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Bankers' Forecasts of Farmland Value

by

Ted Covey

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Bankers exhibit superior information-discrimination skills in contrast to an unbiased, constant-forecast model regarding the future quarterly trend in farmland values. However, this skill has to be weighed against bankers' greater forecast bias. Bankers were especially accurate at assigning low-biased, highly-resolved probabilities to quarterly downtrends. Given that previous land values had experienced a long-term downward trend, this suggests that bankers are able to use recent lessons learned from their experiences with long-term trends in their forecasts of short-term trends for the same direction. Bankers' excessive optimism concerning rising land values suggests they may be holding excessively large proportions of their assets in farm real estate loans, as well as requiring too little farmland as collateral on real estate loans, leaving them more exposed to default risk than they realize.

Introduction

Farmland is farmers' major asset and the asset bankers most rely on as collateral when making real estate loans. The amount of farmland required as collateral partly depends on bankers' expectations of the future direction farmland value will take. Anticipation of an increase in the value of good farmland results in less farmland required as collateral than when bankers anticipate future declines in farmland value. Should bankers make credit decisions based on overly optimistic expectations of the future value of farmland, they would find the amount of land pledged as real estate loan collateral to be insufficiently small given their credit risk exposure. Bankers are more willing to lend to farmers when the bankers anticipate increasing farmland values. Should those expectations prove to be overly optimistic, bankers will find themselves with higher loan/asset ratios and greater risk exposure than warranted by the values of the underlying farmland collateral.

The Seventh Federal Reserve District Bank of Chicago surveys and reports the expectations of their district agricultural bankers concerning quarterly trends in the future value of good farmland for their individual credit area. The Chicago Fed summarizes its quarterly survey results as the percentages of bankers who believe the value of good farmland will either trend up, down, or remain stable in their credit markets over the next quarter. In addition, the Fed reports the quarterly percentage change in the value of good farmland for the Seventh district.

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Probability forecasts are forecasts accompanied by numerical statements expressing the forecaster's degree of certainty. The extent to which probabilistic forecasts correctly anticipate the events that ultimately occur is called *external correspondence*. The better the external correspondence, the more likely the decision will turn out well (Yates and Curley).

This paper interpreted the aggregated expectational data series reported by the Chicago Fed as a time series of probability forecasts by the bankers as a group for the quarterly trend in the value of good farmland for the Seventh Federal Reserve District. The paper then used three measures of external correspondence (the Brier Score, Murphy's New Vector Partition, and Yates' Covariance Decomposition) to evaluate the bankers' probability forecasts.

Brier's Probability Score PS

Suppose that on a particular occasion 'i' event 'A' can occur in only one of K possible outcomes. The probabilities assigned to each possible outcome k are f_1, f_2, . . . ,f_K that the realized outcome or event will occur in outcome k = 1, 2, . . . , K respectively and $0 \leq f_k \leq 1.0$. The greater the forecaster's confidence in k's outcome, the larger f_k. The K possible outcomes are mutually exclusive and exhaustive so that:

$$(1) \quad \sum_1^K f_k = 1.0.$$

In order to assess a forecaster's accuracy in assigning probabilities to the K different possible outcomes, Brier proposed a probability score PS:

$$(2) \quad PS = \sum_1^K (f_k - d_k)^2$$

where the outcome index d_k takes the value '1' if the event occurred in class or outcome k and '0' if it did not; and where $0 \leq PS \leq 2.0$. The forecaster's objective is to minimize PS.

The higher the probability assigned ex ante by the forecaster to the ex post actual outcome k, the lower PS. The optimal result, PS = 0, results from the forecaster having assigned a probability of absolute certainty ($f_k = 1.0$) to the realized event's occurrence ($d_k = 1$). Forecast error is the result of failing to assign complete certainty to the realized outcome and results in $0 < PS \leq 2.0$. The worse possible result, PS = 2.0, results from assigning a probability of absolute certainty ($f_k = 1.0$) to an event which in fact did not occur ($d_k = 0$).

