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Article

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Central Bank Review (CBR)

Provided in Cooperation with:

Central Bank of The Republic of Turkey, Ankara

Suggested Citation: Samad, Abdus; Armstrong, Vaughn S. (2022) : Bootstrap-DEA management efficiency and early prediction of bank failure: Evidence from 2008-2009 U.S. bank failures, Central Bank Review (CBR), ISSN 1303-0701, Elsevier, Amsterdam, Vol. 22, Iss. 3, pp. 119-127, <https://doi.org/10.1016/j.cbrev.2022.08.002>

This Version is available at:

<https://hdl.handle.net/10419/297952>

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Bootstrap-DEA management efficiency and early prediction of bank failure: Evidence from 2008–2009 U.S. bank failures

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ARTICLE INFO

Article history:

Received 14 July 2022

Received in revised form

17 August 2022

Accepted 25 August 2022

Available online 6 September 2022

JEL classification:

G20

G21

Keywords:

Bank failure

Management efficiency

Bootstrap data envelopment analysis

Early prediction

Probit

ABSTRACT

This paper examines prediction of U.S. bank failure with a probit model that uses bias-corrected technical efficiency estimated using bootstrap data envelopment analysis as the measure of management quality. The model is tested on a sample of failed and non-failed banks during the sub-prime mortgage meltdown, 2008–2009. Results demonstrate this measure of management efficiency, together with other CAMEL factors (i.e., capital adequacy, asset quality, earnings quality, and liquidity), is significant for predicting bank failure. This measure of managerial quality allows more accurate prediction of failure than other measures. The model successfully predicts bank failure one and two years prior to failure.

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1. Introduction

The study of bank failures is important from both macro- and microeconomic points of view. Bank failures can have a disastrous impact on a country's economy, affecting both GDP and employment growth. A reluctance of banks to lend in order to avoid failure may also negatively affect the economy.

During 2009–2010 a large number of banks failed in the U.S., 140 (157) during 2009 (2010). (FDIC, Statistics at a Glance). Failure rates during this period were the highest since the 1930s. These failures were coincident with a deep recession in the U.S. economy, in which the unemployment rate was close to 10% and GDP contracted at a 3% rate.

In addition to the economy wide effects, bank failure carries a large financial cost as taxpayer dollars are used to resolve failed banks and/or bail out troubled ones. Early warnings/prediction may allow remediation to avoid failure or reduce the cost of failures, as

well as helping maintain public confidence in the banking system.

Economists have examined bank failure in an effort to predict bank failure and identify factors that signal risk of failure, with particular attention to early prediction of failure. Researchers have proposed a number of mathematical models for timely and accurate prediction beginning with [Secrist \(1938\)](#).

Early detection and prediction of bank failure can assist management. Enhanced ability to predict bank success/failure may provide a clearer signal for managers that action is required and may improve management decisions, especially in periods when a bank is at particular risk.

The study of bank failure is also of interest to bank regulators and examiners charged with monitoring banks' financial health. Models that accurately predict bank failure may aid regulatory authorities in preventing bank failure. It may also reduce the cost of monitoring, improve the efficiency of on-sight examinations, and reduce FDIC expenditures in resolving bank failure situations ([Thomson, 1991](#); [Whalen and Thomson, 1988](#)).

This paper proposes a bank failure prediction model that introduces the use of bootstrap-data envelopment analysis ("bootstrap-DEA") to estimate technical efficiency as a measure of management quality. The bootstrap-DEA method provides bias corrected efficiency scores and confidence intervals at a selected α -

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Peer review under responsibility of the Central Bank of the Republic of Turkey.

level and are more accurate than data efficiency analysis score that do not use bootstrap-DEA (Simar and Wilson, 1998). The empirical results of our examination of bank failures confirm that incorporating the bootstrap-DEA measure of management efficiency with other CAMEL variables (capital adequacy, asset quality, management quality, earnings quality, and liquidity) is an important contribution to the banking literature on prediction of bank failures.

The paper is presented as follows. The CAMEL variables and the importance of management quality are outlined in Section 2. Section 3 provides a survey of literature dealing with prediction of bank failure. Section 4 describes the methodology used in this analysis and the data used to test the model. Empirical results are presented and discussed in Section 5. Conclusions and the policy implications of the paper are presented in Section 6.

2. CAMEL and management quality

This paper relies on the CAMEL variables: capital adequacy; asset quality; management quality; earnings quality; and liquidity to provide early warning/prediction of impending bank failure. The use of CAMEL is not new. U.S. regulators and bank examiners have long used the CAMEL rating system to assess bank health. Cargill (1989) concludes that CAMEL ratings are primarily proxies for market information.

The importance of management quality/efficiency in the success or failure of the firm is easily understood. Management quality takes into account productivity and management competence, and is inversely related to likelihood of bank failure. Inefficient managers do not effectively and efficiently allocate resources while effective management does. Differences in decisions made by good and poor management will, over a period of time, determine each of the other CAMEL variables. In a competitive market, the quality of management is a key factor for the survival of a bank. Inefficient banks are more likely to fail in the long run.

Barr and Siems (1996) cite the importance of management. Managerial ability, according to Meyer and Pifer (1970), is like Lord Acton's elephant-difficult to define but easy to identify. Seballos and Thomson (1990) indicate that the 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. Pantalone and Platt (1987) state that the management of the bank determines success or failure.

