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Deposit Insurance, Regulation, and Efficiency

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EXPLAINING BANK FAILURES: DEPOSIT INSURANCE, REGULATION AND EFFICIENCY

ABSTRACT

This paper uses micro-level historical data to examine the causes of bank failure. For state-charactered Kansas banks during 1910-28, time-to-failure is explicitly modeled using a proportional hazards framework. In addition to standard financial ratios, this study includes membership in the voluntary state deposit insurance system and measures of technical efficiency to explain bank failure. The results indicate that deposit insurance system membership increased the probability of failure and banks which were technically inefficient were more likely to fail than technically efficient banks.

KEYWORDS: Bank failures, banking--U.S. history, banking--U.S. regulation, deposit insurance, technical efficiency

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1. INTRODUCTION

The sharp increase in bank failures in the United States since 1980 has focused attention on the causes of banking instability and the appropriate role of government policy.[1] To gain insight into recent experience with bank failures, researchers have begun to draw on evidence from previous episodes when failures were similarly high. The sharp increase in bank failures during the 1920s resembles the more recent experience of the 1980s; in both decades, branching restrictions left banks vulnerable to localized distress, and failures were confined mainly to regions suffering depressed commodity and real estate prices. Banks in other regions were largely spared in both episodes.[2]

Laws restricting branching and other forms of diversification are one government policy that exacerbated bank failures in both the 1920s and 1980s. Deposit insurance is a second policy that has been linked to banking instability in both decades.[3] Deposit insurance removes the incentive for depositors to monitor bank risk, and thereby encourages banks to substitute deposits for equity and to maintain greater portfolio risk than they otherwise would. Although there was no federal insurance of bank deposits until 1934, several states experimented with insurance during the 19th and early 20th centuries, including eight states that enacted insurance systems between 1907 and 1920 for their state-chartered banks.[4] Calomiris (1992) shows that during the agricultural boom associated with World War I, insured banks grew more rapidly than their uninsured competitors and banks in states without insurance systems. Insured banks then suffered the greatest asset declines and had the highest failure rates after the collapse of commodity prices in mid-1920. Alston, Grove and Wheelock (1993) show that bank failure rates were highest in states with deposit insurance systems, after controlling for branch banking, other government policies, and differences in economic activity across states.[5]

Since the causes of banking instability during the 1920s and 1980s were similar, microeconomic analysis of bank behavior during the 1920s might provide useful insights for the recent experience. In this paper, we use information about a sample of banks operating in Kansas during the period 1910–1928 to examine the causes of bank failure. Roughly one-quarter of Kansas state-chartered banks either failed or merged with other banks during this period. These historical data offer two important advantages over contemporary data. First, the voluntary deposit insurance system existing in Kansas during this period permits comparison of insured and uninsured banks facing otherwise similar regulatory and economic conditions. Second, the data allow construction of a longitudinal data set covering a longer period than is typically possible with contemporary data.

We model time-to-failure explicitly using a proportional hazards framework. We use balance sheet information, deposit insurance system membership status, and measures of technical efficiency to explain failure and survival of individual banks. Although other studies have investigated the relationship between technical efficiency and bank failures, they have typically done so by comparing mean measured efficiency scores among failed and surviving banks (*e.g.,* see Berger and Humphrey, 1992 and Barr *et al.,* 1992). Thus, these studies fail to control for other factors such as risk or competition, and do not explicitly model time-to-failure. We find that both insurance system membership and efficiency provide useful informaton about failure not captured by conventional financial ratios. Our findings indicate that inefficiently operated banks were more likely to fail, as were insured banks. The results suggest that measures of technical efficiency could prove useful for predicting bank failures in other settings.

2. BANKING IN THE EARLY TWENTIETH CENTURY

Whereas bank failures in the 1980s are closely associated with the boom and subsequent bust in real estate markets, bank failures in the 1920s are closely associated with the fortunes of agriculture. American agriculture expanded rapidly during World War I and in the immediate postwar months. Between 1910 and 1920, the total value of farm property nearly doubled, as did farm output prices.[6] Accompanying the increase in farm acreage and value was a 132% increase in farm mortgage debt, much of which was supplied by commercial banks.[7] The number of commercial banks in the United States rose during the decade from 25,151 in 1910 to 30,909 in 1920.[8] After peaking in mid-1920, farm output prices plunged. An index of farm output prices that equaled 150.7 in 1920 fell to 88.4 by 1921 (1926=100).[9] Farm income collapsed, and many farmers were unable to repay debt incurred before 1920. Banks in agricultural regions experienced sharp increases in loan defaults and many became insolvent.[10]

In Kansas, 122 state-chartered banks failed between September 1920 and September 1926.[11] Of those, 94 were members of the state deposit insurance system when they failed, while 28 were not, and the failure rate of insured banks (4.6%) was twice that of uninsured state banks (2.3%). By contrast, just six national banks (0.8%) failed during this period.

The Kansas deposit guaranty system was begun in 1909, and membership was made optional in response to complaints that deposit insurance penalizes conservative banks by forcing them to protect depositors of banks that are more likely to fail. Only state-chartered banks that had operated for at least one year were permitted to join.[12] Insured banks were required to maintain minimum ratios of capital to deposits and of surplus and undistributed profits to capital of .10.[13] Banks were permitted to withdraw from the system with six months notice, but remained subject to levies needed to pay depositors of banks that failed while the bank carried deposit insurance.

Some attempt was made to discourage risk-taking by setting insurance premiums at 1/20th of 1% of a bank's insured deposits *less* capital. The low assessment rate meant, however, that relative to the cost of capital, the incentive to hold additional capital was small.[14] Insured banks were required to deposit $500 of cash or eligible bonds with the state banking commissioner for each $100,000 of insured deposits as a guarantee of assessment payment.

Despite regulations implemented to discourage risk-taking and a reputation for relatively strict supervision, the comparatively high failure rate of insured banks in Kansas suggests that excess risk-taking was not prevented entirely. Wheelock and Kumbhakar (1993) show that during its first ten years, the Kansas system attracted the most risk-prone banks, and that once insured, banks tended to reduce their capital/asset ratios. The evidence indicates, therefore, that the system suffered from both adverse selection and moral hazard problems. Not surprisingly, insured banks had the highest failure rates when farm prices collapsed and loan losses rose.