Individual probability scores PS for each occasion i can be aggregated and averaged for an entire data set of N occasions, resulting in what Brier defined as the mean probability score

or $\overline{PS}$ for N such occasions:

$$(3) \qquad \overline{PS} = 1/N \sum_{k=1}^{K} \sum_{i=1}^{N} (f_{ik} - d_{ik})^2$$

The mean probability score has the same bounds and interpretations as the probability score.

Murphy's New Vector Partition NVP

Murphy's New Vector Partition NVP involves a three-factor decomposition of the mean probability score:

$$(4) \qquad \overline{PS} = \text{outcome uncertainty} + \text{reliability} - \text{resolution}$$

or more formally:

$$\overline{PS}(f,d) = \overline{d}(1 - \overline{d}) + (1/N) \sum_{1}^{J} N_j (f_j - \overline{d_j})^2 - (1/N) \sum_{1}^{J} N_j (\overline{d_j} - \overline{d})^2$$

where J is the number of forecast categories for an event A, f (A) = f_1, f_2, f_3, ..., f_J ; N is the number of occasions the forecasted event may occur; N_j the number of observed occurrences within each of the J forecast categories with $N = \sum N_j$ for j = 1, ..., J; $\overline{d_j}$ the relative frequency of occurrence within each forecast category and $\overline{d}$ is the grand overall mean of the outcome index.

The *outcome uncertainty* term measures factors "outside" the forecaster's control and ranges in the closed interval [0, (N-1)/N]. *Reliability* is a measure as to how well the relative frequencies of the observed outcomes match their assigned probabilities in the long run and ranges in the closed interval [0,2]. *Resolution* is a short-run measure of the forecaster's ability to distinguish when the event will or will not occur and ranges in the closed interval [0, (N-1)/N]. Note that a higher outcome uncertainty and a higher reliability score increase the mean probability score while a higher resolution score reduces it.

Yates' Covariance Decomposition

When calculating the mean probability score for an event A, Yates (1982) noted that the mean PS can be factored into its *covariance decomposition*:

$$(6) \qquad \overline{PS}(f,d) = \text{Var}(d) + \text{MinVar}(f) + \text{Scat}(f) + \text{Bias}^2 \quad 2\text{Cov}(f,d)$$

The forecaster wishes to minimize the mean probability score and to do so must minimize

Cov(f,d)

The covariance of the forecaster's probability assessments f and the outcome indexes d can be expressed as:

$$Cov(f,d) = [Slope][Var(d)]$$

which is entered into the covariance decomposition equation with a multiplier of -2.

The term "slope" is given by:

$$Slope = \overline{f_1} - \overline{f_0} \text{ ,where:}$$

$$\overline{f_1} = (1/N_1) \sum f_{1m} \qquad m = 1, \ldots, N_1$$

is the conditional mean probability judgment for the target event A over these N_1 occasions when that event actually occurs; $\overline{f_0}$ is defined similarly for the remaining N_0 instances when the target event does not occur, with $N = N_1 + N_0$. In the ideal case, the judge always reported $f = 1$ for the realized outcome k.

Slope ranges from -1.00 to its "ideal" value of 1.00. The larger the slope, the better the forecaster's ability to discriminate between information indicating the event's occurrence versus its nonoccurrence. A higher slope indicates better judgement of the future and may be a reflection of different incentive structures or the quality of the information at the forecaster's disposal. A larger slope score leads to a lower mean PS (Yates and Curley).

Scatter(f)

The definition of the Scat(f) term in the covariance decomposition of $\overline{PS}$ is given by:

$$Scat(f) = (1/N)[N_1 Var (f_1) + N_0 Var (f_0)], \text{ where:}$$

$$Var (f_1) = (1/N_1) \sum (f_{1m} - \overline{f_1})^2 \qquad m = 1, \ldots, N_1$$

is the conditional variance of the probability judgments for the target event A on those N_1 occasions when A occurs. Var (f_0) has a similar definition and interpretation for the remaining N_0 occasions when the target event does not occur. Scat (f) is a weighted mean of Var (f_1) and Var (f_0).

