

The Accuracy and Informativeness of Agricultural Baselines

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Abstract

Agricultural baseline projections play an important role in shaping agricultural policy, yet these projections have not been rigorously evaluated. 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) in three steps. 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, 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 jointly. 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. The multi-horizon comparison suggests that neither USDA nor FAPRI projections have uniform or average superior predictive ability over the other for most variables. Our findings are useful for the agencies producing these baselines and for the policymakers, agricultural businesses, and other stakeholders who use them.

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

JEL Codes: C53, Q14

1 Introduction

Long-term market projections play a vital role in both policy and investment decisions. Federal government 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). To satisfy this mandate, ERS leads a team from 10 USDA agencies to produce annual projections of key measures of agricultural market conditions for the next decade. These projections facilitate comparisons of policy alternatives by providing a conditional “baseline” scenario based on specific macroeconomic, weather, policy, and trade assumptions. In addition, the Food and Agricultural Policy Research Institute (FAPRI) produces similar ten-year projections of key agricultural variables. USDA baseline projections are typically released in February, with the FAPRI baseline projections following in March. Over the years, the baseline projections have been used for a variety of 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 this study, we evaluate the accuracy and informativeness of the USDA and FAPRI baselines using novel econometric techniques.

Our study focuses on two important series of projections from USDA and FAPRI: 1) projected bottom-line net cash income and its components, and 2) projected harvested acres, farm price, and yield of three major commodities (corn, soybeans, and wheat). The projections are examined in three steps. First, we 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). As part of our preliminary analysis, we also investigate the degree to which each projection exhibits systematic bias, following 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 et al., 2021; Bora, Katchova, and Kuethe, 2021). Since many USDA forecasts are used as an input for the beginning conditions of the USDA baseline models, baseline projections may show a similar tendency to under-predict.

Second, we examine the extent to which the value of information for each series of projections diminishes across the projection horizon. Both USDA and FAPRI baselines provide projections for ten years into the future, and we test the null hypothesis that the projections become uninformative beyond a given horizon using the encompassing approach developed by Breitung and Knüppel (2021). Our tests of predictive content use the unconditional mean as the uninformative (naïve) benchmark, and compare the mean square error of the projections to the unconditional variance of the target variable in a regression framework. The informativeness tests may be particularly useful for policymakers with an interest in long-run policy concerns, such as climate change, which exceed the current ten-year horizon. If the current projections are uninformative beyond a few years, it will be difficult to provide accurate projections

for longer horizons.

Finally, we formally test whether USDA or FAPRI provide more accurate baseline projections. Traditional forecast evaluation tests examine predictions at a single horizon (e.g., Diebold and Mariano, 1995; Harvey, Leybourne, and Newbold, 1997). Since the full ten-year path of baseline projections are used in policy analysis, these tests may provide inaccurate evaluation of relative accuracy, as one set of projections may perform better than the other at some horizons and worse at the remaining horizons. As a result, we evaluate the relative predictive accuracy of USDA and FAPRI using a novel testing procedure developed by Quaadvlieg (2021) that includes information across all horizons jointly. We test for superior predictive ability using two forms of the Quaadvlieg (2021) test. The first specification tests whether one set of projections perform better than the other across all projection horizons (uniform predictive ability). The second specification relaxes the assumption of uniform predictive ability by testing for differences in accuracy using a weighted average of loss differentials across horizons (average predictive ability). Thus, the second specification allows one baseline to have superior predictive ability over the other, even if it performs worse in some horizons. We further perform regression-based tests to examine whether the FAPRI projections encompass the USDA projections and vice versa (Harvey, Leybourne, and Newbold, 1998).

Our analysis yields a number of significant findings. First, the accuracy measures suggest that projection errors increase across the horizon for most variables, with the notable exception of crop yield projection. Second, our analysis identifies a number of systematic biases. For example, soybean harvested acres are consistently under-predicted while wheat harvested acres are consistently over-predicted at all horizons. In addition, 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 (Isengildina-Massa et al., 2021; Bora, Katchova, and Kuethe, 2021), but the magnitude of bias increases with the projection horizon. Third, the tests of predictive content show that, for most variables, the projections stay informative up to 4-5 years and diminish thereafter. Finally, the multi-horizon comparison tests suggest that neither USDA nor FAPRI projections outperform one another across the entire projection horizon (uniform predictive ability), except for farm-related income, where FAPRI performs better than USDA, and corn price and soybean yield, where USDA perform better than FAPRI. However, the FAPRI projections perform better at shorter horizons, which may be a result of the later release and the potential to include updated information (including USDA baseline projections released a month earlier). These findings may have important implications for the models and processes used to produce the baseline projections by both USDA and FAPRI, as well as for projection users.

The remainder of the paper is organized as follows. The next section provides a detailed description of the agricultural baseline projections produced by USDA and FAPRI, followed by a summary of our data. Subsequent sections describe our empirical approach and findings. The final section provides concluding

remarks.

2 Agricultural Baseline Projections

A number of government agencies, international organizations, and private firms produce long-run projections of key economic variables to help formulate policy and to support long-term planning. For example, within the agricultural sector, the Organisation for Economic Co-operation and Development (OECD) produces a ten-year global outlook report in collaboration with the Food and Agricultural Organization (FAO) which contains projections of agricultural indicators, such as market conditions and consumption (OECD and Food and Agriculture Organization of the United Nations, 2020). In addition, the Congressional Budget Office (CBO) produces long-run cost projections for several mandatory Federal farm programs, such as price loss coverage (PLC), agricultural risk coverage (ARC), crop insurance, disaster assistance, and conservation programs. Each of these reports provide projections on some indicators of U.S. agricultural market conditions, such as prices, acreage, and yields of key commodities. In this study, however, we focus on the baseline projections produced by USDA and FAPRI, which offer the most comprehensive coverage of US agricultural indicators over a ten-year horizon. The USDA and FAPRI baselines provide projections for key indicators of agricultural market conditions, including commodity prices and production, global agricultural trade, and farm income.

USDA baseline projections are produced by the Interagency Agricultural Projections Committee, comprised of experts from 10 USDA agencies and offices. USDA emphasizes 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 the absence of domestic or external shocks affecting global agricultural supply and demand. In addition, the macroeconomic conditions, productivity growth rates, and trade policies are assumed to persist throughout the projection period. USDA’s baseline projections reflect a composite of model results and judgment-based analysis (USDA ERS, 2020). 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). Hjort et al. (2018) provides a detailed description of the USDA baseline model and various processes followed during the preparation of the baseline report. ERS begins the baseline projection process in August and September of the preceding year by developing domestic and international macroeconomic assumptions. Over the next few months, the committee prepares detailed core domestic analysis for program commodities, projections for livestock and other non-program

commodities, and commodity projections for foreign countries. ERS economists then prepare the sector-wide projections for farm income and agricultural trade in January before publication of the baseline report in February.

FAPRI also produces 10-year baseline projections for the U.S. agricultural sector every year. Over the years, the FAPRI baseline procedures have evolved to include five main steps, as outlined in Meyers et al. (2010). First, FAPRI personnel update baseline models, data, and assumptions to include the November World Agricultural Supply and Demand Estimates (WASDE) and the latest macro-economic projections. Second, FAPRI analysts deliberate and produce preliminary baseline projections in late November. Third, the initial projections are subject to peer review from analysts from government and international agencies, agribusinesses, and other universities. Fourth, in mid-January, FAPRI analysts revise the preliminary baseline projections based on comments received during the peer review and update the WASDE and macroeconomic projections. Fifth, the baseline projections are finalized, and a briefing is provided to the U.S. Congress, after which the FAPRI baseline is released to the public. Meyers and Westhoff (2010) stress that the “FAPRI approach” of producing the baseline projections focuses on developing good models, while underlining their use by skilled analysts.

Agricultural baselines produced by USDA and FAPRI are widely used in farm policy debates, particularly as they relate to farm bills and other legislation affecting the agricultural sector. Both agencies play an advisory role in providing long-term budgetary estimates to policymakers and program administrators. It is important to note that one set of baseline projections examined are produced by the USDA, a department of the executive branch of the U.S. Federal government, while the other set is produced by a research institute housed at a Land Grant university. FAPRI was established by the U.S. Congress, part of the legislative branch. Thus, our work is complimentary to previous studies that evaluate forecasts produced by agencies from different branches of the Federal government (for a recent review, see Ericsson and Martinez, 2019).

As previously stated, U.S. agricultural baseline projections have not been rigorously evaluated, despite their role in shaping agricultural policy. There are a few recent exceptions. Irwin and Good (2015) question the use of USDA baseline projections in Farm Bill program choice decisions by demonstrating that corn, soybeans, and wheat price projections tend toward a steady state, leading to high projection errors. Westhoff (2015) extends the analysis in Irwin and Good (2015) to the FAPRI baselines and finds that the projection errors are similar to the USDA baselines across commodities. Irwin and Good (2015) and Westhoff (2015) also compare the commodity price baselines with season-average prices derived from futures markets. In addition, Boussios, Skorbiansky, and MacLachlan (2021) show that USDA baseline projections consistently under-estimate corn harvested area and over-estimate wheat harvested area. Finally, Kuethe, Bora, and Katchova (2021) compare the current year projections of US net cash income and its components to ERS’s forecasts released in the same month. The study suggests

that USDA baseline projections outperform ERS forecasts for government payments and farm-related income. While Kuethe, Bora, and Katchova (2021) underline the potential of USDA baseline projections for short-run predictions, the study examines only current year projections, ignoring all other horizons.

3 Data and Descriptive Analysis

3.1 Data

We examine a set of agricultural baseline projections from both the USDA and FAPRI from 1997 to 2020. Both organizations publish their projections in a similar format. The baseline projections include the most recent USDA estimate at the time of publication, provisional USDA estimates for the previous year, and projections for the year of the current release and the next nine years. For example, the February 2020 USDA baseline report contains realized estimates for 2018, provisional estimates for 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, which include crop receipts, livestock receipts, direct government payments, farm-related cash income, and cash expenses. Net cash income is a sector-wide measure of cash earnings generated by farms that can be used to meet a wide range of obligations, including debt payments (McGath et al., 2009). It is defined as gross cash income less cash expenses. Gross cash income includes crop and livestock cash receipts, direct government payments, and farm-related income. Direct government payments are limited to federal government funds paid directly to farmers to support farm incomes, conserve natural 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:

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

Second, we analyze the projections of harvested acres, farm price, and yield for three commodities: corn, soybeans, and wheat. Together, these three field crops constituted about 70% of the principal crops area planted in the US in 2020 (USDA NASS, 2021).¹ 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, as a result, the estimates for the current year are still provisional, as the marketing years for the various crops have yet to conclude. Similarly, the farm income estimates for the current year will be finalized in August.

We compile our dataset from multiple online sources. The Albert R. Mann Library at Cornell University maintains an electronic archive of USDA baseline projections since 1997 (USDA ERS, 2021b). The majority of FAPRI baseline reports were obtained from the FAPRI website (FAPRI, 2021). For some early years, the baseline reports are available from the Iowa State University Digital Repository (Iowa State University, 2021).² The realized estimates for farm income indicators are taken from ERS’s website (USDA ERS, 2021a). 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 reported in the baseline report are subject to periodic adjustment as new information becomes available from multiple USDA agencies, such as the Census of Agriculture conducted once every five years. Therefore, instead of choosing the USDA or FAPRI release of realized estimates in their baseline reports, we 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 application programming interface (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. (2021). A projection made in year t for future year $t + h$ (at horizon h) by organization $i = \{USDA, FAPRI\}$ is denoted $\hat{Y}_{t+h|t}^i$. Again, we express the projection in natural logarithms of the variables for our analysis: $\hat{y}_{t+h|t}^i = \ln(\hat{Y}_{t+h|t}^i)$. The projection horizon h can take values between $h = 0$ for the projection made during the reference year t and $h = 9$ for projections made for year $t + 9$. Again, for example, the 2020 baseline includes projections for 2020 ($h = 0$) to 2029 ($h = 9$).³

It is important to note that our dataset spans the baseline projections between 1997 and 2020, yet 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 size T for each year increase in the projection horizon h . For example, for $h = 1$, the length of the evaluation period is $T = 23$, as 1-year-ahead projections were not produced for the year $t = 1997$. Similarly, the sample size reduces to $T = 15$ observations for 9-years-ahead projections ($h = 9$), as $h = 9$ projections are available for the years 2006 to 2020. Figure 1 plots 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 fail to capture market shocks.

