The Rationality of USDA Forecasts under Multivariate Asymmetric Loss

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Abstract

A large number of previous studies suggest that many USDA forecasts are biased and/or inefficient. These findings, however, may be the result of the assumed loss function of USDA forecasters. We test the rationality of the USDA net cash income forecasts and the WASDE production and price forecasts between 1988-2018 using a flexible multivariate loss function that allows for asymmetric loss and non-separable forecast errors. Our results provide robust evidence that USDA forecasters are rational expected loss minimizers yet demonstrate a tendency to place a greater weight on under- or over-prediction. As a result, this study provides an alternate interpretation of previous findings of forecast irrationality.

Key words: asymmetric loss, fixed-event forecasts, forecast rationality, net cash income, WASDE.

JEL codes: D84, E37, Q11, Q12, Q13, Q14

> "The U.S. Agriculture Department said on Wednesday it had pulled all staff from an annual crop tour after an employee was threatened, and three sources said the threat of violence was made during a phone call from an angry farmer."
>
> Huffstutter and Polansek (2019)

The Federal government's statistical agencies and programs generate a large volume of data that "the public, businesses, and governments need to make informed decisions" (Office of Management and Budget 2018, pp. 3). The U.S. Department of Agriculture (USDA) plays an important role within the Federal government's statistical agencies and programs. The USDA is responsible for producing a variety of principal federal economic indicators. Further, the USDA is home to two of the Federal government's thirteen principal statistical agencies, the National Agricultural Statistics Service (NASS) and the Economic Research Service (ERS), which accounted for approximately 8% of the $3.2 billion appropriated to primary statistical agencies in fiscal year 2017 (Office of Management and Budget 2018). In order to provide timely information for decision-makers across the agricultural sector, the USDA's statistical agencies and programs provide forecasts of agricultural production, prices, trade, uses, inventories, and farm income. The existing literature, however, suggests that many USDA forecasts are not rational (Bailey and Brorsen 1998; Sanders and Manfredo 2003; Isengildina, Irwin, and Good 2006; Isengildina-Massa, MacDonald, and Xie 2012; Xiao, Hart, and Lence 2017; Kuethe, Hubbs, and Sanders 2018). The overwhelming evidence of irrationality may lead many forecast users to question the usefulness of USDA forecasts.

In this paper, we study the degree to which prior findings of irrationality in USDA forecasts can be attributed to assumptions researchers make about the costs of forecast errors, by examining the forecaster's loss function. The conventional practice is (i) to assume *a priori* that USDA forecasts are generated to minimize a mean squared error (MSE) loss function and (ii) to test the weak form conditions of rationality under MSE loss.[1] Many of the weak form conditions of forecast rationality, however, do not hold under other loss functions (Patton and Timmermann 2007). As a result, rejections of forecast rationality may be due to misspecified loss functions, rather than lack of rationality (Elliott, Timmermann, and Komunjer 2005). Our empirical approach, by contrast, only assumes that the forecaster's loss function belongs to a flexible class of loss functions, of which MSE is a special case. We then back out the parameters of the loss function that are consistent with the observed forecasts.

As Auffhammer (2007) argues, a forecast is only optimal for a particular forecast user when his or her loss function matches that of the forecast producer. As a result, we empirically estimate the loss functions associated with two of USDA's most prominent forecasts from 1988 through 2018. First, we examine USDA's forecasts of annual net farm income and its components. The USDA's farm income forecasts are among the department's most cited statistics (McGath et al. 2009). They are closely monitored by various farm sector stakeholders, including farm input and machinery suppliers, lenders, other farm related industries, and state and local governments (Dubman, McElroy, and Dodson 1993). In addition, USDA's farm income forecasts are frequently cited in farm policy debates in Congress and are inputs in numerous other statistical models, such as the estimation of gross domestic production (McGath et al. 2009). Second, we examine a set of production and price forecasts from the World Agricultural Supply and Demand Estimates (WASDE) for three major commodities: corn, soybeans, and wheat. WASDE is an important source of information for commodity production, consumption, trade, and prices. The existing literature provides robust evidence that WASDE releases move commodity markets (Sumner and Mueller 1989; Fortenbery and Sumner 1993; Isengildina-Massa et al. 2008; McKenzie 2008; Adjemian 2012; Dorfman and Karali 2015; Adjemian and Irwin 2018; Karali et al. 2019; Isengildina-Massa et al. 2020a). Further, the USDA production forecasts were subject to intense scrutiny during the recent 2019 growing season. USDA's corn acreage and yield forecasts were even believed to motivate threats of violence against USDA employees by disgruntled farmers (Huffstutter and Polansek 2019).

This study makes a number of important contributions to the literature. First, our empirical approach relaxes the assumptions of MSE loss. We build on the generalized method of moments (GMM) framework of Elliott, Timmermann, and Komunjer (2005) that jointly estimates the forecaster's loss function and tests for rationality of the forecasts. Elliott, Timmermann, and Komunjer's method is flexible as it allows for several parameterizations, as well as asymmetry in the loss function due to differential costs of over- and under-prediction. As detailed in the next section, there are a number of reasons to believe that the bias and inefficiencies documented in USDA forecasts may be the direct result of asymmetric costs of over- and under-prediction.

Second, we evaluate forecasts in a multivariate framework. The overwhelming majority of prior evaluations of USDA forecasts test rationality on each variable independently, even though the forecasts are released as joint forecasts of several variables.[2] This practice implicitly assumes that the marginal costs for forecast errors in one variable are independent of the costs for other variables or that there are no interactions between variables. Thus, previous researchers implicitly assume separable loss functions. We instead apply the estimation procedure of Komunjer and Owyang (2012) that generalizes the approach of Elliott, Timmermann, and Komunjer (2005) to a multivariate setting with non-separable loss. Both net farm income and WASDE are based on accounting equations, so the forecast errors of each variable likely depend on the errors of other variables. For example, within the farm income forecast, the costs associated with over-predicting cash receipts are compounded when jointly under-predicting cash expenses, or within WASDE, the costs associated with over-predicting yields are compounded when jointly over-predicting acreage.

Third, while our results are generally consistent with previous findings, our analysis yields an alternative interpretation of the results of prior research. Batchelor (2007) draws a distinction between a rational *forecaster* and a "technically" rational *forecast*. A rational forecaster uses all available information when constructing a forecast, as in Muth (1960), and a forecast is "technically" rational when it is unbiased and efficient, as in Diebold and Lopez (1996). Batchelor (2007) identifies three possible explanations why rational forecasters may publish "technically" irrational forecasts. One, the forecaster may lack the skill to use information efficiently and learn from forecasting errors. Two, the forecaster may have the skill to use information efficiently, but the forecaster's information set is insufficient. Three, the forecaster may have skill and sufficient data but responds to incentives to make an optimistic or pessimistic forecast, namely, the forecaster responds to asymmetries in the consequences of over- versus under-prediction. We find robust evidence that USDA forecasts are generated to minimize an asymmetric loss function. While many USDA forecasts are technically irrational under traditional tests (biased and/or inefficient), this study suggests that USDA forecasters are rational expected loss minimizers under asymmetric loss. As Keane and Runkle (1990, pp. 719) state, "if forecasters have differential costs of over- and under-prediction, it could be rational for them to produce biased forecasts. If we were to find that forecasts are biased, it could still be claimed that forecasters were rational if it could be shown that they had such differential costs."

Background

As Elliott and Timmermann (2008, pp. 8) suggest, "no forecast is going to always be correct, so a specification of how costly different mistakes are is needed to guide the procedure." The loss function is a mathematical representation of the costs associated with forecast errors, and forecasters generate projections that minimize the expected loss function. Elliott and Timmermann (2008) argue that the loss function interpretation of forecast evaluation is valid when (i) forecasters care about the accuracy of their forecasts, and (ii) forecasters can adjust their forecasts in a way that incorporates any costs associated with forecast errors. The two most common loss functions employed in the existing literature are mean squared error (MSE) and mean absolute error (MAE).

Forecast evaluation under MSE is particularly popular because rationality implies a number of properties that can be easily tested empirically. A rational forecast under MSE loss is unbiased, forecast errors are serially uncorrelated, and the unconditional variance of the forecast error is a non-decreasing function of the forecast horizon (Diebold and Lopez 1996). However, many forecasts fail to meet these conditions. Traditional tests of forecast rationality under MSE loss suffer from the "joint hypothesis problem," as rejection of rationality stems from either irrationality of the forecasts or a misspecified test (Fritsche et al. 2015). Thus, traditional rationality tests may be misspecified with respect to the assumed loss function of the forecaster.

The loss function is sometimes referred to as the utility function of the forecast producer. Kahneman and Tversky (1973) argue that forecasters may intentionally produce technically irrational forecasts because of behavioral biases in information processing. For example, when forecasters have a large utility of a positive outcome, they may assign greater probability weights to some values out of anticipation, hope, or greed (Weber 1994). Similarly, when forecasters have a large disutility of a negative outcome, they may assign greater probability weights to some values out of fear of the negative consequences associated with underestimating probability (Weber 1994). The asymmetries in probability weights mirrors the asymmetric reaction to gains and losses (Kahneman and Tversky 1979). Asymmetries in the consequences of over- or under-prediction of uncertain quantities are frequently referred to as *asymmetric loss functions*. Weber (1994) demonstrates that asymmetric loss functions can be derived from either an expected utility or a rank-dependent utility framework.

West, Edison, and Cho (1993) argue that an asymmetric loss function is a natural candidate to evaluate forecasts when one seeks to emulate a utility-function-based approach to forecast evaluation. Under asymmetric loss functions, the optimal forecast is the conditional mean (MSE) or median (MAE) plus an optimal bias term (Granger 1969; Zellner 1986b; Christoffersen and Diebold 1997; Granger 1999). The size of the optimal bias will depend on the parameters of the loss function (Granger 1969). In addition, the forecast errors will not be orthogonal to variables in the forecaster's information set (Batchelor and Peel 1998). Patton and Timmermann (2007) assert that optimal forecasts are only unbiased when they meet the "double symmetry" condition, in which both the variable forecasted and the forecaster's loss function are distributed symmetrically.

In addition to internal asymmetric costs, such as anticipation or fear, forecasters may face external asymmetric consequences for forecast errors (Weber 1994). For example, Laster, Bennett, and Geoum (1999) show that when forecasters are rewarded based on both accuracy and their ability to generate publicity, their efforts to attract publicity may compromise forecast accuracy. In an experimental setting, Maddox and Bohil (1998) show that people react in the appropriate direction to asymmetric payoff functions, but they are often too conservative in their reactions. In addition to publicity, forecasters may derive some benefit from cultivating a reputation as optimists or pessimists (Batchelor and Dua 1990). For example, when forecasters rely on others for information, optimism may help to build relationships with information providers (Francis, Hanna, and Philbrick 1997; Francis and Philbrick 1993; Lim 2001). Similarly, forecasters may alter their predictions to make their forecasts more attractive to particular client groups or forecast users (Batchelor 2007). While USDA forecasters may be subject to limited internal asymmetric costs, such as anticipation or fear, they may be subject to external asymmetric consequences for forecast errors, given their reliance on information from farmers and other agricultural sector professionals, who are also USDA forecast users.

Asymmetric loss functions carry important consequences for fixed event forecasts, such as USDA's farm income or WASDE forecasts. Kahneman and Tversky (1973) argue that forecasters may overweight their own past forecasts and under-react to new information. Thus, any bias in initial forecasts will propagate forward. Batchelor (2007) demonstrates that bias in initial forecasts will also propagate forward if forecasters face penalties for forecast revision or are rewarded for consistency. Given that the optimal forecast under asymmetric loss includes an optimal bias, any asymmetric loss early in the forecast process may carry forward throughout later forecast revisions.

An asymmetric loss function in any one forecast may also carry important consequences for later forecasts of other economic variables. When forecasts are made sequentially by different agents, each published forecast becomes part of the information set of the next forecaster. Graham (1999) demonstrates that this process of "information cascades" may lead to herding when later forecasts are biased towards early forecasts.[3] As previously stated, USDA produces a variety of forecasts, and any asymmetries in one USDA forecast may carry over to later USDA forecasts through information cascades. For example, if WASDE forecasts project a significant decline in the production of a particular commodity, this information will likely be incorporated in the USDA farm income forecasts.

Finally, the existing literature offers several explanations as to why forecasts produced by government agencies, such as USDA, may be generated under asymmetric loss. A number of previous studies suggest that government agency forecasts tend to be conservative or cautious (Capistrán 2008; Ellison and Sargent 2012; Caunedo et al. 2018). Government forecasters may be cautious because stability is a crucial economic policy goal (Capistrán 2008), policy-making may require "worst case scenario" forecasts (Ellison and Sargent 2012), or over-predicting prosperity may be worse for policymakers than under-predicting (Caunedo et al. 2018). In addition, government forecasts may also be used to stimulate some private sector response (Estrin and Holmes 1990). For example, Beaudry and Willems (2018) demonstrate that overly optimistic GDP growth forecasts triggers public and private debt accumulation. Finally, it has been argued that government agency forecasts may be used as an instrument to justify a particular policy response (Jonung and Larch 2006; Frankel 2011) or to put the incumbent party in a favorable light (Ulan, Dewald, and Bullard 1995).