Wheelock (1992) estimates a probit model to identify the characteristics of Kansas banks that failed between 1920 and 1926. Using financial ratios suggested by White (1984), Wheelock finds that a bank was more likely to fail the lower was its surplus/loan, bond/asset, reserve/deposit, or deposit/asset ratio.[15] A bank was also more likely to fail, the higher was its loan/asset or short-term borrowed funds/asset ratio.

Wheelock (1992) also investigates the role of deposit insurance. He includes deposit insurance membership (measured with a dummy variable equal to 1 for insured banks and to 0 for uninsured banks) as a regressor. Mis-priced deposit insurance encourages banks to hold riskier assets and less capital than they otherwise would. Although data on financial ratios are available for Kansas banks, the quality of their assets is unknown. Thus, including deposit insurance as a regressor tests whether insurance increased the probability of failure, presumably by encouraging riskier investments, apart from its possible influence on the capital ratios. Wheelock finds that deposit insurance membership is a useful predictor of bank failure, especially the closer a bank was to failure.

This paper builds on Wheelock (1992) in two ways. First, we explicitly model the hazard distribution with time-varying covariates obtained from panel data.[16] Second, we draw on a growing literature that attempts to measure the technical efficiency of banks. Several recent studies have investigated technical efficiency in the banking industry; *e.g.,* Sherman and Gold (1985), Rangan *et al.* (1988), Ferrier and Lovell (1990), Aly *et al.* (1990), Fixler and Zieschang (1992), Fried *et al.* (1993), and others. In measuring technical efficiency, one attempts to answer questions such as how much more output can be produced from the same inputs, or how much less input can be used to produce the same output. Our empirical results suggest that measures of technical efficiency are useful for explaining the probability of failure in our data.

The remainder of the paper is divided as follows. The next section discusses the methodology underlying the measurement of technical efficiency; the fourth section describes the data used to measure efficiency and presents the results of this measurement. The fifth section discusses the hazard model used to investigate bank failures and presents estimation results.

3. EFFICIENCY MEASUREMENT

To measure Technical efficiency among banks in this study we use a linear programming (LP) framework to construct production set boundaries that allow measurement of the relative efficiency of banks in the sample. The LP framework easily allows treatment of multiple inputs and outputs, and avoids the need to specify functional forms for technology and error processes. In the standard approach to measuring technical efficiency, which involves the estimation of parametric production functions, these issues are often problematic. For example, one can account for multiple outputs and multiple inputs by estimating cost functions (*e.g.,* Conrad and Strauss, 1983), but examination of other types of efficiency using a stochastic parametric framework may be difficult or impossible in this case. With regard to the specification of the production process, one can hypothesize an underlying production function, but in some applications such as banking the production process is not easily specified. Similarly, one can arbitrarily impose distributional assumptions so as to satisfy regularity conditions in the resulting likelihood function and to ease the actual estimation, but this can have a potentially large impact on both the magnitude and ordering of the estimated efficiency scores. The method we employ easily allows for multiple outputs, requires minimal assumptions about the underlying functional form of the production process, and requires no assumptions on underlying distributions; no *a priori* specification of an error process is necessary. These characteristics are especially relevant to the study of technical efficiency in settings such as banking where the underlying production process may be ill-defined.

Although there were a few early attempts at nonparametric efficiency measurement (*e.g.,* Boles, 1966), work by Charnes *et al.* (1978, 1979) and Färe *et al.* (1985) gave rise to a large and growing literature that has been termed Data Envelopment Analysis. Färe *et al.* (1985) describe several measures of efficiency that may be computed by simple LP methods which fit piece-wise linear convex boundaries to the production set; efficiency is measured by the distance of each decision-making unit (DMU) from the production set boundary. These efficiency measures have been employed in banking studies by Sherman and Gold (1985), Rangan *et al.* (1988), Ferrier and Lovell (1990), Aly *et al.* (1990), Parkan (1987), Berg *et al.* (1993a, 1993b), and Vassiloglou and Giokas (1990) among others, and in other applications as discussed by Lovell (1993).

Given the discussion in the preceeding section, we use the weak output technical efficiency (WOE) measure discussed by Färe *et al.* (1985). This measure is consistent with the Debreu (1951) and Farrell (1957) notions of technical efficiency. The WOE measure may be computed by solving the LP problem

$$\max\{\theta_k | Xq_k \leq x_k, Yq_k \geq \theta y_k, Cq_k = 1, q_k \in \Re^n_+\} \tag{1}$$

where n DMUs produce s outputs using m inputs, q_k is a $(n \times 1)$ vector of weights to be computed for the kth DMU, $\theta_k \geq 1$ is a scalar, x_k is a $(m \times 1)$ vector of inputs for the kth DMU, y_k is a $(s \times 1)$ vector of outputs for the kth DMU, $X = [x_1, ..., x_n]$ is a $(m \times n)$ matrix of observed inputs, $Y = [y_1, ..., y_n]$ is a $(s \times n)$ matrix of observed outputs, and C is a $(1 \times n)$ vector of ones.

The maximand θ_k in (1) measures the WOE of the kth DMU, with values strictly greater than unity indicating the presence of technical inefficiency. The inequality constraints in (1) define a reference technology with strong disposability of outputs. For the kth DMU, θ_k gives the proportion by which outputs can be increased to move the DMU from the interior of the production set onto the piecewise-linear boundary of the production set corresponding to the reference technology in (1), holding inputs fixed. This is illustrated in Figure 1a for the case of two output quantities y_1, y_2 produced from a constant input quantity x_1. *A, B, C,* and D represent DMUs; A and B lie on the piecewise-linear boundary of the convex production set, while C and D lie within the interior of the production set. DMUs such as C and D may lie in the interior of the production set due to imperfect information, managerial incompetence, or perhaps other reasons. For DMU

C, the WOE measure in (1) is given by the ratio of distances OC'/OC in Figure 1a. By proportionately increasing the output quantities produced by DMU C by OC'/OC, the DMU moves to point C' and would be considered efficient in the WOE sense.