[FIGURE 1 ABOUT HERE]

3.2 Accuracy and Bias

Accuracy measures the difference between realized and predicted values. For each variable, the percent prediction error at horizon h is defined as: $e_{t+h|t}^i = 100 \times (Y_{t+h} - \hat{Y}_{t+h|t}^i) / Y_{t+h}$, where t is the reference year and $i = \{USDA, FAPRI\}$. We use two common measures of the relative accuracy of USDA and FAPRI projections: mean absolute percent error (MAPE) and root mean squared percent error (RMSPE) defined as,

$$\text{MAPE}_h^i = \frac{1}{T} \sum_t |e_{t+h|t}^i| \quad (2)$$

and

$$\text{RMSPE}_h^i = \sqrt{\frac{1}{T} \sum_t (e_{t+h|t}^i)^2}. \quad (2')$$

As MAPE is less susceptible to outliers, it is unaffected by the occasional large prediction errors. RMSPE, on the other hand, measures the square root average of squared errors and gives more weight to large prediction errors. Smaller MAPE or RMSPE values suggest more accurate projections.

In addition, we examine the degree to which the projections consistently differ from their realized values (bias) using the regression-based test of Holden and Peel (1990). For each series of projections, we test for bias at each horizon $h = \{0, 1, \dots, 9\}$:

$$e_{t+h|t}^i = \alpha_h^i + \varepsilon_{t+h}^i. \quad (3)$$

where α_h^i is an unknown constant to be estimated and ε_{t+h}^i is white noise regression residual. The projections are unbiased if they do not consistently differ from realized values, or alternatively, their percent prediction error has an expected value of zero. We evaluate the null hypothesis that the projections are unbiased by testing the regression constraint $H_0 : \alpha_h^i = 0$. A positive and significant coefficient $\hat{\alpha}_h^i$ would suggest that the USDA or FAPRI projections consistently under-predict realized values. Similarly, a negative and significant coefficient $\hat{\alpha}_h^i$ implies that the projections systematically overestimate the realized values. For both USDA and FAPRI projections, we estimate equation (3) separately for each projection horizon h using ordinary least squares (OLS) with heteroskedasticity and autocorrelation consistent (HAC) standard errors (Newey and West, 1987).

Figures 2 and 3 plot the mean absolute percent error (MAPE, solid line) and root mean square percent error (RMSPE, dotted line) of the projections for field crop production and prices (figure 2) and net cash income and its components (figure 3) from 1997 through 2020. The vertical axis represents the MAPE and RMSPE, and the horizontal axis represents the projection horizon h , from 0 to 9.

[FIGURE 2 ABOUT HERE]

As shown in figure 2, both MAPE and RMSPE increase with the projection horizon for harvested

acres and farm price of corn, soybeans, and wheat for both USDA and FAPRI projections. This pattern, however, does not hold for crop yield projections. Corn yield projections exhibit smaller and more stable MAPE and RMSPE, and MAPE and RMSPE for wheat yields decreases across the projection horizon h . The stable or decreasing percent errors may be the result of small deviations in crop yields from long-term upward trends. Further, figure 2 suggests limited differences between USDA and FAPRI commodity price and production projections.

[FIGURE 3 ABOUT HERE]

Figure 3 shows that projection errors for net cash income and its components increase with the horizon h . In addition, 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.

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 (3) along with HAC standard errors. As reported in Boussios, Skorbiansky, and MacLachlan (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 $h = \{0, 1\}$ (Kuethe, Bora, and Katchova, 2021; Isengildina-Massa 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 downward at longer horizons for both FAPRI and USDA projections.

[TABLE 1 ABOUT HERE]

[TABLE 2 ABOUT HERE]

4 Methods

The analysis of accuracy and bias in the previous section suggests that the projections are less accurate at longer horizons. We conduct tests for the predictive accuracy of the projections at different horizons and determine the maximum informative projection horizon for each variable (Breitung and Knüppel, 2021). We then compare the USDA and FAPRI baseline models using multi-horizon tests developed by Quaadvlieg (2021).

4.1 Informativeness

The accuracy and bias measures consider the projections at each horizon independently. The baseline projections, however, are multi-horizon forecasts or *path forecasts*, as in Jordà and Marcellino (2010). An important evaluation criterion for path forecasts is the horizon up to which the projections provide meaningful information. Galbraith (2003) calls the maximum informative horizon of a path forecast the *content horizon*. A number of previous studies develop empirical tests to estimate the content horizon of path forecasts relative to an uninformative or naïve forecast (Galbraith and Tkacz, 2007; Isiklar and Lahiri, 2007).

A popular measure used for quantifying information content is the Theil’s U statistic (Theil, 1958). Theil’s U is a scaled version of the root mean square error (RMSE) that has the advantage of not being affected by the variance of the actual process. It is defined:

$$U_h^i(\hat{y}_{naïve}) = \sqrt{\frac{\sum_{t=1}^T (y_{t+h} - \hat{y}_{t+h|t}^i)^2}{\sum_{t=1}^T (y_{t+h} - \hat{y}_{naïve})^2}} \quad (4)$$

A common choice for the naïve projection, $\hat{y}_{naïve}$, is a no-change projection using the previous year’s estimate. Following Isiklar and Lahiri (2007), we use the previous 5-year’s average as the naïve projection, and calculate $U_h^i(\hat{y}_{naïve})$ for our selected variables for each horizon $h = \{0, 1, \dots, 9\}$, and agency $i = \{USDA, FAPRI\}$. If Theil’s U is less than one, then the baseline is a better predictor than the naïve projection. Conversely, when the naïve benchmark is a better predictor than the agency baseline, Theil’s U is larger than one.

The choice of the naïve projection $\hat{y}_{naïve}$ greatly influences the Theil’s U statistic. As a result, we also estimate the informativeness or content horizon for the agricultural baselines using a method recently proposed by Breitung and Knüppel (2021), which does not require a naïve forecast for comparison. Instead, the Breitung and Knüppel test directly compares the mean-squared forecast error to the unconditional variance of the forecasted variable. The Breitung and Knüppel testing framework is based on a limited set of assumptions. The test 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 Breitung and Knüppel test for the maximum informative prediction horizon compares the mean-squared prediction error of the projections to the variance of the realized values over the evaluation sample. Under quadratic loss, the optimal projection equals the conditional mean of the projection $\mu_{h,t}^i = E(\hat{y}_{t+h}^i | I_t)$, given the information set I_t available at reference year t . In particular, we test the following hypothesis:

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

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

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:

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

$$H_1 : E(\hat{y}_{t+h}^i | I_t) \neq \mu_{h,t} = \mu. \quad (8)$$

This is a more relaxed criterion compared to the *no information* hypothesis as it requires the projection to be uncorrelated with the realized value for it to be uninformative. If the projection $\hat{y}_{t+h|t}^i$ 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 and Knüppel, 2021).

Breitung and Knüppel (2021) suggest considering three scenarios 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 we consider here 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 (Mincer and Zarnowitz, 1969).

Breitung and Knüppel (2021) show that if the baseline projection is generated by a conditional mean of the projection and noise (η_t), $\hat{y}_{t+h|t}^i = \mu_{h,t} + \eta_t^i$, the *no information* hypothesis is equivalent to testing

the null hypothesis $\beta_h^i \leq 0.5$ in the regression:

$$y_{t+h}^i = \beta_{0,h}^i + \beta_h^i \hat{y}_{t+h|t}^i + \nu_{t+h}^i. \quad (9)$$

Breitung and Knüppel (2021) further show that the *constant mean* hypothesis is equivalent to testing the null hypothesis $\beta_h^i \leq 0$ in the same regression, implying that the baseline projection is uncorrelated to the realized values. The tests of the parameters β_h^i can be performed using a HAC t -statistic constructed as:

$$\tau_a = \frac{1}{\hat{\omega}_a \sqrt{T}} \sum_t a_t \quad (10)$$

$$a_t = [y_{t+h} - \overline{y_{t+h}} - 0.5(\hat{y}_{t+h|t} - \overline{\hat{y}_{t+h}})] (\hat{y}_{t+h|t} - \overline{\hat{y}_{t+h}}) \text{ for } H_0 : \beta_h = 0.5 \quad (11)$$

$$a_t = (y_{t+h} - \overline{y_{t+h}})(\hat{y}_{t+h|t} - \overline{\hat{y}_{t+h}}) \text{ for } H_0 : \beta_h = 0 \quad (12)$$

where $\hat{\omega}_a^2$ is a consistent estimator of the long-run variance of a_t . The Lagrange Multiplier 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 null hypothesis is not rejected.

An advantage of the tests proposed by Breitung and Knüppel (2021) is that they do not require a naïve 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 limited observation period. 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.

4.2 Comparing USDA and FAPRI Baseline Projections

4.2.1 Multi-horizon Comparison

The final step in our evaluation compares the relative accuracy of the baseline projections produced by USDA and FAPRI. First, we follow the forecast comparison test procedure developed by Harvey, Leybourne, and Newbold (1997) for each projection at each horizon. The Harvey, Leybourne, and Newbold (1997) test is a modified version of the test procedure introduced by Diebold and Mariano (1995) which incorporates a modified student t distribution and bias correction to improve small sample properties of the tests. The comparison of the USDA and FAPRI projections is based on the mean loss differential between them, $\mu = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_t E(d_t)$.

The modified Diebold-Mariano tests for single horizons compare the USDA and FAPRI projections by calculating a standard t -test:

$$t_{DM}^h = \frac{\sqrt{T} \bar{d}_h}{\hat{\omega}_h} \quad (13)$$

where $\bar{d}_h = \frac{1}{T} \sum d_{t,h}$, and $\hat{\omega}_h^2$ is a HAC estimate of the variance of $d_{t,h}$. We first test the null hypothesis that the mean loss differential at horizon h is less than or equal to zero ($H_0 : \mu_h \leq 0$). A failure to reject the null hypothesis of $\mu_h \leq 0$ suggests that the FAPRI projections do not perform better than USDA, and a rejection of the null would indicate that the FAPRI projections perform better than USDA. We then test the null hypothesis that the mean loss differential at horizon h is greater than or equal to zero ($H_0 : \mu_h \geq 0$). For this test, a failure to reject the null hypothesis of $\mu_h \geq 0$ would indicate that the USDA projections do not perform better than FAPRI, and a rejection of the null would indicate that the USDA projections perform better than FAPRI.

The modified Diebold-Mariano test compares the USDA and FAPRI projections at each horizon. As a result, the test may yield contradictory results for multi-horizon projections, as one set of projections may provide more accurate projections at some horizons but not at others. This shortcoming may limit the use by policymakers who are interested in the relative accuracy of the entire path forecast from horizons 0 through 9. As a result, we also examine the relative accuracy along the entire projection path.