As previously stated, traditional forecast evaluation methods test the weak form properties of rationality under an assumed loss function, such as MSE or MAE, yet whether one can conclude that bias or inefficiency represents irrationality requires knowledge of the shape of the forecaster's loss function (Keane and Runkle 1998). A number of studies develop alternative loss functions that account for asymmetry (Varian 1975; Zellner 1986a; Christoffersen and Diebold 1996; Batchelor and Peel 1998; Granger and Pesaran 2000; Ulu 2013).

Elliott, Timmermann, and Komunjer (2005), in contrast, develop an alternative forecast evaluation framework that maintains the assumption of loss minimizing behavior and estimates the shape of the loss function, or class of loss functions, that are consistent with the observed forecasts. The method is flexible as it allows for several alternative parameterizations of the loss function, with symmetry as a special case. Elliott, Timmermann, and Komunjer's (2005) method jointly estimates the asymmetry parameters of the forecaster's loss function and tests for rationality of the forecasts. Krüger and LeCrone (2019) show that this method has a high power and is robust to fat tails, serial correlation, and outliers. The method has been used to evaluate forecasts of a number of economic variables by professional forecasters (Aretz, Bartram, and Pope 2011; Pierdzioch, Rülke, and Stadtmann 2013; Mamatzakis and Koutsomanoli-Filippaki 2014; Fritsche et al. 2015; Pierdzioch, Reid, and Gupta 2016; Tsuchiya 2016a,b; Christodoulakis 2020), government agencies (Auffhammer 2007; Krol 2013; Tsuchiya 2016a; Giovannelli and Pericoli 2020), international organizations (Christodoulakis and Mamatzakis 2008; Tsuchiya 2016a; Giovannelli and Pericoli 2020), and central banks (Capistrán 2008; Baghestani 2013; Pierdzioch, Rülke, and Stadtmann 2015; Ahn and Tsuchiya 2019; Caunedo et al. 2020). These studies overwhelmingly suggest that forecasts that are biased or inefficient under MSE loss are rational under asymmetric loss.

Description of USDA Forecasts

Farm Income Forecasts

Since 1910, the USDA has produced annual estimates of net farm income, a measure of the return to farm operators for their labor, capital, and management after all production expenses are deducted (Lucier, Chesley, and Ahearn 1986). USDA's official farm income estimates are produced with a significant time lag. They are typically released in August following the reference year. In order to provide more timely information, the USDA produces a series of forecasts each year. The forecasts relate to a calendar year and are typically released in February, August, November, and the following February.[4] The August forecast coincides with the release of the official estimates of the prior year, and the last forecast in February coincides with the release of the first forecast of the new calendar year.

USDA's farm income accounts include a variety of income and wealth measures. Our analysis examines the vector of forecasts related to net cash income. Net cash income (NCI) is a measure of farm-sector earnings, including cash receipts from farming, farm-related income, and government payments less cash expenses. It is calculated using the accounting equation:

$$\begin{aligned} \text{Net Cash Income (NCI)} &= \text{Crop Receipts (CR)} + \text{Livestock Receipts (LR)} \\ &+ \text{Direct Government Payments (GP)} \\ &+ \text{Cash Farm-Related Income (FRI)} \\ &- \text{Cash Expenses (EXP).} \end{aligned} \tag{1}$$

Crop receipts include cash receipts from eight major crops, and livestock receipts include four categories (meat animals, dairy products/milk, poultry and eggs, and miscellaneous livestock). Direct government payments represent funds that the Federal Government pays to farmers and ranchers who produce program commodities, participate in resource conservation, and receive compensation for natural disasters. Cash farm-related income includes income from items such as recreational activities, custom work, machine hire, forest products, and other farm sources. The first four items are added up to calculate gross cash income, after which cash production expenses are subtracted to arrive at net cash income. Since cash farm-related income forecasts are not available for most of the years and since cash farm-related income contributes less than 10% to gross cash income, we exclude this variable from our analysis.

McGath et al. (2009) document the economic model and estimation procedure for each component. The forecast procedure relies on data obtained from a variety of sources, including WASDE, Agricultural Resource Management Survey (ARMS), and NASS. While the data sources remain constant throughout the farm income forecast process, the timing of the release of the forecast revisions is selected to reflect changes in information. For example, the August revision reflects updates in crop production estimates and cash receipts from the USDA's survey-based production and yield estimates, and the November revision reflects updated crop production and harvest information. As time progresses, many of the forecasted values are substituted with the official estimates. For example, by February of next year, the WASDE acreage and yield values are final estimates, however, prices for the marketing year remain forecasts (McGath et al. 2009).

Kuethe, Hubbs, and Sanders (2018) previously found that USDA's bottom-line net farm income forecasts are biased and inefficient. Specifically, initial forecasts systematically under-predict realized values, and later forecast revisions over-react to new information.[5] Isengildina-Massa et al. (2020b) extend the work of Kuethe, Hubbs, and Sanders (2018) by examining the vector of net cash income and its components, including crop receipts, livestock receipts, government payments, gross cash income, and cash expenditures. Isengildina-Massa et al. (2020b) find a similar downward bias in initial net cash income forecasts, which mainly stems from forecasts of crop receipts.

WASDE Forecasts

We also examine USDA production forecasts for area harvested (*Acreage*), yield per harvested acre (*Yield*), and average farm price (*Price*) for three major commodities: corn, soybeans, and wheat. The forecasts were obtained from USDA's WASDE. WASDE is coordinated by the World Agricultural Outlook Board (WAOB) and relies on data and expertise from a variety of USDA agencies including NASS, ERS, Farm Service Agency (FSA), Agricultural Marketing Service (AMS), and Foreign Agricultural Service (FAS). A detailed description of WASDE's balance sheet approach to crop forecast generation is provided by Vogel and Bange (1999).

WASDE forecasts and estimates are produced for marketing year averages. For corn and soybeans, the marketing year is defined as September through August of the following calendar year, and, for wheat, the marketing year is defined as June through May of the following calendar year. WASDE forecasts are released by USDA between the 9th and 12th of each month. The first marketing year forecasts for corn, soybeans, and wheat are released in May. For corn and soybeans, the acreage and yield estimates are finalized in December, and for wheat, the acreage and yield estimates are finalized in September. Season average prices are finalized in November of the following calendar year for corn and soybeans and in September of the following calendar year for wheat.

Isengildina-Massa, Karali, and Irwin (2013) document the bias and inefficiency of WASDE price and production forecasts for corn, soybeans, and wheat. The authors find strong evidence that forecast errors are affected by behavioral and macroeconomic factors. Xiao, Hart, and Lence (2017) similarly show that WASDE forecasts of ending stocks for the same three commodities are inefficient and conservative. Isengildina, Irwin, and Good (2006) also identify informational inefficiencies in NASS corn and soybean production forecasts. Despite the prior findings of bias and inefficiency, Hoffman et al. (2015) find that WASDE projections of season-average corn price provide useful information to the market. The evidence of irrationality for other commodities, however is mixed.

Isengildina-Massa, MacDonald, and Xie (2012) find evidence of bias and inefficiency in WASDE cotton forecasts, yet Lewis and Manfredo (2012) fail to reject the rationality of WASDE sugar production and consumption forecasts.

Preliminary Analysis

Following Isengildina-Massa, Karali, and Irwin (2013), forecasts are expressed as percent changes from the previous year to avoid the impact of changing forecast levels over the study period. The percent change is calculated as: $\mathbf{f}_{t,h} = 100 * \ln(\mathbf{F}_{t,h}/\mathbf{F}_{t-1,h})$, where $\mathbf{F}_{t,h}$ is the forecast level for a reference year t and at horizon h months before the final estimate and $\mathbf{F}_{t-1,h}$ is the forecast from the previous year $t-1$ for the same time horizon h. The forecasts for the previous year are replaced with the final estimates after they are released (in August for farm income, November for corn and soybeans, and September for wheat). The percentage forecast errors at each horizon h are defined as the difference between the estimate and the h-horizon forecast, $\mathbf{e}_{t,h} = \mathbf{f}_{t,0} - \mathbf{f}_{t,h}$. For the farm income forecast, $\mathbf{f}_{t,h}$ represents the vector of net cash income and its components, where the horizon h is February, August, November, and next February. The j-th component of the vector of h-horizon forecasts is ${f^j}_{t,h}$, where $j \in \{NCI, CR, LR, GP, EXP\}$. The WASDE forecasts are similarly expressed with h representing each month of May through December for corn and soybeans and May through September for wheat. For all three commodities, $j \in \{Acreage, Yield, Price\}$. The forecast errors are stationary for all forecast series and horizons, as verified using standard tests of stationarity (Dickey and Fuller 1979; Said and Dickey 1984).

Figures 1 and 2 depict the average annual forecast errors for net cash income and its components and for the WASDE acreage, price, and yield, respectively. Net cash income forecast errors exhibit large variation over time, even though errors in cash expenses tend to offset errors in receipts and government payments. Notably, the 2007-2008 period of sharply increasing crop prices resulted in some of the largest forecast errors for crop prices, but not for farm income, acreage, or yield.

[FIGURE 1 ABOUT HERE]

[FIGURE 2 ABOUT HERE]

Tables 1 - 4 summarize the forecast errors for each variable and horizon h over the period 1988-2018. The summaries include three common measures of forecast accuracy: the mean absolute percent error $MAPE(|e|) = \frac{1}{T}\sum_{t=1}^{T}|e_t|$, the root mean square percent error $RMSPE(\sqrt{e^2}) = (\frac{1}{T}\sum_{t=1}^{T}e_t^2)^{\frac{1}{2}}$, and the mean percent error $MPE(e) = \frac{1}{T}\sum_{t=1}^{T}e_t$. An important implication of forecast rationality is that the forecast should become more accurate as the forecast horizon shortens (Patton and Timmermann 2007). As shown in tables 1 - 4, the $MAPE$, $RMSPE$, and MPE for each variable generally decrease over the forecasting horizon, with few exceptions. In addition, the last two columns of each table report the t-statistic and p-value for the bias test developed by Holden and Peel (1990). The test statistic is calculated by regressing the forecast errors on a constant. As expected, table 1 suggests that net cash income and crop receipts are biased. We also find some evidence of bias in the forecasts of corn acreage (table 2), soybean prices (table 3), and wheat acreage and yield (table 4). In terms of the magnitude of the bias, the $MPEs$ for 12 out of 20 farm income forecasts and its components, 7 out of 24 for corn, 10 out of 24 for soybeans, and 8 out of 15 for wheat forecasts are above 1% in absolute values, which may be considered economically significant. Net cash income has the largest bias when compared to its components which is expected since the bias in its components is additive. For the WASDE forecasts, the bias for the price forecasts is much larger when compared to the bias for the yield and acreage forecasts. In addition, forecasts of farm income and its components have larger bias than that of WASDE production and price forecasts. Lastly, in cases where bias exceeds 1% in absolute value, it is generally positive, which indicates that the forecasts generally under-predict realized values. These results are consistent with our later findings that forecasters have a greater cost of over-prediction than under-prediction.

[TABLE 1 ABOUT HERE]

[TABLE 2 ABOUT HERE]

[TABLE 3 ABOUT HERE]

[TABLE 4 ABOUT HERE]

Methodology

Traditional forecast evaluation assumes that the forecaster's objective is to minimize the univariate mean square error (MSE) loss function:

$$(2) \quad L(f^j_{t,0}, f^j_{t,h}) = (f^j_{t,0} - f^j_{t,h})^2$$

where $L(\cdot)$ is the loss function, $f^j_{t,0}$ is the realized value of variable j for period t, and $f^j_{t,h}$ is the forecast of $f^j_{t,0}$ conducted at a horizon of h months ahead of the realized value.

As previously stated, Elliott, Timmermann, and Komunjer (2005) develop a method for testing forecast rationality under a flexible class of asymmetric loss functions which nest MSE loss as a special case. Their generalized method of moments (GMM) approach jointly estimates the asymmetry parameters of the loss function and tests for rationality. In this study, we follow Komunjer and Owyang (2012), who develop a generalized version of the Elliott, Timmermann, and Komunjer (2005) approach that examines multivariate forecasts and allows for non-separable loss. We define the multivariate loss function $L_p(\boldsymbol{\tau}, \mathbf{e})$ as,

$$(3) \quad L_p(\boldsymbol{\tau}, \mathbf{e}) = \left(||\mathbf{e}||_p + \boldsymbol{\tau}'\mathbf{e}\right) ||\mathbf{e}||_p^{p-1},$$

where $1 \leq p < \infty$, $1/p + 1/q = 1$, $\mathbf{e} \in \mathbb{R}^n$ and $\boldsymbol{\tau} \in \mathfrak{B}^n_q = \{\mathbf{u} \in \mathbb{R}^n : ||\mathbf{u}||_q < 1\}$. The vector $\mathbf{e}$ comprises the forecast errors of n variables. The asymmetry parameter $\boldsymbol{\tau}$ determines the relative losses due to positive and negative errors for each component of the error vector. The scalar p determines the shape of the loss function.