The conditional variances and Scatter scores are measures of noise in the forecasts. Ideally, a forecaster should seek to have no dispersion of forecasts "noise" around the conditional forecast means $\overline{f_1}$ and $\overline{f_0}$. Hence, their ideal values and that of the Scatter score = 0. The larger Scat (f), the more responsive the forecaster is to things not related to event A's occurrence.

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MinVar(f), the minimum forecast variance

(17)   MinVar $(f) = [Slope]^2 [Var(d)]$,

MinVar(f) contains no information not obtained from Cov(f,d)

In order to minimize $\overline{PS}$, the forecaster should try to minimize the overall forecast variance Var (f).   The variance of the forecast is minimized when all the forecasted probabilities for cases in which event A occurs are identical ($f_i = \overline{f}_1$) and all forecasted probabilities for cases in which event A does not occur are identical ($f_i = \overline{f}_0$).   If, under these circumstances, $\overline{f}_1 \neq \overline{f}_0$, one has a situation in which the forecaster offers the decision-maker perfect foresight, in that he exhibits perfect discrimination of instances in which event A does and does not occur.   The only thing that could mar the forecasters' performance is if $\overline{f}_1 < 1$ and $\overline{f}_0 > 0$.

The obvious qualification on this goal is that Var (f) can be reduced to zero by making constant forecasts.   However, this would eliminate Cov (f,d) by setting slope to 0, meaning no "resolution" skills on the part of the forecaster.   Yates thus substitutes a conditional goal: take Cov (f,d) as an indicator of the forecaster's ability to discriminate individual forecasting situations usefully.   This is possible since Cov (f,d) = [slope][Var (d)].   Then minimize Var(f) while maintaining Cov (f,d).   MinVar(f) is thus the conditional minimum forecast variance given Cov (f,d).

Reference Points for Probability Forecasters

Yates (1988) suggested two points of reference for evaluating probability forecasters: (1) the uniform forecaster who behaves as if all K events are equally likely ($f_k = 1/K$ for k = 1, . . . , K); and (2) the "relative frequency forecaster" who always offers $f_k = \overline{d}_k$ (k = 1, . . , K). Note that the relative frequencies used by the second forecaster are for the forecast period. This allows a test of the "forward-lookingness" of bankers' expectations.

The multiple mean probability score $\overline{PS}_{MULT}$ is the sum of the mean probability scores for each of the K outcomes and constitutes an overall measure of the accuracy for multiple-event judgements (Yates 1988).   With K=3 (up, stable, down), the uniform forecaster issues f = 0.33 for all K=3 outcomes on all occasions i, generating a $\overline{PS}_{MULT} = \overline{PS}_{UP} + \overline{PS}_{STABLE} + \overline{PS}_{DOWN} = 1 - (1/K) = 0.67$.

Based on the three outcomes' relative frequencies for the forecast period (Table 2), the relative frequency forecaster issues f = 0.00, 0.96, 0.04 respectively for the likelihood of

lower, stable, and higher at each time i. This forecaster generates $\overline{PS}_{MULT}$ = Var(d). No "constant-forecast" forecaster can do better than the "future" relative frequency forecaster.

Data

The data series representing the series of bankers' probability forecasts f for the three possible future trends in farmland value was obtained from a quarterly survey of Midwestern agricultural bankers conducted in and by the Seventh Federal Reserve District Bank of Chicago (Board of Governors). The data series of N=46 forecast occasions or quarters covered the period starting from the second quarter of 1987 through the third quarter of 1998.

When responding to the survey, the individual bankers do not assign probabilities to the three possible outcomes but simply choose the trend they believe most likely to obtain within their particular credit area. The individual banker's responses are aggregated and reported by the Fed as the percentage of bankers falling in each of the three categories. These percentages are interpreted in this paper as the group's probability forecast for three possible future quarterly trends in farmland value in the Seventh Federal Reserve District for the next quarter.