In sum, quality of management in allocating resources and proper risk management is a key factor for the long run performance and survival of a bank. Correctly measuring management quality is critical to prediction of failure. This paper measures management quality using a bootstrap-DEA efficiency score assuming variable returns to scale. Details about the bootstrap-DEA methodology appear in Section 4.

3. Survey of literature

Secrist (1938) is a pioneering work in the literature of bank failure. He examines national banks that failed and survived during the 1920s. He identifies characteristics of failed and non-failed banks and provides a comparative analysis of differences.

Meyer and Pifer (1970) study bank failure using bank closures between 1948 and 1965 with a multiple discriminant model. They classify bank failure variables into four groups: (1) local economic conditions, (2) general economic conditions, (3) quality of management, and (4) integrity of employees. They find that financial measures can reflect the relative strength of firms even in cases where failure results from embezzlement and other financial irregularities.

Martin (1977) uses both logit and data envelopment analysis statistical methods to predict bank failure during 1975–1976 and finds the two models have similar results in terms of identifying failure/non-failure.

Thomson (1991) studies the factors that influence commercial bank failures from 1984 to 1989. He finds that the economic environment in which banks operate affects the probability of failure.

Barr and Siems (1996) present two new bank failure prediction models. In their models of CAMEL variables, they use a new measure of efficiency to representing management quality, data envelopment analysis (DEA) developed by Charnes et al. (1978). In both one-year-ahead and two-year-ahead model tests, they find that the new efficiency measure is a significant factor among the CAMEL variables in predicting bank failure.

Cole and Gunther (1998) compare on- and off-site monitoring systems for predicting bank failure. They find econometric forecasts provide a more accurate indication of bank failure at a given point in time than variables developed from bank accounting data. This improvement arises from changes that occur after the determination of a CAMEL rating from annual financial statements.

Kolari et al. (2000) empirically examine the efficacy of early warning system models to assess the risk of failure of large U.S. commercial banks and compare the predictive ability of logit regression, a parametric approach, with that of a nonparametric approach. They find the predictive accuracy of the logit models is moderately successful using prior data to predict failure one or two years ahead. When compared, the predictions of trait recognition models are substantially accurate in one-year-ahead and two-years-ahead bank failure prediction.

Kolari et al. (2002), apply logit analysis on a small sample of banks to predict large U.S. commercial bank failures and find the model allows bank failure prediction from one year to two years prior to the failure.

Jordan et al. (2010) study bank failure risk using multiple discriminant analysis. For banks failing between February 2, 2007 and April 23, 2010, the find bank failure can be anticipated up to four years prior to failure.

Samad (2011) examines failed and non-failed banks using ANOVA and Kruskal-Wallis tests and finds that capital ratios of banks that later failed are significantly lower than those of non-failed banks.

Samad (2012) empirically examines the significant determinants of the credit risk variables of U.S. bank failures in 2009. Using a probit model with five credit risk variables, three of the variables, credit loss provision to net charge offs, loan loss allowance to non-current loans ratio, and non-current loans to loans, are significant for predicting bank failure. These factors correctly predict 76.8%–77.25% of total observations, and 97 of 121 failures (80.17%). Two variables, net charge off to loans and loan loss to non-current loans, though most reliable, were not significant predictors.

Using a large quarterly data set of FDIC insured US banks from 1992 to 2012, Mayes and Hanno (2014) contrast two methods, a logit analysis and a discrete survival time analysis, to predict bank failure and draw inferences about the stability of contributing bank characteristics. The models incorporate CAMELS indicators as well as macroeconomic variables and contrast risk-based and non-risked-weighted measures of capital adequacy. (“S” is a sixth variable, market risk sensitivity, added to the traditional CAMEL variables). They find that the non-risk-weighted capital measure and the adjusted leverage ratio explain bank distress and failures best.

Bank failure prediction models have also been applied to foreign bank data. Zaghoudi (2013) examines Tunisian bank failure using logistic regression and finds that a bank's ability to repay its debt, its operational variable, its profitability per employee, and its leverage ratio reduce the probability of failure.

Arabi (2013) estimates bank failure in Sudan using logistic regression and discriminant analysis. He finds that earnings are the most significant factor for bank failure followed by asset quality, liquidity, and capital adequacy.

Using a non-parametric proportional-hazard model on the Venezuelan banking sector, Molina (2014) finds that a bank’s ability to generate more and sounder profits during the crisis is the most important factor in avoiding failure. Banks with greater return on assets and proportionally larger investment in government bonds are less likely to fail.

Efforts to predict failure are not limited to bank failures. Beaver (1966) and Altman (1968) show that bankruptcy prediction based on financial ratios can be used to predict failure of non-financial firms. The former uses a univariate approach of discriminant analysis in order to investigate the predictive ability of financial ratios; the latter, a multivariate discriminant analysis using five financial indicators, working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to total debt, and sales to total assets.

Li and Wang (2014) develop a new “Financial Early Warning” logit model that uses efficiency indicators not derived from financial statements in a data envelopment analysis, and apply the model to non-financial Chinese firms. They indicate the model improves the accuracy of prediction and stability, and suggest that using efficiency indicators that are not subject to manipulation by management significantly ensures the reliability of the model.