The assumption of strong disposability of outputs leads to portions of the production-set boundary that are parallel to the axes in Figure 1a. Dropping the assumption of strong disposability of inputs leads to a congestion problem in the production process considered by Färe and Grosskopf (1983). Such a technology is likely to be relevant for agriculture and highways, but seems unlikely to be relevant in the present application. However, for DMUs such as D in Figure 1a, the optimal solution in (1) giving the WOE score will result in slack in the output constraints. This slack is another source of inefficiency not captured by the WOE measure, and is examined further in the empirical section below. Given a sample of n DMUs, solving (1) for a DMU such as D in Figure 1a will result in an efficient subset of DMUs located on the boundary of the production set; all observations lying outside the cone spanned by this efficient subset (shown by the shaded area in Figure 1a) will have slack in their output constraints (see Lovell, 1993).

Constraining the weights in q_k in (1) to sum to unity allows the reference technology to exhibit variable returns to scale. Alternatively, constraining $Cq_k \leq 1$ results in a reference technology with nonincreasing returns to scale, while omitting the constraint results in a technology with constant returns to scale. Letting θ, θ^{NIRS}, and θ^{CRS} denote the WOE measures computed while imposing variable, nonincreasing, and constant returns to scale, respectively, scale efficiency may be examined by checking for each DMU whether $\theta = \theta^{CRS}$. If $\theta = \theta^{CRS}$, then the DMU is scale-efficient; otherwise, it is located along the decreasing returns portion of the technology if $\theta = \theta^{NIRS}$, or along the increasing returns portion of the technology if $\theta \neq \theta^{NIRS}$.

Finally, note that WOE is a *radial* measures of efficiency; *i.e.,* efficiency for a DMU is measured along a ray emanating from the origin and passing through the DMU in input-output space. Consequently, the efficiency scores calculated from (1) are independent of the units of measurement used for both inputs and outputs. This is important since units of measurement may always be defined arbitrarily. Lovell (1993) observes that some efficiency measurement formulations do not share this property.

Although the paradigm where firms take inputs as given and attempt to maximize outputs seems to best reflect the situation faced by managers of banks in our sample, it is also possible to measure technical inefficiency while assuming inputs may be adjusted subject to fixed outputs. If we assume strong disposability of inputs, this gives rise to the input weak efficiency (IWE) measure suggested by Färe *et al.* (1985). The IWE measure is computed by solving the LP problem

$$\min\{\lambda_k | Xq_k \leq \lambda_k x_k, Yq_k \geq y_k, Cq_k = 1, q_k \in \Re^n_+\}, \tag{2}$$

with variables defined as in (1) above. The minimand λ_k measures IWE for the kth DMU. Clearly, $0 < \lambda_k \leq 1$, with $\lambda_k = 1$ denoting no technical inefficiency.

The IWE measure is illustrated in Figure 1b, where DMUs A, B, and C produce the same output level from input quantities x_1, x_2. DMUs A and B lie on the piecewise-linear boundary of the production set, and are thus regarded as efficient, while DMUs C and D lie in the interior of the production set and are regarded as inefficient. The IWE score for DMU C is given by OC'/OC, and indicates the amount by which DMU C's input levels may be proportionately reduced to reach the production set boundary. DMUs such as D which lie outside the cone spanned by the efficient subset containing A and B (indicated by the shaded area) yield slack in the input constraints when (2) is solved; as before, this slack represents an additional source of inefficiency. Note that the IWE score is also a radial efficiency measure, and thus is independent of units of measurement.

4. RESULTS OF EFFICIENCY MEASUREMENT

The data used in this study consist of a panel of Kansas banks for which we collected balance sheet and other information as of August 31 of each even numbered year from 1910 to 1926 (except 1912 and 1916, when this information was not published).[17] The sample includes 259 banks (approximately one-fourth the total operating in 1914).[18] Of these, 47 had failed by September 1, 1928.

As noted by Aly *et al.* (1990), there is considerable disagreement in the literature on the definition of inputs and outputs for banks. Berger *et al.* (1987) and Clark (1989) discuss two alternative approaches where banks are viewed as either financial intermediaries or as production units. Following Aly *et al.* and Grabowski *et al.* (1993), we use the intermediation approach and define four inputs: capital (X_1), long-term funds (X_2), short-term funds(X_3), and labor(X_4). Capital is measured by the book value of building, furniture, and fixtures. Long-term funds are measured by time and demand certificates, while short-term funds are measured by bills payable, bills rediscounted, and other liabilities not enumerated. Labor is proxied by the number of officers in the bank. No information is available on the actual number of employees in each bank, and hence we must assume that the number of officers was proportional to the total number of employees. Since most of the banks in the sample were quite small, this does not seem an unreasonable assumption. Two outputs are defined, namely total loans (Y_1) and individual deposits (Y_2). For some years covered by the data, loans listed on balance sheets were divided into real estate loans and other loans, but in other years the two types were combined. To maintain consistency throughout the dataset, total loans are used as an output for each period. The individual deposits output corresponds to the use of demand deposits as an output by Aly *et al.*

The LP model in (1) must be solved once for each observation in the sample. For each bank in each year, efficiency was computed relative to all banks in the given year. Summary statistics on the results of this exercise are shown in Table 1. Both mean and median efficiency fluctuate over the 16-year period. Median efficiency is included in Table 1 because the distribution of scores computed from (1) are typically skewed; in such cases the median statistic provides a more robust measure of location than the mean statistic. By comparing the mean and median values, it is clear that the WOE scores are skewed away from unity in each year. Mean inefficiency increases each year from 1910–1924, then sharply declines in 1926.

Table 2 shows mean WOE scores for survivors and failures over six time periods. *Failed* banks are those reported as failed by the bank commissioner; banks that underwent merger, voluntary liquidation, or that changed their charter from the state are regarded as censored. In Table 2, survivors are those banks that operated throughout the period, while failures are those that failed during the indicated period (totals do not add up to the numbers of observations in Table 1 due to censoring of observations). Mean efficiency scores are based on banks' performance at the beginning of each period. For the first three periods shown in Table 2, mean efficiency scores for failing banks are less than mean efficiency scores for surviving banks; however, the number of failures in each period is very low. For the last three periods, when the number of failures was larger, mean efficiency scores are higher for failing banks than for surviving banks. This result is consistent with results obtained by Barr *et al.* (1992) and Berger and Humphrey (1992) for the 1980s suggesting that failing banks are less efficient than non-failing banks.

