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# Accuracy of Qualitative Forecasts of Farmland Values from the Federal Reserve's Land Value Survey

Christopher J. Zakrzewicz, B. Wade Brorsen, and Brian C. Briggeman

This article determines the accuracy of quarterly land value forecasts provided by bankers through the Federal Reserve Bank of Kansas City's *Survey of Agricultural Credit Conditions*. Bankers' qualitative forecasts of up, down, or no change are compared against actual, self-reported changes in land values. A large proportion of bankers forecast no change. Despite this action, aggregates of bankers' qualitative forecasts help predict changing land values and forecast better than naïve models. Thus, the forecasts in the survey are helpful in predicting land values.

*Key Words:* agriculture, forecasting, land value, qualitative

**JEL Classifications:** G21, Q14

Farmland is the primary source of wealth for many agricultural producers, and its value plays an important role in farm financial planning. However, the lack of publicly available land value forecasts makes future planning difficult. The Federal Reserve Bank of Kansas City provides a potential source of land value predictions through its quarterly *Survey of Agricultural Credit Conditions*. The purpose of this article is to determine the ability of the respondents to the *Survey of Agricultural Credit Conditions* to

forecast land value movements. Specifically, qualitative land value forecasts given by bankers are compared with actual changes in land values obtained in the next quarter's survey.

Forecasting or even explaining agricultural land value movements with econometric models has proven difficult. Pope et al. (1979) re-estimate past published econometric models of farmland prices and find considerable structural change. Numerous subsequent researchers have proposed models to explain land price movements based on the present value of future returns (such as Burt, 1986, and Falk, 1991) and additional factors like capital gain movements (Melicahr, 1979) and inflation (Just and Miranowski, 1993). Falk and Lee (1998) show that land price movements are not forecast well using the present value model. Furthermore, Goodwin and Mishra (2003) note the empirical failure of forecasts based on econometric models is attributable to structural shifts, changing market forces, and an uncertain policy environment. Thus, if bankers in the Federal Reserve System's Tenth District could provide

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accurate forecasts, those forecasts would provide a welcome alternative to econometric models.

The bankers' forecasts are qualitative because they are only asked if their expected trend in farmland values in the next 3 months is higher, no change, or lower.<sup>1</sup> We analyze the data using three primary approaches. The first approach uses contingency table methods to determine whether individual bankers can forecast the values that they report the next quarter. When aggregated, the data are interpreted as probability forecasts. The second approach uses qualitative forecast evaluation methods to evaluate the ability of the probability forecasts to predict the direction of district-wide average changes in land values. Finally, we use a regression of land prices on the probability forecasts to predict land values themselves. The forecasts are evaluated out of sample against benchmark, no-change forecasts.

This article extends previous land value forecasting literature by determining if bankers' qualitative opinion forecasts provided in the *Survey of Agricultural Credit Conditions* are indicators of future land value movement. Currently, the Federal Reserve Bank of Kansas City does not make its prediction data publicly available. However, on occasion, these predictions are referenced in the survey write-up. Nonetheless, if survey predictions are shown to be indicators of land value movement, expanded distribution of the forecast results would provide a valuable resource for anyone interested in tracking agricultural land values.

## Data

Each quarter, the Federal Reserve Bank of Kansas City sends the *Survey of Agricultural Credit Conditions* to agricultural banks across the seven states within the Federal Reserve's

Tenth District. The Federal Reserve's Tenth District includes the states of Colorado, Kansas, Nebraska, Oklahoma, and Wyoming plus the northern half of New Mexico and the western third of Missouri. This region contains 650 agricultural banks, which is almost 30% of the nation's total agricultural banks. Of these banks, approximately 250 respond to the survey each quarter. Agricultural banks are defined as banks that have a higher volume of agricultural loans than the national average (approximately 14%). Bankers from these institutions are beneficial to survey because they are privy to unique information concerning farmland values.

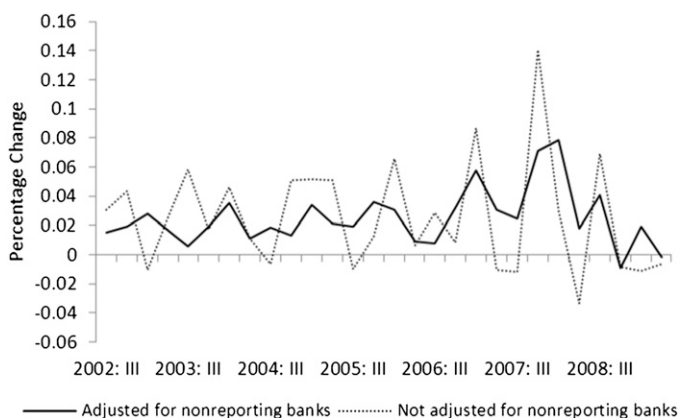
Respondents answer questions concerning current land value levels and the expected directional movement of land values for the next quarter. Estimates are provided for three different classes of land values: good-quality farmland (nonirrigated), irrigated cropland, and ranchland. Each respondent provides a point estimate of local land values for each land category. In addition, each respondent provides an expected directional movement of land values—increase, decrease, or remain stable—for this next quarter.

