Loss Aversion in Farmland Price Expectations

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ABSTRACT *Farmland price expectations play a critical role in farm investment decisions, yet previous studies suggest that market experts' expectations are not rational. That is, market experts do not make efficient use of all available information. This article tests the degree to which expectations are consistent with rational expectations, under symmetric and asymmetric loss, based on aggregate expectations from Purdue Farmland Values and Cash Rent Survey between 1979 and 2019. We find robust evidence that farmland market experts are averse to overpredicting farmland price increases. When this asymmetry is considered, farmland market experts are shown to be rational loss minimizers.* (JEL Q11, C53)

1. Introduction

Farmland is the primary asset of production agriculture. Farm real estate accounts for approximately 83% of the U.S. farm sector's asset base (U.S. Department of Agriculture Economic Research Service 2020) and serves as the primary store of farmers' wealth and the leading source of collateral in farm loans (Nickerson et al. 2012). Farmland owners' expectations of the future path of farmland values play an important role in farmland price discovery (Brown and Brown 1984). Farmers' and lenders' farmland price expectations also play an important role in agricultural investment decisions. When farmland owners expect farmland prices to increase, they leverage existing equity to invest in additional land (Weber and Key 2014, 2015). When lenders expect farmland prices to increase, they extend additional credit to the agricultural sector (Briggeman, Gunderson, and Gloy 2009). Thus, changes in farmland price expectations may have widespread consequences across the agricultural sector. The process by which individuals form expectations is a key area of study in economics, yet the formation of farmland price expectations among farmland market participants is relatively unexplored.

Economists have developed a number of theories to describe the process by which agents form expectations of uncertain future events (Nerlove and Bessler 2001). Chief among them is rational expectations, which posits that economic agents make efficient use of all available information, just as they do other scarce resources (Muth 1961). Rational expectations is contrasted by various forms of adaptive expectations, which posits that agents make predictions based solely on prior experience. Thus, predictions generated under rational expectations reflect both prior and contemporaneous information. A small number of previous studies have examined farmland price expectations. Using competing derivations of the present value model, Tegene and Kuchler (1991b) provide an indirect test of rational and adaptive expectations based on observed current and lagged aggregate farm real estate values and cash rents for three U.S. regions (Lake States, Corn Belt, and Northern Plains) from 1921 to 1989. The empirical tests reject rational expectations but fail to reject adaptive expectations. The study suggests that farmland purchasers do not make efficient use of all available information when forming expectations of future returns. Kuethe and Hubbs (2017) conduct a more direct test of rational expectations by examining quarterly farmland price expectations of agricultural bankers collected through the Federal Reserve

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Bank of Chicago's Land Values and Credit Conditions Survey between 1991Q1 and 2016Q1. Using survey quantification methods on aggregated survey responses, the authors also reject rational expectations. Specifically, they find that agricultural bankers' short-run expectations are unbiased but inefficient, as they tend to repeat mistakes. Most recently, Kuethe and Oppedahl (2021) extend the work of Kuethe and Hubbs (2017) by examining an unbalanced panel of individual responses to the Federal Reserve Bank of Chicago's Land Values and Credit Conditions Survey between 1993Q1 and 2019Q2. Kuethe and Oppedahl (2021) similarly reject rational expectations. The article suggests that agricultural bankers extrapolate recent farmland price changes but are overly cautious, as observed farmland price changes tend to be greater than expected.

This study tests the degree to which farmland price expectations among market experts are consistent with rational expectations. We examine 41 years of farmland price expectations collected through the Purdue Land Values and Cash Rent Survey from 1989 through 2019. Our study period includes dramatic fluctuations in farmland prices, including the rapid decline associated with the 1980s farm financial crisis and rapid increase associated with the 2000s commodity price boom. Survey respondents include a variety of farmland market experts across the state of Indiana. Located in the U.S. Corn Belt region, Indiana is home to nearly 15 million acres of agricultural land, valued at $98.4 billion (U.S. Department of Agriculture National Agricultural Statistics Service 2017). The Purdue survey shares many similarities with surveys conducted by the U.S. Department of Agriculture, Federal Reserve banks, and other land-grant universities (Kuethe and Ifft 2013). Farmland price surveys have a long tradition in the agricultural sector given the many challenges associated with measuring aggregate farmland values using transactions prices (Bigelow, Ifft, and Kuethe 2020). Purdue Land Values and Cash Rent Survey respondents provide subjective opinions of the current per acre price of farmland in their county at the time the survey is administered (in June) and the previous December. In addition, respondents provide point projections for the prevailing per acre price in the coming December (a six-month horizon). The rationality of these projections can be evaluated by comparing them with the realized December values collected in the later iteration of the survey.

This study makes a number of important contributions to the existing literature. First, we leverage the unique characteristics of the Purdue Land Values and Cash Rent Survey to address the shortcomings of prior work. The only two existing studies that directly test the rationality of farmland price expectations are limited to the qualitative expectations of agricultural bankers (Kuethe and Hubbs 2017; Kuethe and Oppedahl 2021). These studies rely on survey quantification methods, the limitations of which are well documented in the existing literature (see Nardo 2003), and address the expectations of a narrow set of farmland market participants. In contrast, the Purdue Land Values and Cash Rent Survey elicits continuous, quantitative expectations of a broader set of farmland market experts, including farm managers, appraisers, land brokers, and agricultural loan officers.

Second, we test the rationality of farmland price expectations using a flexible estimation framework that does not require the stringent assumptions of conventional test procedures. Specifically, traditional rationality tests require stringent assumptions of the costs associated with prediction inaccuracies, called the loss function. Previous studies reject the rationality of farmland price expectations under the mean squared error (MSE) loss function (Tegene and Kuchler 1991b; Kuethe and Hubbs 2017; Kuethe and Oppedahl 2021). A prediction that minimizes MSE loss generates few prediction errors with large deviations from zero. Under MSE loss, a prediction is consistent with rational expectations when the prediction errors are mean zero and serially uncorrelated (Diebold and Lopez 1996). These properties, however, may not hold under other loss functions (Patton and Timmermann 2007), and rationality may be rejected due to a misspecified loss function (Elliott, Timmermann, and Komunjer 2005). Instead of assuming MSE a priori, we estimate the parameters of the loss function that are consistent with the observed expectations and only assume that the loss function belongs to a flexible class of functions, of which MSE is a special case, following Elliott, Timmermann, and Komunjer (2005).

We are specifically interested in the degree to which prior findings of the irrationality of farmland price expectations can be attributed to asymmetries in respondents' loss functions. Similar to the asymmetric reaction to gains or losses (Kahneman and Tversky 1979), expectations may appear irrational because they are generated as a result of internal bias related to certain outcomes (Weber 1994). For example, agents may assign greater probability weights to some potential outcomes due to large positive utility associated with hope or nervous anticipation or assign greater probability weights to other potential outcomes because of large negative utility associated with fear (Weber 1994).