A number of recent studies propose methods to compare the relative accuracy of path forecasts (Capistrán, 2006; Patton and Timmermann, 2012; Martinez, 2020). In our analysis, we use the tests of multi-horizon superior predictive ability proposed by Quaadvlieg (2021) which jointly consider all horizons along the entire projection path. Following Giacomini and White (2006), the procedure developed by Quaadvlieg (2021) tests for finite-sample multi-horizon predictive ability using estimated values of parameters. 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, $\hat{\mathbf{y}}_t^i = [\hat{y}_{t|t-0}^i, \hat{y}_{t|t-1}^i, \dots, \hat{y}_{t|t-9}^i]$, where $\hat{y}_{t|t-h}^i$ is the 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 $\mathbf{L}_t^i = L(\mathbf{y}_t, \hat{\mathbf{y}}_t^i)$ which maps the prediction errors into a 10-dimensional vector since there are 10 projection horizons. 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:

$$\mathbf{d}_t = \mathbf{L}_t^{USDA} - \mathbf{L}_t^{FAPRI}. \quad (14)$$

Quaadvlieg (2021) provides two alternative definitions of multi-horizon predictive ability. First, a path forecast is said to have *uniform* superior predictive ability (uSPA) if it has smaller loss at each horizon when compared to the alternative path forecast. Uniform SPA, however, is a very strict criterion which may not be realistic in practice. As a result, Quaadvlieg (2021) develops the concept of *average* superior predictive ability (aSPA) for a path forecast with larger loss at some horizons that is compensated by superior performance at other horizons when compared to the alternative path forecast. Thus, average SPA relaxes the stringent requirements of uniform SPA. Quaadvlieg construct bootstrap test statistics for both uniform and average SPA, which reduce to the standard DM tests at a single horizon.

The uniform SPA test is based on the minimum loss differential:

$$\mu^{uSPA} = \min_h \mu_h. \quad (15)$$

The uniform SPA test is given by the null hypothesis $H_0 : \mu^{uSPA} \leq 0$ against the alternative hypothesis $H_a : \mu^{uSPA} > 0$. Rejecting the null hypothesis will suggest that the FAPRI projection has uniform superior predictive ability over the USDA projection. In other words, the minimum loss differential between the USDA and FAPRI projection across horizons h should be significantly greater than zero if the FAPRI projection is to be uniformly superior to the USDA projection. To test for uSPA of the USDA projection over FAPRI, we use the same equation (15) for minimum loss differential but reverse the two projections in the loss differentials equation (i.e. $\mathbf{d}_t = \mathbf{L}_t^{FAPRI} - \mathbf{L}_t^{USDA}$). In this case, rejecting the null hypothesis will suggest that the USDA projection has uniform superior predictive ability over the FAPRI projection.

The average SPA test, by contrast, is based on a weighted average of losses across all horizons or whether, for example, the FAPRI baseline projection is on average superior to the USDA baseline projection across all horizons. The average SPA test is based on the minimum loss differential:

$$\mu^{aSPA} = \mathbf{w}'\boldsymbol{\mu} = \sum_h w_h \mu_h. \quad (16)$$

The average SPA allows losses at different horizons to compensate for one another. For example, the FAPRI projection may perform worse at some horizons but still be superior compared to the USDA projection, on average. We test the null hypothesis $H_0 : \mu^{aSPA} \leq 0$ (FAPRI projection does not have aSPA) against the alternative $H_a : \mu^{aSPA} > 0$ (FAPRI projection has aSPA). We also test the null hypothesis $H_0 : \mu^{aSPA} \geq 0$ (USDA projection does not have aSPA) against the alternative $H_a : \mu^{aSPA} > 0$ (USDA projection has aSPA).

The choice of weights (w_h) is flexible but is chosen *a priori*. To make sure our findings are robust to this choice, we examine alternative weighting procedures. We first use equal weights for each horizon h but also consider 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:

$$t_{uSPA} = \min_h \frac{\sqrt{T} \bar{d}_h}{\hat{\omega}_h} \quad (17)$$

and,

$$t_{aSPA} = \frac{\sqrt{T} \bar{d}_h}{\hat{\zeta}_h}, \quad (17')$$

respectively. For the uSPA tests, we calculate two t -statistics: one testing whether the FAPRI projection has uSPA over the USDA and the other testing whether the USDA projection has uSPA over FAPRI, as the minimum loss differentials are different for these two hypotheses. However, for the aSPA tests, we need to calculate only one t -statistic and conduct one-tailed tests in both directions to test aSPA of the FAPRI projection over USDA and vice versa.

We obtain estimates of variances $\hat{\omega}_h^2$ for uSPA from the diagonal elements of the covariance matrix of loss differential \mathbf{d} calculated using an HAC-type estimator (Newey and West, 1987). Similarly, we get the estimates of variance $\hat{\zeta}_h^2$ for aSPA as the diagonal elements of the weighted covariance matrix of \mathbf{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 a Diebold-Mariano 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.

4.2.2 Encompassing Tests

As previously stated, USDA baseline projections are typically released in February and FAPRI baseline projections in March. As a result, FAPRI analysts have the advantage of using more recent information to prepare their projections. The updated information set of the FAPRI analysts includes information

from reviewer comments, the January WASDE and associated reports, and the February USDA farm income estimates. In comparison, the USDA baseline projections are based on the October WASDE (USDA Office of the Chief Economist, 2020). Therefore, one might expect the FAPRI baseline projections to contain new information beyond the USDA baseline projections. On the other hand, there is a bi-directional flow of information between USDA and FAPRI analysts through official meetings, review sessions, and informal conversations, which may lead to herding in the projections produced by both agencies. FAPRI usually finalizes its projections by the time USDA releases its report, and the USDA report does not act as a significant input to FAPRI's forecasting process. We test whether the information content of USDA or FAPRI baseline projections dominates the other using the encompassing test developed by Harvey, Leybourne, and Newbold (1998).

When two competing sets of projections are available for the same variable, a relevant question to ask is whether one set of projections *encompasses* another, that is, the informational content of the preferred projection dominates the other. Harvey, Leybourne, and Newbold (1998) frame this question as a problem of forming a combined projection from the weighted average of the individual ones and estimating the optimal weights assigned to each projection. In this framework, a projection would be preferred if its optimal weight is unity in the weighted average, and the combined projection consists entirely of the preferred projection. Harvey, Leybourne, and Newbold (1998) develop a regression-based test to estimate the optimal weights for the combined projection. For our study, the regression is expressed as:

$$e_{t+h|t}^{USDA} = \alpha_h + \lambda_h(e_{t+h|t}^{USDA} - e_{t+h|t}^{FAPRI}) + \varepsilon_{t+h|t}. \quad (18)$$

where $e_{t+h|t}^{USDA}$ is the prediction error at horizon h of USDA baselines, and $e_{t+h|t}^{FAPRI}$ is the prediction error at horizon h of FAPRI baselines projections. The coefficients α_h and λ_h at horizon h are estimated by OLS regression, and $\varepsilon_{t+h|t}$ is a white noise regression error.

The coefficient λ_h in the regression equation (18) determines the optimal weights assigned to the USDA and FAPRI projections to form a combined projection that would have a smaller expected squared error than either of the two projections. The combined projection is formed by assigning weights $(1 - \lambda_h)$ and λ_h to the USDA projections and FAPRI projections, respectively. We test the null hypothesis that USDA baselines encompass the FAPRI projections using a two-tailed t -test of the restriction $\lambda_h = 0$. If we fail to reject $\lambda = 0$, it implies that USDA is preferred to FAPRI (i.e., the combined projection consists entirely of the USDA baseline). Alternatively, we test the hypothesis that the combined projection consists entirely of the FAPRI baseline by using a two-tailed t -test of the restriction $\lambda_h = 1$. A failure to reject $\lambda_h = 1$ would suggest that the FAPRI baseline is preferred. If we reject both $\lambda_h = 0$ and $\lambda_h = 1$, a combined projection is formed by weighting FAPRI baseline by $\hat{\lambda}_h$ and USDA baseline by $(1 - \hat{\lambda}_h)$. In this case, both baselines contain unique information to contribute to the combined projection. Finally, if we fail to reject both $\lambda_h = 0$ and $\lambda_h = 1$, the optimal composite projection can be either the USDA or

the FAPRI baseline, as the projections are very similar. We perform encompassing tests for our selected variables for each horizon separately.

5 Results

The following section presents the primary findings of our analysis. First, we measure the accuracy of USDA and FAPRI baseline projections for major field crops, as well as U.S. net cash farm income and its components, and test for bias. Second, we estimate the content horizon of each set of projections. Finally, we empirically test the degree to which USDA or FAPRI has superior predictive ability.

5.1 Informativeness

The Theil's U statistic for the commodities and net cash income components are plotted in figures 4 and 5 for USDA and FAPRI baselines. As previously discussed, Theil's U compares the predictive accuracy of FAPRI or USDA baseline projections relative to a naïve prior based on a 5-year moving average, following Isiklar and Lahiri (2007). The USDA or FAPRI baseline projection is a better predictor than the naïve prior if Theil's U is less than 1, which is represented by the horizontal dashed line in figures 4 and 5. Both USDA and FAPRI projections are better predictors of corn harvested acres across all horizons, relative to the naïve prior. However, for harvested acres of soybeans and wheat, the naïve prior is preferred at longer horizons. The predictive accuracy of both FAPRI and USDA baseline projections relative to the naïve prior diminish at longer horizons for all farm price projections. Interestingly, yield projections perform better for both agencies at larger horizons relative to the naïve projection. For net cash income, FAPRI baselines are preferred to the naïve prior for at shorter horizons, yet the naïve prior is preferred to USDA baseline projections beyond the reference year projections. For both crop and livestock receipts, USDA and FAPRI baseline projections are preferred to the naïve prior at all horizons. The projections of government payment, on the other hand, fail to beat the naïve beyond the current year for both agencies. Overall, Theil's U statistics suggest that the baselines beat the naïve projection for most variables across horizons, underlining that baselines contain information. We investigate the informativeness of the baselines further with our empirical tests of predictive content.

[FIGURE 4 ABOUT HERE]

[FIGURE 5 ABOUT HERE]

Our estimates of the content horizon of each projection series, following Breitung and Knüppel (2021), are presented in tables A.1 and A.2. As previously discussed, the empirical test of Breitung and Knüppel (2021) is based on the traditional Mincer-Zarnowitz regression (equation (9)). The two hypotheses tested are $H_0 : \beta_h^i \leq 0.5$ for *no information* and $H_0 : \beta_h^i \leq 0$ for *constant mean*.

As shown in tables A.1 and A.2, 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 ($h = 9$), which suggests a reduction in the predictive content of the USDA projections at longer horizons (table A.1). 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 A.2). The statistical significance of the coefficients tested with a one-tail test show that the projections for corn harvested acres become uninformative after $h = 5$ and then constant mean after $h = 7$.

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 6 and 7. The horizontal dashed line stands for significance at a 5% level. These figures mirror and confirm the results in tables A.1 and A.2. In general, the results show that yield is better predicted than harvested acres, which is better predicted than farm price in terms of becoming uninformative and constant mean at longer horizons.

[FIGURE 6 ABOUT HERE]

[FIGURE 7 ABOUT HERE]

Finally, we calculate the maximum informative projection horizons h^* for both tests at a 5% significance level in table 3. 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 the *no information* hypothesis tests whether the coefficient estimate is less than 0.5 versus the *constant mean* hypothesis that tests whether the coefficient estimate is less than 0, the results imply 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, and for medium horizons, the projections become uninformative. For the longest horizons, the projections are also constant mean.

[TABLE 3 ABOUT HERE]

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. These results vary greatly across variables. Both USDA and FAPRI are able to predict yield per acre for the longest horizons of 9

years ahead, with reduced predictive ability for harvested acres of about 5-7 years ahead and the lowest predictive for farm price of only 2-4 years ahead. These results are not surprising because predicting yield around a long-term trend has proven to be easier than predicting farm prices, which are more volatile. The bottom-line net cash income also remain informative 4-6 years into the future, while some individual components such as crop receipts and cash expenses generally remain informative for shorter horizons of about 2 years. Government payments are notably difficult to predict even in the current year and are not informative after the current year, consistent with previous studies (Isengildina-Massa et al., 2021; Bora, Katchova, and Kuethe, 2021). 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 results only suggest that the projections may stay informative for a longer period using improved models.

