*	0.361*	0.446**	0.475**	0.451**	0.470*	0.472*	0.492**	0.437*
	(0.096)	(0.169)	(0.188)	(0.196)	(0.211)	(0.209)	(0.223)	(0.229)	(0.216)	(0.210)
Farm-related income	0.048	0.092	0.123	0.151	0.193**	0.235**	0.274***	0.314***	0.351***	0.397***
	(0.061)	(0.074)	(0.090)	(0.087)	(0.089)	(0.084)	(0.076)	(0.063)	(0.060)	(0.065)
Cash expenses	0.119***	0.139***	0.154***	0.167***	0.181***	0.199***	0.220***	0.244***	0.268***	0.302***
	(0.012)	(0.022)	(0.031)	(0.036)	(0.043)	(0.025)	(0.040)	(0.037)	(0.044)	(0.047)

Notes: ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively. Standard errors (in parentheses) are heteroskedasticity and autocorrelation consistent (HAC)(Newey & West, 1987). The sample sizes of regressions for h=0,1,2,...,9 are N=24, 23,..., 15 respectively. For farm income variables, sample size for h=9 is 14 as the 1997 USDA baseline didn't publish projections for the year 2006.

Table 2: Estimates of bias in FAPRI baseline projections, 1997–2020

	Projection horizon									
	h=0	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9
Corn										
Harvested acres	−0.005	−0.005	−0.003	0.004	0.007	0.015	0.023	0.031	0.039	0.047
	(0.005)	(0.010)	(0.013)	(0.015)	(0.019)	(0.021)	(0.025)	(0.028)	(0.031)	(0.033)
Farm price	0.024	0.044	0.069	0.092	0.122	0.154	0.186	0.220*	0.280**	0.347**
	(0.045)	(0.077)	(0.101)	(0.076)	(0.087)	(0.111)	(0.119)	(0.109)	(0.115)	(0.145)
Yield	−0.003	−0.001	−0.001	−0.001	−0.002	−0.003	0.002	0.002	−0.004	−0.003
	(0.018)	(0.020)	(0.022)	(0.022)	(0.023)	(0.024)	(0.025)	(0.026)	(0.024)	(0.025)
Soybeans										
Harvested acres	0.003	0.020	0.034**	0.042**	0.054**	0.062***	0.072***	0.079***	0.083***	0.088***
	(0.009)	(0.012)	(0.016)	(0.018)	(0.019)	(0.020)	(0.020)	(0.023)	(0.025)	(0.028)
Farm price	0.079*	0.092	0.107	0.138	0.169**	0.212**	0.251*	0.275**	0.331***	0.393***
	(0.039)	(0.077)	(0.097)	(0.105)	(0.077)	(0.093)	(0.128)	(0.116)	(0.108)	(0.125)
Yield	0.008	0.009	0.008	0.011	0.012	0.012	0.013	0.023	0.022	0.020
	(0.016)	(0.019)	(0.022)	(0.023)	(0.023)	(0.023)	(0.024)	(0.022)	(0.027)	(0.034)
Wheat										
Harvested acres	−0.026***	−0.048**	−0.067**	−0.084**	−0.103**	−0.111**	−0.117***	−0.130***	−0.141***	−0.154***
	(0.008)	(0.017)	(0.029)	(0.036)	(0.037)	(0.042)	(0.038)	(0.032)	(0.036)	(0.034)
Farm price	0.037	0.064	0.085	0.101	0.127	0.154	0.177	0.205	0.247	0.291*
	(0.059)	(0.086)	(0.092)	(0.083)	(0.108)	(0.107)	(0.110)	(0.146)	(0.151)	(0.144)
Yield	0.026*	0.023	0.021	0.019	0.018	0.020	0.031**	0.030**	0.031**	0.035**
	(0.013)	(0.015)	(0.014)	(0.013)	(0.014)	(0.016)	(0.014)	(0.012)	(0.011)	(0.014)
Farm income										
Net cash income	0.125***	0.157***	0.175***	0.201***	0.240***	0.273***	0.312***	0.339***	0.368***	0.388***
	(0.023)	(0.032)	(0.041)	(0.051)	(0.062)	(0.083)	(0.090)	(0.108)	(0.089)	(0.059)
Crop receipts	0.033*	0.051	0.065	0.082**	0.100***	0.124***	0.151***	0.174***	0.208***	0.244***
	(0.016)	(0.039)	(0.050)	(0.032)	(0.020)	(0.029)	(0.046)	(0.057)	(0.053)	(0.062)
Livestock receipts	0.030**	0.045**	0.059**	0.081**	0.108**	0.137**	0.176**	0.206***	0.230***	0.253***
	(0.014)	(0.020)	(0.028)	(0.037)	(0.046)	(0.057)	(0.062)	(0.070)	(0.071)	(0.070)
Govt. payments	0.156	0.226	0.273	0.293	0.303	0.288	0.291	0.288	0.304	0.268
	(0.095)	(0.157)	(0.202)	(0.180)	(0.240)	(0.243)	(0.250)	(0.247)	(0.220)	(0.242)
Farm-related income	0.031	0.056	0.086	0.112	0.156*	0.200**	0.239***	0.282***	0.320***	0.357***
	(0.061)	(0.061)	(0.085)	(0.089)	(0.088)	(0.082)	(0.077)	(0.068)	(0.062)	(0.058)
Cash expenses	0.122***	0.139***	0.155***	0.171***	0.187***	0.210***	0.238***	0.264***	0.294***	0.323***
	(0.012)	(0.019)	(0.027)	(0.035)	(0.041)	(0.045)	(0.041)	(0.047)	(0.054)	(0.054)