Banks responding in one quarter may not always respond in the next, which would cause a simple average of reported land values to be sensitive to the banks included in the sample. For this reason, quarterly changes in land values are calculated using only land value estimates for banks that respond in back-to-back quarters. Using this measure mitigates the effect of banks with high land values entering and exiting the sample. An example of this smoothing effect for nonirrigated cropland is illustrated in Figure 1.

In 2002, the survey was expanded to include forecasts of land values. Specifically, bankers reveal whether they expect land values to increase, decrease, or remain stable in the next quarter. Thus, for any quarter ( $q$ ), survey respondents provide both the realized land value change from  $q-1$  to  $q$  and the anticipated directional movement from  $q$  to  $q + 1$ . Respondents are not asked to make seasonal adjustments. Bank responses are subject to additional validation procedures that remove outliers and data entry errors.

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<sup>1</sup>The exact question asked is "What trend in farmland values do you expect in the next 3 months?" Respondents are then asked to select among higher, no change, and lower under a heading that says "Expected trend in the next 3 months." Although the question could be interpreted as a change in trend, the Federal Reserve and presumably respondents treat the question as asking whether land values are expected to go up or down.



**Figure 1.** Average Percentage Change in Reported Non-irrigated Cropland Prices, 2002:III–2009:II

The Tenth District Federal Reserve Bank of Kansas City summarizes its agricultural survey information by reporting the annual percentage change in farmland for each state plus the annual percentage change in the Tenth District average. Additionally, the quarterly percentage change from the previous quarter's Tenth District average is reported. Forecast data are not directly reported. Instead, the Tenth District Bank alludes to expectations through sentences such as “most bankers expected farmland values to remain at current levels over the next three months” (Henderson and Akers, 2010, p. 1). We use both disaggregate data as well as data that are aggregated at the Tenth District level. The panel contains 28 quarters from 2002:II to 2009:II.

## Methods

To test the forecasting ability of agricultural bankers in the Federal Reserve's Tenth District, both disaggregated and aggregated data from the *Survey of Agricultural Credit Conditions* are used. Three methods are used to analyze the data. First, bankers' average individual prediction accuracy is determined using contingency tables. Second, aggregated responses are used to measure out-of-sample forecasting accuracy. The proportion of banks predicting movement in each direction is interpreted as a probability forecast. These probability forecasts predict discrete outcomes that are based on

observed movement in average land values. Finally, we evaluate bankers' abilities to forecast land values by comparing the accuracy of forecasts from a regression model with forecasts from a naïve no-change model.

## Contingency Tables

The analysis of the disaggregate data is straightforward because both the forecasts and outcomes are discrete. The accuracy of individual bankers in predicting land value changes in their own region is shown using contingency tables. The contingency tables show bankers' forecast accuracy in predicting their own self-reported movements in land value. Thus, the data are limited to banks that give both forecasts and land value estimates in quarter  $q-1$  and provide land value estimates in period  $q$ . Stable movements, although not precisely defined in the survey, are assumed to occur when a banker provides the same land value estimate in two consecutive quarters.

Contingency table rows show the outcome frequency for movement in each direction. Likewise, the columns of the table show the number of banks that forecast each directional movement (up, down, or stable). Thus, each cell in the table ( $n_{ij}$ ) gives the number of banks reporting outcomes categorized by their assigned forecasts. Correct forecasts are located on the main diagonal of the table in cells where  $i = j$ . Separate contingency tables are provided for

each of the three types of farmland considered (nonirrigated cropland, irrigated cropland, and ranchland).

In each contingency table, a total of  $N$  observations is reported. In each table, bankers'  $j^{\text{th}}$  forecasted land value change is reported, and the actual  $i^{\text{th}}$  realized change is reported. As a result, the total number of observations  $N$  is equal to the sum of all  $n_{ij}$ :

$$(1) \quad N = \sum_{i=1}^3 \sum_{j=1}^3 n_{ij}.$$

The probability of occurrence ( $d_i$ ) is the relative frequency of each directional movement within the sampling period:

$$(2) \quad d_i = \sum_{j=1}^3 n_{ij} / N.$$

The forecast likelihood ( $f_j$ ) is similarly the frequency with which bankers forecast each directional movement:

$$(3) \quad f_j = \sum_{i=1}^3 n_{ij} / N.$$

From these contingency tables, additional information about bankers' forecasts can be gleaned. Bankers' forecast accuracies are measured using four statistics: the overall bias, the proportion of correct forecasts ( $PCF$ ), the probability of detection ( $POD$ ), and the proportion correct ( $PC$ ). These statistics provide information on the overall reliability of the survey forecasts.