As noted earlier, slacks in the output constraints in (1) represent an additional source of inefficiency. For each bank, slack in each output was computed as a percentage of the corresponding output by the individual bank; mean values of these percentages are reported for each period for surviving and failing banks in Table 3. Also, mean values for total slack as a percentage of total output for each bank are reported. As in Table 2, the last three rows of Table 3 are of particular interest since most failures occurred during these periods. Failed banks have little or no slack in the loan output (Y_1). Survivors have some slack in this output for the last three periods, and a great deal of slack in the 1918–1920 and 1920–1922 periods. Slack in the individual deposits output (Y_2) for failed banks is greater than the mean percentages for survivors in all but the first period shown in Table 3. Furthermore, total slack as a percentage of total output is larger for failed banks than for survivors in all but the first and third periods. These results are consistent with the results for the WOE score; failed banks appear to be less efficient than survivors.

To examine scale efficiency, define

$$SCALE = \begin{cases} \theta/\theta^{CRS} - 1 & \text{if } \theta \neq \theta^{NIRS}, \\ 1 - \theta/\theta^{CRS} & \text{otherwise.} \end{cases} \tag{3}$$

Then $SCALE$ measures scale inefficiency, with $SCALE = 0$ indicating that a bank is operating at the point of constant returns to scale, and $SCALE$ greater (less) than zero indicating that the bank is operating under the increasing (decreasing) returns portion of the technology. Mean values for $SCALE$, along with the numbers of banks under the increasing, constant, and decreasing returns portions of the production technology are shown in Table 4 for survivors and failures. Although there is considerable fluctuation in the number of banks operating under the decreasing and increasing returns portions of the production technology, no obvious patterns emerge.

5. EXPLICIT MODELING OF BANK FAILURES

We use the proportional hazards model developed by Cox (1972) to model time-to-failure for banks. The proportional hazards model assumes the hazard relationship

$$\theta(t|z) = \theta_0(t)e^{z\beta} \tag{4}$$

where z is a row vector of measured covariates and β is a column vector of parameters with the appropriate dimensions. The hazard $\theta(t|z)$ gives the instantaneous rate of failure per unit time period at time t. This model assumes a baseline hazard, $\theta_0(t)$, which is identical for all banks in the sample; the covariates in z influence the overall hazard for each bank through the exponential term in (4) (the choice of an exponential form here is common throughout the literature on hazard estimation and simplifies the estimation problem relative to choices of other functional forms). The model is semiparametric since the exponential in (4) is a parametric form, while the baseline hazard involves an unspecified form and hence is nonparametric. Consequently, the model is more flexible than models where the failure time distribution is assumed known except perhaps for a few scalar parameters.

Given the hazard specification in (4), the corresponding survivor function (which gives the probability of survival up to time t) may be written as

$$S(t|z) = \exp\left[-\int_0^t \theta_0(u)e^{z\beta}\,du\right], \tag{5}$$

and the density function is then $f(t|z) = \theta(t|z)S(t|z)$. For uncensored observations with failure at time T, the contribution to the likelihood is $f(T|z)$; for observations censored at time T, the contribution to the likelihood is $S(T|z)$, *i.e.*, the probability of survival until time T.

For the data used in this study, each bank i in the sample is observed at J_i different times $t_{i1} < t_{i2} < \ldots < t_{iJ_i}$, with either failure or censoring occurring at time t_{iJ_i}. Note that times here refer not to calendar time, but to time relative to the date of charter for bank i so that $t_{i0} = 0$ where t_{i0} is the date of charter for the ith bank. The balance sheet information and efficiency scores used in z corresponding to time t_{ij}, $j = 1, \ldots, (J_i - 1)$, are assumed to reflect the position of bank i over the interval $[t_{ij}, t_{i(j+1)})$. The model estimated in this paper is time-varying in the sense that covariates in z are assumed constant for intervals of time $[t_{ij}, t_{i(j+1)})$, but may vary across different intervals. Thus for the ith bank there are $(J_i - 1)$ censored observations where the contribution to the likelihood is given by $[S(t_{i(j+1)}|z) - S(t_{ij}|z)]$; again, the J_ith observation represents either failure or censoring.

As discussed in the previous section, balance sheet data for the banks in our sample were reported as of August 31 for even-numbered years (except 1912 and 1916). In addition, the charter date of each bank and the failure date for banks that failed prior to August 31, 1928 are known. Several banks in the sample either merged with other banks during the period of the study or adopted a national charter; in these cases the data are considered censored at the date of merger or change in charter. Data on banks which did not voluntarily liquidate, merge, fail, or change their charter prior to August 31, 1928 were recorded as censored at that date.

To distinguish between failing and non-failing banks, we include measured efficiency and slack, various financial ratios, and deposit insurance system membership status as independent variables in the hazard model. In addition, we include dummy variables corresponding to the last four periods listed in Tables 2–4 (*PER4, PER5, PER6,* and *PER7,* respectively) to capture any systematic determinants of failure not otherwise accounted for by the model.

From the analysis of technical efficiency, we include *WOE,* the efficiency score computed from (1), and *SLACK*, which is defined as total output slack as a percentage of total output quantities. No units of measurement problems arise here since both outputs are measured in dollars. If increasing inefficiency raises the probability of bank failure, as might be expected, then the coefficients on each variable should be positive.

As additional independent variables, we include *CAPRAT,* which is the ratio of the book value of equity to total assets;[19] *BNDRAT,* the ratio of a bank's bond holdings to total assets; *LOANRT,* the ratio of total loans to total assets; *CSHDEP,* the ratio of cash items, currency, coin, and exchange to total deposits; *DEPRAT,* the ratio of total deposits to toal assets; and *LIABRT,* the ratio of bills payable and miscellaneous liabilities to total assets. The probability of failure is expected to be higher for lower values of *CAPRAT, BNDRAT, CSHDEP,* and *DEPRAT.* The first captures a bank's ability to absorb loan losses while remaining solvent. Since the specific bonds that Kansas banks held is unknown, the sign of the coefficient on *BNDRAT* could be either positive or negative. However, U.S. Government bonds probably comprised the largest share of most banks' bond portfolios, especially after U.S. entry into World War I, and hence we expect the coefficient will be negative.[20] Banks with a low ratio of cash and other reserves to deposits were relatively less well protected against suddent deposit withdrawals, and hence had a higher probability of closure from illiquidity. The coefficient on *CSHDEP* is thus expected to be negative.