Notes: ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively. Standard errors (in parentheses) are heteroskedasticity and autocorrelation consistent (HAC)(Newey & West, 1987). The sample sizes of regressions for h=0,1,2,...,9 are N=24, 23,..., 15 respectively.

Table 3: Estimates of the parameter $\hat{\beta}_h^{USDA}$ in the Mincer-Zarnowitz (MZ) regression for USDA projections

	h=0	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9
Corn										
Harvested acres	0.98^{+++}_{**}	0.962^{+++}_{**}	0.995^{+++}_{**}	0.976^{+++}_{**}	0.908^{+++}_{**}	0.729^{+++}_{**}	0.51^{**}	0.196^{**}	0.047	0.07
	(0.078)	(0.138)	(0.173)	(0.215)	(0.308)	(0.293)	(0.226)	(0.150)	(0.181)	(0.221)
Farm price	1.056^{+++}_{**}	1.111^{+++}_{**}	0.999^{+++}_{**}	0.822^{++}_{**}	0.523^{**}	0.191^{*}	-0.161	-0.393	-0.557	-0.604
	(0.124)	(0.213)	(0.247)	(0.237)	(0.252)	(0.243)	(0.174)	(0.212)	(0.362)	(0.342)
Yield	0.818^{+++}_{**}	0.772^{+++}_{**}	0.764^{+++}_{**}	0.751^{+++}_{**}	0.742^{+++}_{**}	0.729^{+++}_{**}	0.662^{+++}_{**}	0.625^{+++}_{**}	0.752^{+++}_{**}	0.803^{+++}_{**}
	(0.131)	(0.148)	(0.157)	(0.158)	(0.158)	(0.158)	(0.131)	(0.159)	(0.139)	(0.192)
Soybean										
Harvested acres	0.806^{+++}_{**}	0.548^{++}_{**}	0.501^{**}	0.645^{+++}_{**}	0.676^{+++}_{**}	0.563^{**}	0.542^{**}	0.492^{**}	0.226^{**}	-0.005
	(0.119)	(0.194)	(0.143)	(0.178)	(0.182)	(0.214)	(0.280)	(0.235)	(0.284)	(0.417)
Farm price	0.986^{+++}_{**}	0.914^{+++}_{**}	0.808^{+++}_{**}	0.67^{++}_{**}	0.49^{**}	0.232^{**}	-0.061	-0.235	-0.375	-0.413
	(0.099)	(0.156)	(0.129)	(0.151)	(0.176)	(0.211)	(0.207)	(0.122)	(0.267)	(0.278)
Yield	1.143^{+++}_{**}	1.241^{+++}_{**}	1.383^{+++}_{**}	1.406^{+++}_{**}	1.513^{+++}_{**}	1.762^{+++}_{**}	2.033^{+++}_{**}	1.825^{+++}_{**}	1.855^{+++}_{**}	1.957^{+++}_{**}
	(0.162)	(0.193)	(0.240)	(0.259)	(0.290)	(0.346)	(0.410)	(0.322)	(0.354)	(0.234)
Wheat										
Harvested acres	0.993^{+++}_{**}	0.918^{+++}_{**}	0.695^{+++}_{**}	0.599^{+++}_{**}	0.54^{**}	0.587^{++}_{**}	0.722^{+++}_{**}	0.672^{+++}_{**}	0.653^{+++}_{**}	0.7^{+++}_{**}
	(0.052)	(0.132)	(0.217)	(0.250)	(0.251)	(0.226)	(0.208)	(0.214)	(0.195)	(0.175)
Farm price	0.967^{+++}_{**}	0.861^{+++}_{**}	0.604^{**}	0.337^{**}	0.035	-0.168	-0.423	-0.643	-0.765	-0.718
	(0.098)	(0.171)	(0.036)	(0.048)	(0.040)	(0.039)	(0.115)	(0.189)	(0.214)	(0.178)
Yield	0.836^{+++}_{**}	0.827^{+++}_{**}	0.9^{+++}_{**}	1.142^{+++}_{**}	1.273^{+++}_{**}	1.189^{+++}_{**}	0.808^{+++}_{**}	0.988^{+++}_{**}	1.244^{+++}_{**}	1.216
	(0.199)	(0.289)	(0.234)	(0.298)	(0.161)	(0.300)	(0.307)	(0.289)	(0.280)	(0.263)
Farm income										
Net cash income	1.006^{+++}_{**}	0.889^{+++}_{**}	0.877^{+++}_{**}	0.888^{+++}_{**}	0.829^{+++}_{**}	0.819^{+++}_{**}	0.65^{+++}_{**}	0.438^{**}	0.285^{**}	0.224^{*}
	(0.082)	(0.139)	(0.180)	(0.213)	(0.225)	(0.201)	(0.196)	(0.304)	(0.366)	(0.241)
Crop receipts	1.035^{+++}_{**}	1.085^{+++}_{**}	1.093^{+++}_{**}	1.039^{+}_{**}	0.94^{**}	0.8^{**}	0.611^{**}	0.422^{*}	0.271	-0.009
	(0.056)	(0.110)	(0.141)	(0.162)	(0.097)	(0.056)	(0.078)	(0.030)	(0.083)	(0.008)
Livestock receipts	0.953^{+++}_{**}	0.927^{+++}_{**}	0.918^{+++}_{**}	0.868^{+++}_{**}	0.806^{+++}_{**}	0.795^{+++}	0.734^{+++}_{**}	0.655^{+++}_{**}	0.622^{++}_{*}	0.535^{**}
	(0.064)	(0.096)	(0.111)	(0.142)	(0.170)	(0.202)	(0.217)	(0.208)	(0.242)	(0.322)
Govt. payments	0.823^{+++}_{**}	-0.315	-0.123	-0.41	-0.452	-0.284	-0.348	-0.335	-0.367	-0.082
	(0.137)	(0.250)	(0.278)	(0.149)	(0.145)	(0.201)	(0.188)	(0.247)	(0.315)	(0.274)
Farm-related income	0.952^{+++}_{**}	0.989^{+++}_{**}	1.003^{+++}_{**}	1.077^{+++}_{**}	1.077^{++}_{**}	1.149^{++}_{**}	1.138^{+++}_{**}	1.111^{+}_{**}	1.148^{+}_{**}	0.695^{+++}
	(0.093)	(0.128)	(0.161)	(0.192)	(0.194)	(0.196)	(0.185)	(0.170)	(0.197)	(0.138)
Cash expenses	0.985^{+++}_{**}	0.994^{+++}	0.976^{++}	0.954^{+}	0.918	0.901^{+}_{*}	0.843^{**}	0.787	0.696	0.449^{*}
	(0.042)	(0.074)	(0.101)	(0.129)	(0.170)	(0.186)	(0.225)	(0.220)	(0.235)	(0.214)