The bootstrap data envelopment analysis method used in this paper has not previously been examined as a means to predict bank failure. It has been applied in examining bank efficiency for other purposes. Stewart et al. (2016) use the methodology to identify factors affecting efficiency of Vietnamese banks. Brissimis et al. (2008) use it to test the effect of reform, and of capital and credit risk and asset liquidity on efficiency and performance of banks in new EU countries. Wijesiri et al. (2015) use bootstrap DEA to examine the social and financial efficiency of microfinance institutions in Sri Lanka.

4. Data and methodology

4.1. Data

The sample includes a total of 754 banks, 202 banks that failed during 2009–2010 and 552 banks, randomly chosen from the population of 8007 non-failed, small, medium and large banks operating in the same states during the period. Data is obtained from the call reports (quarterly financial reports filed with the Federal Deposit Insurance Corporation, “FDIC”, by US banks) for the prior two years using the FDIC web site. The 2008–2009 period is selected because, during those years, similar economic factors affect all banks nationwide. This limits the likelihood that failure of a specific bank is due solely to local conditions. In addition, the concentration of bank failures during those years is more likely to provide robust results than would failures that occur in a year with few failures.

4.2. Measuring management efficiency/quality

Previous bank failure studies, e.g., Martin (1977) and Barr and Siems (1996), use data envelope analysis (DEA) but not the bootstrap-DEA methodology. DEA is a linear programming technique, originally developed by Charnes et al. (1978), for constructing the best practice frontier from the observed inputs and outputs of all the sampled decision-making units (DMUs). By comparing DMUs outside the frontier (inefficient DMUs) with those that lie on the frontier (efficient DMUs), the DEA method provides

measures of efficiency for each DMU (Coelli et al., 2005). DMUs in this study are commercial banks.

Data envelopment analysis has two versions. Charnes et al. (1978) measures efficiency under the assumption of constant returns to scale (CRS). As DMUs do not all operate under the CRS, Banker et al. (1984) proposes an alternative model that assumes that DMUs operate under variable returns to scale (VRS). (Returns to scale under the VRS assumption can be increasing, constant or decreasing, so the Banker et al. model includes the less general, Charnes et al. model). Our sample of banks use a variety of different inputs to produce specified outputs. The technical efficiency score for a particular bank is determined by solving the linear programming problem detailed below.

The difference between the CRS and VRS models for a single input and output is illustrated by the following figure:

The x axis indicates level of the input; the y axis, level of output. Points A, B, C, D and E indicates input and output level for individual banks. The line through FB indicates the constant returns to scale, CRS, efficiency frontier; ABCD, the variable returns to scale, VRS, efficiency frontier. Banks that fall on the frontier are efficient. Distance from the frontier, FE (EC) is a measure of the inefficiency of Bank E with respect to efficient CRS (VRS) production. The distance, FC, measures scale inefficiency for production of G.

The ratio of minimum inputs needed to produce a specified level of output (GF for CRS efficiency; GC for VRS), to the inputs actually used by a bank, GE, is a measure of the bank’s technical inefficiency. The ratio of minimum inputs to produce at CRS to the minimum units to produce at VRS is a measure of scale inefficiency.

The x-axis in Fig. 1 reflects the input level; the y-axis, the output level. Points A, B, C, D, and E represent input output combinations for individual banks. The line through the points F and B represents the CRS efficiency frontier from the Charnes et al. model; the curve, ABCD, represents the VRS efficiency frontier from the Banker et al. model. (These frontiers are analogous to the efficient frontier from modern portfolio analysis.) Each bank on the frontier (banks A, B, C and D) is technically efficient. Bank E is technically inefficient; it requires X_E units of the input to produce G. (X_E is the X value for point E. X_C and X_F are similarly defined). A CRS efficient bank requires only X_F ; a VRS efficient bank, only X_C . The distance FE (CE) measures the technical inefficiency of Bank E with respect to the CRS (VRS) frontier. The difference between the CRS and the VRS

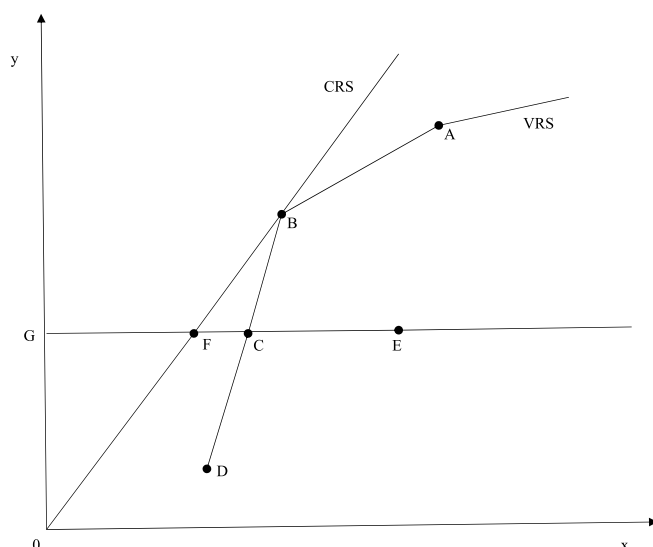


Fig. 1. CRS and VRS efficiency frontiers (See, Coelli et al., 2005.).

frontiers, the distance FC, is a measure of scale inefficiency.

The technical efficiency score under the CRS frontier is the ratio of inputs needed to produce an output of G assuming CRS efficiency, GF, to the inputs used by Bank E to produce that output, GE. That is, technical efficiency assuming CRS, $TE_{CRS} = GF/GE$.