The loss function (3) is flexible as it can accommodate a wide variety of loss functions by varying the shape parameter p. The loss function allows for asymmetry and non-separability for a value of $p \geq 1$, and nests many well-known loss functions, such MSE and MAE loss (Komunjer and Owyang 2012). Figure 3 shows several examples of special cases of univariate loss functions with shape parameters $p = 1$ and $p = 2$. Panel (a) depicts several linear loss functions, such as the symmetric absolute deviation loss (MAE) and the asymmetric lin-lin loss functions where $p = 1$. Panel (b) depicts several quadratic loss functions, such as the symmetric squared loss (MSE) and asymmetric quad-quad loss functions where $p = 2$.

[FIGURE 3 ABOUT HERE]

The magnitude of the asymmetry parameter $\boldsymbol{\tau}$ indicates the direction and degree of asymmetry in the loss function. In equation (3), the sign of the forecast error of a variable enters the loss function only if the asymmetry parameter for that variable is non-zero, $\tau^j \neq 0$. The univariate version of the multivariate loss function in equation (3) for $p = 2$ is given by,

$$(4) \qquad L_2(\tau^j, e^j) = (e^j)^2 + \tau^j sgn(e^j)(e^j)^2,$$

where j is the variable, e^j is the forecast error for variable j, and $sgn(e^j)$ is the sign of e^j.

We define the relative loss of over-prediction as the ratio of the loss due to over-prediction and the loss due to under-prediction of the same magnitude (negative and positive forecast errors of the same magnitude). From equation (4), the relative loss of over-prediction for variable j can be expressed as:

$$(5) \qquad \frac{L_2(\tau^j, -|e^j|)}{L_2(\tau^j, |e^j|)} = \frac{1-\tau^j}{1+\tau^j}.$$

If $\tau^j = 0$, the costs of over-prediction and under-prediction are the same, and the loss function is symmetric in variable j. A negative value of the asymmetry parameter suggests that the relative loss of over-prediction is greater than one, suggesting over-predictions are costlier than under-predictions. Figure 3 shows how the sign and magnitude of the asymmetry parameter influence the univariate lin-lin and quad-quad loss functions.

Under the multivariate loss function (3), losses due to errors in the components of the vector are additively non-separable. If $\boldsymbol{\tau} \neq \mathbf{0}$, the sum of univariate losses does not equal the multivariate loss, i.e. $\sum_j L_2(\tau^j, e^j) \neq L_2(\boldsymbol{\tau}, \boldsymbol{e})$. The non-separability stems from the second term in equation (3) which represents the interaction between the forecast errors of the components that contribute toward the multivariate loss. When the forecaster's loss is symmetric in all components ($\boldsymbol{\tau} = \mathbf{0}$), this term disappears and the multivariate loss function becomes additively separable, i.e., $\sum_j L_2(0, e^j) = L_2(\mathbf{0}, \boldsymbol{e})$. Figure 4 shows the isoloss contours of a separable loss (i.e. the sum of univariate losses) and a non-separable multivariate loss against the symmetric loss using a bivariate loss function as an example. For symmetric loss, the isoloss contours are circular. In the case of separable loss and non-separable loss, the isoloss contours are distorted, and they have different shapes.

[FIGURE 4 ABOUT HERE]

Estimation Procedure

We observe the multivariate forecasts $\mathbf{f}_{t,h}$, realized values $\mathbf{f}_{t,0}$, and a set of d instruments $\mathbf{x}_{t-1,h}$, which are a subset of the forecasters' information set and include the lagged forecasts of the same horizon, for P periods.[6] We assume that the forecaster minimizes an expected loss when constructing the forecasts and that the loss function belongs to the general class of loss functions (3). Using this information, we seek to estimate the asymmetry parameter $\boldsymbol{\tau}_h$ for each forecast horizon that is consistent with the characteristics of $\mathbf{f}_{t,h}$.

We follow Komunjer and Owyang (2012) and use a GMM-based strategy to estimate the asymmetry parameters. The procedure requires two assumptions. First, we assume that the shape parameter p is given. Second, we assume that the forecaster uses a rolling window of information to construct the forecasts. For example, to construct the forecast for the first period under our study, the forecaster uses information from the previous R periods. The information window is then rolled forward to construct all forecasts until the P^{th} period. Under these assumptions, the GMM estimator of the asymmetry parameter is given by,

$$(6) \quad \hat{\boldsymbol{\tau}}_h = \underset{\boldsymbol{\tau} \in \mathfrak{B}_q^n}{\arg\min} \left[P^{-1} \sum_{t=1}^{P} \mathbf{g}_p(\boldsymbol{\tau}; \mathbf{e}_{t,h}, \mathbf{x}_{t-1,h}) \right]' \times \hat{\mathbf{S}}^{-1} \times \left[P^{-1} \sum_{t=1}^{P} \mathbf{g}_p(\boldsymbol{\tau}; \mathbf{e}_{t,h}, \mathbf{x}_{t-1,h}) \right]$$

where,

$$\mathbf{g}_p(\boldsymbol{\tau}; \mathbf{e}_{t,h}, \mathbf{x}_{t-1,h}) = p\nu(\mathbf{e}_{t,h}) + \boldsymbol{\tau}||\mathbf{e}_{t,h}||_p^{p-1} + (p-1)\boldsymbol{\tau}'\mathbf{e}_{t,h}||\boldsymbol{e}_{t,h}||_p^{-1}\nu(\mathbf{e}_{t,h}) \otimes \mathbf{x}_{t,h}$$

$$\nu(\mathbf{e}_{t,h}) = (sgn(e_{t,h}^{j_1})|e_{t,h}^{j_1}|^{p-1}, \ldots, sgn(e_{t,h}^{j_n})|e_{t,h}^{j_n}|^{p-1})$$

The optimal weight matrix $\hat{S}^{-1}$ is iteratively determined during the GMM estimation using the equation,

$$(7) \quad \hat{S}(\tilde{\boldsymbol{\tau}}) = P^{-1} \sum_{t=1}^{P} \mathbf{g}_p(\tilde{\boldsymbol{\tau}}; \mathbf{e}_{t,h}, \mathbf{x}_{t-1,h}) \mathbf{g}_p(\tilde{\boldsymbol{\tau}}; \mathbf{e}_{t,h}, \mathbf{x}_{t-1,h})'$$

For a given shape parameter p, Komunjer and Owyang (2012) outline the conditions on the observed errors so that the GMM estimate of the asymmetry parameter is asymptotically normal (see Theorem 3 pp. 1072). Komunjer and Owyang (2012) also construct a J-statistic with $d > 1$ instruments to test the rationality of the multivariate forecasts.

$$(8) \quad \hat{J}_h = \left[P^{-1} \sum_{t=1}^{P} \mathbf{g}_p(\hat{\boldsymbol{\tau}}_h; \mathbf{e}_{t,h}, \mathbf{x}_{t-1,h}) \right]' \times \hat{\mathbf{S}}^{-1} \times \left[P^{-1} \sum_{t=1}^{P} \mathbf{g}_p(\hat{\boldsymbol{\tau}}_h; \mathbf{e}_{t,h}, \mathbf{x}_{t-1,h}) \right] \sim \chi^2_{n(d-1)}$$

A failure to reject the null hypothesis of rationality would suggest that, for a given set of instruments, there exists some value of the asymmetry parameter for which the forecasts are rational. Komunjer and Owyang (2012) further provide Monte Carlo evidence that the GMM estimation under non-separable loss yields consistent estimates of the asymmetry parameter even when the components of the vector $\mathbf{f}_{t,h}$ are highly correlated. If the loss function is misspecified as separable, it would likely produce biased estimates. Moreover, many equations employed in USDA's forecast models use time-lagged information from several sources as inputs (Dubman, McElroy, and Dodson 1993; McGath et al. 2009; Vogel and Bange 1999). Therefore, it is reasonable to assume that the forecaster uses a rolling window of information to generate the forecasts. These advantages make the GMM approach well-suited for evaluating the USDA forecasts.

Robustness Checks

Our estimation procedure requires two important assumptions: the instrumental variable set $\mathbf{x}_{t-1,h}$ and the shape parameter p. To ensure that our results are not overly influenced by these choices, we offer two important robustness checks. First, following Elliott, Timmermann, and Komunjer (2005), our preferred specification uses an instrument set consisting of a constant and one year lagged forecasts of a single variable of the same horizon (net cash income for net cash income forecasts and average farm prices for WASDE production forecasts). To ensure that our results are robust to the choice of instruments, we compute the asymmetry parameters using several sets of alternative instruments that are plausibly part of the forecaster's information set. Second, in our preferred specification, the shape parameter of the loss function was fixed at $p = 2$, which corresponds to the well-known quadratic loss in the univariate case. Komunjer and Owyang (2012) have shown that different values of the shape parameter p result in consistent estimates of the asymmetry parameter. Yet, to ensure that our results are robust to the choice of p, we estimate the model under different choices for the shape parameter: $p = 1.5, 2, 2.5$. Finally, our preferred specification estimates a single asymmetry parameter over the observation period 1988 – 2018. There may be some concern as to whether the asymmetry parameters are stable over time. The forecast performance may change due to changes in forecasting procedures over time or unexpected shocks, such as price disturbances, that may affect the loss function parameters. Isengildina-Massa, Karali, and Irwin (2013), for example, showed that structural changes in the commodity markets during the mid 2000s accounted for the largest increase in errors in several WASDE forecasts for corn, soybeans, and wheat. Previous research suggests that, if the underlying data generating process of a variable is not stable, it is rational for error-minimizing forecasters to make serially correlated forecast revisions and systematic forecast errors as they learn about changes in the process driving the target variable (Muth 1960; Batchelor 2007). Further, Isengildina-Massa, Karali, and Irwin (2013) demonstrate that WASDE forecast errors grew during periods of economic growth. Higgins and Mishra (2014) show that when forecasters are concerned with missing turning points, the forecasts are biased downward during expansions and biased upward during recessions.

To test for the stability of the estimated loss function parameters, we use an out-of-sample technique of detecting forecast breakdowns proposed by Giacomini and Rossi (2009) which has been used in similar econometric settings (Mamatzakis and Koutsomanoli-Filippaki 2014; Mamatzakis and Tsionas 2015; Christodoulakis 2020). Following Isengildina-Massa, Karali, and Irwin (2013), we specifically examine the potential for forecast breakdowns during the 2007-2008 commodity price boom.

Giacomini and Rossi (2009) defines forecast breakdown as a situation where the out-of-sample performance of a forecast model is significantly inferior to its in-sample performance. The method involves dividing the sample period P into in-sample and out-of-sample windows of length m and n, where $P = m+n$. Then a "surprise loss" is calculated as the difference between the out-of-sample loss and the average in-sample loss:

$$(9) \quad SL_{t+1}(\hat{\boldsymbol{\tau}}_t) = L_{t+1}(\hat{\boldsymbol{\tau}}_t) - \overline{L_t}(\hat{\boldsymbol{\tau}}_t), \quad \text{for} \quad t = m, \ldots, (P-1)$$

The average in-sample loss $\overline{L_t}(\hat{\boldsymbol{\tau}}_t)$ is computed by first estimating the asymmetry parameters $\hat{\boldsymbol{\tau}}_t$ for the in-sample window. Then the out-of-sample loss $L_{t+1}(\hat{\boldsymbol{\tau}}_t)$ is calculated using the in-sample asymmetry parameter estimates. The test is based on the hypothesis that in the absence of forecast breakdowns, the out-of-sample mean of the surprise losses should be zero.

$$(10) \quad H_0 : E\left(n^{-1}\Sigma_{t=m}^{P-1} SL_{t+1}(\boldsymbol{\tau}_t)\right) = 0$$

The test statistic is calculated using a Newey-West standard error as,

$$t_{m,n,1} = n^{1/2} \frac{\overline{SL}_{m,n}}{\hat{\sigma}_{m,n}} \quad (11)$$

If the null hypothesis is rejected, a forecast breakdown is detected. We use three different forecasting schemes which follow different assumptions about the data generating process, (a) a fixed scheme with in-sample window $t = 1, \ldots, m$ for all t; (b) a rolling forecasting scheme with in-sample window $t = t - m + 1, \ldots, t$ at time t; and (c) a recursive forecasting scheme with in-sample window $t = 1, \ldots, t$ at time t. The forecast breakdown test is performed for each of the three forecasting schemes by using the period before 2007 as the in-sample window.

Results

The estimated asymmetry parameters for our preferred specification are presented in table 5 and figure 5 for the USDA net cash income forecasts and in table 6 and figure 6 for the WASDE production and price forecasts for corn, soybean, and wheat. Following Komunjer and Owyang (2012) and Caunedo et al. (2018), we use two instruments to avoid size distortions in the J-test. The instrument sets used for farm income forecasts consist of a constant and one year lagged forecasts of net cash income. For the WASDE forecasts, the instruments include a constant and one year lagged forecasts of the average farm price. In each case, the shape parameter was fixed at $p = 2$.