There may be several explanations why a variable might not stay informative beyond a few years. It may be that the variable under examination is difficult to predict. For example, it is not surprising that the government payments do not stay informative beyond the current year, as policy decisions are often unpredictable. The opposite is true for crop yield projections, where even a linear trend model may predict future yield with low percent errors. Our findings of a short content horizon would suggest that the projection may be improved by using better projection models, more rigorous review processes, and robust information sets. However, errors in the baseline projections may come from two distinct sources. First, the assumptions about macro-economic conditions, weather, trade policies while producing the baselines may not be realized in the future. Second, even if correct assumptions were made, the models used in the projections may be inadequate or inaccurate. Our tests of predictive content do not pinpoint whether a short content horizon may result from incorrect assumptions or incorrect models and analysis, and would merely suggest that future revisions of the baselines should try to improve both the assumptions and the modeling process. The same limitation applies to other tests used in this study.

5.2 Comparing USDA and FAPRI Baseline Projections

We first compare the FAPRI and USDA baselines using the modified Diebold-Mariano (MDM) test of Harvey, Leybourne, and Newbold (1997) using a root mean square error loss function (table A.3). For this MDM test, we compare USDA and FAPRI projections at each horizon separately using the test statistic from equation (13). We then perform multi-horizon uniform SPA test using the test statistic from equation (17) to test whether the FAPRI projections perform better than the USDA projections or whether the USDA projections perform better than FAPRI (table A.4). Then, we conduct two versions of the average SPA test using the test statistic from the equation (17'). The first average SPA test assigns equal weights to each horizon while calculating loss differentials (table A.5). Table A.6 presents the results of the 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. Figures 8 and 9 plot the p -values of the MDM test and the multi-horizon comparison tests.

[FIGURE 8 ABOUT HERE]

[FIGURE 9 ABOUT HERE]

The p -values of all four multi-horizon comparison tests for the commodities projections in figure 8 suggest that the FAPRI projections do not outperform the USDA projections for most variables, as we cannot reject the null hypothesis. Notable exceptions are that the FAPRI projections perform better than USDA for soybean harvested acres and wheat price. The multi-horizon comparison test results shown in figure 9 suggest that the FAPRI projections perform better in shorter horizons ($h \leq 4$) for net cash income and crop receipts, while FAPRI consistently predicts better than USDA farm-related income for all horizons $h \leq 9$. One reason the FAPRI projections may perform better at shorter horizons is that they use the most recent forecasts available in November as inputs to their projections, while the USDA uses forecasts available in October. Also, USDA releases their projections a couple of weeks earlier than FAPRI, so FAPRI may contain additional information, especially expert opinions. Since expert opinions mostly influence shorter horizons of the projections, the FAPRI projections are better for some variables. Additionally, the three multi-horizon comparison tests (uSPA, aSPA equal weights, and aSPA variance weights) yield similar results, and the findings are consistent with the results of the single-horizon MDM test.

The results of multi-horizon comparison tests in tables A.4, A.5, and A.6 provide additional insights to the single-horizon MDM tests presented in table A.3. The MDM test results show that the FAPRI projections perform better in shorter horizons for net cash income, crop receipts, and wheat price. For farm-related income, the FAPRI projection performs better than USDA across the entire projection horizon. The USDA projection performs better at longer horizons for corn price and yield, soybean price, crop receipts, livestock receipts, and cash expenses. The multi-horizon tests, on the other hand, aggregate the loss differential across multiple horizons. We start our multi-horizon tests with the projection for the current year ($h = 0$) and progressively include additional horizons until we cover the entire projection horizon ($h \leq 9$). This allows us to observe how the addition of more horizons affects the results. For shorter horizons, the multi-horizon tests yield similar results to the MDM test. However, as we keep adding horizons, in a multi-horizon framework, the results differ from the single-horizon tests. For example, the tests of uSPA in table A.4 show that, over the projection path ($h \leq 9$), the FAPRI projection performs better for farm-related income, whereas the USDA projection performs better for corn price and soybean yield at 5% significance level. The tests of aSPA in table A.5 and A.6 yield similar conclusions. Interestingly, the full-horizon ($h \leq 9$) multi-horizon comparison tests do not suggest

that either projection performs better than the other for net cash income, crop receipts, and livestock receipts. The single-horizon tests in table A.3 show that the FAPRI projections perform better in shorter horizons and the USDA projections perform better in longer horizons. As the multi-horizon tests consider performance over the entire projection horizon, they conclude that neither the USDA nor the FAPRI projection is superior to the other projection.

[TABLE 4 ABOUT HERE]

The estimates of optimal weight $\hat{\lambda}$ of our encompassing tests in equation (18) is presented in table 4. For corn, either the USDA and FAPRI baseline projections can generally be substituted for one another. For soybean prices, USDA projections are preferred in the short term, while a composite projection can be created by taking the weighted average of both projections at larger horizons ($h = 7$ to 9). The net cash income projections of the FAPRI baseline are preferred in the shorter horizons ($h = 1$ to 3), while USDA net cash income projections are preferred in the larger horizons ($h = 7$ to 9). This finding is consistent with our multi-horizon comparison tests. The government payments of the USDA baseline encompass the FAPRI projections over the length of the horizons. The composite projections created using the encompassing weights are more accurate than either of the two projections (Kuethe, Bora, and Katchova, 2021).

6 Conclusion

Both USDA and FAPRI baseline projections play an important role in shaping agricultural policy in the U.S. The baseline projections provide a conditional scenario against which alternative policies can be evaluated. In recent years, policymakers, agricultural businesses, and program administrators have used these projections extensively in their policy and investment decisions. Given the importance of the baseline projections 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.

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 (Isengildina-Massa et al., 2021; Bora, Katchova, and Kuethe, 2021), and the magnitude of the bias increases as the projection horizon increases. This finding 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, with farm price projections becoming uninformative only after 2-3 years and yield remaining informative for the entire projection horizon. The findings suggest that the projections may

be improved using better models and processes. The single-horizon tests comparing the two projections suggest that the FAPRI projections perform better at shorter horizons for net cash income and crop receipts, potentially due to the updated information available to the FAPRI projection process, which follows the USDA report by a few weeks. On the other hand, the USDA projection performs better at longer horizons for corn price and yield, soybean price, crop receipts, livestock receipts, and cash expenses. However, our multi-horizon comparison tests suggest that neither USDA nor FAPRI baselines outperform one another for most projected variables if we consider the full projection path. A notable exception is the FAPRI projection for farm-related income, which has uniform superior predictive ability over the USDA projection. Similarly, the USDA projection for corn price and soybean yield has uniform superior predictive ability over the FAPRI projection. For the rest of the variables, neither projection performs better than the other.

The findings of this study also underline the importance of stochastic analysis while producing the baselines. While the figures published in the baseline reports are point estimates, both the USDA and FAPRI perform additional stochastic analysis to project distributions for different future scenarios. One can expect the point estimates in the baseline reports to differ from actual values, as many of the analysts' assumptions may not realize. However, the stochastic analysis should account for such changed scenarios, and actual values should ideally lie within the projected distribution. The agencies have not always published the stochastic projections, or the stochastic projections have not received the same attention from users. The agencies may consider releasing stochastic projections in addition to their point projections to allow users to adapt the projections to different scenarios.

One limitation of our study is that some of our findings may be influenced by the projections made in the previous decade(s) as opposed to more recent projections. The baseline models and processes for both agencies have evolved and, hopefully, improved over time. The baseline projection process at both agencies has also been subject to changes in personnel and information technology infrastructure. The newer reports may have already addressed some issues related to bias or informativeness found in this study. Given our small sample size, we cannot undertake sub-sample analysis to see if our estimates of bias and informativeness remain steady over time.

Our findings provide valuable insights which may help improve the models and processes used to produce the projections by each organization. Our tests of informativeness might be especially useful for the desire to provide agricultural sector projections at longer horizons to examine issues related to technology adoption or climate change. The balance between empirical models and the judgment of a panel of experts employed by the baseline may also prove beneficial to other short-term USDA forecasts, including those of commodity production and trade. Furthermore, our findings provide important information to various market participants who use these projections.

To our knowledge, this is the first study to look into the accuracy and usefulness of agricultural

baselines. There are various directions in which agricultural baselines research could go in the future. Using a more comprehensive information set is one way to enhance the projections. For example, distant futures contract prices may be useful in projecting commodity prices, as suggested by Irwin and Good (2015) and extending the approach of Hoffman et al. (2015) beyond one year. Future revisions of the baseline projections may also benefit from examining the factors that may have contributed to systematic deviations from observed values in the past, such as failures to anticipate the ethanol boom, the growth in Chinese soybean demand, and Russia's emergence as a major wheat exporter. Another option is to improve the methodology, potentially using recent advances in machine learning.

Notes

¹Crops included in area planted are corn, sorghum, oats, barley, rye, winter wheat, Durum wheat, other spring wheat, rice, soybeans, peanuts, sunflower, cotton, dry edible beans, chickpeas, potatoes, sugarbeets, canola, and proso millet.

²FAPRI baseline projections are available for a few additional years before 1997, but for comparison with USDA, we limit our analysis to all years in which both sets of projections are available.

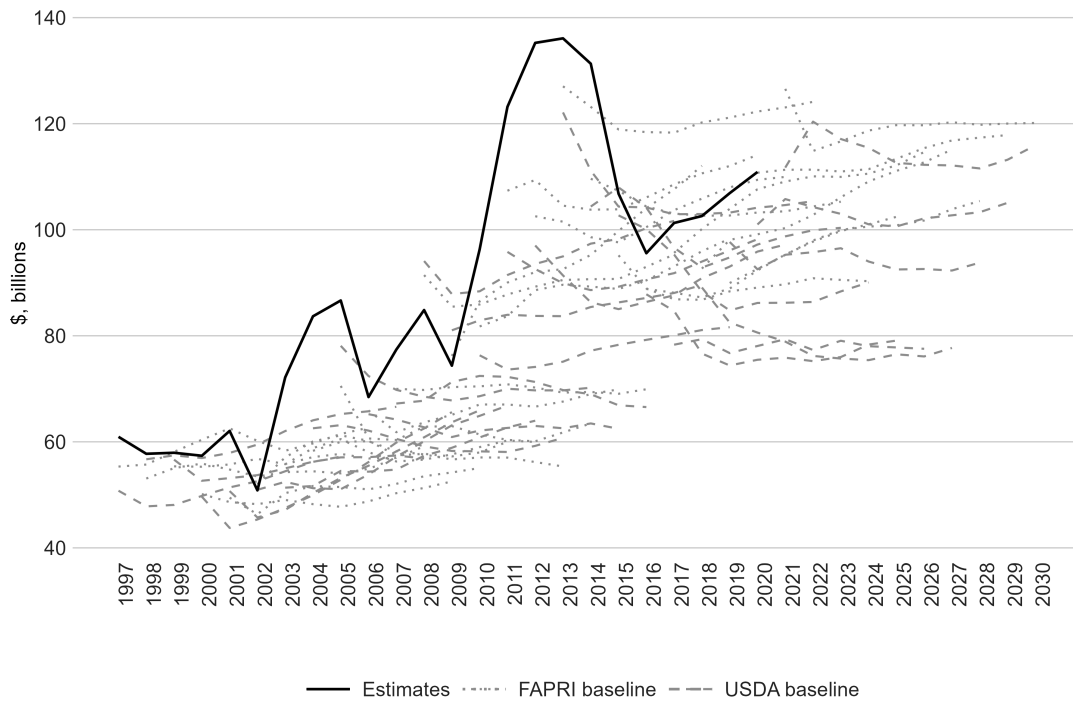
³In the forecast evaluation literature, projections made for $h = 0$ are sometimes referred to as *nowcasts*.