Similarly, the technical efficiency score under the VRS frontier is the ratio of inputs used to produce an output of G assuming VRS efficiency, GC, to the inputs used by Bank E to produce that output, GE. Technical efficiency assuming VRS, $TE_{VRS} = GC/GE$.

The scale efficiency score is the ratio of technical efficiency assuming CRS to technical efficiency assuming VRS, $SE = TE_{CRS}/TE_{VRS} = GF/GC$.

From this, we can deduce that $TE_{CRS} = TE_{VRS} * SE$, the overall technical efficiency of a particular bank, is the product of the bank's pure technical efficiency and its scale efficiency.

4.3. Bootstrap-DEA method for bias corrected management efficiency

Despite its wide application, the DEA method suffers from serious shortcomings. The DEA method is deterministic; the efficiency score obtained by the DEA does not allow for random error such as machine failure, power outages. It thus underestimates the efficiency score and leads to biased efficiency. (Simar and Wilson, 1998). In addition, the DEA method does not provide a confidence interval.

To correct this shortcoming, this paper employs the bootstrap-DEA approach. Bootstrap is a data-based simulation method introduced by Efron (1979). The main idea or objective of bootstrap is to simulate the data generating process with repeated sampling. That is, it replicates repeated sampling from the data. As the replicated data set approximates the original data, the sampling distributions of sample mean and standard deviation generated from the repeated sampling are close to originals.

The bootstrap-DEA, introduced by Simar and Wilson (1998), provides bias corrected efficiency scores together with confidence intervals at a selected α -level. As a result, the bootstrap-DEA efficiency scores have measurable accuracy and useful statistical properties that the DEA method efficiency scores lack.

Empirically, an estimate of the radial Debreu-Farrell output-based measure of technical efficiency can be calculated (for CRS) by solving a linear programming problem for each bank:

$$\hat{F}_k^0(Y_k, Y_k, Y, X|CRS) = \max_{\theta, Z} \theta \tag{1}$$

$$\text{such that } \sum_{k=1}^K z_k Y_{km} \geq Y_{km} \theta_m, \quad m = 1, \dots, M$$

$$\sum_{k=1}^K z_k X_{kn} \geq X_{kn}, \quad n = 1, \dots, N$$

$$z_k \geq 0$$

where:

individual banks are identified by the k subscript;

Y is a K x M matrix of available outputs, X is a K x N matrix of available inputs. CRS specifies constant returns to scale. For variable return to scale, a convexity constraint.

$$\sum_{k=1}^K z_k = 1 \text{ is added.}$$

The linear programming model estimates, θ_k represents the efficiency score for Bank k, with a range of $0 \leq \theta \leq 1$. When θ equals

one, the bank's operations fall on the frontier, i.e., it is technically efficient; the bank's output cannot be increased without increasing inputs. A bank is inefficient when the value of θ is less than one. When $\theta < 1$, the given output can be produced by with lower inputs.

Bias in the efficiency score,

$$bias_k = E(\hat{\theta}_k) - \hat{\theta}_k,$$

is estimated using the bootstrap estimates of efficiency, $\hat{\theta}_k^*$, as follows:

$$\widehat{bias}_k = K^{-1} \sum_{k=1}^K (\hat{\theta}_k^*) - \hat{\theta}_k.$$

The bias corrected technical efficiency score can be expressed as:

$$\tilde{\theta}_k = \hat{\theta}_k - \widehat{bias}(\hat{\theta}_k) = 2\hat{\theta}_k - K^{-1} \sum_{k=1}^K (\hat{\theta}_k^*). \tag{2}$$

Two bias corrected technical efficiency index values (TEI_{bc}) are computed for each bank, one using data from one year before the year of failure, the other using data from two years before the year of failure. The resulting values are used as the measure of management quality/efficiency in the probit model described in section 4.5.

4.4. Input-output controversy and model selection

In a simple production firm such as a coal mine, inputs and outputs are easy to find. The output is the amount of coal and the inputs are labor and capital. However, in multiproduct firms such as banks which produce series of services and use a vector of inputs, selecting inputs and outputs is controversial. A lengthy debate about regarding what constitute the inputs and outputs for a bank is still unresolved.

According to the production approach from Benston (1965), a bank produces services for bank account holders. Thus, outputs are deposit accounts and loan services; inputs are labor and capital. In this sense, the number of deposit account or deposits can be used as output.

Under the intermediation approach, Sealey and Lindley (1977), banks, as financial intermediaries, collect deposits from the savers and channel funds to borrowers. In this approach, earning assets (loans, investments in securities, and advances) are outputs while labor, capital, deposits, and expenses related to them are inputs.

This paper follows the intermediation approach and estimates the bias corrected technical efficiency using bootstrap-DEA based on the VRS model. The efficient frontier is estimated based on output for each bank equal to the natural logarithm of the bank's total loans and total securities. Inputs for each bank are: $\ln(\text{labor})$; $\ln(\text{fixed capital})$; $\ln(\text{salaries})$; $\ln(\text{interest expense})$; $\ln(\text{non-interest expenses})$; and $\ln(\text{fixed capital})$.

4.5. Methodology for predicting bank failure

4.5.1. Probit model and variables

As bank failure or non-failure is a binary variable, failure = 1 and non-failure = 0, probit or logit is an appropriate model. This paper employs a probit model to identify key factors predicting bank failure, significance of the factors, and the accuracy of predicting bank failure/success.