The results for the J-test for rationality under $\hat{\tau}$ are presented in the bottom two rows of tables 5 and 6. The results show that the null hypothesis of rationality could not be rejected for any of the forecasts at the 5% significance level, for both separable and non-separable losses. This suggests that the USDA net cash income and WASDE forecasts are rationalizable under asymmetric loss.

Table 5 shows the GMM estimates of the asymmetry parameters for each component of the net cash income forecast under separable and non-separable loss, along with their standard errors. Figure 5 graphically presents the asymmetry parameters for net cash income and its components with 95% confidence intervals under non-separable loss. While the magnitude of τ^j is generally larger in absolute terms for separable loss than for non-separable loss, the sign and significance are mostly consistent under separable and non-separable loss. For example, the asymmetry estimate for the February (18-month-ahead) forecast of net cash income is –0.624 assuming separable loss, but only –0.458 under non-separable loss. The estimates of the asymmetry parameters for crop and livestock receipts and cash expenses are much closer to symmetric under non-separable loss, yet the asymmetry parameters are still significantly different from zero. In contrast, the estimates are markedly asymmetric under separable loss. These results are consistent with Komunjer and Owyang (2012), who demonstrate that rationality could be achieved with smaller degree of asymmetry under non-separable loss relative to separable loss. The pattern also follows the empirical findings of Caunedo et al. (2018), who show that Federal Reserve's forecasts of growth, inflation, and unemployment are asymmetric, yet the degree of asymmetry is less under non-separable loss. For example, the asymmetry parameter for growth and unemployment were -0.30 and 0.32 under separable loss and -0.29 and 0.03 under non-separable loss.

[TABLE 5 ABOUT HERE]

[TABLE 6 ABOUT HERE]

[FIGURE 5 ABOUT HERE]

Given that USDA's net cash income forecasts are constructed using the accounting identity (1), we focus our discussion on the results under non-separable loss which is a more realistic assumption. The relative losses associated with the asymmetry parameters are calculated using equation (5) and presented in figure 7. The estimates of the asymmetry parameter of net cash income are negative and significant, which suggests that USDA has

2.7 times higher costs associated with over-predicting 1% in the February net cash income forecast than under-predicting it by 1%. This finding provides an alternative explanation of the bias findings in table 1 and of previous studies' findings that the February (18-month-ahead) forecasts tend to under-predict net cash income and net farm income (Isengildina-Massa et al. 2020b; Kuethe, Hubbs, and Sanders 2018). Following Granger (1969), USDA's initial forecasts appear biased because because over-predictions are costlier, and therefore, the forecasts are rationally conservative. Among the components of net cash income, the asymmetry parameter estimate is significant and negative, particularly for the February forecast of government payments. On the other hand, the asymmetry parameter estimates for crop and livestock receipts and production expenses are closer to zero (symmetry) even though they are significant in most cases. These asymmetry parameters suggest that USDA has 1.2 to 1.5 times higher costs associated with over-predicting crop and livestock receipts and cash expenses.

[FIGURE 7 ABOUT HERE]

The estimates of asymmetry parameters generally move closer to symmetry as the terminal event of releasing the USDA official estimates approaches, with the exception of government payments (figure 5). One implication of forecast rationality is that the forecast error should be a weakly non-decreasing function of the forecast horizon (Patton and Timmermann 2007), or alternatively, that the forecasts become more accurate as the forecast horizon reduces from say 18 months ahead to 6 months ahead of the final estimate. As a result, a smaller degree of asymmetry is required to rationalize the forecasts as the horizon reduces. Direct government payments, however, show an interesting pattern across the forecast horizon. The asymmetry parameter is negative for the February (18-month-ahead) forecast of government payments, suggesting over-predictions by 1% percent are 2.8 times costlier than under-predictions by 1%. However, for the November (9-month-ahead) forecasts of government payments, and to some extent, for the next February (6-month-ahead) forecasts, the asymmetry estimate is positive, suggesting under-predictions are costlier. That is, before production, at the beginning of the calendar year USDA does not want to over-predict government outlays. However, in November, after the growing season, the USDA does not want to under-predict government program payments to farmers. This behavior, while curious, is consistent with the bias in USDA forecasts of government payments previously reported by Isengildina-Massa et al. (2020b) and shown in table 1.

Several of the findings described above for the USDA farm income forecasts also hold for the WASDE production and price forecasts for corn, soybeans, and wheat. The estimates of the asymmetry parameters for the WASDE acreage, yield, and price forecasts are presented in table 6 and graphically presented in figure 6 under non-separable loss, while the separable loss results are presented in table 7. Most of the asymmetry parameters for acreage are positive or not significant, with some negative asymmetry parameters particularly for the November and December forecasts for soybean acreage. The asymmetry parameters for acreage are relatively small in magnitude, suggesting that although USDA tends to over- or under-predict some acreage forecasts, the relative costs of over-predicting are not very high. The asymmetry parameters for price, on the other hand, are mostly negative and large in magnitude. Further, the asymmetry does not appear to decrease over the forecast horizon. In the case of corn and soybeans, the asymmetry parameters are highest during planting and harvest. For example, the asymmetry parameter of –0.524 for the soybean price forecast in May shows that the relative cost of over-predicting soybean price by 1% is 3.2 times higher than the cost of under-predicting it by 1%. Similarly, the asymmetry parameter estimates for yield are mostly negative and significant, but they generally move toward more symmetry over the time horizon, particularly during the last couple of months before harvest. These findings closely correspond to the bias results shown in tables 2 – 4. Overall, these findings show that the relative costs of over-predicting prices and yields are higher, while the relative costs of under-predicting acreage are generally higher, particularly for wheat.

[FIGURE 6 ABOUT HERE]

[TABLE 7 ABOUT HERE]

Beyond our preferred specification, we also show that our findings are robust to both the choice of shape parameter and the instrument sets used in the estimation procedure. Through Monte Carlo simulation, Komunjer and Owyang (2012) show that different values of the shape parameter p result in consistent estimates of the asymmetry parameter. As a robustness check, we obtain similar results using different shape parameters. In figure 8, we plot non-separable asymmetry estimates with shape parameter values $p = 1.5$ and $p = 2.5$ along with our preferred specification of $p = 2$. In both cases, the asymmetry parameter estimates have the same sign as reported in the main results, and the magnitudes are similar, except for government payments in the August forecasts. These estimates show that our main results are not driven by the shape of the loss function, and the presence of asymmetry cannot be ruled out under alternative specifications. As an additional robustness check, we hold the shape parameter at $p = 2$ but vary the instruments sets. These estimates are plotted in figure 9. The results show that the estimates of the asymmetry parameters are similar to those reported in table 5, both in terms of sign and magnitude, except for the August forecast of government payments.

[FIGURE 8 ABOUT HERE]

[FIGURE 9 ABOUT HERE]

The results of the structural breakdown test of Giacomini and Rossi (2009) are presented in table 8 for the net cash income forecasts and in table 9 for the WASDE acreage, yield, and price forecasts. Using the fixed, rolling, and recursive forecasting schemes to test for structural breaks before and after the 2007 commodity price spikes, the test statistics are not significant at the 5% level, with the exception of the November and December soybean forecasts. Our interpretation is that even though crop prices sharply increased in

2007 resulting in high price forecast errors, the forecast errors for farm income and crop production were not the highest in 2007 as compared to the rest of the years in our sample (figures 1 and 2). Even though we do not find evidence of structural breakdown before and after 2007 when considering the vector of forecasts for net cash income and WASDE production and prices, our test does not preclude the possibility that individual asymmetry parameters for specific components at specific time horizons may differ across sub-periods.

[TABLE 8 ABOUT HERE]

[TABLE 9 ABOUT HERE]

Conclusions

Previous studies suggest that many of the forecasts generated by the USDA are technically irrational (biased and/or inefficient). A rejection of rationality, however, may be the result of either the forecaster's inefficient use of information or a misspecification of the forecaster's loss function (Elliott, Timmermann, and Komunjer 2005). In this study, we jointly estimate the parameters of USDA forecasters' loss function and test for rationality for two important sets of USDA forecasts: net cash income and WASDE production and price forecasts for corn, soybeans, and wheat. Following Komunjer and Owyang (2012), the loss function is estimated under a flexible multivariate loss function that allows for asymmetry and non-separability in the forecast errors.

Our analysis yields two important findings. First, we find evidence of asymmetric loss in both net cash income and WASDE forecasts. These results are consistent with previous findings of bias and inefficiency (Isengildina-Massa, Karali, and Irwin 2013; Kuethe, Hubbs, and Sanders 2018; Isengildina-Massa et al. 2020b), yet our empirical approach provides an alternate interpretation of these results. For example, Isengildina-Massa et al. (2020b) find that initial USDA net cash income forecasts are downward biased. Our results suggest that a 1% over-prediction of the initial net cash income is 2.7 times as costly as an under-prediction of the same percent. Thus, USDA is averse to over-predicting net cash income at the early stages of the forecasting process. We similarly find that USDA has a higher cost over-predicting both price and yield for corn, soybeans, and wheat. Second, we find that under asymmetric loss, the USDA forecasters are rational expected loss minimizers. Economic theory provides a variety of internal and external costs that may lead otherwise rational forecasters to release "technically irrational" forecasts (Weber 1994; Batchelor 2007).

Our findings are important for a variety of USDA forecast users, including farmers, lenders, agricultural business leaders, and agricultural policymakers. As Auffhammer (2007) argues, a forecast is only optimal for a particular forecast user when his or her loss function matches that of the forecast producer. Accurately describing the loss function of USDA forecasters is therefore an important first step in forecast evaluation. Given the important role that USDA's farm income forecasts play in farm policy debates and WASDE's influence in commodity markets, the USDA should consider the internal and external forces that influence the cost of forecast errors. Merola and Pérez (2013) argue that government forecasting processes can be improved by increasing (i) transparency on data reporting, (ii) accountability of forecasters, and (iii) *ex ante* incentives to release unbiased forecasts. Previous research suggests that biased public forecasts can influence private decision making. For example, Beaudry and Willems (2018) demonstrate that over-optimistic GDP growth forecasts leads to higher public and private debt accumulation and later recessions. Thus, our findings may also help inform future revisions of USDA forecast models and procedures.

Notes

[1]Notable exceptions include evaluations of USDA's interval forecasts of commodity prices, including Sanders and Manfredo (2003), Isengildina, Irwin, and Good (2004), and Isengildina-Massa and Sharp (2012). These studies examine the proportion of actual market prices that fall in the forecasted range, or "hit rate," of various USDA interval forecasts. In a spirit similar to the current study, Isengildina, Irwin, and Good (2004) examine the degree to which inaccuracy of USDA's interval forecasts of corn and soybean price forecasts can be attributed to inefficient use of information or the utility function of the forecasters. The authors find evidence of the latter.

[2]Isengildina-Massa et al. (2020b) is one recent exception.

[3]Fritsche et al. (2015), conversely, identify an "anti-herding" behavior in professional forecasters where later forecasters strategically differentiate their forecasts from those previously published.

[4]USDA may further revise the estimates in subsequent releases, mainly to correct errors or to incorporate information that was not available earlier. However, to maintain consistency, we consider the first official estimates as the realized values throughout the study, following Kuethe, Hubbs, and Sanders (2018) and Isengildina-Massa et al. (2020b).

[5]Kuethe, Hubbs, and Sanders (2018) examine bottom-line *net farm income* which includes non-cash income and expenses. The differences between the two measures is documented in McGath et al. (2009).

[6]The instrumental variables must be stationary with a full rank covariance matrix and satisfy the standard exclusion restrictions, as outlined in Komunjer and Owyang (2012), Appendix pp. 1078-1080.