This study provides robust evidence that farmland market experts are averse to overpredicting farmland price changes. The Purdue Land Values and Cash Rent Survey provides a long history of mean observed and expected farmland prices at the state level and for six regions, each representing approximately 15 counties, from 1979 through 2019. In addition, the survey provides mean observed and expected values for three land-quality grades (top, average, and poor) for each region and the state. Finally, the survey provides mean observed and expected farmland values for land transitioning out of agricultural production at the state level. Thus, we examine a total of 22 series of farmland price expectations. Traditional rationality tests under MSE loss suggest that price expectations for poor-quality farmland are generally downwardly biased, and expectations for top- and average-quality farmland are generally inefficient. However, across a variety of specifications, the overwhelming majority of results (80%) suggest that the respondents' loss functions heavily weight errors associated with overprediction. When this asymmetry is considered, rationality cannot be rejected. Thus, farmland owners, farmers, and agricultural lenders should consider this loss aversion when using price expectations provided by farmland market experts.

2. Methodology

Following Muth (1961), predictions generated under rational expectations follow a number of weak (necessary but not sufficient) form conditions that can be tested empirically. Specifically, rational expectations suggests that predictions should be unbiased, efficient, and optimal. A prediction is unbiased if it does not consistently differ from realized values. A prediction is efficient if it contains all of the information available at the time it is generated. A prediction is optimal if it minimizes the agent's loss function.

The existing literature presents a number of empirical tests of bias, efficiency, and optimality. Let y_t be the variable of interest at time t. Economic agents form expectations of realizations of the variable of interest τ periods ahead, denoted $y_{t+\tau}$, conditional on the information set Ω_t available at time t. The prediction of $y_{t+\tau}$ made at time t is denoted $f_{t+\tau}(\Omega_t)$. Mincer and Zarnowitz (1969) develop an early regression-based test of bias and optimality, which takes the form:

$$y_{t+\tau} = \alpha + \beta f_{t+\tau} + \epsilon_{t+\tau}, \qquad [1]$$

where α and β are unknown parameters to be estimated and $\epsilon_{t+\tau}$ is the standard white noise regression residual. A prediction is unbiased if $\alpha = 0$. A prediction is optimal if there is a unitary elasticity of predictions such that $\beta = 1$. Thus, we conclude that a projection satisfies rational expectations when we fail to reject the joint restriction $(\alpha, \beta) = (0,1)$. The correlation implied by β in equation [1] may be spurious, however, if either series contain a unit root. As a result, Holden and Peel (1990) develop a preferred specification of equation [1] by constraining $\beta = 1$ and rearranging terms, such that

$$y_{t+\tau} - f_{t+\tau} = \alpha + \epsilon_{t+\tau} \qquad [1']$$

The Holden and Peel (1990) test is preferred because it does not require that predictions $f_{t+\tau}$ to be uncorrelated with the residual term $\epsilon_{t+\tau}$, and standard inference tests can be applied to equation [1'], even if the realized values are nonstationary. The null hypothesis of unbiasedness can be directly tested using the restriction $\alpha = 0$ in equation [1']. A positive and significant α suggests that predictions systematically underpredict realized values ($f_{t+\tau} < y_{t+\tau}$), and a negative and significant α suggests that forecasts systematically overpredict realized values ($f_{t+\tau} > y_{t+\tau}$).

Nordhaus (1987) develops a regression-based test of efficiency based on the (weak form) condition that under rational expectations, prediction errors are orthogonal to prior prediction errors. As in equation [1'], prediction error is defined as the difference between the future realization $y_{t+\tau}$ and the prediction $f_{t+\tau}, e_{t+\tau} = y_{t+\tau} - f_{t+\tau}$. The memoryless property of prediction errors can be tested with regression:

$$e_{t+\tau} = \alpha_1 + \rho e_{t+\tau-1} + \epsilon_{t+\tau} \qquad [2]$$

The predictions are efficient if $\rho = 0$.

The existing literature frequently concludes that predictions fail to satisfy the weak conditions of rational expectations. Batchelor (2007) suggests three possible explanations. First, agents may lack the skill to use information efficiently and learn from prediction errors. Second, agents may have the skill to use information efficiently, but their information set Ω_t is insufficient. Third, agents may possess the skill and sufficient information but respond to incentives to make optimistic or pessimistic predictions. Kahneman and Tversky (1973) similarly argue that agents' behavioral biases in information processing may lead to the formation of intentionally biased or inefficient predictions.

Implicit in the theories of expectation formation is the notion that agents generate predictions to minimize the costs of prediction error. That is, agents seek to minimize the costs associated with $e_{t+\tau}$, as represented by their loss function $L(\cdot)$. The loss function is sometimes referred to as the utility function of the forecast producer. Weber (1994) demonstrates that through either expected or rank-dependent utility, technically irrational predictions can be generated as a result of internal bias related to certain outcomes. For example, when agents have a large utility of a given outcome, they may assign greater probability weights to some values out of anticipation, hope, or greed (Weber 1994). Alternatively, large disutility of some outcomes may assign greater probability weights from fear of the negative consequences associated with underestimating probability (Weber 1994). These asymmetries mirror the asymmetric reaction to gains and losses (Kahneman and Tversky 1979). Asymmetries in the consequences of over- or underprediction of uncertain future outcomes are known as asymmetric loss functions.

Under asymmetric loss functions, many of the weak form properties of rational expectations do not hold (Patton and Timmermann 2007). Thus, rationality may be rejected because of a misspecified loss function. For example, under asymmetric loss, prediction errors will not be orthogonal to variables in the forecaster's information set (Batchelor and Peel 1998), and the expected value of prediction error is nonzero. Instead, the prediction error also contains an optimal bias term that depend on the parameter of the loss function (Granger 1969). As a result, we empirically estimate the loss function of the Purdue Land Values and Cash Rent Survey respondents following Elliott, Timmermann, and Komunjer (2005). As Auffhammer (2007) notes, predictions are only optimal for users when their loss function matches the loss function used to create the predictions. The estimation of the respondents' loss function is therefore a necessary first step to determine whether predictions are rational.