The bias statistic represents the overall miscalculation in bankers' expectations of future land value movement. This statistic is measured by taking the difference of the frequency of prediction and the frequency of occurrence for each directional movement:

$$(4) \quad bias_i = f_i - d_i.$$

The  $PCF$  indicates the proportion of correct forecasts out of the total number of forecasts made for each category:

$$(5) \quad PCF_i = n_{ii} / f_i.$$

The  $POD$  shows how bankers' forecasting accuracies differ based on the eventual outcome. The  $POD$  represents the proportion of outcomes that were correctly predicted given a specific outcome:

$$(6) \quad POD_i = n_{ii} / d_i.$$

The  $PC$  is the proportion of all  $N$  observations that are correctly forecasted. The  $PC$  is calculated by summing the frequency of correctly forecast outcomes ( $i = j$ ) and dividing the total by the total number of observations,  $N$ . Alternatively, the  $PC$  is the sum of the probability of detection across all  $i$  outcomes:

$$(7) \quad PC = \sum_{i=1}^3 n_{ii} / N.$$

Using Pearson's chi-squared test, we test the null hypothesis of independence between bankers' forecasts ( $j$ ) and actual outcomes ( $i$ ). If bankers' forecasts are independent of the observed outcome, the expected value for each cell is the product of the corresponding forecast likelihood and outcome frequency:

$$(8) \quad E[n_{ij}] = d_i * f_j,$$

where  $E[n_{ij}]$  is the expected value of the cell  $n_{ij}$ . The corresponding chi-squared test statistic for testing the independence of bankers' forecasts is:

$$(9) \quad \chi^2 = \sum_{j=1}^3 \sum_{i=1}^3 (n_{ij} - E[n_{ij}])^2 / E[n_{ij}].$$

Although we are working with  $3 \times 3$  contingency tables, the rows and columns are mutually exclusive and exhaustive so that the chi-squared critical value has four degrees of freedom. If the test statistic exceeds the critical value, then we reject the null that outcomes are independent of predictions and assume that a relationship exists between forecasts and outcomes.

#### *Forecasting Discrete Qualitative Outcomes: Brier's Probability Score*

When directional forecasts are aggregated, the data are then the proportion of banks predicting up, down, or no change. These proportions are often interpreted as predictions of the probability of a movement in the given direction and are called probability forecasts (Diebold and Lopez, 1996). These data are conducive to using Brier's probability score and Yates' decomposition to assess the forecasting ability of

bankers (e.g., Bessler and Ruffley, 2006). For example, in a previous study of Federal Reserve qualitative land value forecasts, Covey (1999a, 1999b) used Brier's mean probability scores (Brier, 1950) to analyze aggregated land value data from the Chicago Federal Reserve Bank's *Agricultural Newsletter*. In each period, survey respondents predict land value movement in any one of  $K = 3$  possible directions (up, stable, down). The proportion of bankers expecting movement in each direction represents the forecasted probability of each outcome  $k$  and is denoted  $f_{up}$ ,  $f_{stable}$ ,  $f_{down}$  such that:

$$(10) \quad \sum_k f_k = 1.$$

An outcome index is also created using the observed change in average land values reported by bankers in the same survey. Each quarter, the actual change in land values follows one of the  $K = 3$  directions. The discrete outcome index ( $d_k$ ) is likewise denoted  $d_{up}$ ,  $d_{stable}$ , and  $d_{down}$ . The values of the outcome index are assigned by:

$$(11) \quad \begin{aligned} d_k &= 1, && \text{If average land values move} \\ &&& \text{in the } k^{\text{th}} \text{ direction,} \\ &= 0, && \text{If average land values do not move} \\ &&& \text{in the } k^{\text{th}} \text{ direction.} \end{aligned}$$

Covey (1999a) used a  $\pm 4\%$  change in land value to determine which quarters were assigned upward and downward land value movements.<sup>2</sup> A minimum change of 4% is used to distinguish quarters in which land values moved either up or down from quarters in which land remained stable.