The probit model used is:

$$Pr(Y_k = 1|X_k, \beta) = 1 - \Phi(-X'_k - \beta) = \Phi(X'_k\beta) \tag{3a}$$

where: Φ is the cumulative density function of the standard normal distribution which takes a real value ranging between zero and one. The probability functions used in the probit model have standard normal distributions, symmetric around zero with variance equal to one, and bounded between 0 and 1. Amemiya (1981).

Using the conventions of notation, the estimated model can be written in general form:

$$Pr(Y_k = 1) = X_{kj}\beta + U_k, \tag{3b}$$

where:

Y_k , the dependent variable, represents the final outcome, $Y_k = 1$ for failed banks, $Y_k = 0$ for non-failed banks; X_{kj} is a (1 x J) vector of CAMEL variables that impact bank failure or success;

β is a (J x 1) vector of unknown parameters to be estimated from the sample; and.

U_k is white noise.

4.5.2. Selection of variables for probit model

The vector of independent variables, that proxy for the CAMEL variables, are as follows:

- the percentage of total equity capital to total assets (EQTA) represents capital adequacy;
- the percentage of nonperforming loans to total loans (NPL) represents asset quality;
- bias-corrected technical efficiency derived from the bootstrap-DEA equation (2) (TE_{bc}) represents management quality;
- percentage return on asset ratio, net profits to total assets (ROA) represents earnings quality; and

the percentage of loans to total deposits (LOANDEP) represents bank liquidity.

Descriptive statistics of the sample and the independent variables are provided in Table 1.

Failed banks have on average relatively less equity, lower management efficiency, lower earnings, and a higher proportion of

non-performing loans than non-failed banks. One year prior to failure, failed banks are less liquid than non-failed banks. However, two years before failure, failed banks are more liquid than non-failed banks. The mean of each variable except the bias corrected managerial efficiency scores (TE_{bc}), and the total equity capital to total asset ratio (EQTA) in the two year ahead model differs significantly for failed and non-failed banks.

Although some of these variables are used in previous bank failure models, this model is the first to use the bootstrap DEA efficiency score for its advantage over the Simar and Wilson (1998), DEA score.

The model is tested using independent variables from one year before failure, and from two years before failure. Results for both tests are provided.

Expected signs of the coefficients for the model are as follows:

$\frac{\partial Y_k}{\partial EQTA} < 0$; greater equity capital as percentage of total assets reduces the probability of bank failure.

$\frac{\partial Y_k}{\partial NPL} > 0$; more nonperforming loans as percentage of total loans increases the probability of bank failure.

$\frac{\partial Y_k}{\partial TE_{bc}} < 0$; greater management efficiency reduces the probability of bank failure.

$\frac{\partial Y_k}{\partial ROA} < 0$; greater return on assets reduces the probability of bank failure.

$\frac{\partial Y_k}{\partial LOANDEP} > 0$; more loans as a percentage of total assets increases the probability of bank failure.

4.6. Marginal effect on failure

As the probit regression is non-linear, the value of coefficient of X_{kt} , β_i , cannot be interpreted in the same way as in an OLS model. The probit coefficient for equation (3) is the sensitivity of the Y value to the X value. Although the effect of X on the Y-value is linear, its effect on the probability is non-linear. Marginal effects of probit model coefficients are estimated to determine the elasticity of variables predicting bank failures. In the probit model, as $Y(\text{failure})$ is the density function of $\alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3$, i.e. $Y = F(\alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3)$, the marginal effect of X_i is calculated as:

Table 1

Characteristics of sample banks.

Panel A indicates the number of small (total assets \leq \$100 million), medium (\$100 million, total assets \leq \$1 billion) and large (total assets $>$ \$1 billion) banks including banks that failed during 2009–2010 and randomly selected, non-failed banks operating during the same period. Panel B provides descriptive statistics for CAMEL variables: Capital adequacy, total equity/total assets*100 (EQTA); Asset quality, nonperforming loans/total loans*100 (NPL); Management quality, bias-corrected technical efficiency (TE_{bc}); earnings quality, net income/total assets*100 (ROA); and Liquidity, loans/total deposits*100 (LOANDEP). Data is obtained from the banks' Call Reports for one and two years before bank failure, 2008 and 2009.

Significance measures compare mean value to zero.

Panel A. Sample banks				
	Failed banks		Non-failed banks	
Number of banks in sample	202		552	
Small banks	35 (17.3%)		180 (32.6%)	
Medium banks	121 (59.9%)		238 (43.1%)	
Large banks	46 (22.8%)		134 (24.3%)	
Panel B. Mean CAMEL variables used in the analysis				
Variable	One Year Ahead		Two Year Ahead	
	Failed Banks	Non-failed banks	Failed Banks	Non-failed banks
EQTA (%)	7.636	11.214*	10.358	10.768
NPL (%)	8.256	1.028*	2.416	0.860*
TE_{bc}	0.517	0.520	0.517	0.528
ROA (%)	-2.588	1.146*	0.521	1.146**
LOANDEP (%)	92.074	81.984*	81.815	101.284*
Observations	202	552	202	552

Difference between independent variables for non-failed and failed banks are.

