Forecasting Bank Failure: A Non-Parametric Frontier Estimation Approach†

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Abstract

The dramatic rise in bank failures over the last decade has led to a search for leading indicators so that costly bailouts might be avoided. While the quality of a bank's management is generally acknowledged to be a key contributor to institutional collapse, it is usually excluded from early-warning models for lack of a metric. This paper describes a new approach for quantifying a bank's managerial efficiency, using a data-envelopment-analysis model that combines multiple inputs and outputs to compute a scalar measure of efficiency. This new metric captures an elusive, yet crucial, element of institutional success: management quality. New failure-prediction models for detecting a bank's troubled status which incorporate this explanatory variable have proven to be robust and accurate, as verified by in-depth empirical evaluations, cost sensitivity analyses, and comparisons with other published approaches.

Introduction

Over the past decade there has been a renewed interest due to the increasing number of failures of US banking institutions. As figure 1 indicates, the number of failures has risen from a average of seven per year prior to 1980 to a failure rate in excess of 200 per year for recent years. With the number of failures surging, the need for more effective failure-prediction models has become evident.

Banking regulators are particularly interested in improved failure prediction models for several reasons. Foremost is the belief that failure can be avoided, or the bailout costs minimized, through early detection of an institution's troubled status and intervention by regulatory authorities. An accurate and timely identification of a bank's potential for failure would also assist in the targeting of audits and allow for a more effective allocation of resources. Failure prediction models help to identify causes of failure and thus lead to a better understanding of bank operations. Finally, while an early-warning system could never replace on-site examinations, it can complement the on-site process by identifying troubled institutions that need early examination or possible intervention.

† This work was supported in part by National Science Foundation grant DDM-9313346 and the Federal Reserve Bank of Dallas. The opinions expressed herein are those of the authors and do not necessarily reflect those of the National Science Foundation, the Federal Reserve Bank of Dallas, or the Federal Reserve System.

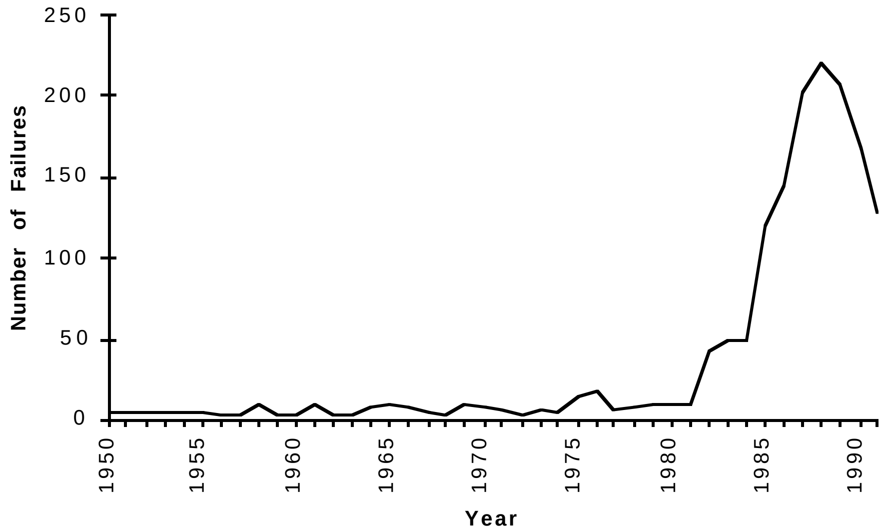

Figure 1: Total U.S. Bank Failures per Year

In the U. S., when examiners evaluate a bank's health, they develop an overall rating based on Capital adequacy, Asset quality, Management quality, Earnings ability, and Liquidity position—hence the term CAMEL rating. Federal regulators developed the numerical CAMEL rating system in the early 1970s to help structure their examination process. Since then, the use of CAMEL factors has become widespread, due to its simplicity and use by regulators. Financial data and relationships are the principal ingredients for scoring capital, asset quality, earnings, and liquidity. Assessing management quality, however, is more difficult; it typically requires professional judgment of a bank's compliance to policies and procedures, aptitude for risk-taking, development of strategic plans, and the degree of involvement by the bank's officers and directors in making decisions.

Most failure-prediction models include variables that can be categorized under four of the five CAMEL factors; the variable that is usually missing is the one which assesses management quality. This is a rather curious paradox. Since Secrist (1938), bank failure prediction studies have continually concluded that the quality and efficiency of bank management are the leading causes of failure. As Seballos and Thompson (1990) state "the ultimate determinant of whether or not a bank fails is the ability of its management to operate the institution efficiently and to evaluate and manage risk." Yet few researchers have attempted to quantify management quality or incorporate realistic surrogates for management performance in predictive models.