Notes: *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively for testing the null hypotheses $H_0 : \beta_h^{USDA} \leq 0$. Likewise, +, ++, and +++ denote statistical significance at 10%, 5%, and 1% respectively for testing the null hypothesis $H_0 : \beta_h^{USDA} \leq 0.5$.

Table 4: Estimates of the parameter $\hat{\beta}_h^{FAPRI}$ in the Mincer-Zarnowitz (MZ) regression for FAPRI projections

	h=0	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9
Corn										
Harvested acres	0.996^{+++}_{**}	0.942^{+++}_{**}	0.927^{+++}_{**}	0.878^{+++}_{**}	0.835^{+++}_{**}	0.657^{+++}_{**}	0.471^{**}	0.209^{**}	0.062	-0.044
	(0.074)	(0.147)	(0.193)	(0.209)	(0.264)	(0.262)	(0.206)	(0.162)	(0.197)	(0.185)
Farm price	1.068^{+++}_{**}	0.957^{+++}_{**}	0.818^{+++}_{**}	0.673^{**}	0.449^{**}	0.178	-0.056	-0.191	-0.353	-0.388
	(0.128)	(0.189)	(0.187)	(0.235)	(0.257)	(0.266)	(0.226)	(0.164)	(0.169)	(0.242)
Yield	0.828^{+++}_{**}	0.762^{+++}_{**}	0.777^{+++}_{**}	0.769^{+++}_{**}	0.747^{+++}_{**}	0.698^{+++}_{**}	0.621^{+++}_{**}	0.569^{+}_{**}	0.702^{+++}_{**}	0.709^{+++}_{**}
	(0.138)	(0.167)	(0.163)	(0.150)	(0.154)	(0.171)	(0.141)	(0.152)	(0.139)	(0.181)
Soybean										
Harvested acres	0.764^{+++}_{**}	0.68^{+++}_{**}	0.608^{+++}_{**}	0.625^{+++}_{**}	0.518^{**}	0.663^{+++}_{**}	0.612^{++}_{**}	0.716^{++}_{**}	0.624^{+}_{**}	0.416^{**}
	(0.121)	(0.204)	(0.182)	(0.149)	(0.149)	(0.148)	(0.246)	(0.293)	(0.209)	(0.288)
Farm price	0.922^{+++}_{**}	0.84^{+++}_{**}	0.75^{+++}_{**}	0.603^{+}_{**}	0.442^{**}	0.233^{**}	0.009	-0.108	-0.198	-0.242
	(0.097)	(0.156)	(0.132)	(0.162)	(0.162)	(0.182)	(0.194)	(0.108)	(0.127)	(0.165)
Yield	1.165^{+++}_{**}	1.263^{+++}_{**}	1.476^{+++}_{**}	1.533^{+++}_{**}	1.666^{+++}_{**}	1.803^{+++}_{**}	1.891^{+++}_{**}	1.62^{+++}_{**}	1.465^{+++}_{**}	1.368^{+++}_{**}
	(0.180)	(0.217)	(0.251)	(0.217)	(0.285)	(0.351)	(0.353)	(0.217)	(0.232)	(0.248)
Wheat										
Harvested acres	0.983^{+++}_{**}	0.904^{+++}_{**}	0.708^{+++}_{**}	0.655^{+++}_{**}	0.551^{**}	0.551^{**}	0.673^{+++}_{*}	0.697^{+++}_{**}	0.697^{+++}_{**}	0.715^{++}_{**}