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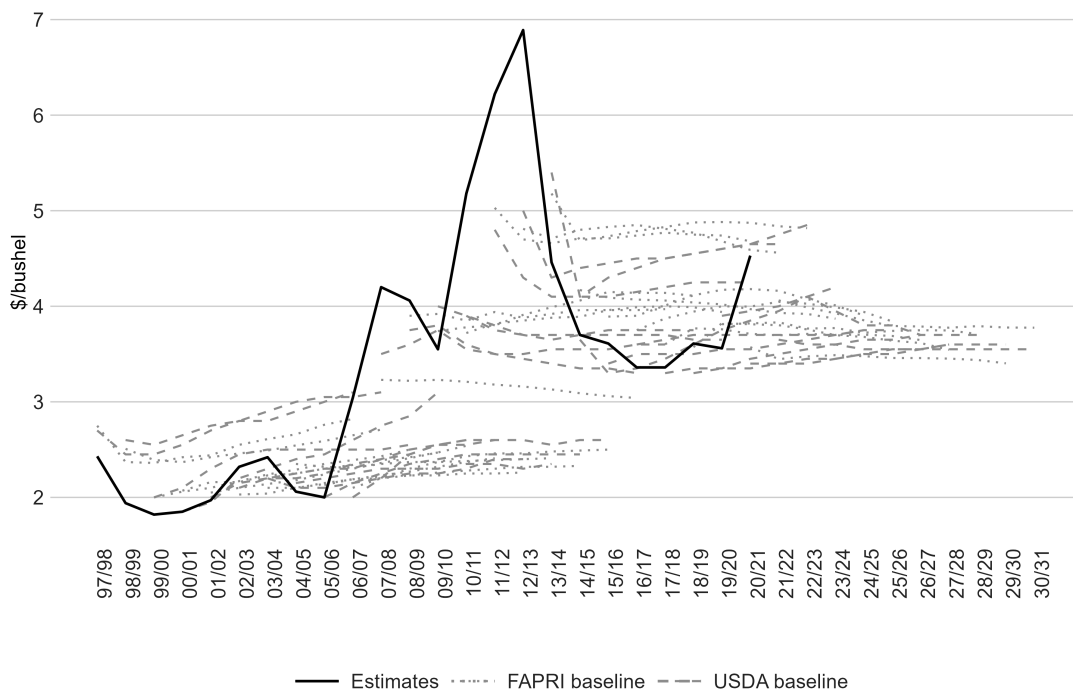
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(a) Net cash income realized values and baseline projections, 1997-2021



(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

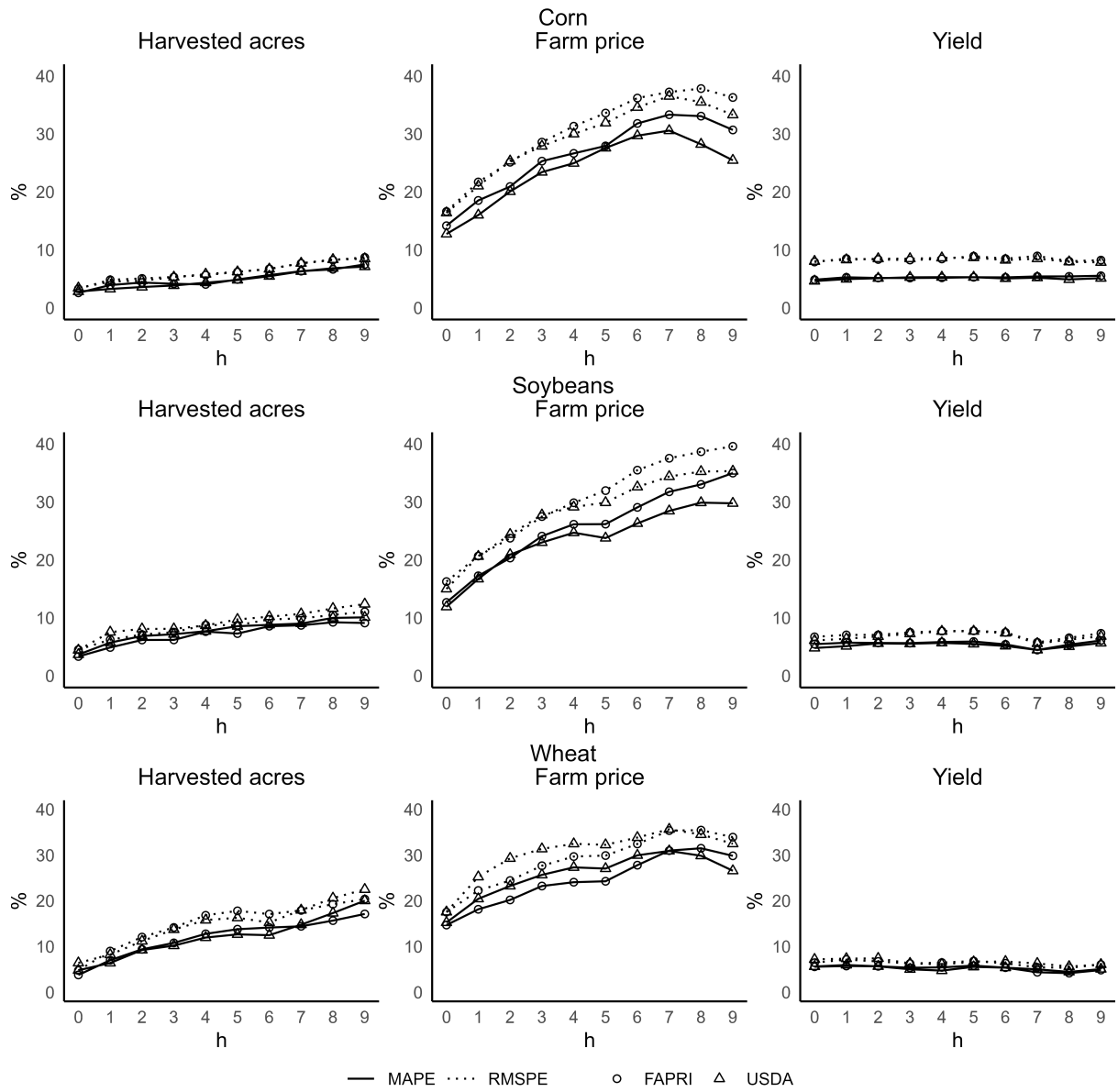


Figure 2: Mean absolute percent error (MAPE) and root mean square percent error (RMSPE) for baseline projections of corn, soybeans and wheat by projection horizon h , 1997–2020

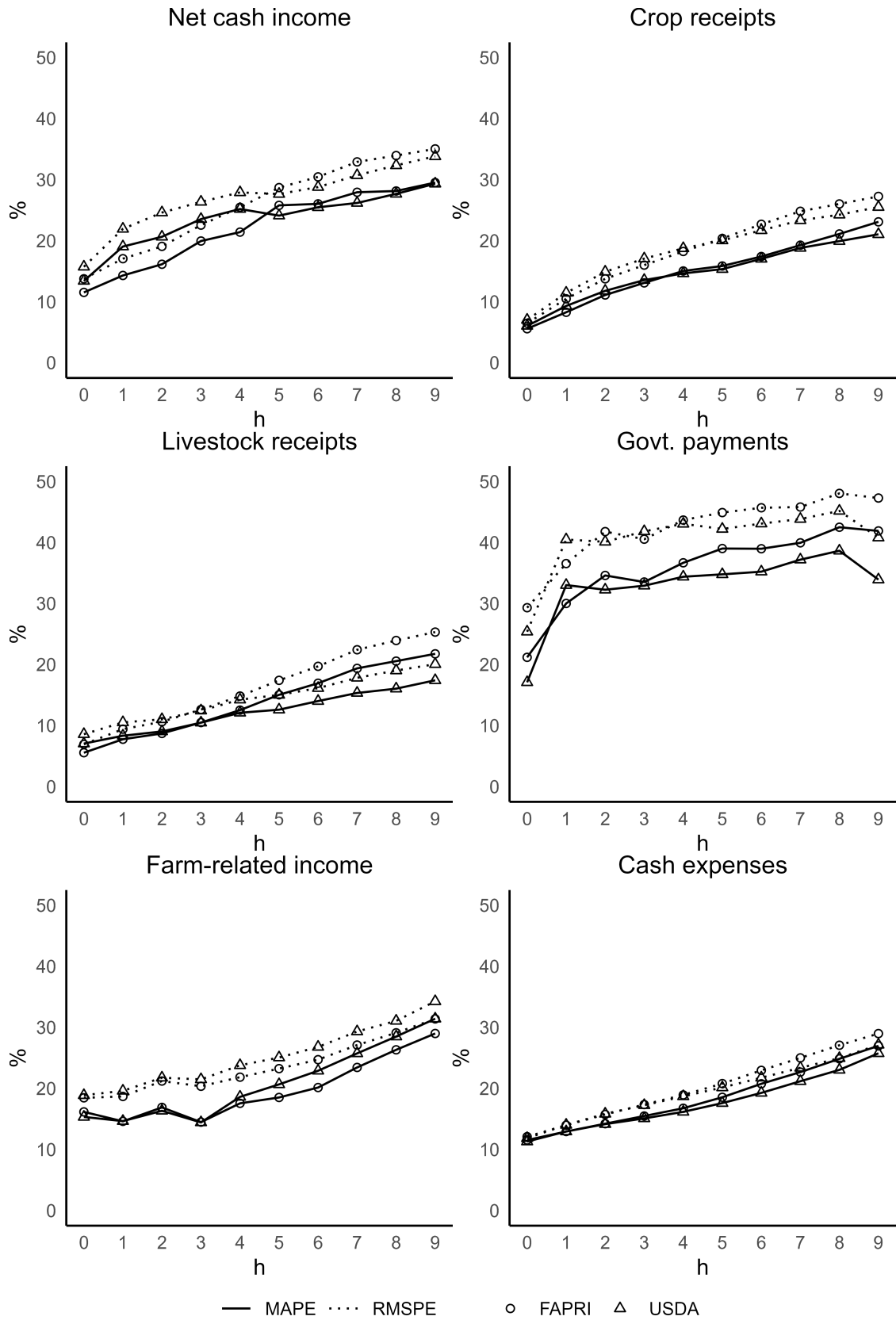


Figure 3: Mean absolute percent error (MAPE) and root mean square percent error (RMSPE) for baseline projections of net cash income and its components by projection horizon h , 1997–2020