Brier's Probability Score ( $PS$ ) measures the accuracy of the probabilistic forecasts using the sum of squared errors between bankers' probability forecasts and the realized outcome index:

$$(12) \quad PS_t = \sum_k (f_{kt} - d_{kt})^2 \quad ; 0 \leq PS \leq 2,$$

where  $f_{kt}$  is the forecasted probability for  $k^{\text{th}}$  directional movement in time  $t$ , and  $d_{kt}$  is the outcome index value for  $k^{\text{th}}$  directional movement in time  $t$ , and the probability score ranges between zero and two. A probability score of zero represents assigning a forecast of absolute certainty to an outcome that eventually occurs. A probability score of two results from assigning a probability of zero to the occurring directional outcome.

The mean probability score ( $\overline{PS}$ ) measures the total forecast accuracy for all directional forecasts over all  $T = 28$  periods in the sample:

$$(13) \quad \overline{PS} = \frac{1}{T} \sum_{t=1}^T \sum_k (f_{kt} - d_{kt})^2 \quad ; 0 \leq \overline{PS} \leq 2.$$

#### Yates' Covariance Decomposition

Yates (1982) derived a decomposition of  $\overline{PS}$  called the covariance decomposition, which can be used with either discrete or continuous forecasts. The Yates covariance decomposition may be expressed as:

$$(14) \quad \overline{PS}(f, d) = \bar{d}(1 - \bar{d}) + \bar{f}(1 - \bar{f}) + (\bar{f} - \bar{d})^2 - 2\text{Cov}(f, d),$$

where  $\bar{d}$  is the outcome frequency overall  $N$  periods,  $\bar{d}(1 - \bar{d})$  is the  $\text{Var}(d)$ ,  $\bar{f}$  is the mean probability forecast over all  $N$  periods,  $\bar{f}(1 - \bar{f})$  is the  $\text{Var}(f)$ , and  $\text{Cov}(f, d)$  is the covariance between the forecast and outcome indices.

The bias is defined by

$$(15) \quad \text{Bias} = \bar{f} - \bar{d},$$

where  $\bar{f}$  is the mean probability forecast over all  $N$  occasions. The bias statistic shows how well forecast frequencies match outcome frequencies for the event of interest.

The  $\text{Cov}(f, d)$  contributes negatively to the probability score and should, therefore, be maximized. Thus, the covariance may be expressed as:

$$(16) \quad \text{Cov}(f, d) = [\text{slope}][\text{Var}(d)],$$

where *slope* is the *slope* of the regression line when forecast values are regressed on outcomes.

<sup>2</sup>The results can be sensitive to the bounds of the no-change category. Alternative bounds of [0, 3.5] are examined in Zakrzewicz (2010). The alternative bounds still reach the same overall conclusion regarding the bankers' forecasting abilities, but have reduced bias and increased slope scores and probability scores with two of the three land classes.



When the outcomes take discrete values of zero or one, the slope can be defined as:

$$(17) \quad \text{slope} = \bar{f}_c - \bar{f}_0 \quad ; \quad -1 \leq \text{slope} \leq 1,$$

$$\text{where: } \bar{f}_c = \frac{1}{T_c} \sum_m f_{cm} \quad m = 1, \dots, T_c$$

is the conditional probability judgment for the target event over those  $T_1$  occasions when the event actually occurs, and  $\bar{f}_0$  is defined similarly for the remaining  $T_0$  instances when the event does not occur, with  $T = T_1 + T_0$ . In the ideal case, the forecaster always provides  $f_k = 1$  when the realized outcome  $k$  occurs and  $f_k = 0$  when it does not. The slope measures the average amount by which the average probability estimates change conditional on the occurrence of the forecasted outcome. The more expertise bankers demonstrate in effectively discriminating directions of land value movements, the higher the *slope* score will be. The optimal *slope* score is one and occurs when bankers offer perfect foresight.

It should be noted that  $\text{Var}(f)$  contributes positively to the probability score, and the forecaster should minimize the forecast variance. However, when the variance of the forecasts is at an absolute minimum of zero, the forecaster is providing constant forecasts, which forces the covariance to zero by eliminating the *slope* value. Thus, a proper objective of the forecaster should be to minimize the variance of the forecasts conditional on the attainment of a given slope (Yates, 1988). As a result, forecasts should generally have a lower variance than outcomes.

The probability forecasts for bankers are measured against two models. Both of these no-skill forecasters provide constant forecast probabilities each quarter, which causes the slope score to be zero. The first is a uniform model in which the probability of directional movement is equal across outcomes ( $f_k = 1/K$  for all  $k = 1, \dots, K$ ). For this application, forecasts of probability equal to one-third are assigned to increases, decreases, and stable land value movement for each quarter.

The second model is a relative frequency model that assigns probabilities based on the relative frequency of the actual outcomes

( $f_k = \bar{d}_k$  for all  $k = 1, \dots, K$ ). The relative frequency model is calculated in-sample from all observed outcomes. The model provides constant, unbiased forecasts, and no constant probability forecaster can perform better than the relative frequency forecast; decomposition shows that the probability score for the relative frequency forecaster is equal to the outcome variance ( $\text{Var}[d]$ ). Because forecasts are generated in-sample, this model takes advantage of future information and provides a test of how well bankers provide forward-looking predictions.