	(0.049)	(0.130)	(0.220)	(0.258)	(0.301)	(0.276)	(0.246)	(0.247)	(0.245)	(0.250)
Farm price	1.055^{+++}_{**}	0.925^{+++}_{**}	0.768^{+}_{**}	0.55^{**}	0.321^{**}	0.098	-0.143	-0.367	-0.532	-0.539
	(0.132)	(0.233)	(0.209)	(0.216)	(0.227)	(0.185)	(0.184)	(0.205)	(0.228)	(0.187)
Yield	0.967^{+++}_{**}	0.908^{+++}_{**}	1.028^{+++}_{**}	1.17^{+++}_{**}	1.192^{+++}_{**}	1.155^{+++}_{**}	0.888^{+++}_{**}	1.128^{+++}_{**}	1.258^{+++}_{**}	1.234^{+++}
	(0.213)	(0.252)	(0.249)	(0.258)	(0.224)	(0.307)	(0.226)	(0.234)	(0.148)	(0.243)
Farm income										
Net cash income	0.99^{+++}_{**}	0.942^{+++}_{**}	0.934^{+++}_{**}	0.84^{+++}_{**}	0.692^{+++}_{**}	0.559^{**}	0.431^{**}	0.316^{**}	0.282^{**}	0.236^{**}
	(0.060)	(0.099)	(0.163)	(0.178)	(0.162)	(0.138)	(0.170)	(0.199)	(0.237)	(0.114)
Crop receipts	1.038^{+++}_{**}	1.028^{+++}_{**}	0.983^{+++}_{*}	0.898	0.785	0.649	0.5	0.367	0.265	0.163
	(0.050)	(0.091)	(0.124)	(0.141)	(0.083)	(0.064)	(0.104)	(0.047)	(0.070)	(0.126)
Livestock receipts	0.94^{+++}_{**}	0.931^{+++}_{**}	0.923^{+++}_{**}	0.869^{+++}_{**}	0.798^{+++}_{**}	0.736^{+++}_{**}	0.641^{+++}_{**}	0.521^{**}	0.468^{**}	0.402^{**}
	(0.050)	(0.080)	(0.119)	(0.153)	(0.166)	(0.149)	(0.148)	(0.157)	(0.186)	(0.229)
Govt. payments	0.648^{+++}_{**}	-0.103	-0.296	-0.133	-0.38	-0.435	-0.366	-0.245	-0.254	-0.068
	(0.128)	(0.224)	(0.252)	(0.238)	(0.143)	(0.180)	(0.092)	(0.140)	(0.208)	(0.211)
Farm-related income	0.995^{+++}_{**}	0.961^{+++}_{**}	0.95^{+++}_{**}	0.998^{+++}_{**}	1.013^{+++}_{**}	1.087^{++}	1.061^{++}_{*}	1.068^{++}	1.091^{*}	0.9^{*}
	(0.122)	(0.127)	(0.154)	(0.179)	(0.189)	(0.172)	(0.171)	(0.157)	(0.189)	(0.151)
Cash expenses	0.993^{+++}_{**}	0.973^{+++}	0.95^{++}	0.911^{+}	0.857	0.821^{**}	0.762^{**}	0.657^{*}	0.56^{**}	0.462^{*}
	(0.045)	(0.077)	(0.092)	(0.104)	(0.138)	(0.165)	(0.174)	(0.178)	(0.196)	(0.188)

Notes: *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively for testing the null hypotheses $H_0: \beta_h^{FAPRI} \leq 0$. Likewise, +, ++, and +++ denote statistical significance at 10%, 5%, and 1% respectively for testing the null hypothesis $H_0: \beta_h^{FAPRI} \leq 0.5$.