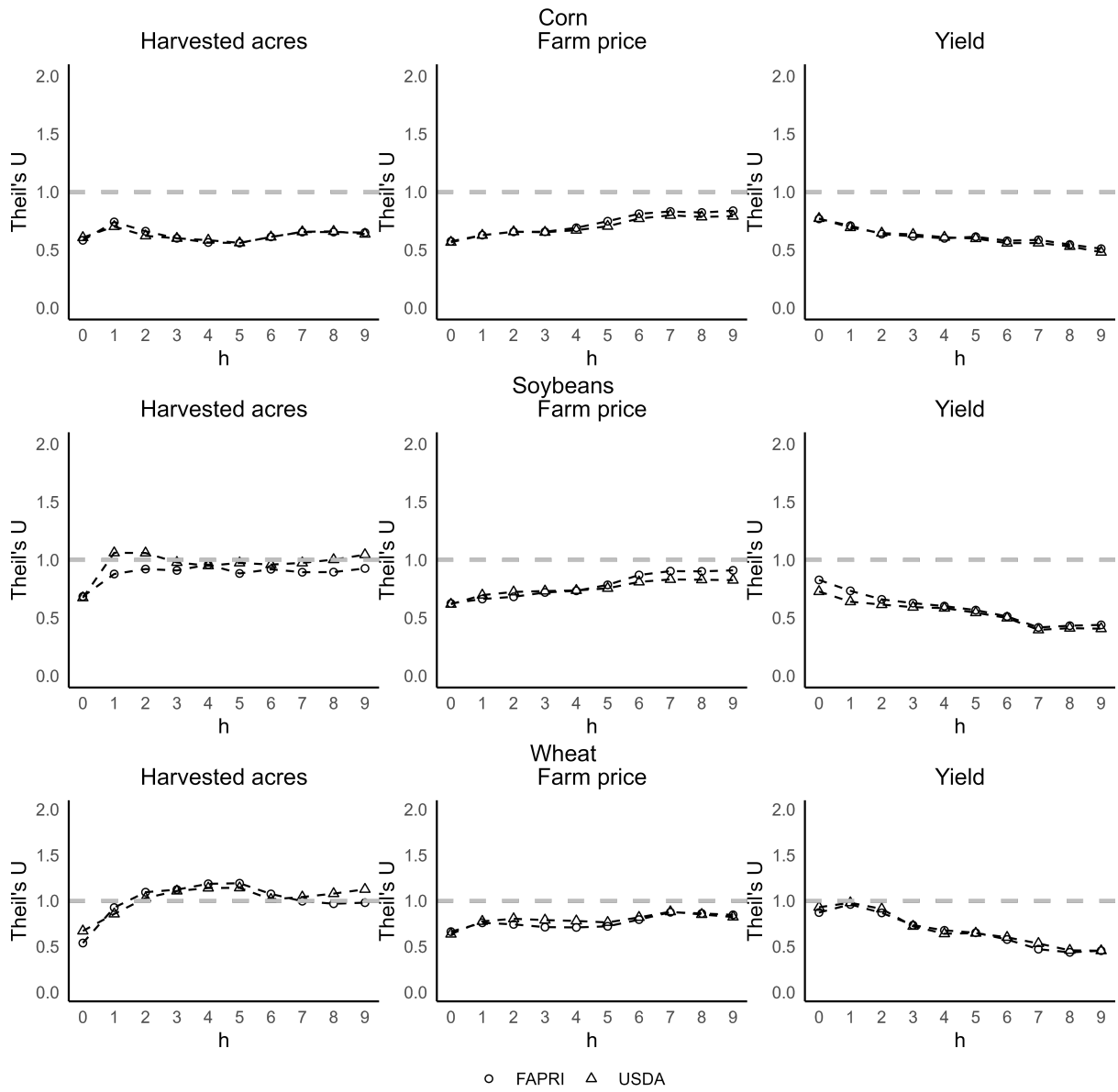


Figure 4: Theil's U for USDA and FAPRI baseline projections of corn, soybeans and wheat by projection horizon h , 1997–2020

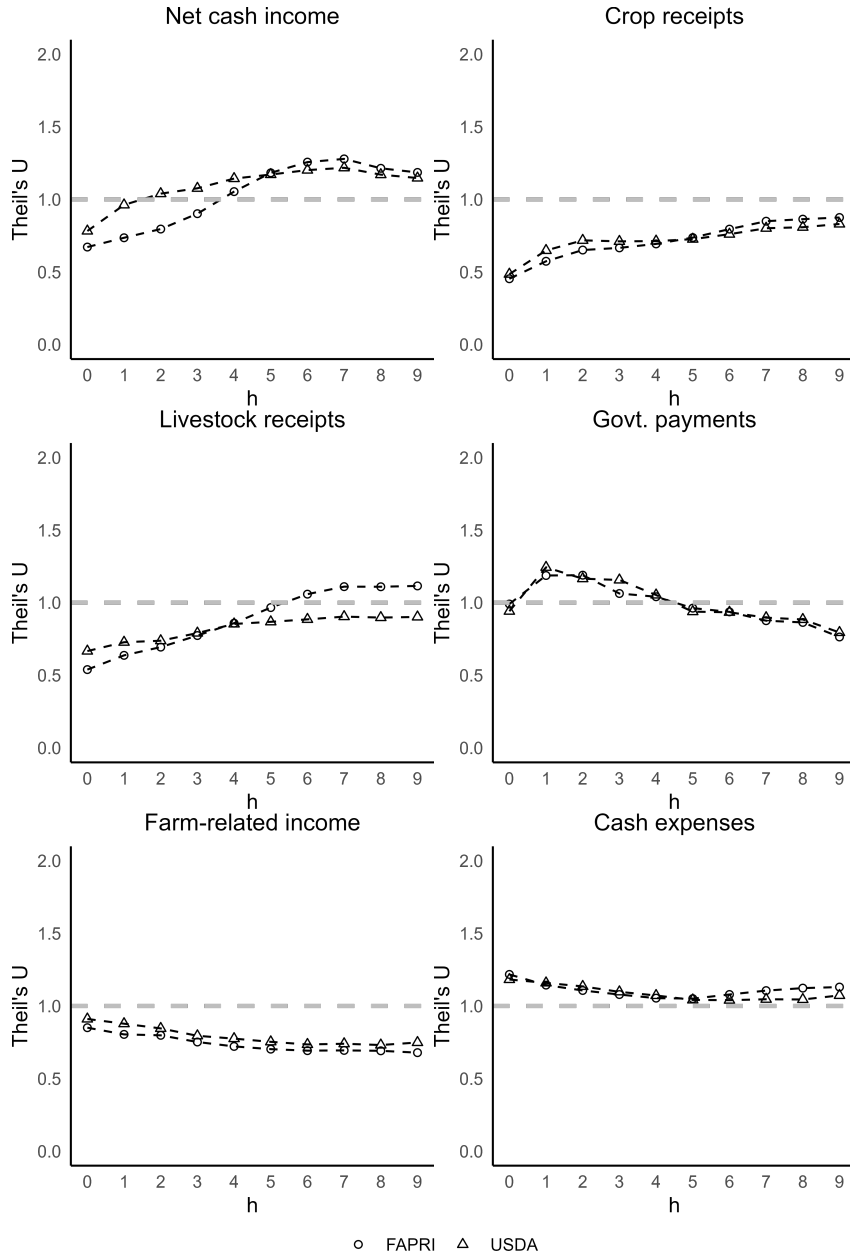


Figure 5: Theil's U for USDA and FAPRI baseline projections of net cash income and its components by projection horizon h , 1997–2020

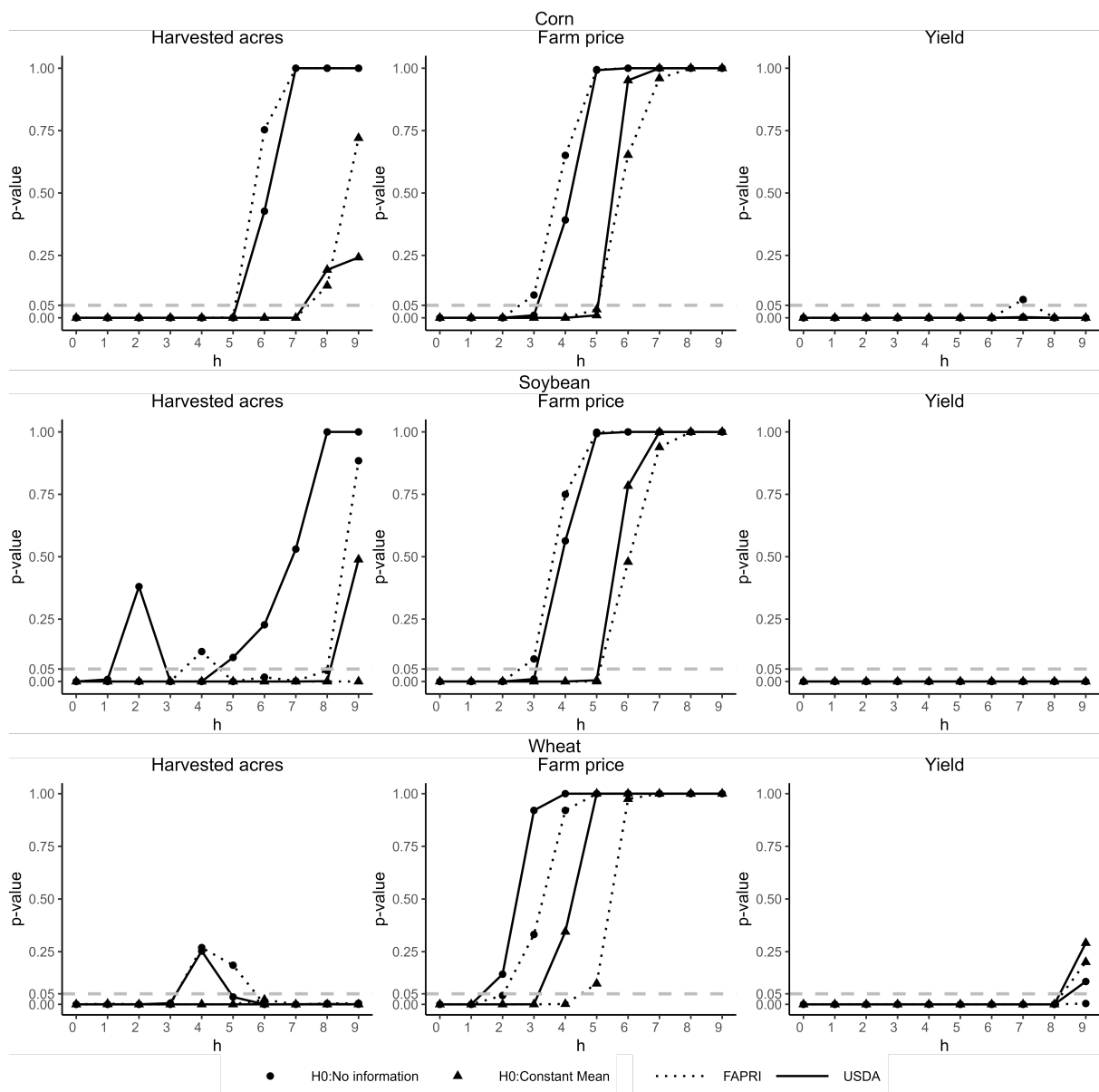


Figure 6: P-values for the tests of predictive content of the USDA and FAPRI commodity projections by horizon, 1997–2020

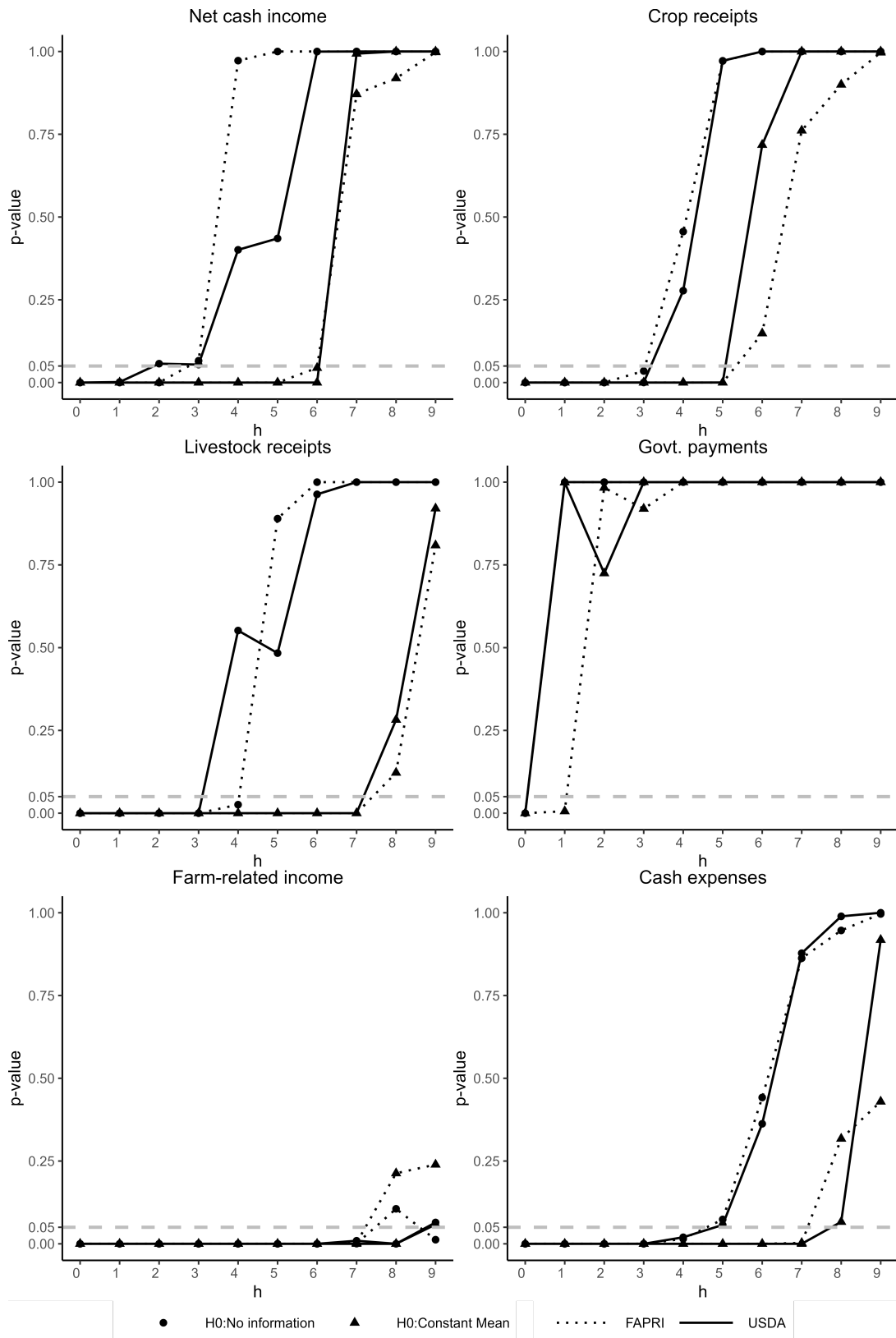


Figure 7: P-values for the tests of predictive content of the USDA and FAPRI farm income components projections by horizon, 1997–2020