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Figures

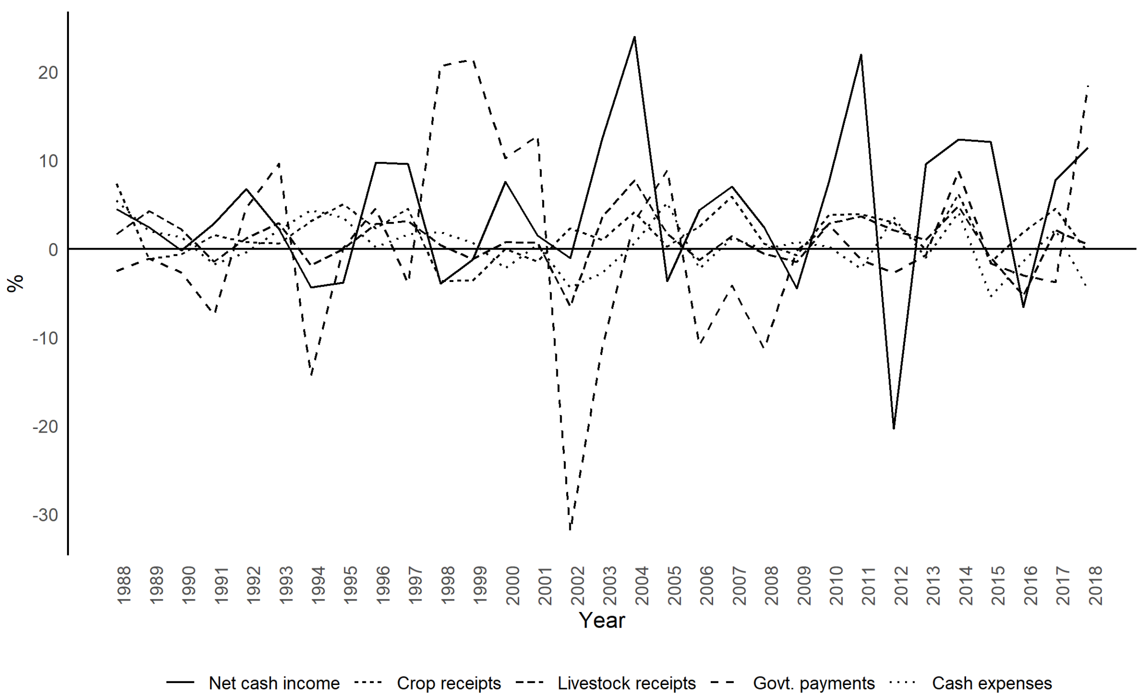


Figure 1. Average annual errors of net cash income forecasts and its components, 1988-2018

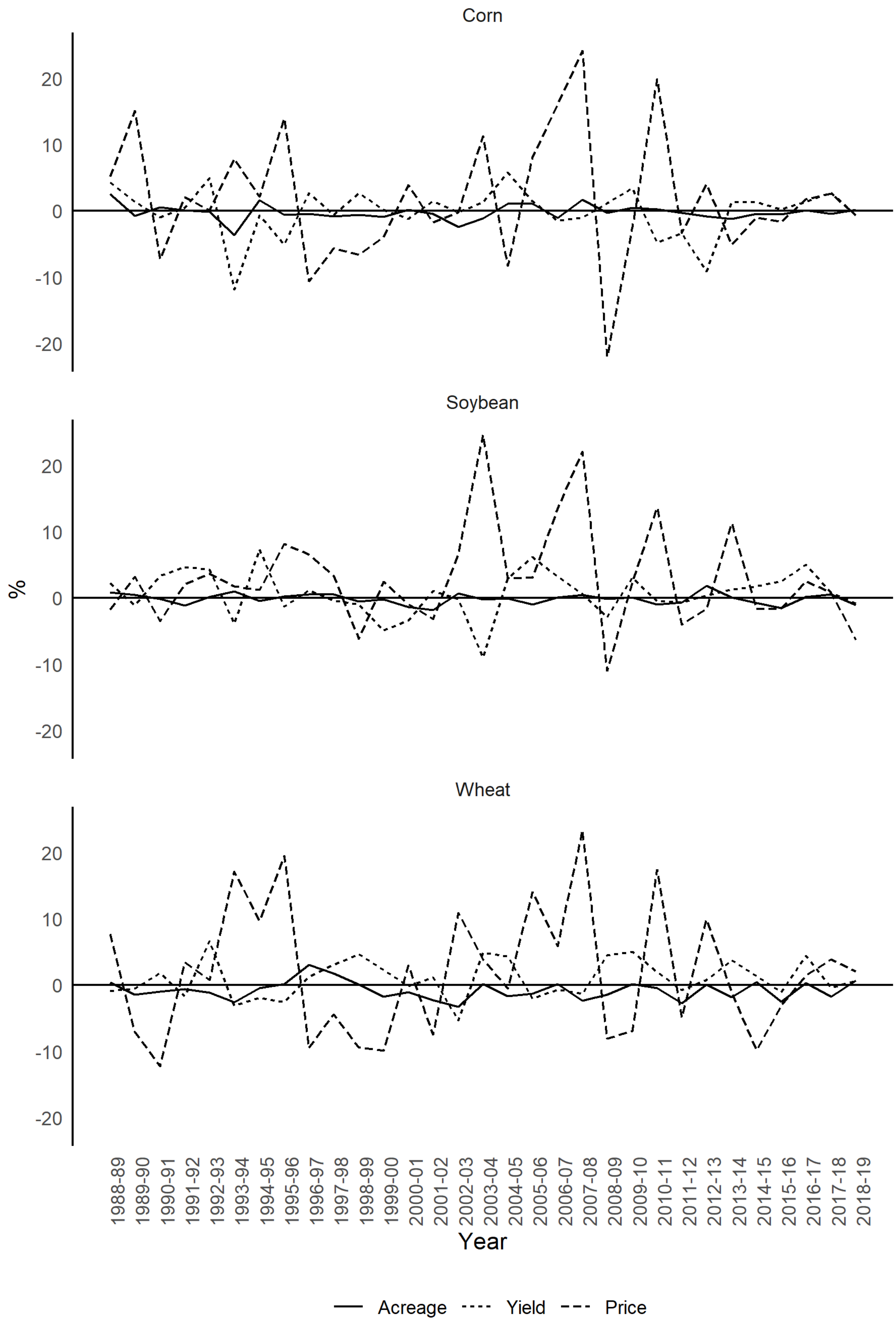
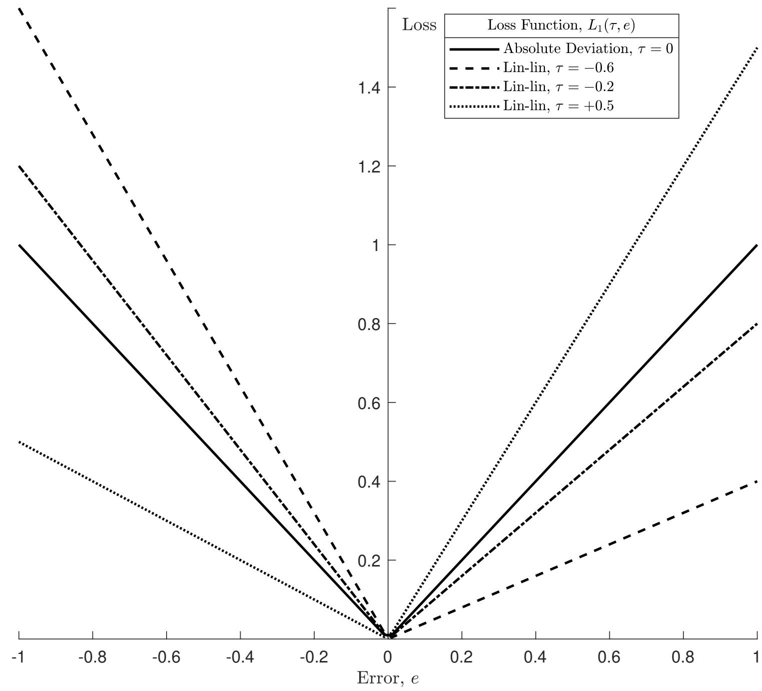
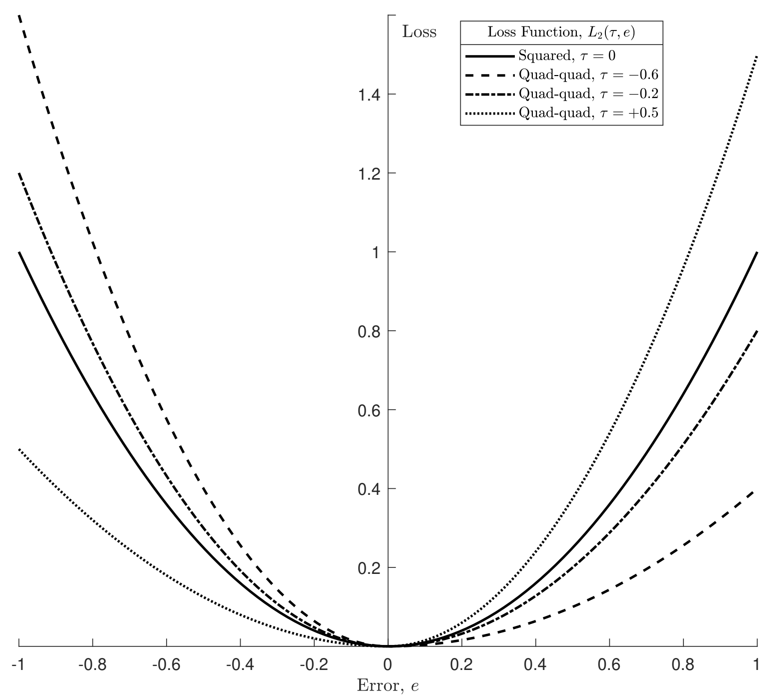


Figure 2. Average annual errors of WASDE forecasts for acreage, yield, and price, 1988-2018

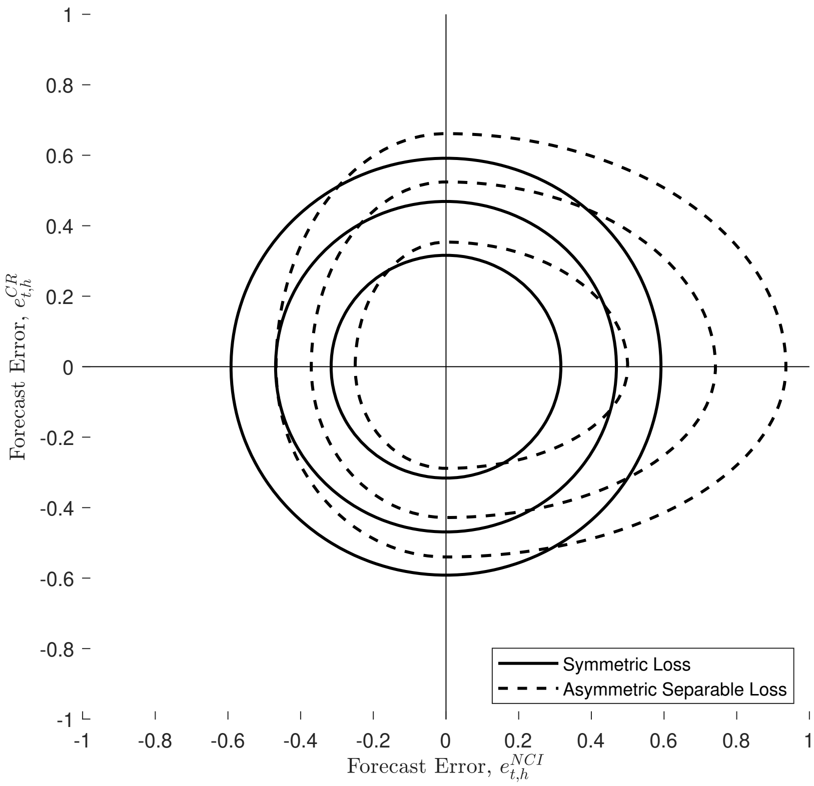


(a) Absolute deviation loss and lin-lin loss with shape parameter p=1

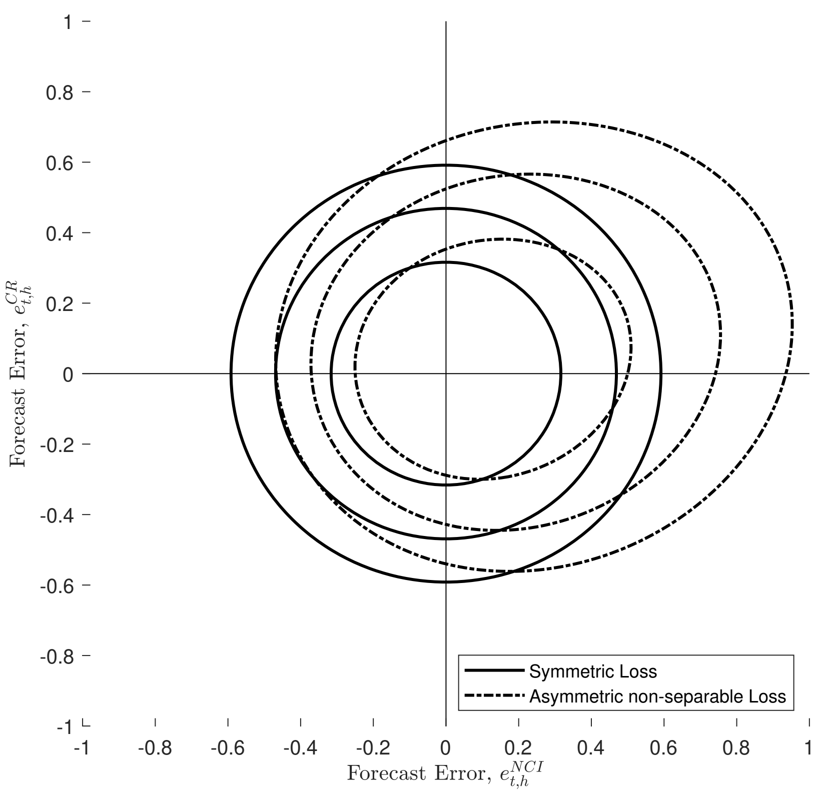


(b) Squared loss and quad-quad loss with shape parameter p=2

Figure 3. Special cases of univariate loss functions



(a) Asymmetric separable loss, $(\tau_h^{NCI}, \tau_h^{CR}) = (-0.6, -0.2)$, $p = 2$