The empirical rationality tests of equations [1], [1'], and [2] all implicitly assume that agents generate predictions to minimize the standard (symmetric) MSE loss function. The loss function is assumed a priori, and the empirical tests evaluate the degree to which the predictions conform to the weak conditions of rationality. Elliott, Timmermann, and Komunjer (2005) develop an alternative approach to evaluate expectations by directly estimating the parameters of the loss function and simultaneously testing for rationality. The potential class of loss functions is flexible in that it allows for several parameterizations, including asymmetries related to differing costs of over- and underprediction. The general class of loss functions $L(\cdot)$ can be expressed as

$$L(e_{t+\tau};\gamma,p)=[\gamma+(1-2\gamma)I(e_{t+\tau}<0)]\cdot\left|e_{t+\tau}\right|^{p} \quad [3]$$

The loss function depends on two parameters, γ and p. The parameter $p>0$ determines the curvature of the loss function. The quadratic or squared error loss function is obtained by setting $p=2$, and the linear loss function is obtained by setting $p=1$. The parameter $\gamma\in(0,1)$ measures the degree of asymmetry in the loss function. As the indicator function $I(\cdot)$ takes the value of one when $e_{t+\tau}<0$ and 0 otherwise, γ captures the relative cost of over- and underprediction. For $\gamma<0.5$, the loss function more heavily weights negative errors associated with overprediction than negative errors associated with underprediction. For $\gamma>0.5$, the reverse weighting holds, and when $\gamma=0.5$, the loss function is symmetric. Thus, the standard MSE loss function is obtained when $\gamma=0.5$ and $p=2$, and the mean absolute error (MAE) function is obtained when $\gamma=0.5$ and $p=1$.

Elliott, Timmermann, and Komunjer (2005) show that when p is fixed, the unknown asymmetry parameter γ can be estimated by linear instrumental variables (IV). The estimator is derived from the first-order condition:

$$E(L'(e_{t+\tau};\gamma,p)|\Omega_t)=0. \quad [4]$$

Here $L'(\cdot)$ is the derivative of equation [3] with respect to $e_{t+\tau}$. Following Hansen (1982), γ in equation [3] can be estimated through generalized method of moments (GMM) by minimizing the target function $\bar{\boldsymbol{h}}(\gamma)'\boldsymbol{S}^{-1}\bar{\boldsymbol{h}}(\gamma)$ with $\bar{\boldsymbol{h}}(\gamma)=\frac{1}{T}\sum_{t=1}^{T}(\gamma-I(e_{t+\tau}<0)\cdot\left|e_t\right|^{p-1}\cdot\omega_t$, where ω_t is a d-dimensional set of IV $\omega_t\in\Omega_t$, and $\boldsymbol{S}=\frac{1}{T}\sum_{t=1}^{T}\omega_t\omega_t'(I(e_{t+\tau}<0)-\gamma)^2\left|e_{t+\tau}\right|^{2p-2}$. The initial weighting matrix S is set to the identity matrix I_d. Using the initial S, one can compute the initial $\hat{\gamma}_1$, which can be used to update the precision matrix $\boldsymbol{S}^{-1}=\boldsymbol{S}^{-1}(\hat{\gamma}_1)$. These steps are repeated until convergence.

Elliott, Timmermann, and Komunjer (2005) develop two important statistical tests that can be obtained from their estimation procedure. First, the symmetry of the loss function can be directly tested by examining the difference between $\hat{\gamma}$ and γ_0 following

$$\sqrt{T}(\hat{\gamma}-\gamma_0)\rightarrow\mathcal{N}(0,(\bar{\boldsymbol{h}}(\gamma)'\boldsymbol{S}^{-1}\,\bar{\boldsymbol{h}}(\gamma))^{-1}) \quad [5]$$

A test of asymmetry is obtained by setting $\gamma_0=0.5$.

Second, we can test whether the predictions are rational under the estimated loss function by testing whether the restriction in equation [4] is satisfied. When the restriction holds, the test suggests that the agent uses all the available information Ω_t efficiently. The test is conducted by checking the orthogonality condition:

$$E([\gamma-I(e_t<0)]\cdot\left|e_t\right|^{p-1}\cdot\omega_t)=0 \quad [6]$$

The orthogonality condition for information efficiency implies that the objective function of the GMM estimation should be zero at the optimum. Elliott, Timmermann, and Komunjer (2005) prove that the rationality can be tested using

$$J(\hat{\gamma})=\frac{1}{T}(\boldsymbol{x}(\hat{\gamma})'\boldsymbol{S}^{-1}\boldsymbol{x}(\hat{\gamma}))\sim\chi^2_{d-1}, \quad [7]$$

where $\boldsymbol{x}(\hat{\gamma})=\sum_{t=1}^{T}\omega_t[I(e_{t+\tau}<0-\hat{\gamma}]\left|e_{t+\tau}\right|^{p-1}$. For a symmetric loss function, $J(0.5)\sim\chi^2_d$. By comparing $J(\hat{\gamma})$ with $J(0.5)$, we can assess whether the estimated asymmetric loss function, rather than the symmetric loss function, weakens the evidence against forecast rationality.

Elliott, Timmermann, and Komunjer's (2005) approach has been widely applied in the forecast evaluation literature. These studies consistently demonstrate that forecasts that are biased or inefficient under MSE loss are rational under asymmetric loss. Krüger and LeCrone (2019) show that this method has a high power and is robust to fat tails, serial correlation, and outliers.

3. Data

We examine the rationality of farmland market experts' farmland price expectations collected through the annual Purdue Land Value and Cash Rent Survey. The survey collects market information from a variety of experts, including farm managers, appraisers, land brokers, and agricultural loan officers. Respondents provide estimates of the market value of bare farmland in a given county for three land-quality grades (top, average, and poor) and farmland transitioning out of agricultural production. The land-quality grades are subjectively defined, but each respondent also reports an estimate of the long-term corn yield for each.

Respondents report price information for three points in time. They provide estimates of the current prevailing market price (June) and of the previous December. In addition, respondents provide a projection of the prevailing market price in the coming December (six-month horizon). For example, in 2018, each survey respondent provided an estimate of the market price for bare farmland in their region in June 2018 and in December 2017, and a projection of the market price for bare farmland in their market area in December 2018.

Archived summary results were obtained from *Purdue Agricultural Economics Report* (*PAER*) extension publication from 1979 through 2020.[1] *PAER* reports the mean market value estimates and projections for each land-quality grade (top, average, and poor) and land transitioning out of agricultural production at the state level. In addition, the report includes mean market value estimates and projections for each land-quality grade for six regions across Indiana. Each region consists of 10–19 counties.[2] In sum, archived reports provides 41 annual observations of farmland price projections and realized values for 22 series.

[1] https://ag.purdue.edu/commercialag/Pages/Resources/Farmland/Land-Prices/PAER-Archive. aspx (accessed August 15, 2020).

[2] North region: Cass, Elkhart, Fulton, Jasper, Kosciusko, Lake, LaPorte, Marshall, Miami, Newton, Porter, Pulaski, St. Joseph, and Starke. Northeast region: Adams, Allen, Blackford, DeKalb, Grant, Huntington, Jay, LaGrange, Noble, Randolph, Steuben, Wabash, Wells, and Whitley. West Central region: Benton, Carroll, Fountain, Montgomery, Parke, Putnam, Tippecanoe, Vermillion, Warren, and White. Central region: Bartholomew, Boone, Clinton, Decatur, Fayette, Franklin, Hamilton, Hancock, Hendricks, Henry, Howard, Johnson, Madison, Marion, Rush, Shelby, Tipton, Union, and Wayne. Southwest region: Clay, Daviess, Dubois, Gibson, Green, Knox, Martin, Owen, Perry, Pike, Posey, Spencer, Sullivan, Vanderburgh, Vigo, and Warrick. Southeast region: Brown, Clark, Crawford, Dearborn, Floyd, Harrison, Jackson, Jefferson, Jennings, Lawrence, Monroe, Morgan, Ohio, Orange, Ripley, Scott, Switzerland, and Washington.