Since deposits tend to be a relatively low-cost source of funds, conservative banks would likely have been able to attract sufficient deposits to meet their need for funds. Banks that were less conservative, on the other hand, may have had to rely more on high-cost sources, such as bills payable. Hence the coefficient on *DEPRAT* should be negative, and that on *LIABRT* is expected to be positive. The coefficient on *LOANRT* is also expected to be positive since loans typically are riskier than other bank investments.[21]

Wheelock (1992) found that in 1920 the balance sheets of Kansas commercial banks with deposit insurance differed markedly from those of uninsured banks. For example, as predicted by models of bank behavior with insurance (*e.g.,* Merton, 1977), insured banks maintained lower capital/asset ratios than uninsured banks. These models also predict that insured banks will hold riskier assets, and since we do not have information about the riskiness of bank portfolios, we include an indicator variable of whether or not a bank had deposit insurance as an additional regressor. The variable *INS* equals 1 if a bank was a member of the state deposit insurance system, and 0 otherwise.

The high number of bank failures in Kansas that followed the collapse of commodity prices in 1920 put a severe strain on the state deposit insurance system. The failure of the state's largest insured bank, the American State Bank of Wichita, in early 1923, marked the beginning of a decline in deposit insurance system membership. Although the bank's depositors were eventually made whole, it was generally recognized that the insurance fund would go bankrupt without higher insurance premiums and a marked decline in failures.[22] Although premiums were increased to their legal maximum, the number of failures did not decline, and in March 1925 the state bank commissioner suspended the payment of insurance claims. In April 1926, the state supreme court ruled that banks could leave the system without liability for future claims by simply forfeiting the bonds they had deposited to guarantee payment of insurance assessments. Membership then declined rapidly. In December 1925, 62% of eligible banks belonged to the insurance system. By December 1926, membership was down to 42%, and by December 1927, just 9% of eligible banks remained insured (FDIC, 1956, p. 68).

Although the supreme court ruling in 1926 effectively ended the insurance of bank deposits in Kansas, depositors may have doubted the credibility of insurance much earlier, especially after the payment of claims was suspended in early 1925. If depositors lost faith in the system, they should have begun to monitor their banks, demand risk premiums on deposit interest rates and withdraw their funds from banks taking unacceptable risks. In other words, if depositors did not believe an insurance payoff was likely in the event of failure, they should have demanded the same terms from an insured bank as from a uninsured bank. Hence the ability (and incentive) for insured banks to take greater risks than uninsured banks would have disappeared. By 1925, therefore, the relationship between insurance system membership and the probability of failure might have changed. To test for this possibility, we include two addtional variables: $INSBEF$ equals INS prior to September 1, 1924, and 0 otherwise; $INSAFT$ equals INS for September 1, 1924 and thereafter, and 0 otherwise.

As a final independent variable, we include $LIAB$, the sum of all bank liabilities and equity (thus equal to total assets), to capture possible economies of scale. If larger banks were less likely to fail, the coefficient on $LIAB$ should be negative.

The proportional hazard model described above was estimated using using the partial likelihood method described by Kalbfleisch and Prentice (1980, pp. 70–142). Results of the estimation of the parameters in β are reported in Table 5. Since the covariates in the hazard model are time-varying, estimates of the baseline hazard are difficult to obtain and are inconsistent; furthermore, since the baseline hazard has ambiguous meaning when time-varying covariates are used, it is not reported here.

Table 5 contains the estimation results from five specifications of the hazard model. Model I contains both the WOE and $SLACK$ variables; t-ratios indicate that $SLACK$ is significant at .05 while WOE is insignificantly different from zero. To allow for possible effects caused by multicollinearity among the covariates, the model was reestimated while first deleting *SLACK* and then deleting *WOE;* these models are labelled *II* and *III*, respectively. When *SLACK* is deleted in model *II*, the coefficient on *WOE* increases relative to the value in model *I* and becomes significant at .01. Computing the likelihood-ratio statistic $-2(LLF_{restricted} - LLF_{free})$ for models *II* and *III* produces values 3.022 and 0.042, respectively, which are each distributed chi-square with one degree of freedom. Thus, the restriction in model *II* is significant at .10, while the restriction in model *III* is insignificant. These results suggest that *SLACK* is important for explaining bank failure. However, when both *SLACK* and *WOE* are deleted as in model *IV*, the log-likelihood declines (relative to model *I*) to -134.104, yielding a likelihood-ratio statistic of 6.102, which with two degrees of freedom is significant at .05. Hence *WOE* is also important in explaining bank failure, although estimation of the precise effect of *WOE* is difficult due to rather strong correlation between *WOE* and *SLACK* (the Pearson correlation coefficient for these variables is 0.5882). The positive signs on both variables indicate that increasing inefficiency raises the probability of failure.

In models *I-IV*, *INSBEF* is significant at .05, while *INSAFT* is insignificant. Furthermore, the positive sign on *INSBEF* indicates that prior to 1924 insured banks were more likely to fail than uninsured banks; the results indicate that insurance played an insignificant role in determining bank failure after 1924. In model *V, INSBEF* and *INSAFT* were replaced by *INS*, which amounts to restricting the coefficients on *INSBEF* and *INSAFT* to be equal. Comparing model *V* with model *I*, the likelihood-ratio statistic is 7.158, which, with one degree of freedom, is significant at .01. Thus the null hypothesis that insurance played the same role before and after 1924 is soundly rejected.[23]

Among the financial ratios, the coefficients on *CAPRAT* and *CSHDEP* have the expected signs and are significant at the .05 level across the five specifications. The lower a bank's capital/assets or cash/deposits ratios, the more likely it was to fail. *LIABRT* is significant at the .10 level, except in Equation *IV.* As expected, the higher this ratio, the more likely a bank was to fail. *BNDRAT* and *LOANRT* are significant only in Equation *IV,* however, and the sign on *LOANRT* is opposite what was expected, which is likely due to multicollinearity among the various financial ratios.[24] Finally, the coefficient on *LIAB* is not statistically significant, suggesting that after controlling for the various financial ratios, technical efficiency and deposit insurance, failure was not a function of size.