### Forecasting Land Values

The previous sections have considered only forecasting the direction of land price movements, but the forecasts can also be used to forecast land prices themselves. To convert bankers' qualitative forecasts into a forecast of land values, the percentage changes in land values are regressed against bankers' forecasts:

$$(18) \quad \% \Delta \text{Land Value}_t = \beta_0 + \beta_1 \text{fup}_{t-1} + \beta_2 \text{fdwn}_{t-1} + \varepsilon_t$$

where  $\text{fup}_{t-1}$  is the proportion of bankers forecasting increasing land values for period  $t$  and  $\text{fdwn}_t$  is the proportion of banks forecasting decreases in land values. The proportion of banks forecasting stable movement is removed from the equation to prevent perfect collinearity among the independent variables. The dependent variable  $\% \Delta \text{Land Value}_t$  is the average percent change reported by all banks in the Federal Reserve's Tenth District in time  $t$ . The last eight quarters are forecasted out-of-sample as one-step-ahead predictions.

Bankers' land value forecasts are evaluated against a naive no-change benchmark model. This model forecasts the expected percentage change in land value as the change reported in the previous period:

$$(19) \quad \% \Delta \text{Land Value}_t = \% \Delta \text{Land Value}_{t-1} + \varepsilon_t$$

Testing bankers' forecasts against this benchmark will determine if bankers provide forward-looking forecasts. Forecast errors are evaluated using root mean squared error (RMSE).

## Results

### *Contingency Tables Using Disaggregated Data*

The contingency tables in Table 1 use disaggregated data. Bankers are most likely to forecast no change in farmland values. Irrigated cropland has the fewest responses, presumably as a result of some bankers not responding when there is little irrigated cropland in their market area. Summary statistics from the contingency tables are in Table 2. Notice in Table 2 that the forecast frequencies are similar across land types. Across all sample periods, approximately 75% of bankers expected no change in land values, 20% expected land values to rise, and 5% forecast declining land values.

As a result of bankers being more likely to forecast stable land values, their forecast frequencies are biased toward the no-change category (Table 2). Across all land types, the largest bias estimate, the difference between forecasted and realized land value movements is on stable land values, bias equal to 16%. This result is typical of qualitative business surveys. Keeton and Verba (2004) argue that when given a choice of categories such as up, down, and no change, an implausibly large number of respondents tend to choose the no-change

category. Furthermore, this bias toward the no-change category is expected because forecast variability is expected to be less than actual variability.

The proportion of forecasts that were correct is also found in Table 2. Again, the results are consistent across the type of farmland considered. Approximately 40% of the time that bankers forecast upward movement, land values actually increased. Bankers were best able to forecast no change 63% of the time they were correct. Additionally, 17–22% of downward forecasts were correct.

Bankers' proportions of total correct forecasts (calculated as the number of correct up, down, or no-change forecasts divided by the number of observations) are 0.562, 0.544, and 0.564 for nonirrigated cropland, irrigated cropland, and ranchland, respectively. The tendency for bankers to forecast no change causes the probability of bankers detecting stable land values to be extremely high (approximately 80%). Bankers had difficulty in predicting the infrequent decreases in land values. In fact, when land values declined, bankers had forecast increasing land values twice as often as they had forecast decreases. Depending on the type of land considered, bankers correctly predicted between 25% and 28% of increases in farmland values.

**Table 1.** Contingency Table of Federal Reserve Tenth District Bankers Forecasted and Realized Quarterly Farmland Value Movements

Land Type	Realized Change	Forecasted Change			Total
		Up	No Change	Down	
Nonirrigated cropland	Up	509	1230	72	1811
	No change	569	2923	160	3652
	Down	179	514	66	759
	Total nonirrigated	1257	4667	298	6222
Irrigated cropland	Up	325	868	57	1250
	No change	397	2137	136	2670
	Down	117	366	53	536
	Total irrigated	839	3371	246	4456
Ranchland	Up	422	1212	59	1639
	No change	540	2924	164	3628
	Down	164	487	47	698
	Total ranchland	1126	4623	270	6019

Note: These data are based on the individual bank responses and are not publicly available.