(b) Asymmetric non-separable loss, $(\tau_h^{NCI}, \tau_h^{CR}) = (-0.6, -0.2)$, $p = 2$

Figure 4. Isoloss contours in a bivariate case

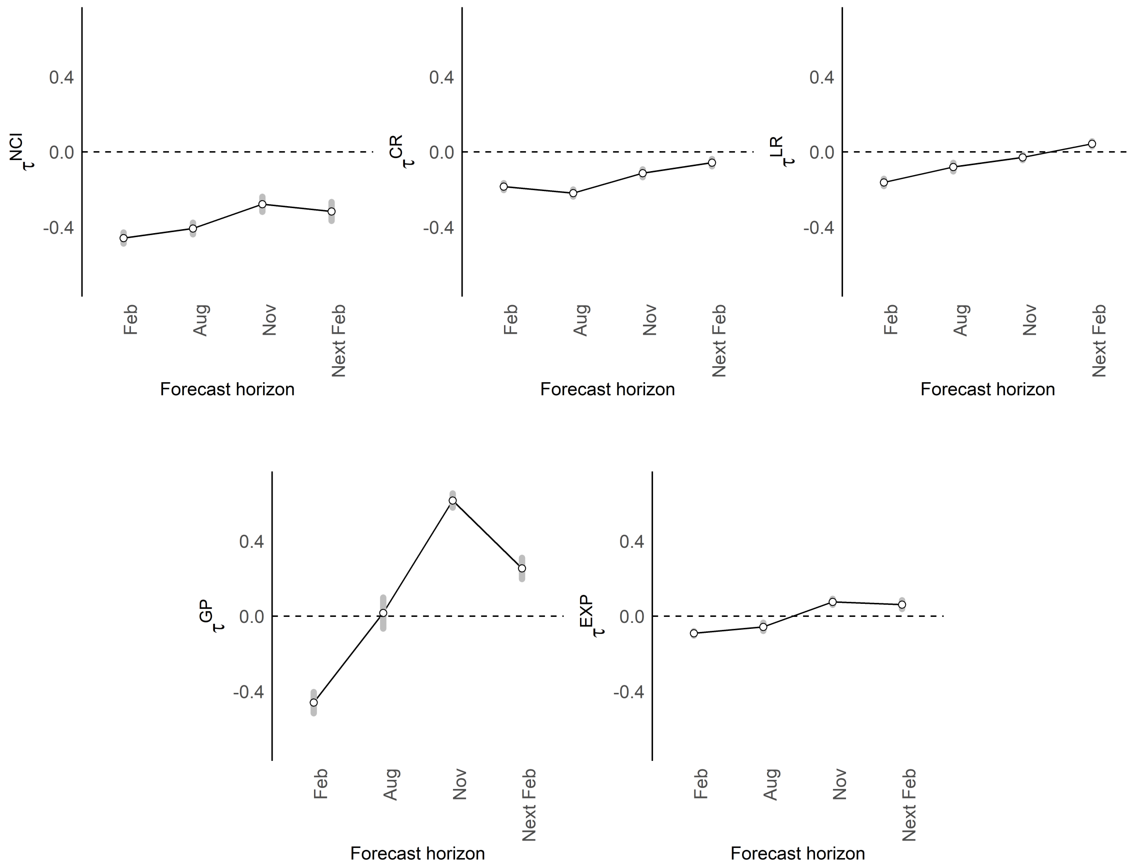


Figure 5. Asymmetry parameter estimates under non-separable loss for net cash income forecasts with 95% confidence intervals

Note: (a) The instrument set consists of a constant and one year lagged forecasts of net cash income. (b) Estimates are plotted for non-separable loss with shape parameter $p = 2$

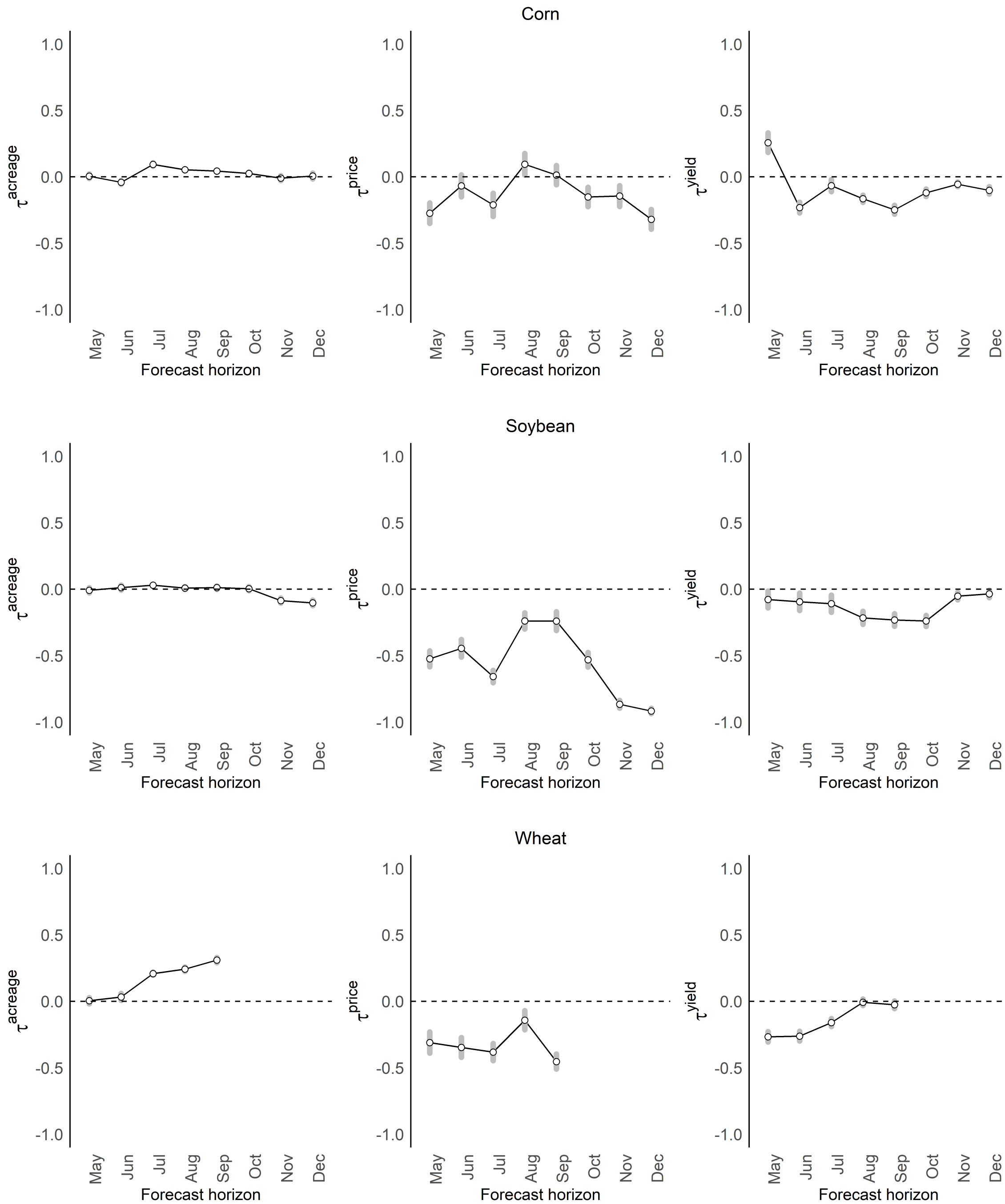


Figure 6. Asymmetry parameter estimates under non-separable loss for WASDE forecasts with 95% confidence intervals

Note: (a) The instrument set consists of a constant and one year lagged forecasts of price. (b) Estimates are plotted for non-separable loss with shape parameter $p = 2$

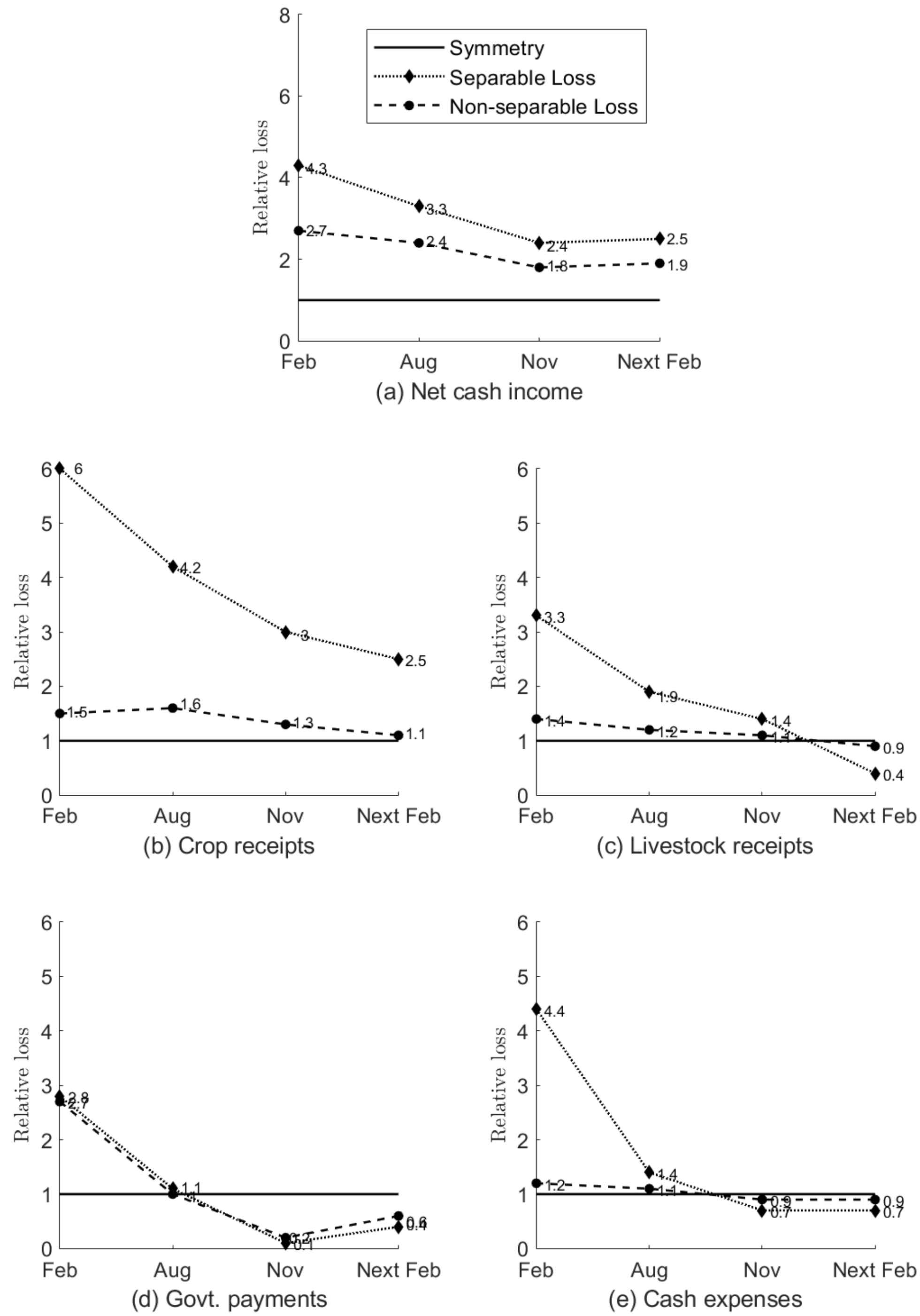


Figure 7. Relative losses for net cash income and its components, $p = 2$

Note: The instrument set consists of a constant and one year lagged forecasts of net cash income.