For our analysis, projected and realized values are expressed in percentage change to avoid the effect of changing price levels over the study period and the likely nonstationarity of observed farmland prices (Phipps 1984; Tegene and Kuchler 1991a; Falk and Lee 1998). Projected and realized values are calculated as

$$f_t = \left(\frac{\hat{P}_t^{12} - P_t^6}{P_t^6}\right) \times 100 \qquad [8]$$

and

$$y_t = \left(\frac{P_t^{12} - P_t^6}{P_t^6}\right) \times 100, \qquad [8']$$

where P_t^6 is the observed June price level, $\hat{P}_t^{12}$ the projected December price level, and P_t^{12} the observed December price level for year t.

The prediction errors ($e_t = y_t - f_t$) for each series are plotted in Figure 1. Table 1 reports the mean and standard deviation of each series. Table 1 also reports two standard measures of prediction error the root mean square error (RMSE) and MAE). RMSE measures the average squared prediction error over the observation period $t = 1, \ldots, T$:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_t^2} \qquad [9]$$

A prediction that minimizes RMSE generates few errors with large deviations from zero. In contrast, MAE measures the average absolute prediction error over the observation period $t = 1, \ldots, T$:

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |e_t|. \qquad [10]$$

A prediction that minimizes MAE generates errors that are close to zero but allows for the occasional large error. Across all regions and at the state level, RMSE and MAE are largest for poor-quality land.

Table 1 demonstrates that mean observed farmland price changes exceed the projected price changes for top-, average-, and poor-quality farmland at the state level and across all six regions. This suggest that survey respondents in aggregate tend to underpredict farmland price growth. However, this pattern

Figure 1
Prediction Errors, 1979–2019

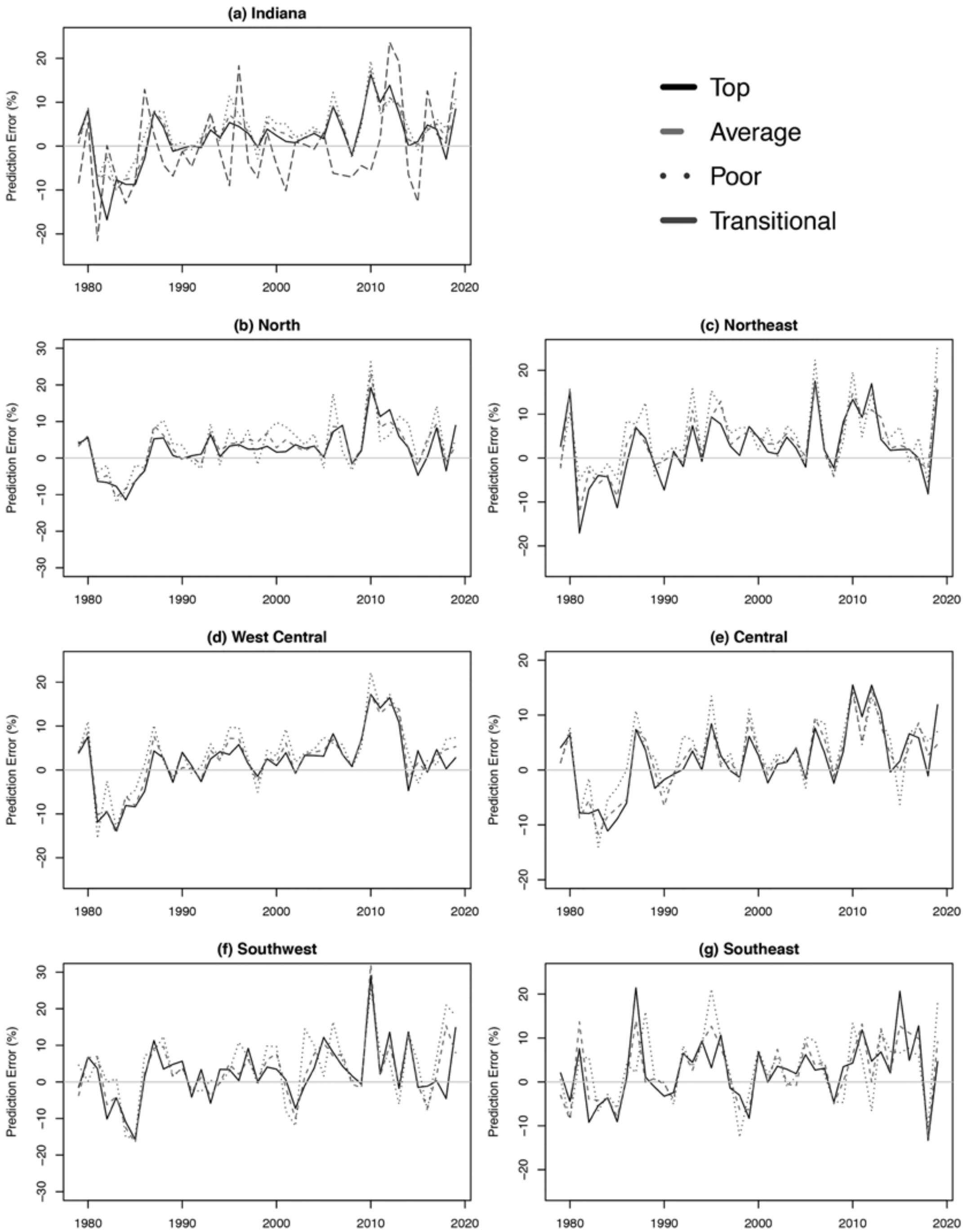


Table 1
Summary Statistics, 1979–2019

	Observed		Projected			
	Mean	Std.Dev.	Mean	Std.Dev.	RMSE	MAE
Indiana						
Top	2.421	6.320	0.471	2.089	6.453	4.907
Average	2.893	6.146	0.255	2.251	6.025	4.790
Poor	3.739	6.213	0.071	2.432	6.749	5.500
Transitional	1.742	9.298	2.424	2.789	9.323	7.164
North						
Top	2.504	6.707	0.212	2.354	6.247	4.831
Average	2.886	6.563	–0.068	2.613	6.569	5.216
Poor	3.888	7.481	–0.025	3.095	7.959	6.215
Northeast						
Top	2.602	7.912	0.088	2.175	7.745	5.893
Average	3.664	7.136	0.054	2.234	7.674	5.896
Poor	4.637	7.945	–0.441	2.716	9.069	6.777
West Central						
Top	2.386	7.175	0.462	2.252	6.861	5.315
Average	2.877	7.205	0.418	2.518	6.917	5.417
Poor	3.874	7.476	0.23	2.547	7.942	6.238
Central						
Top	2.087	6.578	0.173	2.711	6.461	5.048
Average	2.324	6.51	0.261	2.659	6.211	5.005
Poor	3.254	6.511	0.188	2.863	6.842	5.553
Southwest						
Top	2.815	8.245	0.429	1.681	8.141	5.826
Average	3.254	8.409	0.461	2.194	8.612	6.289
Poor	4.16	9.106	0.045	2.379	9.735	7.535
Southeast						
Top	3.029	7.663	0.564	1.879	7.539	5.858
Average	3.334	7.403	0.679	1.891	7.435	5.977
Poor	3.789	7.818	0.668	2.255	8.134	6.597