**Table 2.** Statistics of Individual Banker Directional Forecasts of Quarterly Farmland Values Movements

Land Type	Forecast Direction	Frequency of Forecast Direction ( $f_j$ )	Frequency of Realized Direction ( $d_i$ )	Bias ( $f_j - d_i$ )	Proportion of Correct Forecasts ( $PCF$ )	Proportion of Realized Directions ( $POD$ )
Nonirrigated cropland	Up	0.202	0.291	-0.089	0.405	0.281
	No change	0.750	0.587	0.163	0.626	0.800
	Down	0.048	0.122	-0.074	0.221	0.087
Irrigated cropland	Up	0.188	0.281	-0.092	0.387	0.260
	No change	0.757	0.599	0.157	0.634	0.800
	Down	0.055	0.120	-0.065	0.215	0.099
Ranchland	Up	0.187	0.281	-0.094	0.375	0.257
	No change	0.759	0.603	0.165	0.632	0.806
	Down	0.045	0.116	-0.071	0.174	0.067

Note: Bias is defined as the forecast frequency minus the frequency of occurrence. Forecasts correct are the percentage of all forecasts that are correct for the specified direction. Probability of detection is the percentage of all outcomes that are correctly forecast.

*Accuracy of Probability Forecasts*

Bankers’ forecast accuracy is now assessed using aggregated data. The first statistic to examine forecast accuracy is the Brier’s probability score. This statistic measures the accuracy of the probabilistic forecasts by assigning probabilities for discrete outcomes based on the proportion of bankers predicting increases and decreases in land values. Thus, for each period, qualitative forecast data provide probability estimates for one-step-ahead out-of-sample directional movements. Bankers’ forecasts are evaluated against a naïve model that assigns a uniform probability, one-third, to each of the three potential land value movements. In addition, bankers’ forecasts’ are compared with a relative frequency model that uses in-sample information to create unbiased estimates. With this model, the frequencies of realized directions in Table 2 are used as the probability forecast in every quarter. The relative frequency model represents the best unbiased, no-skill forecaster.

As indicated in Table 3, bankers provide more accurate forecasts than the two alternative methods. For all three land types, the probability scores produced by bankers are lower than the naïve uniform model and the relative frequency forecasting model. For increasing and stable farmland value movements,

bankers’ forecasts are superior to the relative frequency forecasts. This result suggests that bankers are able to distinguish quarters in which land value is likely to increase. Although bankers’ probability scores are higher than relative frequency forecasts for downward movement, this result is because there are no quarters in which farmland values declined by more than 4%. The key result in Table 3 is that the bankers have the lowest total probability scores for all three land types, which indicates that bankers have forecasting ability.

The next statistic to assess bankers’ forecasting ability is to decompose the Brier’s probability score. Through Yates covariance decomposition, further insights are gleaned as to why bankers produce better forecasts than no-skill forecasting models. The bankers’ bias scores are small, but they nevertheless do show some bias. Bias scores are negative for predictions of downtrend resulting from attaching positive probability to price drops that never occurred (Table 4). Positive bias scores for upward movements with irrigated and non-irrigated cropland and stable movement for ranchland indicate that bankers predicted more occurrences in these categories than actually occurred. However, of importance to note is that directional bias is directly related to the definition of the range of “stable” land values.

**Table 3.** Brier’s Probability Score across Various Forecasters and Land Types

Land Type	Mean PS	Forecast		
		Bankers	Uniform	Relative Frequency
Nonirrigated	Up	0.0897	0.2302	0.1224
	Stable	0.1042	0.3254	0.1224
	Down	0.0065	0.1111	0.0000
	Total	0.2004	0.6667	0.2448
Irrigated	Up	0.0762	0.1468	0.0957
	Stable	0.0935	0.4087	0.0957
	Down	0.0064	0.1111	0.0000
	Total	0.1761	0.6667	0.1913
Ranch	Up	0.1828	0.2063	0.2041
	Stable	0.1893	0.3492	0.2041
	Down	0.0057	0.1111	0.0000
	Total	0.3778	0.6667	0.4082

Note: These statistics and the remaining tables are based on data that are aggregated across bankers. This table shows the calculated probability scores for three different forecasts. Each directional forecasts has its own probability score and the total probability score (PS) is equal to the sum of up, stable, and down probability scores.

Caution should be taken in comparing and interpreting the different bias statistics across land types because they would change if the definition of stable land values changed.