The data used for the outcome index d was the quarterly percentage change in the market value of all good farmland for the Seventh Federal Reserve District, also collected in the same survey.

The failure of the Fed to define "stable" in its survey leads to the empirical problem of determining how large a quarterly percentage change is needed in the value of good farmland to be construed by bankers as an "up or down trend" rather than "stable."

An examination of the bankers' expectations or probability forecasts contrasted to the actual quarterly percentage changes in the value of good farmland in the Seventh Federal Reserve District from 1981 through 1986 indicated at least a four percent change in value had occurred in the quarters where a majority of bankers indicated a belief in a future up- or downtrend. Thus a minimum quarterly change of four percent in the value of good farmland was used to distinguish between those quarters in which the change was 'stable' from those quarters in which an 'up' or a 'down' trend was considered to have occurred.

Brier's Probability Score Results

A contrast of the multiple PS for each of the three forecasters (Table 1) indicates that bankers failed to assign realistic probabilities as well as the relative frequency model. However, bankers outperformed the naive, equal-likelihood-outcome forecaster.

Contrasting the bankers' and relative frequency forecaster's multiple PS suggest that the information bankers use to develop their expectations of future quarterly trends in the value of

good farmland yields probability assessments that are less "reliable" or more biased than that contained in the future long-run relative frequencies for the forecast period. It is interesting to note that an earlier study indicated that bankers assigned more realistic probabilities (i.e., achieved a lower $\overline{PS}_{MULT}$) to quarterly trends in interest rates on farm loans than those assigned by a relative frequency forecaster (Covey). These different results could be due to bankers having greater familiarity and control over the interest rates charged on their farm loans than they do regarding the value of good farmland.

Contrasting the bankers' mean PS for each of the three outcomes indicates bankers generally do better at assigning probabilities to down trends than they do in assigning probabilities to the likelihood of stable or upward trends in farmland value. However, this was during a period of upward rising values in good farmland. Further research is needed to determine if this relationship continues to hold across periods with different trends and for different outcome evaluation rules.

Bias and Slope Scores

Contrasting the bankers' average assigned probabilities to the relative frequencies of the three outcomes yields the bankers' bias scores (Table 2). Bankers were least biased in their assignment of probabilities to a 'down trend' in land values. Bankers were generally overconfident in their assignment of probabilities to an increase or 'up' trend. This is consistent with past research (O'Connor et al.) which has shown that human forecasters generally assign too large a likelihood to the direction in which the forecasted variable is moving.

The positive slope scores for 'stable' and 'up' indicate bankers have at least some ability to discriminate information regarding the movement of farmland values in these directions. The range for the slope scores for these two outcomes is 1.0 to -1.0, with 1.0 the optimal score. Given that no outcomes were judged as 'down', the greatest possible slope score for 'down' was zero, with a range of zero to -1. Hence a slope score of -0.05 is very close to optimal. The very slight bias and relatively strong slope scores are the reasons bankers mean PS were much lower for the outcome 'down.'

Results from Yates' Covariance Decomposition

Given a downtrend Var(d) = 0, the respective Cov(f,d) and MinVar is also zero (Table 3). Bankers' mean PS for 'down' depends solely on their Bias and Scatter scores, which are both very small relative to the same scores for the other two outcomes. The small score for Scat is due to the relatively tight distribution of the assigned probabilities to the likelihood of a downtrend when a downtrend did not in fact occur. The lower scores for bankers in 'down' versus the other two possibilities may be the result of bankers having just come out of the learning experience of a downward trend in farmland values in the early to mid-1980s.

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Contrasting the bias-squared scores in the covariance decompositions for 'stable' and 'up' indicate bankers had less miscalibration in their assignment of probabilities to up-trends and somewhat better discrimination abilities as indicated by a higher Cov(f,d) score. This advantage was offset by a larger amount of noise in their distinguishing when up-trends will and will not occur. The MinVar score for "up" is about double the score for "stable," indicating that assigning probabilities to the likelihood of an up trend requires about twice as much "necessary" variance as do assessing probabilities of stable farmland values.