Table 5:
Maximum informative projection horizons, h^*

	H0:No information		H0: Constant mean	
	FAPRI	USDA	FAPRI	USDA
Corn				
Harvested acres	5	5	7	7
Farm price	2	3	4	5
Yield	6	9	9	9
Soybean				
Harvested acres	3	1	9	8
Farm price	2	3	5	5
Yield	9	9	9	9
Wheat				
Harvested acres	3	3	9	9
Farm price	1	1	4	3
Yield	9	8	8	8
Farm income				
Net cash income	4	6	9	9
Crop receipts	2	2	2	7
Livestock receipts	6	8	9	4
Govt. payments	0	0	0	0
Farm-related income	7	6	4	8
Cash expenses	2	2	0	0

Table 6: Modifield Diebol Mariano (DM) test comparing FAPRI and USDA baselines (Harvey et al., 1997)

	$h = 0$	$h = 1$	$h = 2$	$h = 3$	$h = 4$	h=5	$h = 6$	$h = 7$	$h = 8$	$h = 9$
Corn										
Harvested acres	0.412	-1.141	-0.912	0.003	0.987	0.298	-0.004	0.296	0.438	-0.829
	(0.342)	(0.867)	(0.814)	(0.499)	(0.167)	(0.384)	(0.501)	(0.385)	(0.333)	(0.792)
Farm price	-0.385	-0.321	0.15	-0.128	-0.827	-2.072	-2.36	-2.056	-2.727	-4.112
	(0.648)	(0.624)	(0.441)	(0.551)	(0.792)	(0.975)	(0.986)	(0.974)	(0.994)	(1.000)
Yield	0.022	-1.274	0.726	1.234	0.508	-1.376	-1.766	-1.542	-0.831	-2.651
	(0.491)	(0.892)	(0.237)	(0.115)	(0.308)	(0.909)	(0.955)	(0.932)	(0.793)	(0.993)
Soybean										
Harvested acres	-0.172	2.518	2.052	1.244	-0.006	1.731	0.955	1.793	1.861	2.24
	(0.567)	(0.010)	(0.026)	(0.113)	(0.502)	(0.048)	(0.175)	(0.043)	(0.038)	(0.018)
Farm price	-1.111	0.416	0.961	0.328	-0.511	-2.106	-3.699	-3.93	-4.675	-5.839
	(0.861)	(0.341)	(0.173)	(0.373)	(0.693)	(0.977)	(0.999)	(1.000)	(1.000)	(1.000)
Yield	-2.196	-1.863	-1.197	-0.859	-0.371	-0.514	-0.845	-0.767	-1.311	-2.11
	(0.981)	(0.962)	(0.878)	(0.800)	(0.643)	(0.694)	(0.797)	(0.774)	(0.899)	(0.977)
Wheat										
Harvested acres	1.377	-1.115	-0.788	-0.579	-1.072	-1.415	-1.461	-0.037	0.907	1.782
	(0.091)	(0.862)	(0.781)	(0.716)	(0.853)	(0.915)	(0.921)	(0.515)	(0.187)	(0.044)
Farm price	0.012	1.564	2.509	2.405	2.339	2.366	1.694	0.68	0.016	-0.511
	(0.495)	(0.066)	(0.010)	(0.012)	(0.014)	(0.013)	(0.052)	(0.252)	(0.494)	(0.693)
Yield	0.985	0.704	0.906	-0.05	-1.245	-0.359	0.841	1.959	0.784	-0.203
	(0.168)	(0.244)	(0.187)	(0.520)	(0.887)	(0.638)	(0.204)	(0.031)	(0.220)	(0.579)
Farm income										
Net cash income	1.704	3.46	3.502	2.586	1.988	-0.644	-1.38	-1.404	-1.313	-2.047
	(0.051)	(0.001)	(0.001)	(0.008)	(0.029)	(0.737)	(0.910)	(0.913)	(0.899)	(0.974)
Crop receipts	1.555	2.107	1.815	1.453	0.68	-0.65	-2.019	-2.911	-3.587	-5.748
	(0.067)	(0.023)	(0.041)	(0.080)	(0.252)	(0.739)	(0.972)	(0.996)	(0.999)	(1.000)
Livestock receipts	1.628	1.357	0.304	-0.154	-0.597	-2.417	-3.189	-4.214	-4.201	-4.56
	(0.059)	(0.094)	(0.382)	(0.561)	(0.722)	(0.988)	(0.998)	(1.000)	(1.000)	(1.000)
Govt. payments	-0.961	2.144	0.119	1.467	1.138	-0.095	1.11	1.544	1.49	1.226
	(0.827)	(0.021)	(0.453)	(0.078)	(0.133)	(0.537)	(0.139)	(0.068)	(0.075)	(0.116)
Farm-related income	0.814	1.387	1.263	1.743	2.691	2.444	2.239	2.509	2.531	2.701
	(0.212)	(0.089)	(0.110)	(0.047)	(0.007)	(0.011)	(0.018)	(0.010)	(0.009)	(0.006)
Cash expenses	-0.822	0.076	0.357	-0.008	-0.188	-0.952	-1.72	-2.73	-3.465	-3.937
	(0.790)	(0.470)	(0.362)	(0.503)	(0.574)	(0.824)	(0.951)	(0.994)	(0.999)	(1.000)

Notes: The estimates are DM-statistic of Modified DM test comparing FAPRI and USDA baselines. The p-values are given in parentheses. The rejection of the null hypothesis would mean that FAPRI model performed better than USDA. Tests were conducted for each horizon separately. Root mean square error was used to calculate loss differentials.