Bankers’ forecasting skills are measured by the calculated slope scores (Table 4). For all upward and stable movement, slope scores are positive, suggesting bankers have forecasting

**Table 4.** Bankers’ Bias and Slope Scores

Land Type		Direction		
		Down	Stable	Up
Nonirrigated	$\bar{f}_k$	0.049	0.760	0.202
	$\bar{d}_k$	0.000	0.857	0.143
	Bias	0.049	−0.097	0.059
	$\bar{f}_c$	0.000 (0)	0.771 (24)	0.367 (4)
	$\bar{f}_1$	0.049 (28)	0.622 (4)	0.174 (24)
	Slope	−0.049	0.149	0.193
Irrigated	$\bar{f}_k$	0.056	0.756	0.188
	$\bar{d}_k$	0.000	0.893	0.107
	Bias	0.056	−0.137	0.081
	$\bar{f}_c$	0.000 (0)	0.772 (25)	0.363 (3)
	$\bar{f}_0$	0.056 (28)	0.628 (3)	0.167 (25)
	Slope	−0.056	0.144	0.196
Ranchland	$\bar{f}_k$	0.046	0.767	0.187
	$\bar{d}_k$	0.000	0.714	0.286
	Bias	0.046	0.053	−0.099
	$\bar{f}_c$	0.000 (0)	0.782 (20)	0.252 (8)
	$\bar{f}_D$	0.046 (28)	0.732 (8)	0.161 (20)
	Slope	−0.046	0.050	0.091

Note: Stable land values are within  $\pm 4\%$  of previous quarter. The variable  $\bar{f}_k$  is the average probability forecast. The variable  $\bar{d}_k$  is the average outcome frequency. The bias is calculated as  $\bar{f}_k - \bar{d}_k$ . The variable  $\bar{f}_c$  is the average forecast on occasions when land values move in the forecasted direction. The variable  $\bar{f}_D$  is the average forecast on occasions when land values do not move in the forecasted direction. Values in parentheses indicate the number of observations assigned to each outcome. The slope is calculated as  $\bar{f}_c - \bar{f}_D$ .

**Table 5.** Regression Results for Forecasted Quarterly Percentage Change in Land Values

Land Type	LHS Variable	Estimated Coefficients			$R^2$	2009:III Forecast
		Intercept	$fup_{t-1}$	$fdown_{t-1}$		
Nonirrigated	$\% \Delta \text{ Land Value}_t$	-0.000 (0.010)	0.123*** (0.037)	0.021 (0.061)	0.392	0.008
Irrigated	$\% \Delta \text{ Land Value}_t$	-0.005 (0.010)	0.141*** (0.035)	0.030 (0.066)	0.495	0.002
Ranchland	$\% \Delta \text{ Land Value}_t$	0.008 (0.012)	0.125* (0.050)	-0.031 (0.064)	0.416	0.021

Note: Asterisk (\*), double asterisk (\*\*), and triple asterisk (\*\*\*) denote variables significant at 10% and 5%, and 1%, respectively. Values in parentheses are standard errors.

ability with respect to increasing and stable land value movement. For downward movement, slope scores are approximately -0.05 for all land types, which are the result of having no occasions of decreasing land value in the aggregate data. For ranchland, the proportion of bankers forecasting upward movement is 9.1% higher in quarters in which land values increased. Contrasting these values to cropland, the difference in the banks predicting increases is 19% higher in quarters when cropland values actually increased. These results show that bankers have some ability to distinguish quarters in which land values are likely to increase.

*Forecasting Land Values*

The final evaluation procedure directly estimates the change in aggregate land values as a function of the proportion of bankers forecasting this movement. Forecasts for the third quarter of 2009 are in Table 5. The coefficients for forecasted increases take expected signs, but coefficients for forecasted decreases do not take appropriate signs for irrigated or non-irrigated cropland. Each model explains substantial in-sample variation with  $r^2$  values ranging from 0.392–0.495. Out of sample, bankers forecast better than the naïve model for each land type as shown by the lower RMSE values (Table 6). Thus, the Federal Reserve Bank of Kansas City’s *Survey of Agricultural Credit Conditions* does provide useful information that can be used to forecast land values.

**Conclusions**

The results of this article suggest that bankers in the Tenth District of the Federal Reserve were able to forecast land value movements. Contingency tables based on disaggregated forecasts show that bankers forecast no change at an extremely high rate, allowing them to forecast stable land value movement well. Approximately 40% of bankers’ forecasts for upward movement were correct, but only 20% of downward forecasts were correct. Bankers correctly forecast 60% of all reported outcomes.

Aggregate data also show bankers’ ability to forecast land value movements. First, bankers’ probability forecasts are superior to an unbiased relative frequency forecast for all land types considered. Further, average land value changes, which were directly forecasted from aggregate directional predictions, demonstrated that bankers’ forecasts are superior to forecasts produced by a naïve no-change model. For each forecasting method used, bankers outperform

**Table 6.** Accuracy of Bankers Forecast and Naïve No-Change Out-of-Sample Forecasts for Changing Land Values 2007:III–2009:II

Land Type	Model	Root Mean Squared Error
Nonirrigated	Bankers’ forecast	0.023
	Naïve no change	0.031
Irrigated	Bankers’ forecast	0.027
	Naïve no change	0.038
Ranchland	Bankers’ forecast	0.026
	Naïve no change	0.036

the selected naïve or no-skill benchmark models. These results show that bankers are able to forecast the direction of land value movement.