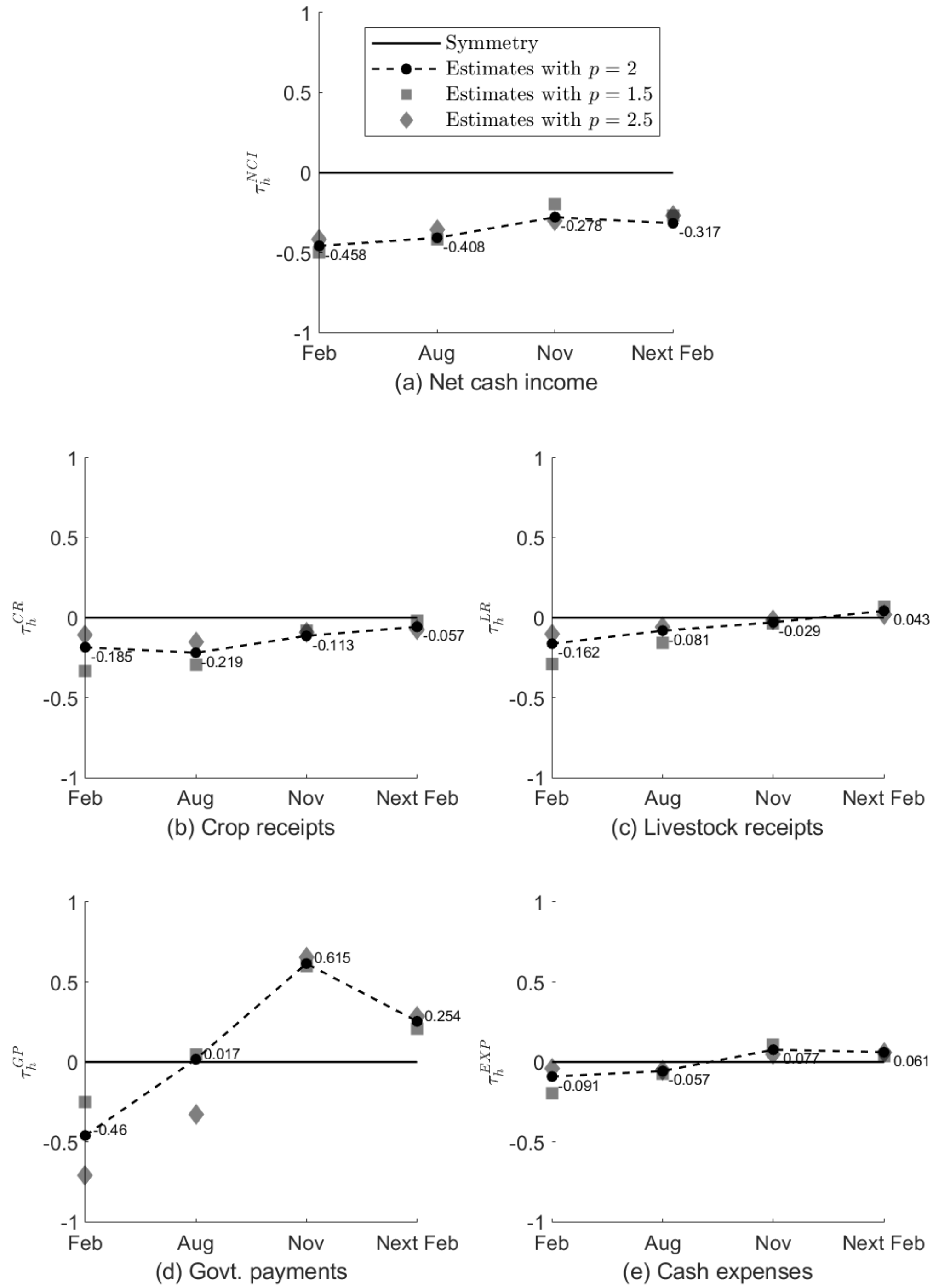


Figure 8. Robustness of net cash income asymmetry parameters to choice of shape parameter

Note: (a) Non-separable loss function with shape parameter, $p = 2$. (b) The instrument set consists of a constant and one year lagged forecasts of net cash income (same as Table 5 in the paper).

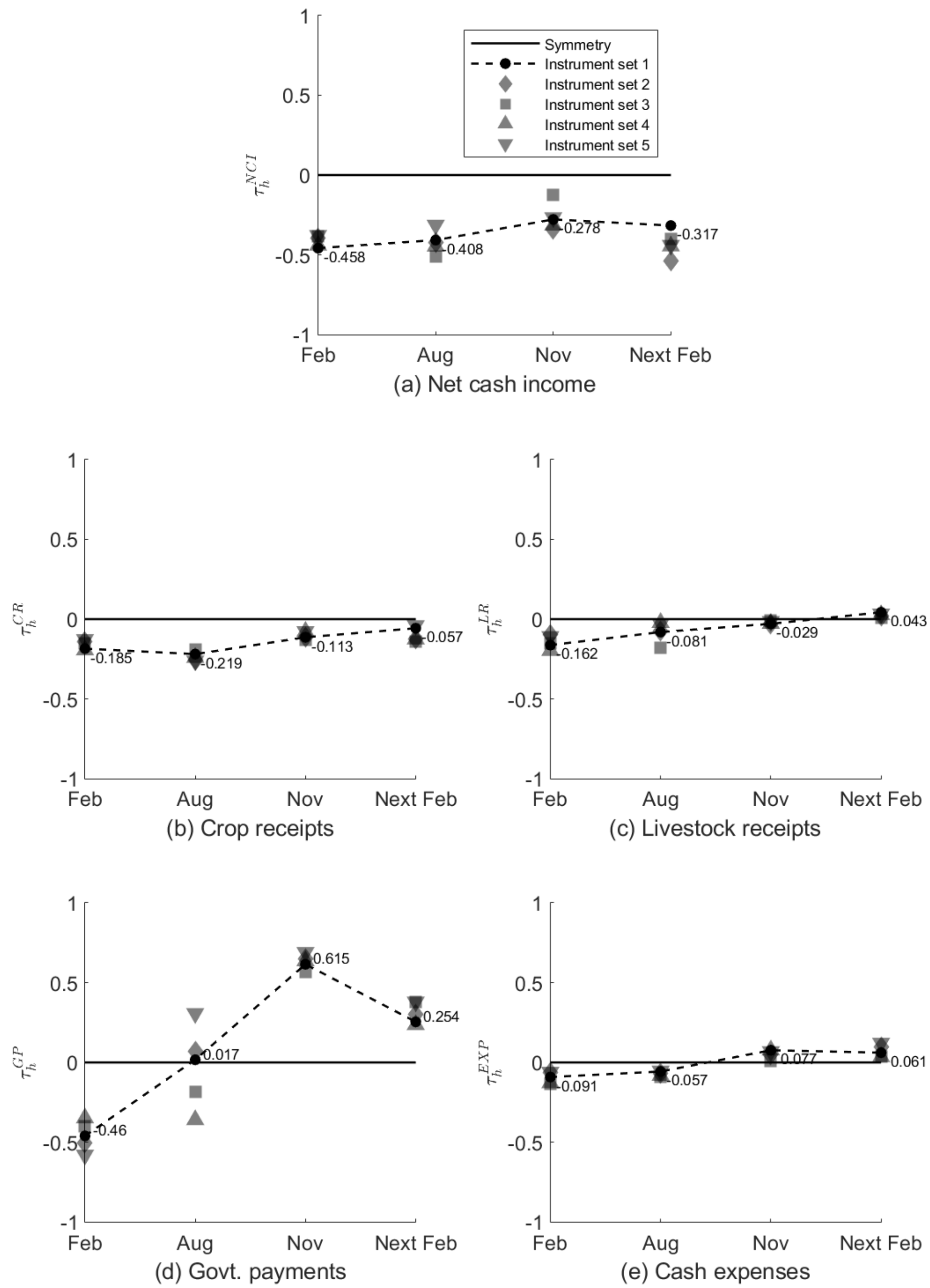


Figure 9. Robustness of net cash income asymmetry parameters to choice of instruments

Note: (a) Non-separable loss function with shape parameter, $p = 2$. (b) The instrument consists of a constant and one year lagged forecasts of 1) net cash income(same as Table 5 in the paper), 2) crop receipts, 3) livestock receipts, 4) government payments, and 5) net cash income and crop receipts.

Tables

Table 1. MAPE, RMSPE and MPE of USDA net cash income forecasts, 1988-2018

Variable	Forecast	MAPE ($\lvert e \rvert$)	RMSPE ($\sqrt{e^2}$)	MPE (e)	Bias (t-statistic)	p-value
Net cash income	February	13.177	16.001	8.153	3.225	0.003
	August	7.620	11.196	3.742	1.999	0.055
	November	5.817	8.208	2.373	1.742	0.092
	Next February	5.861	8.305	2.584	1.972	0.058
Crop receipts	February	4.314	5.339	3.048	3.459	0.002
	August	2.943	3.724	1.761	2.999	0.006
	November	2.389	3.026	1.018	2.076	0.047
	Next February	1.863	2.332	0.813	2.051	0.049
Livestock receipts	February	6.278	7.832	3.147	2.358	0.025
	August	2.261	2.778	0.415	0.739	0.466
	November	1.482	1.888	0.280	0.791	0.435
	Next February	1.076	1.529	-0.101	-0.363	0.719
Govt. payments	February	19.311	27.815	7.564	1.209	0.236
	August	11.374	18.518	-0.066	-0.017	0.986
	November	7.425	11.427	-4.967	-2.643	0.013
	Next February	4.934	7.100	-1.162	-0.876	0.388
Cash expenses	February	3.551	4.307	1.805	2.659	0.012
	August	2.683	3.282	0.470	0.734	0.469
	November	1.960	2.436	-0.375	-0.852	0.401
	Next February	1.926	2.665	-0.251	-0.575	0.570

Table 2. RMSPE, MAPE and MPE of WASDE corn forecasts, 1988/89-2018/19

Variable	Forecast	MAPE ($\|e\|$)	RMSPE ($\sqrt{e^2}$)	MPE (e)	Bias (t-statistic)	p-value
Acreage	May	2.043	2.807	-0.729	-1.383	0.179
	June	1.802	2.542	-0.341	-0.732	0.471
	July	1.145	1.651	-0.755	-2.891	0.008
	August	0.745	0.961	-0.339	-2.367	0.025
	September	0.763	0.961	-0.195	-1.310	0.200
	October	0.604	0.827	-0.041	-0.267	0.791
	November	0.534	0.737	0.047	0.350	0.729
	December	0.534	0.737	0.047	0.350	0.729
Price	May	13.255	17.153	5.467	1.900	0.067
	June	13.194	16.932	3.612	1.265	0.216
	July	10.962	14.161	2.202	0.934	0.358
	August	10.335	13.374	-0.245	-0.101	0.921
	September	9.456	12.079	0.720	0.326	0.746
	October	7.641	9.363	1.171	0.662	0.513
	November	4.853	6.599	1.083	0.929	0.360
	December	3.722	5.126	1.100	1.239	0.225
Yield	May	6.543	12.256	-3.427	-1.122	0.273
	June	5.204	8.382	-0.685	-0.411	0.685
	July	4.554	6.329	-0.156	-0.127	0.900
	August	3.687	4.943	0.736	1.052	0.302
	September	3.459	4.380	0.942	1.542	0.134
	October	2.028	2.758	0.333	0.907	0.372
	November	0.771	0.952	-0.058	-0.351	0.728
	December	0.805	1.028	-0.023	-0.128	0.899

Notes: (a) For acreage and yield, the May, June and July forecasts were available for the years 1993/94-2018/19 while the August forecasts were missing for the year 1988/89. (b) Other forecasts were available for 1988/89-2018/19.

Table 3. RMSPE, MAPE and MPE of WASDE soybean forecasts, 1988-2018

Variable	Forecast	MAPE ($\|e\|$)	RMSPE ($\sqrt{e^2}$)	MPE (e)	Bias (t-statistic)	p-value
Acreage	May	1.600	1.913	0.104	0.252	0.803
	June	1.411	1.752	-0.085	-0.244	0.809
	July	0.996	1.165	-0.485	-2.150	0.041
	August	0.838	1.057	-0.254	-1.332	0.193
	September	0.852	1.073	-0.239	-1.257	0.218
	October	0.621	0.850	-0.047	-0.288	0.775
	November	0.620	0.846	0.028	0.167	0.869
	December	0.620	0.846	0.028	0.167	0.869
Price	May	9.934	13.762	6.025	2.841	0.008
	June	9.865	13.647	4.788	2.192	0.036
	July	9.508	13.506	4.317	2.003	0.054
	August	8.961	12.243	1.992	1.071	0.293
	September	7.533	10.578	1.108	0.618	0.541
	October	6.086	7.997	2.260	1.443	0.159
	November	4.416	6.412	2.286	2.217	0.034
	December	3.643	5.348	1.733	1.957	0.060
Yield	May	5.136	6.666	-0.173	-0.121	0.905
	June	5.115	6.659	-0.088	-0.061	0.952
	July	4.816	6.275	0.705	0.548	0.589
	August	4.330	5.510	1.533	1.568	0.127
	September	3.908	4.757	1.538	1.791	0.083
	October	1.977	2.528	0.951	2.207	0.035
	November	0.930	1.110	0.128	0.598	0.554
	December	0.930	1.110	0.128	0.598	0.554

Notes: (a) For acreage and yield, the May, June and July forecasts were available for the years 1993/94-2018/19. (b) Other forecasts were available for 1988/89-2018/19.