Results from Murphy's NVP

The results from Murphy's NVP (Table 4) show that the bankers' $\overline{PS}_{MULT}$ of 0.2183 depends mostly on the reliability factor of their forecast skills. Their resolution skills (0.0614) fail to offset most of their $\overline{PS}_{MULT}$ resulting from their reliability score (= 0.1965).

The forecasts issued by the relative frequency forecaster and the uniform forecaster do not distinguish between when the target event occurs or not, offering the same probability assessment in either and all cases. Hence, their Resolution score always equals 0.

The relative frequency forecaster yields a much lower $\overline{PS}_{MULT}$ (0.0832) than do bankers (0.2189). But the NVP indicates this advantage is not "across the board," but is due to the relative frequency forecaster's superior reliability skills, the "unbiasedness" advantage of having advanced information regarding the forecasted variable's relative frequencies. However, bankers exhibit superior resolution and discrimination skills, a distinction that may be critical to a consumer of forecast information (Yates et al. 1996).

Summary and Conclusions

The results suggest that bankers generate better probability forecasts of quarterly trends in the value of good farmland than obtained from a naive or equally-likely-outcome uniform model. Probabilities assigned by bankers to the three possible trends were not as realistic in light of the actual outcomes as those probabilities assigned by a model with advanced information regarding the trends' relative frequencies over the forecast period. However, bankers' superior ability to discriminate information regarding the occurrence or nonoccurrence of the three possible trends may prove more useful than the superior reliability of the unbiased forecaster.

Bankers' relatively superior external correspondence when assigning probabilities to quarterly down trends may have been a consequence of the previous prolonged decline in farmland values. This suggests that bankers do learn from past long-run experiences, allowing them to sharpen their probability forecast skills for a similar short-term trend.

Bankers' overly optimistic assignment of increases in farmland values suggests that they may be holding excessively large proportions of real estate farm loans in their asset portfolios. It further suggests bankers may be requiring too little collateral on their real estate farm loans, leaving themselves more vulnerable to farmer credit risk than they have estimated.

Future research is needed to evaluate bankers' probability forecasts in periods experiencing downtrends in farmland values. Future research is also needed to determine the range within which an economic variable, such as interest rates or the value of farmland, may vary and yet be considered stable by economic agents.

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Table 1. Mean Probability Scores

	Forecaster		
Mean PS	**Bankers**	**Uniform**	**Rel. Freq.**
Down	0.0059	0.1109	0.0000
Stable	0.1176	0.4304	0.0416
Up	0.0954	0.1254	0.0416
Multiple	0.2189	0.6667	0.0832

Multiple = Down + Stable + Up

Table 2. Bankers' Bias and Slope Scores

	Down	**Stable**	
$\overline{f}$	0.05	0.69	
$\overline{d}$	0.00	0.96	0.04
Bias	**0.05**	**-0.27**	
$\overline{f}_1$	0.00	0.69	0.43
	(0)	(44)	(2)
$\overline{f}_0$	0.05	0.56	0.25
	(46)	(2)	(44)
Slope	**-0.05**	**0.13**	**0.18**

( ) indicates the number of observations.

Table 3. Bankers' Covariance Decompositions

	Down	Stable	Up
VAR(d)	0.0000	0.0416	0.0416
BIAS^2	0.0025	0.0729	0.0484
2COV(f,d)	0.0000	0.0108	0.0150
MINVAR	0.0000	0.0007	0.0013
SCATTER	0.0032	0.0144	0.0193

Mean PS = Var(d) + Bias^2-2Cov(f,d) + MinVar + Scatter

$$PS_{MULTIPLE} = PS_{DOWN} + PS_{STABLE} + PS_{UP}$$

Table 4. Murphy's New Vector Partition

Forecaster	PS	Uncert	Relblty	Resltn
Bankers	0.2183	0.0832	0.1965	0.0614
Uniform	0.6667	0.0832	0.5835	0.0000
Rel Freq	0.0832	0.0832	0.0000	0.0000

PS = Uncertainty + Reliability - Resolution