Table 7: Tests of uniform superior predictive ability (uSPA) of FAPRI baselines over USDA baseline

	$h = 0$	$h \leq 1$	$h \leq 2$	$h \leq 3$	$h \leq 4$	h $\leq$ 5	$h \leq 6$	$h \leq 7$	$h \leq 8$	$h \leq 9$
Corn										
Harvested acres	0.515	-1.683	-1.995	-2.016	-1.952	-1.634	-1.503	-1.425	-1.215	-1.188
	(0.278)	(0.886)	(0.851)	(0.709)	(0.724)	(0.577)	(0.498)	(0.417)	(0.279)	(0.184)
Farm price	-0.686	-0.586	-1.094	-1.088	-0.854	-1.59	-1.791	-2.102	-3.419	-4.309
	(0.783)	(0.542)	(0.648)	(0.579)	(0.435)	(0.599)	(0.589)	(0.649)	(0.820)	(0.840)
Yield	0.022	-1.583	-1.504	-1.285	-1.091	-1.306	-1.362	-1.36	-1.349	-1.72
	(0.440)	(0.746)	(0.651)	(0.537)	(0.511)	(0.506)	(0.433)	(0.396)	(0.370)	(0.449)
Soybean										
Harvested acres	-0.187	-0.187	-0.296	-0.31	-0.345	-0.305	-0.411	-0.517	-0.537	-0.591
	(0.631)	(0.257)	(0.226)	(0.157)	(0.104)	(0.043)	(0.037)	(0.053)	(0.047)	(0.052)
Farm price	-1.194	-1.144	-0.653	-0.458	-0.45	-1.748	-2.656	-2.598	-3.075	-3.542
	(0.907)	(0.797)	(0.518)	(0.412)	(0.347)	(0.648)	(0.730)	(0.644)	(0.720)	(0.719)
Yield	-1.619	-1.594	-1.665	-2.204	-2.424	-2.445	-2.434	-2.124	-2.155	-2.239
	(0.932)	(0.883)	(0.870)	(0.900)	(0.867)	(0.782)	(0.784)	(0.767)	(0.731)	(0.667)
Wheat										
Harvested acres	1.381	-1.048	-1.105	-1.464	-1.405	-1.213	-1.312	-1.206	-1.407	-1.707
	(0.107)	(0.719)	(0.679)	(0.712)	(0.666)	(0.526)	(0.533)	(0.440)	(0.529)	(0.546)
Farm price	0.016	0.016	-0.064	-0.09	-0.061	-0.056	-0.409	-0.305	-0.749	-0.958
	(0.496)	(0.244)	(0.198)	(0.151)	(0.101)	(0.060)	(0.137)	(0.063)	(0.126)	(0.124)
Yield	1.281	0.713	0.031	-0.195	-1.107	-1.283	-1.738	-1.205	-1.313	-1.376
	(0.069)	(0.045)	(0.188)	(0.210)	(0.482)	(0.418)	(0.538)	(0.438)	(0.381)	(0.314)
Farm income										
Net cash income	1.891	1.676	1.77	1.813	1.761	-0.635	-1.567	-1.684	-1.457	-1.213
	(0.061)	(0.019)	(0.002)	(0.004)	(0.000)	(0.307)	(0.595)	(0.585)	(0.432)	(0.305)
Crop receipts	1.354	1.209	1.089	0.995	0.461	-0.447	-1.405	-1.798	-2.156	-2.996
	(0.112)	(0.005)	(0.000)	(0.002)	(0.003)	(0.159)	(0.457)	(0.526)	(0.547)	(0.623)
Livestock receipts	1.461	1.108	0.249	-0.115	-0.432	-1.535	-2.108	-2.555	-2.496	-2.527
	(0.099)	(0.072)	(0.201)	(0.267)	(0.339)	(0.660)	(0.716)	(0.786)	(0.731)	(0.739)
Govt. payments	-1.018	-1.021	-1.112	-1.018	-0.808	-0.767	-0.237	-0.193	-0.191	-0.863
	(0.872)	(0.664)	(0.602)	(0.468)	(0.307)	(0.274)	(0.103)	(0.088)	(0.098)	(0.317)
Farm-related income	0.875	0.906	0.914	0.862	0.922	0.982	0.991	0.952	0.958	1.021
	(0.077)	(0.044)	(0.020)	(0.017)	(0.015)	(0.014)	(0.001)	(0.000)	(0.000)	(0.000)
Cash expenses	-0.747	-0.458	-0.455	-0.278	-0.346	-0.617	-1.15	-1.685	-2.12	-2.264
	(0.786)	(0.470)	(0.356)	(0.225)	(0.170)	(0.216)	(0.361)	(0.493)	(0.499)	(0.508)

Notes: The estimates are t-statistics for test of uSPA of FAPRI baseline over USDA. The p-values are given in parentheses. The rejection of the null hypothesis would mean that FAPRI model performed better than USDA. Horizon $\leq h$ means the tests are performed using projections upto horizon h. A square loss function was used to calculate loss differentials.