does not hold for transitional land (only reported at the state level), as observed price growth is below projected. In addition, RMSE and MAE for poor-quality land are higher than those of average- and top-quality land in all six regions and at the state level. This suggests that respondents are least skilled in predicting poor-quality farmland price changes. At the state level and in three regions, average-quality farmland had the lowest RMSE and MAE.

4. Results

The results of the regression-based bias tests under MSE loss equations [1] and [1'] are reported in Table 2. The reported standard errors are heteroskedasticity and autocorrelation consistent (Newey and West 1987). The empirical tests by Mincer and Zarnowitz (1969) and Holden and Peel (1990) indicate that respondents systematically underpredict realized farmland price changes for poor-quality farmland at the state level. Similar results are found in the North and Northeast regions. In addition, the Holden and Peel (1990) test equation [1'] suggest that poor-quality farmland price expectations are downwardly biased in the Central and Southwest regions.

The results of the regression-based efficiency test equation [2] are reported in Table 3. Again, the reported standard errors are

Table 2
Bias Test Results, 1979–2019

	MZ Test					HP Test
	Equation [1]		Restrictions			Equation [1]
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha} = 0$	$\hat{\beta} = 1$	$(\hat{\alpha}, \hat{\beta}) = (0,1)$	$\hat{\alpha}$
Indiana						
Top	2.123	0.633	2.006	0.322	1.149	1.950
	(1.499)	(0.647)				(1.633)
Average	2.572	1.260	5.777*	0.442	3.577*	2.638
	(1.070)	(0.391)				(1.371)
Poor	3.668	0.981	11.897**	0.003	5.952**	3.667**
	(1.064)	(0.346)				(1.211)
Transitional	0.867	0.361	0.139	1.121	0.792	−0.683
	(2.328)	(0.604)				(1.530)
North						
Top	2.200	1.436	3.870	1.851	2.746	2.292
	(1.118)	(0.320)				(1.432)
Average	2.959	1.070	6.791*	0.036	3.525*	2.954*
	(1.135)	(0.372)				(1.377)
Poor	3.909	0.851	10.608**	0.193	5.485**	3.913**
	(1.200)	(0.338)				(1.179)
Northeast						
Top	2.487	1.302	4.265*	0.387	2.664	2.514*
	(1.204)	(0.486)				(1.236)
Average	3.616	0.893	9.966**	0.049	5.132*	3.610**
	(1.145)	(0.485)				(1.105)
Poor	5.014	0.855	19.659**	0.160	10.284**	5.078**
	(1.131)	(0.361)				(1.084)
West Central						
Top	1.835	1.193	2.253	0.171	1.406	1.924
	(1.223)	(0.467)				(1.919)
Average	2.369	1.215	5.486*	0.189	2.971	2.459
	(1.011)	(0.496)				(1.791)
Poor	3.674	0.875	8.202**	0.055	4.136*	3.645*
	(1.283)	(0.533)				(1.652)
Central						
Top	1.950	0.789	2.474	0.335	1.244*	1.914
	(1.240)	(0.365)				(1.567)
Average	2.060	1.010	3.874	0.001	1.961	2.063
	(1.047)	(0.412)				(1.394)
Poor	3.114	0.746	9.161**	0.399	4.727*	3.066*
	(1.029)	(0.401)				(1.112)
Southwest						
Top	2.153	1.542	2.294	0.577	3.561*	2.386
	(1.422)	(0.713)				(1.251)
Average	2.894	0.780	3.556	0.151	2.213	2.793
	(1.535)	(0.566)				(1.435)
Poor	4.126	0.777	7.763**	0.189	3.882*	4.116**
	(1.481)	(0.514)				(1.488)

(table continued on following page)

Table 2
Bias Test Results, 1979–2019 *(continued)*

	MZ Test					HP Test
	Equation [1]		Restrictions			Equation [1]
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha} = 0$	$\hat{\beta} = 1$	$(\hat{\alpha}, \hat{\beta}) = (0,1)$	$\hat{\alpha}$
Southeast						
Top	2.213	1.447	2.942	0.462	3.369*	2.466*
	(1.290)	(0.658)				(1.125)
Average	2.485	1.251	4.045	0.157	2.950	2.655*
	(1.236)	(0.633)				(1.095)
Poor	3.238	0.825	6.858*	0.092	3.487*	3.121*
	(1.237)	(0.577)				(1.207)

Note: Standard errors in parentheses are heteroskedasticity and autocorrelation consistent.
**, * Significance at the 1% and 5% levels, respectively.

Table 3
Efficiency Test Results, 1979–2019

	$\hat{\alpha}$	$\hat{\rho}$		$\hat{\alpha}$	$\hat{\rho}$
Indiana			*Central*		
Top	0.926	0.565**	Top	1.014	0.508**
	(0.902)	(0.111)		(0.947)	(0.156)**
Average	1.377	0.520**	Average	1.239	0.421
	(0.892)	(0.147)		(0.949)	(0.129)
Poor	2.547*	0.341*	Poor	2.563*	0.184
	(1.083)	(0.138)		(1.160)	(0.141)
Transitional	−0.413	0.069			
	(1.622)	(0.172)			
North			*Southwest*		
Top	1.227	0.481**	Top	2.316	0.081
	(0.975)	(0.154)		(1.605)	(0.171)
Average	1.709	0.421**	Average	2.513	0.166
	(1.154)	(0.145)		(1.586)	(0.157)
Poor	3.402*	0.128	Poor	3.299	0.214
	(1.652)	(0.181)		(1.690)	(0.136)
Northeast			*Southeast*		
Top	2.237	0.125	Top	2.435*	0.017
	(1.260)	(0.185)		(1.203)	(0.124)
Average	3.483*	0.085	Average	2.758*	0.016
	(1.314)	(0.204)		(1.214)	(0.168)
Poor	6.076**	−0.183	Poor	3.057*	0.047
	(1.754)	(0.176)		(1.190)	(0.168)
West Central					
Top	0.740	0.597**			
	(0.808)	(0.154)			
Average	0.997	0.595**			
	(0.815)	(0.149)			
Poor	2.148*	0.418**			
	(0.963)	(0.145)			

Note: Standard errors in parentheses are heteroskedasticity and autocorrelation consistent.
**, * Significance at the 1% and 5% levels, respectively.

heteroskedasticity and autocorrelation consistent (Newey and West 1987). The test results suggest that state-level farmland price expectations for top- and average-quality farmland are inefficient. In both cases, the expectations errors are positively autocorrelated, suggesting that prediction mistakes tend to repeat over time. In addition, seven of the regional series are inefficient: top- and average-quality land in the North and Central regions, and all three land-quality gradients in the West central region.