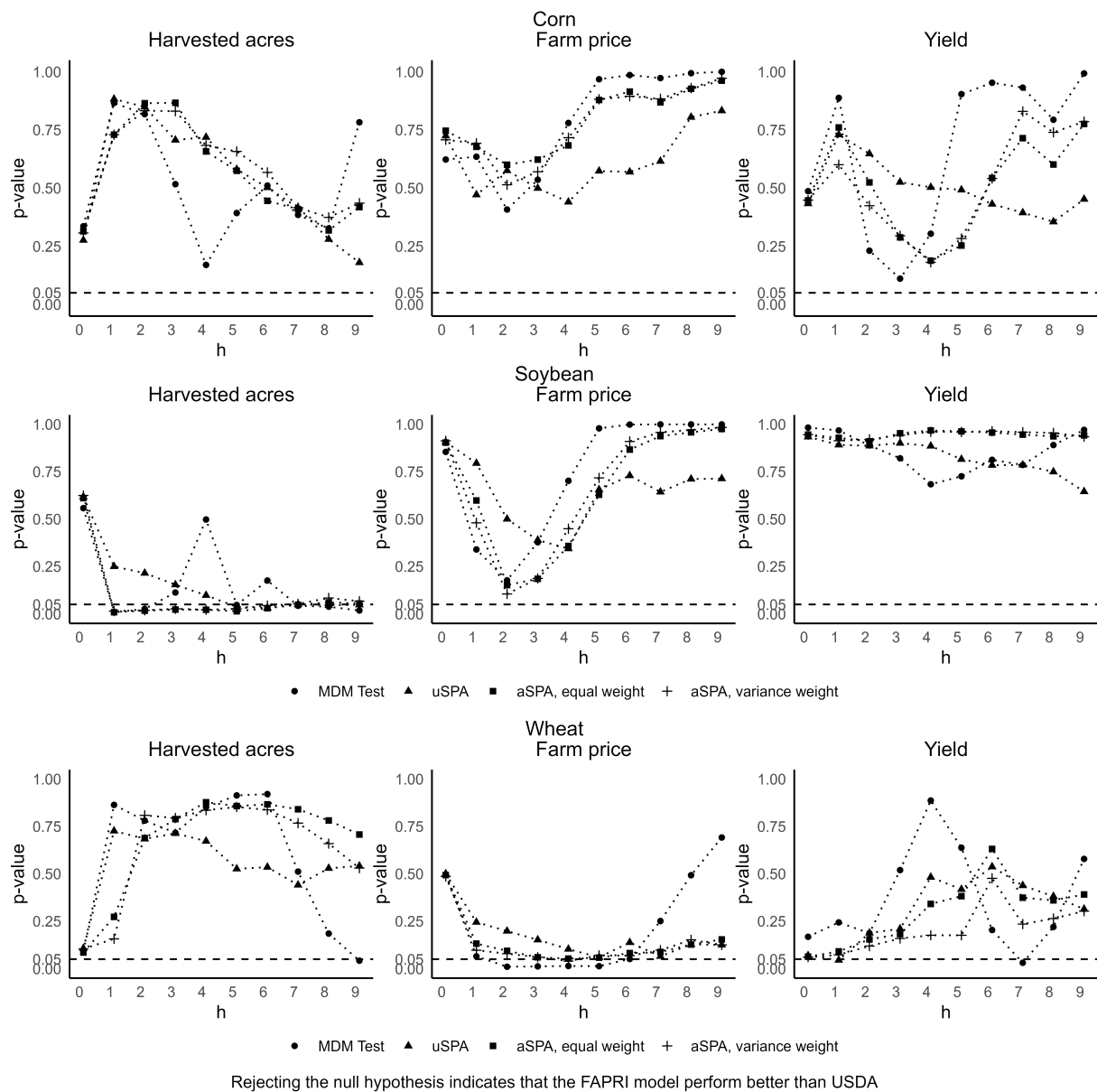
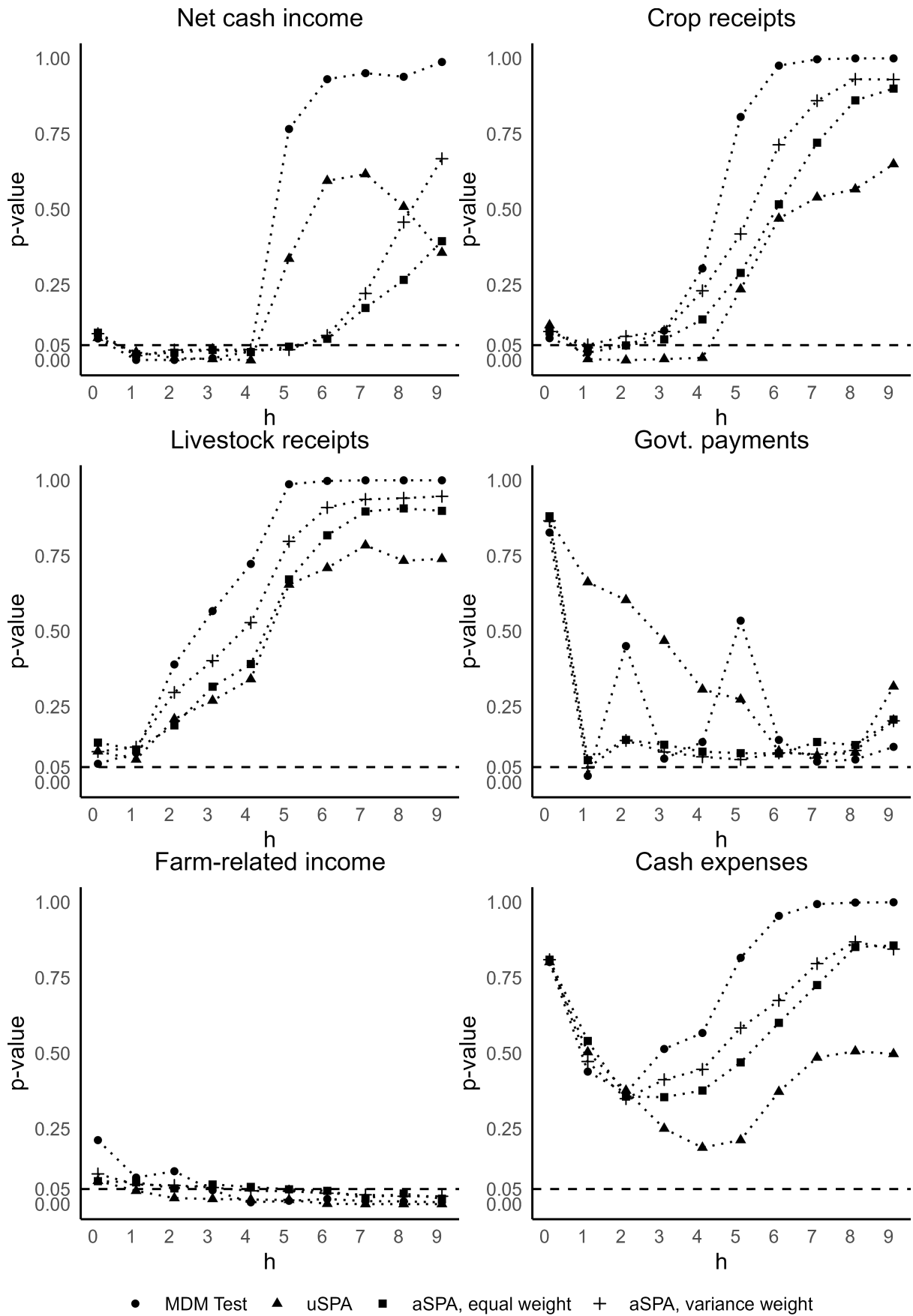


Figure 8: Multi-horizon comparison tests of USDA and FAPRI commodity projections by horizon, 1997–2020



Rejecting the null hypothesis indicates that the FAPRI model perform better than USDA

Figure 9: 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 (0.007)	−0.001 (0.009)	0.008 (0.012)	0.011 (0.014)	0.015 (0.018)	0.021 (0.021)	0.028 (0.025)	0.035 (0.027)	0.043 (0.030)	0.054 (0.031)
Farm price	0.049 (0.039)	0.080 (0.069)	0.095 (0.095)	0.113 (0.084)	0.136* (0.072)	0.160** (0.069)	0.181 (0.105)	0.207* (0.098)	0.262** (0.095)	0.322** (0.129)
Yield	−0.010 (0.018)	−0.008 (0.020)	−0.007 (0.021)	−0.006 (0.022)	−0.006 (0.023)	−0.005 (0.023)	0.000 (0.024)	0.002 (0.024)	−0.003 (0.022)	−0.002 (0.023)
Soybeans										
Harvested acres	0.008 (0.009)	0.028* (0.016)	0.040** (0.019)	0.055*** (0.018)	0.064*** (0.019)	0.072*** (0.020)	0.078*** (0.025)	0.085** (0.030)	0.090** (0.032)	0.098** (0.034)
Farm price	0.104*** (0.036)	0.133* (0.067)	0.147 (0.092)	0.164 (0.098)	0.184*** (0.060)	0.212*** (0.061)	0.236** (0.097)	0.251*** (0.071)	0.302*** (0.081)	0.360*** (0.082)
Yield	−0.002 (0.014)	−0.002 (0.016)	−0.002 (0.020)	0.002 (0.021)	0.005 (0.022)	0.005 (0.024)	0.009 (0.024)	0.019 (0.022)	0.018 (0.026)	0.016 (0.032)
Wheat										
Harvested acres	−0.040*** (0.008)	−0.046** (0.016)	−0.056* (0.028)	−0.071* (0.034)	−0.090** (0.038)	−0.102** (0.036)	−0.112*** (0.031)	−0.134*** (0.032)	−0.155*** (0.030)	−0.179*** (0.027)
Farm price	0.059 (0.047)	0.102 (0.088)	0.126 (0.101)	0.146* (0.080)	0.166* (0.094)	0.182** (0.069)	0.189** (0.084)	0.205* (0.116)	0.240** (0.112)	0.278* (0.137)
Yield	0.019 (0.015)	0.018 (0.017)	0.016 (0.015)	0.015 (0.014)	0.015 (0.013)	0.016 (0.015)	0.027 (0.017)	0.025 (0.015)	0.026* (0.014)	0.028* (0.015)
Farm income										
Net cash income	0.132*** (0.027)	0.194*** (0.041)	0.238*** (0.045)	0.267*** (0.038)	0.284*** (0.055)	0.288*** (0.065)	0.312*** (0.072)	0.330*** (0.088)	0.347*** (0.099)	0.376*** (0.096)
Crop receipts	0.036* (0.020)	0.060 (0.043)	0.081 (0.055)	0.097*** (0.033)	0.113*** (0.015)	0.134*** (0.012)	0.152*** (0.026)	0.172*** (0.042)	0.198*** (0.036)	0.249*** (0.066)
Livestock receipts	0.022 (0.018)	0.042* (0.023)	0.059** (0.028)	0.072** (0.033)	0.084* (0.044)	0.096* (0.049)	0.121** (0.052)	0.147** (0.053)	0.163** (0.057)	0.189*** (0.058)
Govt. payments	0.164 (0.096)	0.297* (0.168)	0.361* (0.188)	0.445** (0.196)	0.474** (0.210)	0.451** (0.209)	0.469** (0.222)	0.472* (0.228)	0.491** (0.214)	0.436* (0.209)
Farm-related income	0.048 (0.061)	0.092 (0.074)	0.124 (0.090)	0.151* (0.087)	0.193** (0.089)	0.235** (0.084)	0.274*** (0.076)	0.314*** (0.063)	0.351*** (0.060)	0.397*** (0.064)
Cash expenses	0.121*** (0.011)	0.140*** (0.021)	0.156*** (0.030)	0.168*** (0.035)	0.183*** (0.040)	0.201*** (0.020)	0.222*** (0.034)	0.246*** (0.032)	0.270*** (0.038)	0.305*** (0.042)