Table 8: Tests of average superior predictive ability (aSPA) of FAPRI baselines over USDA baseline, equal weights

	$h=0$	$h \leq 1$	$h \leq 2$	$h \leq 3$	$h \leq 4$	h $\leq$ 5	$h \leq 6$	$h \leq 7$	$h \leq 8$	$h \leq 9$
Corn										
Harvested acres	0.515	-0.669	-1.357	-1.143	-0.498	-0.167	0.101	0.153	0.34	0.146
	(0.324)	(0.745)	(0.864)	(0.862)	(0.655)	(0.564)	(0.421)	(0.397)	(0.307)	(0.410)
Farm price	-0.686	-0.44	-0.254	-0.312	-0.683	-1.52	-2.085	-2.27	-3.212	-4.651
	(0.797)	(0.680)	(0.617)	(0.636)	(0.703)	(0.894)	(0.925)	(0.885)	(0.936)	(0.974)
Yield	0.022	-0.746	-0.044	0.447	0.767	0.57	-0.183	-0.617	-0.271	-0.787
	(0.458)	(0.768)	(0.540)	(0.299)	(0.193)	(0.264)	(0.566)	(0.736)	(0.629)	(0.784)
Soybean										
Harvested acres	-0.187	3.953	3.173	3.035	3.022	3.581	2.442	2.234	2.363	2.662
	(0.619)	(0.010)	(0.017)	(0.023)	(0.021)	(0.014)	(0.031)	(0.048)	(0.062)	(0.056)
Farm price	-1.194	-0.258	0.813	0.695	0.264	-0.434	-1.464	-2.138	-2.968	-4
	(0.905)	(0.607)	(0.152)	(0.181)	(0.353)	(0.627)	(0.865)	(0.939)	(0.957)	(0.974)
Yield	-1.619	-1.565	-1.45	-1.781	-2.071	-2.27	-2.411	-2.23	-2.234	-2.253
	(0.942)	(0.923)	(0.902)	(0.946)	(0.965)	(0.957)	(0.956)	(0.950)	(0.938)	(0.940)
Wheat										
Harvested acres	1.381	0.49	-0.41	-0.596	-0.867	-0.901	-1.017	-0.861	-0.65	-0.486
	(0.085)	(0.272)	(0.688)	(0.789)	(0.878)	(0.858)	(0.867)	(0.841)	(0.782)	(0.709)
Farm price	0.016	1.185	1.637	1.786	1.761	1.764	1.82	1.795	1.553	1.282
	(0.492)	(0.132)	(0.094)	(0.060)	(0.053)	(0.060)	(0.082)	(0.089)	(0.128)	(0.155)
Yield	1.281	1.331	0.793	0.624	0.368	0.206	-0.422	0.162	0.308	0.234
	(0.063)	(0.091)	(0.154)	(0.182)	(0.341)	(0.382)	(0.632)	(0.374)	(0.360)	(0.391)
Farm income										
Net cash income	1.891	2.835	2.988	2.848	2.868	2.478	2.047	1.395	0.949	0.663
	(0.081)	(0.016)	(0.026)	(0.035)	(0.027)	(0.050)	(0.083)	(0.128)	(0.203)	(0.295)
Crop receipts	1.354	2.071	1.708	1.394	1.035	0.577	-0.033	-0.599	-1.179	-1.905
	(0.087)	(0.043)	(0.046)	(0.062)	(0.122)	(0.263)	(0.479)	(0.694)	(0.857)	(0.902)
Livestock receipts	1.461	1.422	0.919	0.569	0.263	-0.411	-1.132	-1.763	-2.083	-2.175
	(0.130)	(0.106)	(0.186)	(0.311)	(0.391)	(0.669)	(0.818)	(0.897)	(0.907)	(0.899)
Govt. payments	-1.018	1.113	0.848	1.299	1.423	1.408	1.495	1.427	1.363	0.824
	(0.881)	(0.073)	(0.140)	(0.123)	(0.101)	(0.095)	(0.095)	(0.133)	(0.123)	(0.207)
Farm-related income	0.875	1.006	1.092	1.267	1.526	1.785	2.158	2.598	2.808	3.046
	(0.076)	(0.073)	(0.053)	(0.066)	(0.057)	(0.051)	(0.044)	(0.020)	(0.035)	(0.018)
Cash expenses	-0.747	-0.197	0.268	0.277	0.208	-0.011	-0.35	-0.774	-1.212	-1.405
	(0.804)	(0.558)	(0.360)	(0.353)	(0.378)	(0.473)	(0.601)	(0.727)	(0.852)	(0.858)

Notes: The estimates are t-statistics for test of aSPA of FAPRI baseline over USDA. The p-values are given in parentheses. The rejection of the null hypothesis would mean that FAPRI model performed better than USDA. Horizon $\leq h$ means the tests are performed using projections upto horizon h. Each horizon was given equal weights. A square loss function was used to calculate loss differentials.