* = Significant at 1 percent level.
 ** = Significant at 5 percent level.

$$\frac{\partial Y_k}{\partial X_{ki}} = F(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n) \beta_i$$

Fortunately, statistical packages, such as Stata, provide marginal effects.

4.7. Fitness of model

Robustness i.e. expectation–prediction of the model as well as the likelihood ratio (LR) statistics are examined. The LR statistics test the joint null-hypothesis that all slope coefficients are simultaneously equal to zero and is computed as $-2\ln(\hat{\beta}_{restricted}) / \ln(\hat{\beta}_{unrestricted})$. The fitness of the model is tested/estimated using the Hosmer-Lameshow and Andrews tests. Then the observed dependent variable Y_i^* , is determined by whether y exceeds a threshold value, 0.5, in this paper. That is,

$$Y_i^* = \begin{cases} 1 & \text{if } Y^* \geq 0.5 \\ 0 & \text{if } Y^* < 0.5 \end{cases}$$

5. Empirical results

Table 2 provides the probit regression results for the one-year ahead model and the two-year ahead model. The regression omits six failed and ten non-failed banks from the one-year ahead model, eight failed and eight non-failed from the two-year ahead model, due to missing variables. Results of probit estimates, in Table 2, show that, with the exception of EQTA in the two-year ahead model, all of the independent variables, are significant factors for predicting during 2008–2009 one-year ahead and two-year ahead U.S. bank failures. (Z-statistics indicate significance at the 1% level.)

As expected, capital adequacy (EQTA), earnings (ROA), and management efficiency (TEI_{bc}) are inversely (negatively) related to bank failures, while the percentage of nonperforming loans (NPL) and illiquidity (LOANDEP) are positively related to bank failure.

Table 2
Effect of CAMEL variables on probability of bankruptcy.

This table presents the results of the one-year ahead and two-year ahead bankruptcy prediction model. The following probit regression model is estimated for each time period:

$$Pr(Y_k = 1) = X_{ij}\beta + U_k$$

where the dependent variable equals 1 for failed banks, 0 for non-failed banks; and the independent variables are proxies for CAMEL variables measuring bank health: EQTA = total equity/total assets; NPL = nonperforming loans/total loans; TEI_{bc} = bias-corrected technical efficiency estimated from the bootstrap-DEA model; ROA = net income/total assets; and LOANDEP = loans/total deposits.

	1-Year Ahead Probit Model		2-Year Ahead Probit Model	
	Coefficient	Z-statistic	Coefficient	Z-statistic
X variables				
EQTA	-0.14	-3.58 ^a	0.006	0.40
NPLOAN	0.34	8.75 ^a	0.28	7.41 ^a
TEI _{bc}	-5.87	-3.75 ^a	-8.63	-8.24 ^a
ROA	-0.53	-6.13 ^a	-0.29	-4.76 ^a
LOANDEP	0.03	4.96 ^a	0.05	10.41 ^a
Constant	2.70	2.04 ^b	3.38	3.69 ^a
LR χ^2	618.29		269.13	
Prob > χ^2	0.0000		0.0000	
Pseudo R ²	0.72		0.32	
Number of Obs	738		738	
	196 (542) failed (non-failed)		194 (544) failed (non-failed)	

^a = Significant at 1 percent level.

^b = Significant at 5 percent level.

Findings of this model are similar to those of Barr and Siems (1996) though variables used are not the same. Differences between this model and other bankruptcy prediction models are illustrated in the Appendix.

Pseudo (McFadden) R² is analogous to the R² in an OLS model. The Pseudo R² = 0.72 (0.32) for the 1-year ahead (2-year ahead) model suggests that the variables of this model explain 72% (32%) of variability associated with bank failures.

The LR statistics, 618.29 (269.13) and the corresponding probability of Prob > $\chi^2 = 0.0000$ (0.0000), reject the joint null hypothesis that all slope coefficients equal zero.

The marginal impact of the variables on bank failure are presented in Table 3. An examination of the marginal impact of the one-year-ahead model, in Table 3, shows that all variables are significant. A 1% increase in EQTA (ROA) reduces the probability of bank failures by 1.3% (4.9%). A 1% increase of the percentage of nonperforming loans (loan to deposit ratio) increases the probability bank failure by 3.1% (0.3%). Managerial efficiency (TEI_{bc}), among all variables, has the greatest impact on bank failures in this sample. A 1% increase in managerial efficiency reduces the probability of bank failure by 53.4%. The magnitude of the effect of this variable is attenuated by the fact that range of TEI_{bc} values is narrow and the difference in TEI_{bc} for failed and non-failed banks (-0.30%) is much smaller than the difference in values of other variables for failed and non-failed banks. For example, the difference between mean EQTA (LOANDEP) of failed and non-failed firms is -3.578% (10.070%).

Table 3 also illustrates the predictive power of each independent variable and of the model using the difference in mean values of the independent variables for failed and non-failed firms. The greatest effect is due to asset quality. Risk of bank failure increases 22.38% for a bank with asset quality (NPL) equal to the mean for failed banks relative to a bank with NPL equal to the mean for non-failed banks. Similarly, failed bank's lower earnings quality (ROA) increases risk of failure 18.17%; lower management efficiency (TEI_{bc}) increases risk 16.01%; lower capital adequacy (EQTA), 4.66%; and lower bank liquidity (LOANDEP), 3.47%. In total, the model indicates that the probability of failure for a bank with CAMEL quality measures equal to "failed bank" mean values is 64.69% greater than for a bank with quality measure values equal to "non-failed bank" means.