The time dummy variables *PER5, PER6,* and *PER7* are significant at .05 or higher in each specification shown in Table 5. *PER4* is insignificant in all cases. The positive signs indicate that banks were more likely to fail in these periods, holding other factors constant, perhaps due to overall business conditions.

We repeated the hazard model estimation using the IWE efficiency score and information about input slack obtained from (2). The results were qualitatively similar, although the coefficient on the IWE score was not significantly different from zero at the .10 confidence level in any specification.

6. CONCLUSIONS

As in the 1980s, during the 1920s a collapse of commodity and real estate prices precipitated a high number of bank failures. Though hundreds of banks failed, many more survived. What characteristic distinguish the failures from the survivors? As other researchers have found using both historical and modern data, our results indicate that in Kansas weakly capitalized banks, those holding few reserves, and those relying heavily on short-term borrowed funds *ex ante,* had a higher probability of failure than their more conservatively managed competitors. We also found that members of the state deposit insurance system had a higher probability of failure than non-members, consistent with the hypothesis that insurance encourages banks to hold higher-risk portfolios than they otherwise would.

Finally, we found that the more adept a bank was at transforming inputs — savings deposits, borrowed funds, labor and capital — into loans and demand deposits, the better its chance of surviving Kansas' economic downturn. In the empirical model of bank failures, measures of output efficiency and slack contributed significant explanatory power, and did not simply mimic the effects of deposit insurance and management behavior captured by various financial ratios. Whether measures of technical efficiency will prove useful for explaining bank failures generally awaits its application to other data sets. Our findings suggest, however, that efficiency may well be an important determinant of which banks fail and which survive during periods of significant economic distress.

NOTES

1. See, for example, Mishkin (1992) and Kane (1989).

2. This is in contrast to the Great Depression, when failures were widespread. Even then, however, failure rates were highest among small, unit banks in rural areas. White (1983) and Alston, Grove and Wheelock (1993) trace the banking instability of the 1920s to branch banking restrictions. O'Driscoll (1988, 1991) makes the case for the 1980s.

3. For the 1980s, see O'Driscoll (1988), Kane (1989), Mishkin (1992), and the references therein. Robert Forrestal, President of the Federal Reserve Bank of Atlanta, argued that branching restrictions and deposit insurance were responsible for many of the problems in the modern banking system in a speech delivered in Atlanta September 25, 1992 at the Conference on Efficiency in the Financial Services Industries.

4. The eight states and the years in which their insurance systems operated are Oklahoma (1907-23), Texas (1909-25), Kansas (1909-29), Nebraska (1909-30), South Dakota (1909-31), North Dakota (1917-29), Washington (1917-29), and Mississippi (1914-30). Cooke (1909), Robb (1921), American Bankers Association (1933), Federal Deposit Insurance Corporation (1956), and Calomiris (1989) compare the features and performance of the systems.

5. See also Thies and Gerlowski (1989).

6. An index of farm product prices equaled 74.3 in 1910 and 150.7 in 1920 (1926=100) [*Historical Statistics of the United States* (1960, series E15)].

7. Moreover, the ratio of farm debt to value rose from 27.3% to 29.1% [*Abstract of the 14th Census of the United States* (1920, p. 737)].

8. Board of Governors of the Federal Reserve System (1959), *All Bank Statistics, 1896-1955.* The number of banks reached its all-time record of 31,076 in 1921.

9. *Historical Statistics of the United States* (1960, series E15).

10. The north central states of Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska and Kansas accounted for 2652 of the 5712 bank suspensions in the U.S. during the 1920s. Kansas alone had 220 failures. By contrast, New England had just 14, and California 31. Board of Governors of the Federal Reserve System (1943, pp. 284-85). See Alston, Grove and Wheelock (1993) for analysis of state differences in bank failure rates during the 1920s.

11. We focus our study on this period because, as discussed below, a state supreme court ruling in 1926 reduced the cost of withdrawal from the deposit insurance system for Kansas banks. Most banks then withdrew, effectively ending deposit insurance even though the system was not closed officially until 1929.

12. This requirement was waived if there were no other insured banks in an applicant's town. National banks, trust companies, unincorporated banks and state banks not meeting the various requirements for membership were ineligible for deposit insurance.

13. The minimum capital/deposit ratio was eliminated in 1917 [Warburton (1958)].

14. For example, a bank with $100,000 of deposits and $10,000 of capital would pay $45 per year, versus $42.50 if it had $15,000 of capital.

15. Surplus refers to paid-in capital beyond the par value of a bank's stock plus undistributed profits.

16. Espahdobi (1991) uses a similar model for bank failures in the 1980s.

17. The source of our data is the *Biennial Report of the Commissioner of Banking* for Kansas.

18. We dropped seven banks for missing data. Others fall out of the panel after failing, closing voluntarily, merging with other banks, or switching to a national charter.

19. Total equity includes the par value of bank stock, paid in surplus, and undistributed profits.

20. Only bonds issued by the Federal Government, State of Kansas, or Kansas municipalities were eligible for deposit with the state banking commissioner as a guarantee of deposit insurance assessment.

21. See White (1984) or Wheelock (1992) for further development of the specific hypotheses tested with each of these variables.

22. The state deposit insurance systems of the 1920s were not guaranteed by state governments. If a fund had insufficient assets to pay depositors, it was the depositors, not taxpayers, who lost.

23 Rather than arbitrarily dividing the effect of insurance status at 1924 as with the *INSBEF* and *INSAFT* variables, the switching point could (in principle) be estimated from the data. Unfortunately, this is difficult in the context of hazard models with time-varying covariates. However, we redefined *INSBEF* and *INSAFT* with the break occurring at September 1, 1922; reestimating model *I* yields a log-likelihood of −134.545, which is well below the value obtained from the original specification reported in Table 5.