In this paper, we describe a bank failure prediction model developed around a new paradigm for assessing a bank's management quality. This paradigm views a bank as processing multiple inputs to produce multiple outputs, and focuses on its key financial intermediation functions of acquiring deposits and making loans and investments. Using data envelopment analysis (DEA), a management quality metric is established that is designed as a proxy for the 'M' in the CAMEL rating.

The results from an analysis of 930 banks over a five year period validate this metric and confirm that the quality of management is crucial to a bank's survival. (DEA) scores for surviving institutions are statistically higher than the scores for failed banks. Furthermore, banks that are nearer failure are found to have lower efficiency scores.

For failure prediction, the management quality metric is combined with variables representing the other four factors in the CAMEL rating, as well as a proxy for local economic conditions. The resultant probit-regression model is not only dramatically superior to all other approaches, but underscores the validity and importance of the management quality metric in forecasting. The result not only advances the state-of-the-art in institutional failure prediction, but pioneers the use of DEA as a predictive factor that has far-reaching applications.

Quantifying Management Quality

Clearly, the quality of a bank's mangement is critical to its long-term survival. But does it require an on-site inspection? Barr, Seiford, and Siems (1993) (BSS) develop a methodology for quantifying a bank's managerial quality using only publically available financial information. Their approach (indicated in figue 2) captures the efficiency of bank management with a transformational efficiency model described by six inputs and three outputs. The model uses data envelopment analysis (DEA) to gauge a bank's performance relative to others.

DEA, a non-parametric frontier estimation methodology initiated by Charnes, Cooper, and Rhodes (1978), constructs an *empirical* production function[1] which is used to compute a bank's transformational efficiency, relative to its peers. More precisely, DEA is a non-parametric estimation method which involves the application of mathematical programming to observed data to locate a frontier which can then be used to evaluate the efficiency of each of the organizational units responsible for the observed output and input quantities. As such, DEA is a methodology directed to frontiers rather than central tendencies. Because of this unique orientation, DEA has proven particularly adept at uncovering relationships that remain hidden for other methodologies.[2] A thorough discussion of the DEA methodology is beyond the scope of this paper. The interested reader is referred to Ali and Seiford (1992), Charnes, Cooper, Lewin, and Seiford (in press) and Seiford and Thrall (1990).

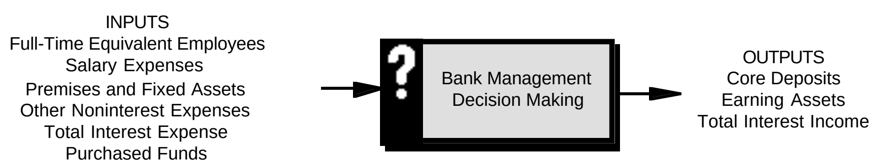

Figure 2: Bank Management Quality Model

As shown in Figure 2, BSS model a bank as a transformer of six inputs into three outputs. A bank's (DEA) efficiency score which results from the BSS model should be a good proxy for managerial quality. Overall, bank managers must integrate policies and techniques for transforming inputs (resources) into outputs, i.e., for managing the money position, providing liquidity, lending profitably, and investing rationally into a practical asset/liability management framework. The most efficient banks do this by controlling operating expenses, managing interest rate sensitivity, utilizing risk management techniques, and strategically planning for the bank and its future markets [Siems (1992)].

Empirical evidence in the BSS study supported the above view. Specifically, the research revealed that significant statistical differences in average management quality scores existed up to three years prior to failure. Figure 3 illustrates the study's finding that from December 1984 to June 1987 the average DEA scores for a sample of surviving banks ranged between 0.8142 and 0.8315; whereas, for banks which failed during the first half of 1988, the average scores dropped from 0.7986 in December 1984 to 0.6694 in June

[1] In standard microeconomic theory, the concept of a production function forms the basis for a description of input-output relationships in a firm, i.e., it shows the maximum amount of outputs that can be achieved by combining various quantities of inputs.

[2] The widespread use and applicability of the technique is evidenced by the large number of studies that employ DEA compiled by Seiford (1994).

1987.