The empirical tests reported in Tables 2 and 3 suggest that farmland experts' expected farmland price changes fail to satisfy the conditions of rational expectations for top-, average-, and poor-quality land at the state level. The only state-level series that is both unbiased and efficient is the expected change in the price of land transitioning out of agriculture. In addition, only six of the 18 regional series (33%) are both unbiased and efficient: top-quality land in the Northeast region, top- and average-quality land in the Southwest region, and all three land classes in the Southeast region. In sum, only seven of the 22 observed series (32%) meet the weak form conditions of rational expectations. The findings are consistent with previous studies of agricultural bankers' farmland price expectations (Kuethe and Hubbs 2017; Kuethe and Oppedahl 2021), and the indirect tests of Tegene and Kuchler (1991b).

As previously stated, the bias and efficiency tests reported in Tables 2 and 3 assume a priori that survey respondents seek to minimize the standard MSE loss function. However, the standard properties of mean zero and orthogonal prediction errors may not hold under alternate loss functions (Patton and Timmermann 2007), and the rejection of rationality may be due to a misspecified loss function (Elliott, Timmermann, and Komunjer 2005). As a result, we also examine each series following the procedure of Elliott, Timmermann, and Komunjer (2005). The method requires a few assumptions. First, we must select the shape parameter p. We examine the forecasts under quadratic ($p = 2$) and linear ($p = 1$) loss. Under symmetric loss $\hat{\gamma} = 0.5$, the loss functions represent MSE and MAE loss, respectively. Second, the estimation of the shape parameter γ requires the selection of appropriate IV. Following Elliott, Timmermann, and Komunjer (2005), we use three sets of IV to ensure that our results are robust to the choice of IV: (a) $\omega_t = (1, e_t)$, (b) $\omega_t = (1, y_t)$, and (c) $\omega_t = (1, e_t, y_t)$.

Table 4 reports the coefficient estimates for the asymmetry parameter γ in equation [3] under quadratic ($p = 2$) and linear ($p = 1$) loss. We report the coefficient estimates and robust standard errors for each region and land-quality class for the three sets of instruments.

The results in Table 4 provide robust evidence that farmland price expectations are generated under asymmetric loss. At the state level, the asymmetry parameter $\hat{\gamma}$ is statistically different from 0.50 at the 1% level under quadratic and linear loss across all three instrument sets for top-, average-, and poor-quality land. As previously stated, state-level projections for top- and average-quality land were shown to be inefficient under MSE loss. State-level projections of poor-quality land were also found to be biased under MSE loss. The only state-level series for which asymmetry could not be rejected was land transitioning out of agricultural production, which prior tests suggest is unbiased and efficient under MSE loss. For top-, average-, and poor-quality land, the estimated coefficient $\hat{\gamma} < 0.5$, which suggests that respondents were averse to overpredicting farmland price changes. In other words, the errors associated with overprediction had a larger weight than errors associated with underprediction.

The estimated loss functions for state-level top-quality farmland are plotted in Figure 2. The three dashed lines in panel A plot the estimated quadratic ($p = 2$) loss functions under the three instrument sets relative symmetric loss ($\hat{\gamma} = 0.5$, solid line). Panel B similarly plots the results under linear loss ($p = 1$). Figure 2 shows the degree of asymmetry in the estimated loss functions. Under both quadratic and linear loss, negative loss ($e_t = y_t - f_t < 0$) associated with overprediction ($y_t < f_t$) implies a greater loss than implied by a symmetric ($\hat{\gamma} = 0.5$) loss function. However, underprediction ($y_t > f_t$) implies a smaller loss relative to the symmetric loss function. From equation [3], it can be seen that the relative cost of overprediction relative to under prediction