24 Inspection of the correlation matrix for the ratios and the variance-covariance matrix of the parameter estimates indicates considerable multicollinearity.

REFERENCES

Alston, Lee J., Grove, Wayne A. and David C. Wheelock (1993), Why do banks fail? Evidence from the 1920s, *Explorations in Economic History,* forthcoming.

Aly, Hassan Y., Richard Grabowski, Carl Pasurka, and Nanda Rangan (1990), Technical, scale, and allocative efficiencies in U.S. banking: an empirical investigation, *The Review of Economics and Statistics* 72, 211–218.

American Bankers Association (1933), *The Guaranty of Bank Deposits*, New York.

Association of Reserve City Bankers (1933), *The Guaranty of Bank Deposits*, Chicago.

Barr, R. S., L. M. Seiford, and T. F. Siems (1992), "An Envelopment-Analysis Approach to Measuring the managerial Quality of Banks," unpublished working paper, Department of Computer Science and Engineering, Southern Methodist University.

Berg, S. A., F. R. Førsund, and E. S. Jansen (1993a), Bank output measurement and the construction of best practice frontiers, *Journal of Productivity Analysis,* forthcoming.

Berg, S. A., F. R. Førsund, and E. S. Jansen (1993a), Malmquist indices of productivity growth during the deregulation of Norwegian banking 1980–1989, *Scandanavian Journal of Economics,* forthcoming.

Berger, A. N., G. A. Hanweck, and D. B. Humphrey (1987), Competitive viability in banking: scale, scope and product mix economies, *Journal of Monetary Economics* 20, 501–520.

Berger, A. N., and D. B. Humphrey (1992), "Measurement and Efficiency Issues in Commercial Banking," in *Output Measurement in the Service Sectors,* ed. by Zvi Griliches, Chicago: University of Chicago Press, Inc.

Board of Governors of the Federal Reserve System (1943), *Banking and Monetary Statistics, 1914-1941*, Washington, D.C.

Board of Governors of the Federal Reserve System (1959), *All Bank Statistics, 1896-1955*, Washington, D.C.

Boles, J. (1966), Efficiency squared: efficient computations of efficiency indexes, *Western Farm Economics Association Proceedings,* 137–142.

Calomiris, Charles W. (1989), Deposit insurance: lessons from the record, *Economic Perspectives*, Federal Reserve Bank of Chicago, pp. 10–30.

Calomiris, Charles W. (1992), "Do 'Vulnerable' Economies Need Deposit Insurance? Evidence from U.S. Agriculture in the 1920s," in Philip L. Brock, ed., *If Texas Were Chile: A Primer on Banking Reform,* San Francisco: Institute for Contemporary Studies.

Charnes, A., W. W. Cooper, and E. Rhodes (1978), Measuring the efficiency of decision making units, *European Journal of Operational Research* 2, 429–444.

Charnes, A., W. W. Cooper, and E. Rhodes (1979), Measuring the efficiency of decision making units, *European Journal of Operational Research* 3, 339.

Clark, J. A. (1989), The economies of scale and scope at depsitory financial institutions: a review of the literature, *Economic Review, Federal Reserve Bank of Kansas City* 73, 16–33.

Cooke, Thornton (1909), The insurance of bank deposits in the west, *Quarterly Journal of Economics* 24, 85–108.

Cox, D. R. (1972), Regression models and life-tables, *Journal of the Royal Statistical Society Series B* 34, 187–220.

Debreu, G. (1951), The coefficient of resource utilization, *Econometrica* 19, 273–292.

Department of Commerce (1923), *Abstract of the Fourteenth Census of the United States, 1920*, Government Printing Office, Washington, D. C.

Department of Commerce (1960), *Historical Statistics of the United States, Colonial Times to 1957*, Government Printing Office, Washington, D. C.

Espahbodi, P. (1991), Identification of problem banks and binary choice models, *Journal of Banking and Finance* 15, 53–72.

Färe, R., and S. Grosskopf (1983), Measuring congestion in production, *Zeitschrift für Nationalökonomie* 43, 257–271.

Färe, R., S. Grosskopf, and C. A. K. Lovell (1985), *The Measurement of Efficiency of Production,* Boston: Kluwer-Nijhoff Publishing.

Farrell, M. J. (1957), The measurement of productive efficiency, *Journal of the Royal Statistical Society A* 120:3, 253–281.

Federal Deposit Insurance Corporation (1956), *Annual Report*, Government Printing Office, Washington, D. C.

Ferrier, G., and C. A. Knox Lovell (1990), Measuring cost efficiency in banking: econometric and linear programmin evidence, *Journal of Econometrics* 46, 229–245.

Fixler, D. J., and K. D. Zieschang (1992), "Ranking U. S. Banks According to Efficiency: A Multilateral Index Number Approach," unpublished working paper, U. S. Bureau of Labor Statistics.

Fried, Harold O., C. A. Knox Lovell, and Philippe Vanden Eeckaut (1993), Evaluating the performance of U. S. credit unions, *Journal of Banking and Finance* 17, 251–265.

Furlong, Frederick T. and Michael C. Keeley (1989), Capital regulation and bank risk-taking: a note, *Journal of Banking and Finance* 13, 883–891.

Grabowski, R., N. Rangan, and R. Rezvanian (1993), Organizational forms in banking: an empirical investigation of cost efficiency, *Journal of Banking and Finance* 17, 531–538.

Harger, Charles Moreau (1926), An experiment that failed: what kansas learned by trying to guarantee bank deposits, *Outlook* 143, 278–279.

Kalbfleisch, J. D., and R. L. Prentice (1980), *The Statistical Analysis of Failure Time Data,* John Wiley and Sons, Inc., New York.

Kane, Edward J., *The S&L Insurance Mess: How Did It Happen?* (Washington, D.C., 1989).

Kansas, *Biennial Report of the Bank Commissioner*, (Topeka, various years).

Kareken, John H. and Neil Wallace (1978), Deposit insurance and bank regulation: a partial-equilibrium exposition, *Journal of Business* 51, 413–438.

Keeley, Michael C. (1990), Deposit insurance, risk, and market power in banking, *American Economic Review* 79, 1183–1200.