Table 4 summarizes the predictive success of model. Using the cut-off-value $C \leq 0.5$ for failure and $C > 0.5$ for survival, the one-year-ahead model of this paper correctly identifies 534 non-failed banks out of the total 542; that is, 98.5% correct for non-failed banks. The two-year-ahead model correctly predicts 96.0% of non-failed banks.

With regard to failure, the one-year-ahead model correctly identifies 169 failed banks out of the total 196, 86.2% correct prediction. The two-year-ahead model correctly predicts 49.0% of failed banks. The overall correct prediction, combining non-failed and failed, for the one-year-ahead (two-year ahead) model is 95.3% (83.6%).

Out-of-sample prediction of the model for non-failed banks is stronger than the in-sample prediction. The prediction of the one-year-ahead (two-year-ahead) model for the out-of-the sample testing is 100% (90%) correct for non-failed banks. The level of significance is 1 percent for both predictions.

Comparison of current model with previous early bank failure model prediction is presented in Table 5. The current model provides better in-sample prediction than previous bank failure prediction models. Total in-sample correct prediction of this model is 95.3% compared to 92.4% for the next best, Barr and Siems (1996), model. Prediction for non-failed banks by this model is higher than

Table 3

Marginal effects and predictive power of independent variables.

Panel A presents the marginal effects of each independent variable on the probability of bankruptcy for the one-year ahead probit model that uses bias corrected technical efficiency estimated from the bootstrap-DEA model as the proxy for managerial efficiency. Marginal effect for each independent variable on probability of banks failure is calculated as:

$$\frac{\partial Y_k}{\partial X_{ki}} = F(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n) \beta_i \phi.$$

Panel B shows the predictive power of each independent variable. Predictive power is illustrated by comparing the product of the variable's marginal effect and the mean of the variable for the non-failed banks and the product of the variable's marginal effect and the mean of the variable for the non-failed banks.

Panel A. Marginal effects of independent variables.						
Delta-method	dy/dx	Std. Err.	Z	P> z	95% Conf. Interval	
EQTA	-.01302	.0036	-3.57	0.000	-.0202	-.0059
NPL	.03096	.0039	9.15	0.000	.0243	.0376
TE _{bc}	-.53,364	.1380	-3.87	0.000	-.8040	-.2633
ROA	-.04867	.0076	-6.42	0.000	-.0635	-.0338
LOANDEP	.00344	.0007	4.99	0.000	.0021	.0048

Panel B. Predictive power of independent variables					
	Independent variable means from Table 1, Panel B (%)		Predictive power		
	Failed banks	Non-failed banks	Difference:		Difference * marginal effect (%)
			Failed – Non-failed		
EQTA	7.636	11.214	-3.578		4.65
NPL	8.256	1.028	7.228		22.38
TE _{bc}	51.70	52.00	-0.300		16.01
ROA	-2.588	1.146	-3.734		18.17
LOANDEP	92.074	81.984	10.090		3.43
Total					64.69

Table 4

Predictive success of the model.

Panel A indicates the number of failed and non-failed banks correctly identified by the one-year ahead and two-year ahead probit models estimated using the bias corrected technical efficiency from the bootstrap-DEA analysis as a proxy for management quality. Prediction uses the cutoff value, C = 0.5; non-failure (failure) is predicted when Pr(Y = 1) ≤ 0.5 (Pr(Y = 1) > 0.5). Panel B presents out-of-sample predictions of the model.

Panel A. Predictions from estimated probit models						
	1-year ahead model			2-year ahead model		
	Non-failed banks	Failed banks	Total	Non-failed banks	Failed banks	Total
P(Y = 1) ≤ C	534	27	561	522	99	621
P(Y = 1) > C	8	169	177	22	95	117
Total	542	196	738	544	194	738
Correct	534	169	703	522	95	617
% correct	98.52	86.22	95.26	95.96	48.97	83.60
% incorrect	1.48	13.78	4.78	4.04	51.03	16.40
Total gain	-1.48	86.2	21.14	-4.04	48.97	9.89

Panel B. Out-of-sample predictions			
	1-year ahead model		2-year ahead model
	Non-failure	100%	Non-failure
	Failure	85.5%	Failure
			90%
			5%

Table 5

Comparison of the current model with other models.

This table contrasts the predictive power of the model estimated in this paper using bias corrected technical efficiency estimated from the bootstrap-DEA model with previous bank failure prediction models. Variables used in the model of Barr and Siems (1996), Martin (1977), Hanweck (1977), and Pantalone and Platt (1987) are presented in the Appendix.

Model	Pseudo R ²	Correct prediction (%)					
		In-sample			Out-of-sample		
		Failed	Non-failed	Total	Failed	Non-failed	Total
Current model	.72	86.2	98.5	95.3	85.5	100.0	92.0
Barr and Siems (1996)	.72	89.5	94.4	92.4	96.6	96.1	96.3
Martin (1977)	.42	71.1	93.0	84.3	94.1	89.5	91.5
Hanweck (1977)	.40	70.1	92.8	83.8	86.6	94.7	91.1
Pantalone and Platt (1987)	.50	77.9	89.7	85.0	90.8	90.1	90.4

for prior models. The correct in-sample (out-of-sample) predictions of this model are 98.5% (100%); next best is 94.4% (96.1%). No other model has a higher Pseudo R² = 0.72 than the current model.