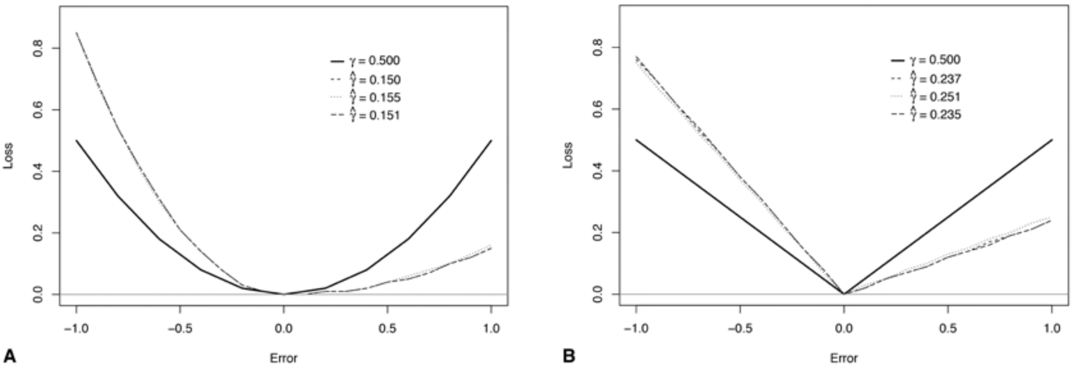
Table 4
Asymmetry Parameter Estimates

	Quadratic Loss (p = 2)			Linear Loss (p = 1)		
Instrument Set	(1)	(2)	(3)	(4)	(5)	(6)
Indiana						
Top	0.150**	0.155**	0.151**	0.237**	0.251**	0.235**
	(0.072)	(0.074)	(0.072)	(0.067)	(0.069)	(0.067)
Average	0.117**	0.126**	0.117**	0.202**	0.228**	0.188**
	(0.059)	(0.060)	(0.059)	(0.063)	(0.066)	(0.062)
Poor	0.110**	0.112**	0.110**	0.167**	0.180**	0.165**
	(0.054)	(0.052)	(0.052)	(0.059)	(0.061)	(0.059)
Transitional	0.539	0.534	0.584	0.550	0.551	0.551
	(0.104)	(0.104)	(0.103)	(0.079)	(0.079)	(0.079)
North						
Top	0.143**	0.142**	0.140**	0.210**	0.206**	0.206**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Average	0.098**	0.107**	0.096**	0.225*	0.229*	0.225*
	(0.046)	(0.047)	(0.045)	(0.066)	(0.066)	(0.066)
Poor	0.125**	0.115**	0.112**	0.338	0.331	0.330
	(0.047)	(0.041)	(0.040)	(0.075)	(0.074)	(0.074)
Northeast						
Top	0.297	0.297	0.290	0.322	0.331	0.314**
	(0.091)	(0.090)	(0.089)	(0.074)	(0.074)	(0.073)
Average	0.191**	0.191**	0.191**	0.224**	0.237**	0.221
	(0.069)	(0.069)	(0.069)	(0.066)	(0.067)	(0.066)
Poor	0.120**	0.121**	0.109**	0.239**	0.234**	0.233**
	(0.045)	(0.045)	(0.042)	(0.067)	(0.067)	(0.067)
West Central						
Top	0.213**	0.201**	0.198**	0.260**	0.245**	0.239**
	(0.083)	(0.081)	(0.080)	(0.069)	(0.068)	(0.067)
Average	0.152**	0.158**	0.151**	0.263**	0.250**	0.248**
	(0.069)	(0.070)	(0.069)	(0.070)	(0.068)	(0.068)
Poor	0.186**	0.193**	0.182**	0.166**	0.177**	0.163**
	(0.080)	(0.080)	(0.080)	(0.059)	(0.060)	(0.058)
Top	0.183**	0.219**	0.179**	0.411	0.418	0.408
	(0.068)	(0.077)	(0.067)	(0.078)	(0.078)	(0.078)
Average	0.180**	0.204**	0.181**	0.296**	0.316**	0.291**
	(0.072)	(0.075)	(0.072)	(0.072)	(0.074)	(0.072)
Poor	0.188**	0.180**	0.188**	0.235**	0.256**	0.222**
	(0.072)	(0.067)	(0.066)	(0.067)	(0.069)	(0.066)
Southwest						
Top	0.239**	0.222**	0.205**	0.348	0.346	0.335
	(0.079)	(0.075)	(0.072)	(0.075)	(0.075)	(0.075)
Average	0.174**	0.162**	0.163**	0.346	0.342	0.335
	(0.064)	(0.062)	(0.062)	(0.075)	(0.075)	(0.075)
Poor	0.169**	0.176**	0.164**	0.255**	0.259**	0.254**
	(0.068)	(0.070)	(0.067)	(0.069)	(0.069)	(0.069)
Southeast						
Top	0.294	0.291**	0.301	0.345	0.349	0.318**
	(0.085)	(0.085)	(0.085)	(0.075)	(0.075)	(0.074)
Average	0.270**	0.268**	0.231**	0.375	0.375	0.365
	(0.080)	(0.080)	(0.075)	(0.077)	(0.077)	(0.076)
Poor	0.261**	0.265**	0.253**	0.288**	0.300**	0.285**
	(0.078)	(0.078)	(0.076)	(0.072)	(0.072)	(0.071)

Note: Standard errors in parentheses are heteroskedasticity and autocorrelation consistent.
**, * Restriction rejected at the 1% and 5% levels, respectively.

Figure 2

Estimated Loss Functions for Top-Quality Indiana Farmland: *a*, Quadratic Loss (p = 2); *b*, Linear Loss (p = 1)



is $[\hat{\gamma}+(1+2\hat{\gamma})]/\hat{\gamma}$. Table 4 shows that the estimated asymmetry coefficient for top-quality land at the state level ranged from 0.150 to 0.155. The asymmetry coefficients therefore suggest that an overprediction is 5.5 to 5.7 times more costly than underprediction of the same degree. Under linear loss, the estimated asymmetry coefficients range from 0.235 to 0.251, suggesting that overprediction is 3.0 to 3.3 times as costly as underprediction of the same degree. The direction of asymmetry is consistent with Kuethe and Oppedahl (2021), who find that agricultural bankers were overly conservative in predicting short-run farmland price changes.

The regional projections generally confirm the state-level results. Asymmetry was rejected for all three instrument sets for top, average, and poor land quality in two of the six regions: North and West central. Only two of the regional series were unable to reject symmetry for a majority instrument sets under quadratic loss: top-quality land in the Northeast and Southeast regions. However, under linear loss, we fail to reject symmetry under the majority of instrument sets for six series: top-quality land in the Northeast, Central, Southwest, and Southeast regions and average-quality land in the Southwest and Southeast regions.

The results of joint rationality test of Elliott, Timmermann, and Komunjer (2005) (7) are reported in Table 5. For quadratic and linear loss, we test rationality under symmetric ($\gamma = 0.5$) and asymmetric ($\gamma = \hat{\gamma}$) loss. A failure to reject the null hypothesis of rationality suggests that the projections are rational for a given set of instruments. At the state level, rationality is rejected for top-, average-, and poor-quality land under symmetric quadratic and linear loss for the majority of instrument sets. However, when evaluated at the estimated asymmetry parameter, we fail to reject rationality under all instrument sets. Thus, we conclude that at the state level, the projections for top-, average-, and poor-quality land can be rationalized under asymmetric loss. Again, the only state-level exception is the projected value of land transitioning out of agricultural land for which rationality cannot be rejected under symmetric quadratic or linear loss.

Again, the regional projections generally confirm the state-level results under quadratic loss. We fail to reject rationality under quadratic symmetric loss for only two series: top-quality land in the Northeast and Southeast regions. In these cases, the asymmetry coefficient was statistically indistinguishable from 0.5 (Table 4). In the remaining series, we fail to reject rationality under asymmetric quadratic loss in all cases. As previously stated, the estimated degree of asymmetry under linear loss is less than that of quadratic loss. It is therefore not surprising that we fail to reject rationality under symmetric linear loss for seven of the 18 regional projections (39%): poor-quality land in the North region; top-quality land in the Northeast, Central, Southwest, and Southeast regions; and average-quality land in the Southwest and Southeast regions. However, in the cases where rationality is rejected under symmetric