Having an early indication of future land value movement may improve a banker's or bank regulator's (i.e., the Federal Reserve) ability to manage loan portfolio risk. Since the 2008 financial crisis, many bankers and lenders conduct stress tests on their loan portfolio. For agricultural bankers, stress testing farmland values is important because the primary source of collateral for many agricultural loans (real estate and even some not real estate) is farmland. Thus, having an indication of future movements in an agricultural bank's primary source of collateral would yield more precise stress tests.

Knowing the direction of land value movements also benefits the broader agricultural community. As the primary source of wealth for many agricultural producers, movements in land values will largely shape the financial stress within agriculture. Since 2007, agricultural land values have risen sharply, which has eased the financial stress of producers, yet history has shown that land values are susceptible to significant declines. Thus, having an early indication that land values might be falling would be beneficial information for the agricultural industry.

Future research, or even the Federal Reserve Bank of Kansas City, should consider using these as well as potentially other bankers' forecasts as a way to look ahead to potential financial stress within agriculture. This article has demonstrated that bankers do have forecasting ability in regard to land values. In addition to land value forecasts, potentially bankers could provide accurate and informative forecasts of other pertinent financial variables in agriculture such as loan interest rates, credit quality, and farm income. Collecting this information may allow one to construct an agricultural stress index. Although constructing such an index is beyond the scope of this article, an important first step is identified in this article: bankers are able to accurately forecast future quarterly movements in agricultural land values.

## References

- Bessler, D.A., and R. Ruffley. "Prequential Analysis of Stock Market Returns." *Applied Economics* 36,5(2006):399–412.
- Brier, G.W. "Verification of Forecasts Expressed in Terms of Probability." *Monthly Weather Review* 78,1(1950):1–3.
- Burt, O.R. "Econometric Modeling of the Capitalization Formula for Farmland Prices." *American Journal of Agricultural Economics* 68(1986):10–26.
- Covey, T. 1999a. "Bankers' Forecasts of Farmland Value." Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL. Internet site: [http://www.farmdoc.illinois.edu/nccc134/conf\\_1999/pdf/confp28-99.pdf](http://www.farmdoc.illinois.edu/nccc134/conf_1999/pdf/confp28-99.pdf). Accessed October 2012.
- . "Evaluating Bankers' Probability Forecasts of Intermediate-Term Loan Rates." Presented at the Southern Agricultural Economics Association Annual Meeting, Louisville, TN, February 1, 1999b.
- Diebold, F.X., and J.A. Lopez. "Forecast Evaluation and Combination." *Handbook of Statistics* 4(1996):241–68.
- Falk, B. "Formally Testing the Present Value Model of Farmland Prices." *American Journal of Agricultural Economics* 73,1(1991):1–10.
- Falk, B., and B. Lee. "Fads versus Fundamentals in Farmland Prices." *American Journal of Agricultural Economics* 80,4(1998):696–707.
- Goodwin, B.K., and A.K. Mishra. "What's Wrong with Our Models of Agricultural Land Values?" *American Journal of Agricultural Economics* 85,3(2003):744–52.
- Henderson, J., and M. Akers. "Despite Low Incomes, Farmland Values Rise Further." *Survey of Tenth District Agricultural Credit Conditions*. Federal Reserve Bank. Second quarter, 2010.
- Just, R.E., and J.A. Miranowski. "Understanding Farmland Price Changes." *American Journal of Agricultural Economics* 75(1993):156–68.
- Keeton, W.R., and M. Verba. "What Can Regional Manufacturing Surveys Tell Us?—Lessons from the Tenth District." *Economic Review: Federal Reserve Bank of Kansas City* 89(2004):39–70.
- Melichar, E. "Capital Gains versus Current Income in the Farming Sector." *American Journal of Agricultural Economics* 61(1979):1085–92.

- Pope, R.D., R.A. Kramer, R.D. Green, and B.D. Gardner. "An Evaluation of Econometric Models of U.S. Farmland Prices." *Western Journal of Agricultural Economics* 4(1979):107–19.
- Yates, J.F. "External Correspondence: Decompositions of the Mean Probability Score." *Organizational Behavior and Human Performance* 30,1(1982):132–56.
- . "Analyzing the Accuracy of Probability Judgments for Multiple Events: An Extension of the Covariance Decomposition." *Organizational Behavior and Human Decision Processes* 41,3(1988):281–99.
- Zakrewicz, C.J. "Measures and Forecasts of Agricultural Land Values." MS thesis, Oklahoma State University, Stillwater, OK, 2010.