6. Conclusions and policy implications

The paper first estimates the bias-corrected technical efficiency (TE_{bc}) for bank management quality applying bootstrap data

envelopment analysis (bootstrap-DEA) to take advantage of the method's advantage over the DEA. It then develops a new bank failure prediction model, a probit model incorporating this bias-corrected technical efficiency (TE_{bc}) as the proxy variable for management quality in CAMEL. The model is tested using independent variables from one year and two years before bank failure.

The probit estimates for both models for a sample of U.S. banks that failed during 2009 and 2010, and non-failed banks for the same period, show that the bias corrected technical efficiency is a significant factor for bank failure prediction, suggesting that management efficiency is an important factor for bank survival or failure during this period. Other CAMEL variables, capital adequacy (estimated by the stockholders equity to total asset ratio), asset quality (estimated by nonperforming loans as a percent of total loans), earnings ability (estimated by return on assets), and liquidity (estimated by the ratio of loans to deposits) are also significant factors.

Results of marginal estimates indicate that asset quality and earnings quality, together with managerial efficiency have the highest impact on the U.S. bank failure. A 1% increase in management efficiency reduces the probability of bank failure by 53%. A 1% increase in asset quality (earnings quality), reduces the probability of bank failure by 3% (5%).

The overall correct prediction, combining survivor and failure, for the one-year-ahead (two-year ahead) model was 95.26% (63.60%). The one-year-ahead model correctly predicts 98.52% of the non-failed banks and 86.22% of the banks that failed.

The significance of the factors in predicting bank failures provides important policy implications for bank management and regulators. First, as management quality measured by the bootstrap-DEA-bias-corrected efficiency score is an important factor for predicting bank survival or failure for both one-year-ahead and two-year-ahead models, bank managers and bank regulators can use this score to analyze bank's strength or weakness. Banks receiving low bootstrap-DEA efficiency scores have higher likelihood of failure; those with higher scores are more efficient and, thus, are more likely to survive.

In addition, capital inadequacy, poor asset quality, poor earnings, and illiquidity, are significant factors for bank failure. Bank regulators and bankers can also utilize these factors for examining and determining banks' strength or weakness. We note, however, that management efficiency has a direct effect on these values.

Third, bankers and bank regulators should use the model that has the highest accuracy in correct prediction to detect and classify weak financial institutions. Identification of the weakest financial institutions, those threatening to fail is important for bank regulators. Accurate and earlier identification helps regulators act to reduce losses incurred due to bank failure.

7. Further research

This study also suggests opportunities for future research. The difference in accuracy for the two-year-ahead and one-year-ahead models raises a question about the reason for “unexpected survivors” and “unexpected failures”. That is, for “unexpected survivors”, did banks that were identified as “failed” (i.e., likely to fail) by the two-year-ahead model and yet did not fail, adjust their activities in a manner that enabled them to avoid failure and, were those adjustments captured by the one-year ahead model in the following year. Similarly, what was the reason for the “unexpected failures”, banks that were identified by the two-year-ahead model as “non-failed” (i.e., likely to fail) and yet had failed two years later.

The methodology described in this paper can also be applied to U.S. banks during different time periods and/or to banks from other countries. Management efficiency based on the bias corrected

technical efficiency using the bootstrap-DEA method could also be tested with other proxies for other CAMEL variables (or for the expanded CAMELS variables) to determine whether the model can be improved. The methodology can also be applied using the production approach, rather than the intermediation approach, for identifying bank inputs and outputs. Studies using samples from longer time periods may need to include additional variables to capture economic changes during longer periods.

Finally, the results of this paper suggest that it may be useful to include a management efficiency variable such as the bias corrected technical efficiency score based on the bootstrap-DEA method to failure prediction models that are based on econometric forecasts, instead of CAMEL variables. Incorporating the ability of management to respond effectively to changes in the economy may improve the predictive ability of those models.

Appendix

Table A.1

Variables used in early bank failure prediction models. This table presents the independent variables used in the current paper and in other early bank failure prediction models, together with the estimated coefficient for each independent variable and the level of significance for each.

Model	Variable	Coefficient
Current paper	EQ/TANPL/Loans	-0.14*
	Bootstrap-DEA technical efficiency	0.34*
	ROA	-5.87*
	Loans/Deposits	-0.53*
Barr and Siems (1996)	EQ/Loan	0.03*
	DEA-technical efficiency	-9.69*
	NPL	-7.76*
	ROA	17.80*
	Deposit/TA	-22.06*
Martin (1977)	δ in Cons. Loan	5.89*
	ROA	-2.70*
	ROA	-120.86**
Hanweck (1977)	Gross Charge off/net operating income	2.20**
	Commercial & industrial loan/total loan	7.89**
	Gross capita/Risk assets	-35.63**
	ROA	-69.49**
Pantalone and Platt (1987)	EQ/TA	14.86
	% δ in operating income/TA	-0.01
	% δ in TA	-1.18
	Loans/Capital	0.26**
	Size: log TA	0.02
Arabi, K.A.M., 2013	ROA	-71.39**
	EQ/TA	11.79**
	Loans/TA	7.71**
	Commercial & industrial loan/Loans	3.72**
	% δ in Cons. Loan	0.10

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