Table 5
Rationality Test

Instrument Set		Quadratic Loss ($p = 2$) (1)	Quadratic Loss ($p = 2$) (2)	Quadratic Loss ($p = 2$) (3)	Linear Loss ($p = 1$) (4)	Linear Loss ($p = 1$) (5)	Linear Loss ($p = 1$) (6)
Indiana							
Top	$\hat{\gamma} = 0.5$	27.356**	25.791**	27.359**	19.983**	17.182**	20.523
	$\gamma = \hat{\gamma}$	3.876	3.860	3.884	4.762	3.953	4.904
Average	$\hat{\gamma} = 0.5$	45.900**	41.592**	45.881**	26.897**	20.192**	31.096
	$\gamma = \hat{\gamma}$	3.657	3.283	3.698	4.892	3.436	5.579
Poor	$\hat{\gamma} = 0.5$	54.962**	57.061**	58.194**	35.490**	30.641**	36.058**
	$\gamma = \hat{\gamma}$	2.513	2.088	2.515	3.499	2.824	3.569
Transitional	$\hat{\gamma} = 0.5$	0.288	0.108	3.845	0.571	0.682	0.775
	$\gamma = \hat{\gamma}$	0.146	0.001	3.180	0.160	0.267	0.356
North							
Top	$\hat{\gamma} = 0.5$	37.314**	34.827**	38.672**	22.985**	24.173**	24.209**
	$\gamma = \hat{\gamma}$	3.944	4.430	4.425	2.748	3.002	3.009
Average	$\hat{\gamma} = 0.5$	79.392**	72.915**	86.023**	20.925**	20.005**	21.076**
	$\gamma = \hat{\gamma}$	3.976	3.593	3.983	3.622	3.387	3.659
Poor	$\hat{\gamma} = 0.5$	65.602**	90.684**	96.214**	6.219	7.447	7.545
	$\gamma = \hat{\gamma}$	2.144	2.188	2.360	1.511	2.272	2.331
Northeast							
Top	$\hat{\gamma} = 0.5$	5.350	5.297	6.055	8.980**	7.468	10.284
	$\gamma = \hat{\gamma}$	0.325	0.234	0.537	3.162	2.285	3.865
Average	$\hat{\gamma} = 0.5$	20.096**	20.103**	20.101**	21.154**	18.296**	22.026**
	$\gamma = \hat{\gamma}$	0.129	0.122	0.129	3.678	2.920	3.887
Poor	$\hat{\gamma} = 0.5$	71.482**	71.148**	85.760**	15.819**	16.947**	17.123**
	$\gamma = \hat{\gamma}$	0.107	0.002	0.927	0.841	1.189	1.242
West Central							
Top	$\hat{\gamma} = 0.5$	16.401**	18.343**	18.820**	15.258**	18.348**	19.582**
	$\gamma = \hat{\gamma}$	4.449	4.676	4.720	3.316	4.306	4.654
Average	$\hat{\gamma} = 0.5$	29.629**	27.618**	29.743**	14.709**	17.322**	17.710**
	$\gamma = \hat{\gamma}$	3.995	3.861	4.008	3.121	3.996	4.116
Poor	$\hat{\gamma} = 0.5$	18.107**	16.513**	19.118**	35.640**	31.757**	36.823**
	$\gamma = \hat{\gamma}$	2.613	1.869	3.129	3.517	2.992	3.661
Central							
Top	$\hat{\gamma} = 0.5$	26.330**	17.685**	28.224**	4.445	2.934	5.177
	$\gamma = \hat{\gamma}$	4.945	4.276	4.982	3.137	1.815	3.763
Average	$\hat{\gamma} = 0.5$	24.282**	19.261**	24.339**	13.359**	9.951**	14.098**
	$\gamma = \hat{\gamma}$	4.555	3.688	4.651	5.327	3.690	5.639
Poor	$\hat{\gamma} = 0.5$	20.584**	24.305**	24.099**	18.546**	14.054**	21.779**
	$\gamma = \hat{\gamma}$	1.824	1.409	1.823	2.991	1.555	3.829
Southwest							
Top	$\hat{\gamma} = 0.5$	12.144**	15.225**	18.985**	4.326	4.762	6.641
	$\gamma = \hat{\gamma}$	1.210	1.661	2.464	0.256	0.553	1.778
Average	$\hat{\gamma} = 0.5$	27.951**	31.852**	32.040**	4.622	5.423	6.712
	$\gamma = \hat{\gamma}$	2.188	2.588	2.913	0.459	0.995	1.821
Poor	$\hat{\gamma} = 0.5$	25.395**	23.149**	27.029**	14.172**	13.465**	14.388**
	$\gamma = \hat{\gamma}$	1.827	1.627	1.998	1.597	1.340	1.674

(table continued on following page)

Table 5
Rationality Test *(continued)*

Instrument Set		Quadratic Loss (p = 2) (1)	(2)	(3)	Linear Loss (p = 1) (4)	(5)	(6)
Southeast							
Top	$\hat{\gamma} = 0.5$	5.914	6.085	6.574	4.949	4.130	9.645
	$\gamma = \hat{\gamma}$	0.028	0.012	1.042	0.680	0.121	3.527
Average	$\hat{\gamma} = 0.5$	8.285	8.476**	15.213**	2.682	2.734	4.584
	$\gamma = \hat{\gamma}$	0.114	0.009	2.195	0.012	0.052	1.450
Poor	$\hat{\gamma} = 0.5$	9.895**	9.248**	11.275**	12.275**	10.063**	12.707**
	$\gamma = \hat{\gamma}$	0.489	0.184	0.766	3.498	2.473	3.684

**, * Significance at the 1% and 5% levels, respectively.

linear loss, we fail to reject rationality under asymmetric linear loss. Thus, in 11 of the 18 series (61%), the projections can be rationalized by asymmetric loss.

5. Conclusions

Farmland price expectations play an important role in farmland price discovery and agricultural investment decisions (Brown and Brown 1984; Briggeman, Gunderson, and Gloy 2009; Weber and Key 2014, 2015). Previous studies suggest that farmland price expectations of farmland owners and agricultural bankers are not consistent with rational expectations (Tegene and Kuchler 1991b; Kuethe and Hubbs 2017; Kuethe and Oppedahl 2021). We examine 41 years of short-run farmland price expectations of market experts collected through the Purdue Farmland Values and Cash Rent Survey. Our analysis considers mean observed and predicted farmland price changes for top-, average-, and poor-quality land for Indiana and for six regions. In addition, we examine state-level observed and predicted farmland price changes for land transitioning out of agricultural production.

Traditional empirical tests under symmetric MSE loss suggest that respondents' expectations for low-quality farmland systematically underpredict realized values at the state level (Mincer and Zarnowitz 1969; Holden and Peel 1990). Similar downward bias was found for poor-quality land in four of the six regions. In addition, expectations for top- and average-quality farmland are inefficient under symmetric MSE loss at that state level and in three of six regions. In sum, only seven of the 22 (32%) observed series satisfy the weak form conditions for rational expectations under MSE loss.

Kuethe and Oppedahl (2021) previously found that agricultural bankers were overly cautious in predicting future farmland price expectations. As a result, we examine the potential for asymmetric response to over- and underpredictions in farmland market experts' farmland price expectations following Elliott, Timmermann, and Komunjer (2005). We estimate quadratic and linear loss functions using three combinations of IV. The estimated asymmetry parameter is statistically significant and less than 0.5 in the 80% of our specifications. Thus, we provide robust evidence that farmland market experts are averse to overpredicting farmland price increases. Once this asymmetry is considered, the 15 of the 22 series (68%) that were not consistent with rational expectations under MSE loss can be rationalized under either quadratic or linear loss.

As noted, predictions are only optimal for users when their loss function matches the loss function used to create the predictions (Auffhammer 2007). Our findings suggest that when farmland owners or lenders make financial decisions based on the expectations of farmland market experts, they should consider the potential that such predictions were generated under loss aversion. That is, these predictions are likely conservative as a result of the larger weight given to overprediction.

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