Notes: The bias term $\hat{\alpha}_h^{USDA}$ is estimated from the equation (3). ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively. Standard errors (in parentheses) are heteroskedasticity and autocorrelation consistent (HAC) (Newey and West, 1987). The sample sizes of regressions for $h=0,1,2,\dots,9$ are $T=24, 23,\dots, 15$ 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)	−0.006 (0.010)	−0.003 (0.013)	0.004 (0.015)	0.007 (0.020)	0.014 (0.021)	0.022 (0.025)	0.031 (0.028)	0.039 (0.032)	0.047 (0.033)
Farm price	0.026 (0.045)	0.047 (0.076)	0.071 (0.101)	0.094 (0.078)	0.124 (0.087)	0.156 (0.109)	0.189 (0.120)	0.223* (0.105)	0.284** (0.112)	0.350** (0.140)
Yield	−0.003 (0.018)	−0.001 (0.020)	−0.002 (0.022)	−0.002 (0.022)	−0.002 (0.023)	−0.003 (0.024)	0.001 (0.025)	0.001 (0.026)	−0.004 (0.024)	−0.003 (0.025)
Soybeans										
Harvested acres	0.003 (0.009)	0.020 (0.013)	0.034** (0.016)	0.042** (0.018)	0.054** (0.019)	0.062*** (0.020)	0.072*** (0.020)	0.079*** (0.023)	0.084*** (0.025)	0.089*** (0.028)
Farm price	0.077* (0.039)	0.091 (0.078)	0.105 (0.097)	0.137 (0.105)	0.168** (0.076)	0.211** (0.094)	0.249* (0.127)	0.273** (0.117)	0.329*** (0.109)	0.391*** (0.128)
Yield	0.009 (0.016)	0.009 (0.019)	0.009 (0.022)	0.012 (0.023)	0.013 (0.023)	0.013 (0.023)	0.014 (0.024)	0.024 (0.022)	0.023 (0.027)	0.022 (0.034)
Wheat										
Harvested acres	−0.026*** (0.008)	−0.048** (0.017)	−0.067** (0.029)	−0.084** (0.036)	−0.103** (0.036)	−0.111** (0.042)	−0.116*** (0.038)	−0.130*** (0.032)	−0.141*** (0.036)	−0.154*** (0.034)
Farm price	0.038 (0.059)	0.064 (0.086)	0.086 (0.092)	0.102 (0.083)	0.128 (0.108)	0.155 (0.106)	0.178 (0.110)	0.205 (0.145)	0.248 (0.150)	0.291* (0.143)
Yield	0.026* (0.013)	0.023 (0.015)	0.021 (0.014)	0.019 (0.013)	0.018 (0.014)	0.020 (0.016)	0.031** (0.014)	0.030** (0.012)	0.031** (0.011)	0.035** (0.014)
Farm income										
Net cash income	0.116*** (0.023)	0.147*** (0.032)	0.164*** (0.041)	0.190*** (0.055)	0.228*** (0.068)	0.261*** (0.087)	0.299*** (0.094)	0.326** (0.122)	0.354*** (0.100)	0.372*** (0.086)
Crop receipts	0.030* (0.017)	0.048 (0.040)	0.062 (0.053)	0.078** (0.035)	0.096*** (0.026)	0.121*** (0.036)	0.147*** (0.049)	0.170** (0.066)	0.203*** (0.061)	0.239*** (0.072)
Livestock receipts	0.030** (0.014)	0.044** (0.020)	0.059* (0.028)	0.080** (0.037)	0.107** (0.047)	0.136** (0.058)	0.175** (0.063)	0.206** (0.071)	0.230*** (0.072)	0.252*** (0.071)
Govt. payments	0.156 (0.094)	0.226 (0.157)	0.272 (0.202)	0.292 (0.178)	0.303 (0.239)	0.287 (0.242)	0.290 (0.249)	0.287 (0.246)	0.303 (0.218)	0.267 (0.241)
Farm-related income	0.032 (0.061)	0.056 (0.061)	0.087 (0.085)	0.113 (0.089)	0.156* (0.088)	0.201** (0.082)	0.240*** (0.077)	0.282*** (0.068)	0.321*** (0.062)	0.357*** (0.058)
Cash expenses	0.123*** (0.011)	0.140*** (0.018)	0.156*** (0.026)	0.172*** (0.034)	0.189*** (0.038)	0.212*** (0.038)	0.240*** (0.037)	0.266*** (0.042)	0.296*** (0.049)	0.325*** (0.050)

Notes: The bias term $\hat{\alpha}_t^{FAPRI}$ is estimated from the equation (3). ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively. Standard errors (in parentheses) are heteroskedasticity and autocorrelation consistent (HAC)(Newey and West, 1987). The sample sizes of regressions for h=0,1,2,...,9 are T=24, 23,..., 15 respectively.

Table 3:
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	5	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	2	1	4	3
Yield	9	8	8	8
Farm income				
Net cash income	2	1	6	6
Crop receipts	3	3	5	5
Livestock receipts	4	3	7	7
Govt. payments	0	0	1	0
Farm-related income	7	8	7	8
Cash expenses	4	4	7	7

Table 4: Encompassing Tests

item	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	0.599 (0.393)	0 ⁺⁺ (0.365)	0.061 ⁺⁺⁺ (0.280)	0.319 (0.405)	0.631 (0.538)	-0.013 (0.840)	-0.149 (0.723)	0.271 (1.267)	0.188 (0.750)	-1.091 (1.333)
Farm Price	0.132 ⁺⁺ (0.372)	0.009 ⁺ (0.550)	0.353 (0.838)	0.189 (1.000)	-0.247 (1.165)	-0.985 (1.600)	-1.18 (1.826)	-0.729 (1.565)	-1.043 (1.194)	-0.939 ⁺ (1.022)
Yield	-0.185 (1.462)	-2.067 (2.932)	1.201 (1.839)	2.058* (1.113)	1.244 (1.462)	-1.546 (1.978)	-1.996 (1.803)	-2.831 (2.391)	-0.53 (1.565)	-1.628 ⁺⁺ (0.934)
Soybean										
Harvested acres	0.298 (0.650)	1.761 ^{***} (0.618)	1.539 ^{***} (0.496)	0.369 ⁺⁺ (0.293)	-0.597 ⁺⁺ (0.568)	1.018 (0.715)	0.792 (0.701)	1.574 ^{***} (0.394)	2.396 ⁺⁺⁺⁺ (0.371)	2.204 ^{***} (0.678)
Farm Price	-0.888 ⁺⁺⁺ (0.519)	-0.884 ⁺⁺ (0.717)	-0.002 (0.840)	-0.287 (1.415)	-0.479 (1.150)	-1.094 ⁺ (1.029)	-1.578 ⁺ (1.220)	-1.529 ⁺⁺⁺⁺ (0.681)	-1.615 ⁺⁺⁺⁺ (0.418)	-2 ⁺⁺⁺⁺ (0.458)
Yield	-2.578 ⁺⁺⁺⁺ (1.021)	-2.215 ⁺⁺ (1.140)	-0.768 ⁺⁺ (0.714)	-0.286 (1.337)	0.417 (0.855)	-0.041 (1.387)	0.026 (0.933)	0.073 (1.575)	-0.323 (1.356)	-1.199 ⁺⁺ (0.927)
Wheat										
Harvested acres	0.745 ^{***} (0.222)	-0.081 ⁺ (0.612)	0.489 (0.549)	0.747 (0.744)	0.484 (0.533)	0.071 ⁺⁺ (0.359)	-0.326 ⁺⁺⁺ (0.435)	0.216 ⁺ (0.443)	0.371 (0.407)	0.085 ⁺⁺⁺ (0.231)
Farm Price	0.301 (0.486)	0.896 (0.798)	1.509 (0.883)	1.748 ^{**} (0.695)	1.847 ^{**} (0.787)	1.486 ^{**} (0.693)	1.444 (0.858)	1.006 (1.038)	0.657 (1.202)	0.47 (0.776)
Yield	1.93 ^{**} (0.725)	1.493 [*] (0.780)	2.089 [*] (1.086)	0.733 (0.691)	-0.124 ⁺ (0.562)	0.48 (0.681)	1.463 [*] (0.805)	2.012 ^{***} (0.623)	1.207 ^{**} (0.409)	0.907 (0.618)
Farm Income										
Expenses	0.374 (0.597)	0.691 (0.629)	1.252 (0.881)	1.261 (0.791)	1.141 (0.777)	0.733 (0.698)	0.482 (0.690)	-0.139 ⁺⁺ (0.400)	-0.41 ⁺⁺⁺⁺ (0.160)	-0.956 ⁺⁺⁺⁺ (0.526)
Crop Receipts	1.134 (0.700)	1.421 (1.099)	0.88 (1.233)	0.56 (1.250)	0.186 (1.140)	-0.296 (1.076)	-0.631 (1.151)	-0.761 (1.176)	-0.87 (1.132)	-1.491 ⁺⁺⁺⁺ (0.673)
Farm-related Income	1.511 (0.967)	1.813 (1.301)	0.781 (1.218)	0.486 (0.914)	1.125 (1.057)	0.619 (0.917)	0.392 (0.884)	0.944 (0.639)	0.678 (0.737)	1.673 ^{**} (0.449)
Government Payments	0.156 ⁺⁺⁺ (0.198)	0.697 ^{**} (0.309)	0.153 ⁺⁺ (0.397)	0.363 (0.487)	-0.283 ⁺⁺ (0.603)	-0.739 ⁺⁺ (0.610)	-0.626 ⁺⁺ (0.633)	-0.392 ⁺⁺ (0.590)	-0.445 ⁺⁺ (0.553)	-0.238 ⁺⁺⁺ (0.380)
Livestock Receipts	1.469 ^{***} (0.437)	1.34 ^{**} (0.595)	0.671 (0.657)	0.672 (0.667)	0.942 (0.674)	0.197 (0.636)	-0.152 ⁺⁺ (0.487)	-0.531 ⁺⁺⁺ (0.431)	-0.571 ⁺⁺⁺ (0.391)	-0.958 ⁺⁺⁺⁺ (0.284)
Net Cash Income	0.858 ^{***} (0.286)	1.196 ^{***} (0.275)	1.061 ^{***} (0.268)	0.484 ⁺⁺⁺⁺ (0.202)	-0.026 (0.595)	-0.747 ⁺⁺⁺⁺ (0.406)	-0.67 ⁺⁺⁺⁺ (0.382)	-0.503 ⁺⁺⁺ (0.370)	-0.161 ⁺⁺ (0.485)	-0.351 ⁺⁺ (0.475)

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