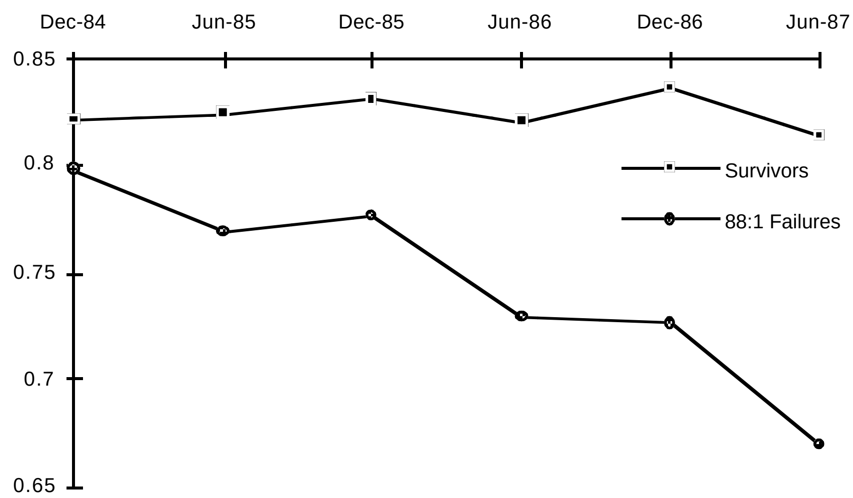

Figure 3: Average DEA Scores for Survivors and First-half 1988 Failures

Furthermore, when pooling the data to compute average scores for one year prior to failure, 94.6% of the survivors had scores above 0.7, but only 50% of the failed banks. Additionally, over 50 percent of the survivors scored above 0.8, while only 13.9 percent of the failures did. The average DEA score for failures one year prior to failure was 0.7032 and for survivors it was 0.8203.

The empirical results of the BSS study confirm that the quality of management is crucial to a bank's survival. Scores for surviving institutions are statistically higher than the scores for failed banks. Furthermore, banks that are nearer failure are found to have lower efficiency scores. These results are significant in that banks that survive can be statistically differentiated from banks that fail based on the management quality scores generated by the DEA model.

Early-Warning Models

An early-warning model is simply an established procedure (usually statistical) for classifying banks into groups (usually *failure* and *non-failure*). This is typically done using only financial characteristics of candidate institutions. The goal of an early-warning model is to identify an institution's financial weakness at the initial stage in its process of deterioration so as to warn interested parties of its potential failure.

Modern studies of institutional failure began with Beaver (1966) who used financial ratios to predict bankruptcy of non-financial firms; this was also the first model to forecast solvency from accounting data. Early-warning models for banks began with Meyer and Pifer (1970); since then, various researchers have used multivariate techniques to explain past closures and predict future failures.[4]

Barr and Siems (1992) have developed new failure-prediction models which combine the DEA management quality metric described in the preceding section with variables representing the other four factors in the CAMEL rating, as well as a proxy for local economic conditions. The new models were compared with three prominent models from the literature: Martin (1977), Hanweck (1977), and Pantalone and Platt (1987). Barr and Siems selected these as competitors to benchmark the DEA-based models "because they use economic and publicly-available financial data, none of which require on-site examination." All models

[4] See Martin (1977), Hanweck (1977), Sinkey (1975, 1977, and 1978), Bovenzi, Marino, and McFadden (1983), West (1985), and Pantalone and Platt (1987) for various approaches to developing bank failure-prediction equations. A review of this literature is in Siems (1991).

utilize probit or logit regression as the statistical classification technique and the data used for the survivors in each analysis were randomly selected.

As summarized in Table 1, the competing three models have other similarities: (1) all reflect capital adequacy with a single ratio of capital to assets; (2) each contains two asset quality variables; and (3) each represents earnings with a net-income-to-total-assets ratio. (Hanweck includes an additional earnings variable to capture the percentage change in net operating income.) The models are differentiated by the fact that Hanweck included an institutional scale variable and Pantalone and Platt included a local economic conditions term. Table 1 shows model coefficients and their significance when applied to their reported data sets.

Table 1. Summary of the Test Set of Bank-Failure-Prediction Models

		Model			Test Data Employed		
					Survi-	Fail-	Years
Source	Type	Variables Used	Coeff	Sig	vors	ures	Covered
Martin	Logit	Constant	-5.33	***	5,642	58	1970-76
(1977)		Net income / total assets	-120.86	***			
		Gross charge-offs / net operating income	2.20	***			
		Commercial & industrial loans / total loans	7.89	***			
		Gross capital / risk assets	-35.63	***			
Hartweck	Probit	Constant	-4.14	**	177	32	1973-75
(1977)		Net operating income / total					
		assets	-69.49	***			
		Equity capital / total assets	14.86				
		% change in net operating income / total assets	-0.01				
		% change in total assets	-1.18				
		Loans / capital	0.26	***			
		Size: log(assets)	0.02				
Pantalone	Logit	Constant	-0.01		226	113	1983-84
and		Net income / total assets	-71.39	***			
Platt		Equity capital / total assets	-11.79	***			
(1987)		Total loans / total assets	7.71	***			
		Commercial & industrial loans / total loans	3.72	***			
		% change in residential construction	0.10				

** Significant at the 0.05 level
*** Significant at the 0.01 level

The DEA-based models are developed from a regulator's viewpoint and designed to operate on current data. In other words, for a model devised to predict failure t periods ahead, the variables considered in the model must be available at least t periods prior to the time of failure. The new models embody two forecast lead-times: prediction 12 to 18 months prior to failure (referred to as a *one-year-ahead* model) and 24 to 30 months prior (referred to as a *two-year-ahead* model). For both lead-times, models based on the probit regression classification methodology are implemented.