Table 4. MAPE, RMSPE and MPE of WASDE wheat forecasts, 1988-2018

Variable	Forecast	MAPE ($\|e\|$)	RMSPE ($\sqrt{e^2}$)	MPE (e)	Bias (t-statistic)	p-value
Acreage	May	2.158	2.700	-0.407	-0.763	0.452
	June	2.142	2.663	-0.301	-0.535	0.598
	July	1.272	1.625	-1.145	-5.660	0.000
	August	1.056	1.351	-0.903	-4.839	0.000
	September	1.056	1.351	-0.903	-4.839	0.000
Price	May	11.840	14.839	2.583	0.935	0.357
	June	11.083	13.653	2.220	0.886	0.383
	July	8.570	10.794	2.709	1.401	0.172
	August	6.435	7.866	1.169	0.797	0.432
	September	4.812	5.774	1.056	1.004	0.324
Yield	May	4.759	5.923	2.149	1.943	0.063
	June	3.957	4.749	1.985	2.302	0.030
	July	2.470	3.358	0.797	1.591	0.123
	August	1.674	2.173	0.259	0.736	0.468
	September	1.230	1.607	0.186	0.638	0.528

Notes: (a) For acreage and yield, the May and June forecasts were available for the years 1993/94-2018/19 while the July forecasts were missing for the year 1988/89. (b) Other forecasts were available for 1988/89-2018/19.

Table 5. Estimates of asymmetry parameters and rationality tests for net cash income forecasts, 1988-2018

Asymmetry Parameters	Separable Loss				Non-separable Loss			
	Feb	Aug	Nov	Next Feb	Feb	Aug	Nov	Next Feb
Net cash income, τ^{NCI}	-0.624**	-0.530**	-0.403**	-0.421**	-0.458**	-0.408**	-0.278**	-0.317**
	(0.024)	(0.029)	(0.038)	(0.038)	(0.015)	(0.016)	(0.020)	(0.026)
Crop receipts, τ^{CR}	-0.714**	-0.613**	-0.501**	-0.432**	-0.185**	-0.219**	-0.113**	-0.057**
	(0.030)	(0.025)	(0.030)	(0.033)	(0.009)	(0.009)	(0.010)	(0.010)
Livestock receipts, τ^{LR}	-0.532**	-0.309**	-0.151**	0.477**	-0.162**	-0.081**	-0.029**	0.043**
	(0.031)	(0.044)	(0.041)	(0.035)	(0.010)	(0.011)	(0.008)	(0.007)
Govt. payments, τ^{GP}	-0.468**	-0.066	0.822**	0.397**	-0.460**	0.017	0.615**	0.254**
	(0.041)	(0.055)	(0.017)	(0.045)	(0.029)	(0.042)	(0.019)	(0.029)
Cash expenses, τ^{EXP}	-0.627**	-0.182**	0.193**	0.148**	-0.091**	-0.057**	0.077**	0.061**
	(0.026)	(0.040)	(0.039)	(0.040)	(0.006)	(0.011)	(0.008)	(0.012)
J-statistic	4.074	1.715	4.146	7.276	3.263	4.164	3.034	6.098
p-value	0.539	0.887	0.529	0.201	0.660	0.526	0.695	0.297

Notes: (a) The numbers are estimates of asymmetry parameters, $(\tau^{NCI}, \tau^{CR}, \tau^{LR}, \tau^{GP}, \tau^{EXP})'$, and standard errors (SE) are reported in parentheses. (b) Instruments used are a constant and one year lagged forecasts of net cash income. (c) Number of periods, P=31. (d) (**) denotes significant at 5%. (e) p-values of the J-test correspond to a χ^2 distribution with 5 degrees of freedom (f) Shape parameter, $p = 2$.

Table 6. Estimates of asymmetry parameters and rationality tests for WASDE forecasts under non-separable loss, 1988/89-2018/19

Asymmetry Parameters	May	June	July	August	September	October	November	December
Corn								
$\tau^{acreage}$	0.005	-0.041**	0.093**	0.053**	0.043**	0.025**	-0.010	0.006
	(0.009)	(0.008)	(0.007)	(0.005)	(0.005)	(0.006)	(0.009)	(0.011)
τ^{price}	-0.274**	-0.068	-0.211**	0.095**	0.013	-0.152**	-0.145**	-0.321**
	(0.039)	(0.042)	(0.044)	(0.041)	(0.037)	(0.037)	(0.040)	(0.038)
τ^{yield}	0.257**	-0.232**	-0.066**	-0.165**	-0.248**	-0.120**	-0.057**	-0.102**
	(0.038)	(0.020)	(0.023)	(0.014)	(0.017)	(0.014)	(0.009)	(0.014)
J-statistic	4.591	4.542	0.258	1.570	4.380	4.215	4.342	5.356
p-value	0.204	0.209	0.968	0.666	0.223	0.239	0.227	0.148
Soybean								
$\tau^{acreage}$	-0.009	0.012	0.030**	0.009	0.012	0.004	-0.086**	-0.103**
	(0.010)	(0.009)	(0.004)	(0.005)	(0.006)	(0.008)	(0.010)	(0.011)
τ^{price}	-0.524**	-0.445**	-0.657**	-0.239**	-0.240**	-0.532**	-0.866**	-0.917**
	(0.031)	(0.034)	(0.023)	(0.031)	(0.036)	(0.028)	(0.015)	(0.010)
τ^{yield}	-0.078**	-0.095**	-0.109**	-0.216**	-0.232**	-0.239**	-0.052**	-0.036**
	(0.032)	(0.033)	(0.033)	(0.025)	(0.024)	(0.021)	(0.014)	(0.014)
J-statistic	1.345	1.487	4.213	3.249	3.144	1.617	3.340	3.736
p-value	0.718	0.685	0.239	0.355	0.370	0.655	0.342	0.291
Wheat								
$\tau^{acreage}$	0.004	0.033**	0.208**	0.242**	0.310**	-	-	-
	(0.012)	(0.013)	(0.006)	(0.008)	(0.010)	-	-	-
τ^{price}	-0.310**	-0.347**	-0.382**	-0.142**	-0.453**	-	-	-
	(0.040)	(0.038)	(0.033)	(0.037)	(0.029)	-	-	-
τ^{yield}	-0.267**	-0.263**	-0.160**	-0.007	-0.026	-	-	-
	(0.020)	(0.019)	(0.015)	(0.012)	(0.014)	-	-	-
J-statistic	1.862	2.943	1.374	3.789	3.916	-	-	-
p-value	0.602	0.400	0.712	0.285	0.271	-	-	-

Notes: (a) The numbers are estimates of asymmetry parameters, $(\tau^{acreage}, \tau^{yield}, \tau^{price})'$, and standard errors (SE) are reported in parentheses. (b) Instruments used are a constant and one year lagged forecasts of average farm price. (c) (**) denotes significant at 5%. (d) p-values of the J-test correspond to a χ^2 distribution with 5 degrees of freedom. (e) Non-separable loss function with shape parameter, $p = 2$. (f) Corn estimates are conducted for the period 1994/95-2018/19 for the May, June and July forecasts, and 1990/91-2018/19 for the August forecasts. (g) Soybean estimates are conducted for the period 1994/95-2018/19 for the May, June and July forecasts. (h) Wheat estimates are conducted for the period 1994/95-2018/19 for the May and June forecasts, and 1990/91-2018/19 for the July forecasts.

Table 7. Estimates of asymmetry parameters for WASDE forecasts under separable loss, 1988/89-2018/19

Asymmetry Parameters	May	June	July	August	September	October	November	December
Corn								
$\tau_h^{acreage}$	0.416**	-0.007	0.630**	0.430**	0.265**	0.013	-0.085	-0.081
	(0.042)	(0.046)	(0.034)	(0.034)	(0.035)	(0.043)	(0.045)	(0.045)
τ_h^{price}	-0.303**	-0.123**	-0.200**	0.088	-0.105**	-0.182**	-0.229**	-0.307**
	(0.046)	(0.047)	(0.049)	(0.043)	(0.039)	(0.038)	(0.041)	(0.040)
τ_h^{yield}	0.477**	-0.337**	-0.136**	-0.386**	-0.627**	-0.416**	0.095**	0.091**
	(0.053)	(0.053)	(0.056)	(0.032)	(0.025)	(0.033)	(0.037)	(0.039)
J-statistic	4.071	4.455	0.798	2.440	5.208	5.193	4.421	4.120
p-value	0.254	0.216	0.850	0.486	0.157	0.158	0.219	0.249
Soybean								
$\tau^{acreage}$	-0.038	0.092	0.828**	0.326**	0.274**	0.052	-0.143**	-0.115**
	(0.050)	(0.049)	(0.027)	(0.039)	(0.039)	(0.047)	(0.048)	(0.048)
τ^{price}	-0.571**	-0.463**	-0.506**	-0.194**	-0.159**	-0.495**	-0.818**	-0.918**
	(0.032)	(0.036)	(0.033)	(0.035)	(0.042)	(0.033)	(0.020)	(0.010)
τ^{yield}	-0.048	-0.065	-0.118	-0.365**	-0.396**	-0.478**	-0.134**	-0.141**
	(0.058)	(0.059)	(0.059)	(0.039)	(0.033)	(0.034)	(0.040)	(0.040)
J-statistic	2.256	2.129	4.014	4.018	2.904	1.653	6.722	8.331
p-value	0.521	0.546	0.260	0.260	0.407	0.647	0.081	0.040
Wheat								
$\tau^{acreage}$	0.163**	0.185**	0.913**	0.869**	0.855**	-	-	-
	(0.048)	(0.047)	(0.009)	(0.011)	(0.012)	-	-	-
τ^{price}	-0.232**	-0.230**	-0.343**	-0.227**	-0.449**	-	-	-
	(0.048)	(0.045)	(0.036)	(0.037)	(0.031)	-	-	-
τ^{yield}	-0.553**	-0.609**	-0.348**	-0.062	-0.012	-	-	-
	(0.038)	(0.033)	(0.036)	(0.036)	(0.038)	-	-	-
J-statistic	1.222	1.341	0.564	5.560	5.074	-	-	-
p-value	0.748	0.719	0.905	0.135	0.166	-	-	-

Notes: (a) Shape parameter, $p = 2$. (b) The numbers are estimates of asymmetry parameters, $(\tau^{acreage}, \tau^{price}, \tau^{yield})'$, and standard errors (SE) are reported in parentheses. (c) Instrument set consists of a constant and one year lagged forecasts of average farm price. (d) (**) denotes significant at 5%. (e) p-values of the J-test correspond to a χ^2 distribution with 5 degrees of freedom. (f) Corn estimates are conducted for the period 1994/95-2018/19 for the May, June and July forecasts, and 1990/91-2018/19 for the August forecasts. (g) Soybean estimates are conducted for the period 1994/95-2018/19 for the May, June and July forecasts. (h) Wheat estimates are conducted for the period 1994/95-2018/19 for the May and June forecasts, and 1990/91-2018/19 for the July forecasts.

Table 8. Tests of forecast breakdown for net cash income forecasts, 1988-2018

Forecast Horizon	Forecasting scheme					
	Fixed		Rolling		Recursive	
	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value
February	-1.499	0.134	-0.468	0.640	-0.764	0.445
August	-0.885	0.376	-1.071	0.284	-0.887	0.375
November	0.030	0.976	0.022	0.983	0.135	0.893
Next February	0.299	0.765	0.428	0.668	0.389	0.698

Note: (a) T-test statistics and corresponding p-values of structural break test using surprise loss are reported. Rejection of the null hypothesis would suggest presence of structural break. (b) Non-separable loss with shape parameter, $p = 2$.

Table 9. Tests of forecast breakdown for WASDE forecasts, 1988/89-2018/89

Forecast Horizon	Forecasting scheme					
	Fixed		Rolling		Recursive	
	test statistic	p-value	test statistic	p-value	test statistic	p-value
	Corn					
May	0.150	0.880	0.344	0.731	0.118	0.906
June	1.029	0.303	0.453	0.651	0.787	0.431
July	0.910	0.363	-0.315	0.752	0.494	0.621
August	0.424	0.672	0.141	0.888	0.229	0.819
September	0.438	0.662	0.257	0.797	0.336	0.737
October	0.332	0.740	0.273	0.785	0.310	0.757
November	0.505	0.613	-0.002	0.998	0.131	0.896
December	0.073	0.942	-0.043	0.966	-0.002	0.998
	Soybean					
May	0.571	0.568	0.979	0.328	0.299	0.765
June	0.943	0.346	0.608	0.543	0.452	0.651
July	0.388	0.698	0.355	0.723	0.207	0.836
August	0.141	0.888	-0.102	0.919	-0.004	0.996
Sepember	0.353	0.724	0.206	0.837	0.208	0.836
October	-0.431	0.667	-0.691	0.489	-0.939	0.348
November	-1.964	0.049	-2.184	0.029	-1.882	0.060
December	-2.825	0.005	-4.027	0.000	-3.118	0.002
	Wheat					
May	-0.334	0.738	0.085	0.932	-0.439	0.661
June	-0.171	0.864	-0.182	0.855	-0.446	0.656
July	-0.079	0.937	-0.094	0.925	-0.283	0.778
August	-0.235	0.814	-0.181	0.857	-0.385	0.700
September	0.279	0.780	0.354	0.723	0.115	0.909

Note: (a) T-test statistics and corresponding p-values of structural break test using surprise loss are reported. Rejection of the null hypothesis would suggest presence of structural break. (b) Non-separable loss with shape parameter, $p = 2$.