Table 9: Tests of uniform superior predictive ability (aSPA) of FAPRI baselines over USDA baseline, variance weights

	$h = 0$	$h \leq 1$	$h \leq 2$	$h \leq 3$	$h \leq 4$	h ≤ 5	$h \leq 6$	$h \leq 7$	$h \leq 8$	$h \leq 9$
Corn										
Harvested acres	0.515	-0.616	-1.172	-1.026	-0.593	-0.445	-0.101	0.13	0.293	0.088
	(0.311)	(0.743)	(0.833)	(0.825)	(0.677)	(0.653)	(0.555)	(0.411)	(0.367)	(0.432)
Farm price	-0.686	-0.379	-0.083	-0.151	-0.611	-1.577	-2.121	-2.371	-3.251	-4.297
	(0.766)	(0.689)	(0.533)	(0.591)	(0.731)	(0.890)	(0.910)	(0.896)	(0.938)	(0.976)
Yield	0.022	-0.343	0.082	0.436	0.68	0.427	-0.148	-0.958	-0.665	-0.797
	(0.454)	(0.614)	(0.433)	(0.300)	(0.181)	(0.290)	(0.564)	(0.841)	(0.748)	(0.799)
Soybean										
Harvested acres	-0.187	3.357	2.896	2.858	2.962	2.925	1.71	1.703	1.919	2.049
	(0.639)	(0.015)	(0.019)	(0.027)	(0.022)	(0.027)	(0.045)	(0.053)	(0.084)	(0.067)
Farm price	-1.194	-0.039	1.201	0.776	0.064	-0.775	-1.898	-2.549	-3.21	-4.043
	(0.914)	(0.493)	(0.100)	(0.184)	(0.445)	(0.712)	(0.910)	(0.956)	(0.970)	(0.984)
Yield	-1.619	-1.549	-1.479	-1.782	-2.075	-2.302	-2.531	-2.051	-2.053	-2.06
	(0.938)	(0.905)	(0.919)	(0.938)	(0.960)	(0.960)	(0.966)	(0.955)	(0.954)	(0.930)
Wheat										
Harvested acres	1.381	0.822	-0.655	-0.577	-0.824	-0.873	-0.986	-0.726	-0.266	0.005
	(0.104)	(0.157)	(0.809)	(0.793)	(0.836)	(0.853)	(0.838)	(0.768)	(0.660)	(0.531)
Farm price	0.016	1.299	1.72	1.859	1.828	1.741	1.794	1.792	1.42	1.127
	(0.485)	(0.097)	(0.080)	(0.060)	(0.040)	(0.072)	(0.068)	(0.100)	(0.151)	(0.127)
Yield	1.281	1.312	0.823	0.739	0.661	0.639	-0.053	0.597	0.599	0.553
	(0.061)	(0.073)	(0.119)	(0.159)	(0.176)	(0.176)	(0.476)	(0.235)	(0.264)	(0.303)
Farm income										
Net cash income	1.891	2.947	2.813	2.488	2.512	2.344	1.995	1.229	0.684	0.11
	(0.058)	(0.019)	(0.036)	(0.039)	(0.031)	(0.045)	(0.060)	(0.138)	(0.285)	(0.452)
Crop receipts	1.354	1.703	1.412	1.166	0.782	0.255	-0.566	-1.184	-1.776	-2.358
	(0.092)	(0.052)	(0.074)	(0.091)	(0.209)	(0.372)	(0.694)	(0.851)	(0.926)	(0.929)
Livestock receipts	1.461	1.38	0.618	0.25	-0.079	-0.96	-1.793	-2.282	-2.423	-2.426
	(0.102)	(0.114)	(0.289)	(0.400)	(0.526)	(0.798)	(0.911)	(0.937)	(0.942)	(0.947)
Govt. payments	-1.018	1.618	0.955	1.319	1.343	1.39	1.484	1.473	1.407	0.856
	(0.866)	(0.047)	(0.138)	(0.100)	(0.084)	(0.074)	(0.097)	(0.095)	(0.105)	(0.203)
Farm-related income	0.875	0.984	1.065	1.152	1.321	1.513	1.827	2.22	2.373	2.623
	(0.099)	(0.065)	(0.062)	(0.055)	(0.044)	(0.043)	(0.036)	(0.031)	(0.026)	(0.027)
Cash expenses	-0.747	-0.052	0.287	0.179	0.037	-0.251	-0.696	-1.114	-1.573	-1.708
	(0.809)	(0.498)	(0.351)	(0.407)	(0.448)	(0.587)	(0.672)	(0.796)	(0.869)	(0.845)

Notes: The estimates are t-statistics for test of aSPA of FAPRI baseline over USDA. The p-values are given in parentheses. The rejection of the null hypothesis would mean that FAPRI model performed better than USDA. Horizon $\leq h$ means the tests are performed using projections upto horizon h. Weights were calculated for each forecast horizon by dividing variance of the loss differential by sum of all variances across horizons. A square loss function was used to calculate loss differentials.