Both the one-year-ahead (1YA) and two-year-ahead (2YA) models were tested on the population of commercial banks which failed from 1986 through 1988 and a random sample of banks which survived through 1989. The following restrictions were in place: (1) banks had to have been in operation for at least three years, and (2) only banks with total asset size of between $20 and $300 million were included.

The parameters of the new 1YA and 2YA probit models are given with the corresponding t-ratios and respective significance levels for each CAMEL and local-economy variable in Table 2. As expected the likelihood ratio (LR) index is smaller for the 2YA case. For each model, the classification accuracy, both on the in-sample training dam and out-sample testing cases, are given for a cut-off value of 0.5. The 1YA model is extremely accurate, especially on the holdout sample where 96.3% of all cases were correctly identified, and 96.6% of the failures. Although the 2YA model is slightly less accurate, it properly classified 93.0% of the holdout banks and 94.4% of the holdout's failures.

Table 2. Full Models and Classification Results

	One Year Ahead (LR Index: .72)		Two Years Ahead (LR Index: .58)	
Variable	Coefficient	t-ratio	Coefficient	t-ratio
Constant	5.1395	6.747 ***	2.9100	3.901 ***
Equity Capital/Total Loans	-9.6993	-4.982 ***	-9.4078	-4.854 ***
DEA Efficiency Score	-7.7682	-8.457 ***	-4.6943	-5.500 ***
Nonperforming Loans / Total Assets	17.8065	5.442 ***	24.5388	4.990 ***
Net Income/Total Assets	-22.0646	-4.080 ***	-3.9871	-.635
Large Deposits / Total Assets	5.8907	7.060 ***	5.9031	8.209 ***
Construction	-2.7024	-4.567 ***	-3.0982	-4.850 ***
Percent Correctly Classified	In-Sample	Out-Sample	In-Sample	Out-Sample
Survivors	94.4%	96.1%	92.1%	92.1%
Failures	89.5%	96.6%	82.9%	94.4%
Total	92.4%	96.3%	88.9%	93.0%

***Significant at the 0.01 level.

To assess the performance of the DEA-based models, their classification rates are compared with the established models described in Table 1. The coefficients of all five models were computed from the 1YA and 2YA training data and tested with a 0.5 cutoff value. The percentage of surviving and falling banks correctly classified in both the training sample and the holdout test sample are shown. For the 1YA models, the new model with the DEA management variable dramatically out-performed all other approaches. With the 2YA data, the Martin and Hanweck models excelled on classflying survivors, but the new models clearly excelled in identifying the more important failing banks. Robustness is reflected in the accuracy of the new model with the DEA management variable removed, but in all instances but one the DEA variable improved the classification performance.

Table 3. Comparative Classification Accuracy Results for All Models

Model	LR index	In-Sample Classification (% Correct)			Out-of-Sample Classification (% Correct)		
		Survivors	Failures	Total	Survivors	Failures	Total
One Year Ahead							
Martin	.42	93.0%	71.1%	84.3%	89.5%	94.1%	91.5%
Hanweck	.40	92.8	70.1	83.8	94.7	86.6	91.1
Panalone & Platt	.51	89.7	77.9	85.0	90.1	90.8	90.4
New model w/o DEA	.62	92.4	84.0	89.0	96.1	93.3	94.8
New model with DEA	.72	94.4	89.5	92.4	96.1	96.6	96.3
Two Years Ahead							
Martin	.22	94.1	46.O	77.2	96.5	61.9	83.2
Hanweck	.18	93.9	41.7	75.6	97.0	54.8	80.8
Panalone & Platt	.38	89.8	71.1	83.2	92.6	84.1	89.3
New model w/o DEA	.54	91.3	80.6	87.5	90.6	95.2	92.4
New model with DEA	.58	92.1	82.9	88.9	92.1	94.4	93.0

Conclusions

The multiple-input, multiple-output DEA model presented in this paper has proven to be effective in quantifying management quality. Banks that survive can be statistically differentiated from banks that fail using the managerial efficiency scores generated by the DEA model. Long before failure occurs, significant differences in the efficiency metric appear which can be statistically detected.

Two new bank-failure prediction models were presented in which the incorporation of the management quality metric results in a significant improvement in classification accuracy. Both the one-year-ahead and two-year-ahead models use proxy variables for each factor in the CAMEL rating plus a variable to capture local economic conditions.

The results confirm that management is, indeed, important to the successful operation of a bank. When the management variable was removed from the full model, the results were worse in terms of the model's classification accuracy. The newly-developed DEA-based models show superior results to leading published approaches.

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