Lane, William R., Stephen W. Looney, and James W. Wansley (1986), An application of the Cox proportional hazards model to bank failure, *Journal of Banking and Finance* 10, 511–532.

Lovell, C. A. K. (1993), "Production Frontiers and Productive Efficiency," in *The Measurement of Productive Efficiency: Techniques and Applications,* ed. by Hal Fried, C. A. Knox Lovell, and Shelton Schmidt, Oxford: Oxford University Press, Inc.

Merton, Robert C. (1977), An analytic derivation of the cost of deposit insurance and loan guarantees, *Journal of Banking and Finance* 1, 3–11.

Mishkin, Frederic S. (1992), An evaluation of the treasury plan for banking reform, *Journal of Economic Perspectives* 6, 133–153.

O'Driscoll, Gerald P. (1988), Bank failures: the deposit insurance connection, *Contemporary Policy Issues* 6, 1–12.

O'Driscoll, Gerald P. (1990), "Banking Reform," research paper no. 9004, Federal Reserve Bank of Dallas.

Parkan, C. (1987), Measuring the efficiency of service operation: an application to bank branches, *Engineering Costs and Production Economics* 12, 237–242.

Rangan, Nanda, Hassan Y. Aly, Carl Pasurka, and Richard Grabowski (1988), The technical efficiency of U. S. banks, *Economics Letters* 28, 169–175.

Robb, Thomas B. (1921), *The Guaranty of Bank Deposits*, Houghton-Mifflin Co., Boston.

Sherman, H. D., and Franklin Gold (1985), Bank branch operation efficiency: evaluation with data envelopment analysis, *Journal of Banking and Finance* 9, 297–316.

Thies, Clifford F. and Daniel A. Gerlowski (1989), Deposit insurance: a history of failure, *Cato Journal* 8, 677-693.

Vassiloglou, M., and D. Giokas (1990), A study of the relative efficiency of bank branches: an application of data envelopment analysis, *Journal of the Operational Research Society* 41, 591–597.

Warburton, Clark (1958), "Deposit Guaranty in Kansas," unpublished manuscript, Federal Deposit Insurance Corporation.

Wheelock, David C. (1992), Deposit insurance and bank failures: new evidence from the 1920s, *Economic Inquiry* 33, 530–543.

Wheelock, David C. and Subal C. Kumbhakar (1993), Which banks choose deposit insurance? Evidence of adverse selection and moral hazard in a voluntary insurance system, *Journal of Money, Credit, and Banking,* forthcoming.

White, Eugene N. (1983), *The Regulation and Reform of the American Banking System, 1900-1929*, Princeton University Press, Princeton.

White, Eugene N. (1984), A reinterpretation of the banking crisis of 1930, *Journal of Economic History* 44, 119–138.

TABLE 1

Results of Output Technical Efficiency Estimation

Year	n	Mean	Median	Std. Dev.	Maximum
1910	227	2.9141	2.4225	2.2552	22.3958
1914	252	2.5210	2.3554	1.2862	10.7056
1918	246	3.3274	2.9918	1.8823	11.3600
1020	242	3.5411	3.4257	1.7702	11.6324
1022	233	3.6434	3.3912	2.3767	14.7427
1924	213	4.8661	4.2837	3.1009	23.4874
1926	198	1.9877	1.8330	0.8461	4.5721

TABLE 2

Mean WOE Score for Survivors and Failures

Period	Number Survivors	Number Failures	Mean WOE, Survivors	Mean WOE, Failures
1914–1918	246	1	2.4982	1.7576
1918–1920	242	1	3.3187	2.7954
1920–1922	233	4	3.5675	2.8098
1922–1924	213	13	3.5390	3.9295
1924–1926	198	10	4.7566	7.1281
1926–1928	181	11	1.9879	2.1840

TABLE 3

Slacks for Survivors and Failures

Period	Survivors Y_1	Survivors Y_2	Survivors $Y_1 + Y_2$	Failures Y_1	Failures Y_2	Failures $Y_1 + Y_2$
1914–1918	4.58	146.28	39.41	0.0	18.72	7.62
1918–1920	117.96	23.39	64.20	0.0	310.64	83.23
1920–1922	27.40	77.90	44.51	0.0	83.43	26.96
1922–1924	4.34	195.22	71.80	0.0	523.57	138.05
1924–1926	8.57	373.04	76.36	1.38	401.01	257.52
1926–1928	2.20	44.04	15.93	0.0	99.88	29.96

NOTE: Figures represent slack in each output as a percent of output for individual bank, averaged over all banks either surviving or failing.

TABLE 4

Scale Efficiency for Survivors and Failures

Period	Survivors				Failures			
	SCALE	# DRS	# CRS	# IRS	*SCALE*	# DRS	# CRS	# IRS
1914–1918	0.2568	45	25	176	0.2964	0	0	1
1918–1920	0.1756	108	9	125	−0.2194	1	0	0
1920–1922	0.2025	18	67	148	0.2029	1	0	3
1922–1924	0.6616	20	11	182	0.1727	2	0	11
1924–1926	−0.0977	120	14	64	−0.1238	5	0	5
1926–1928	0.1350	53	20	108	0.0854	4	1	6

TABLE 5
Results of Proportional Hazard Estimation
(t-ratios in parentheses)

	I	*II*	*III*	*IV*	*V*
WOE	0.02442	0.1567*	—	—	0.01261
	(0.21)	(1.84)			(0.11)
SLACK	0.003418**	—	0.003655**	—	0.003731**
	(1.99)		(2.94)		(2.20)
PER4	0.8622	0.7331	0.8962	0.9996	0.9432
	(0.92)	(0.79)	(0.97)	(1.09)	(1.00)
PER5	2.896**	2.898**	2.918**	3.135**	2.047**
	(3.07)	(3.09)	(3.11)	(3.37)	(2.35)
PER6	3.242**	3.264**	3.271**	3.608**	2.130**
	(3.14)	(3.18)	(3.21)	(3.61)	(2.30)
PER7	4.267**	4.328**	4.255**	4.232**	3.220**
	(4.25)	(4.31)	(4.25)	(4.23)	(3.59)
INSBEF	1.366**	1.428**	1.355**	1.393**	—
	(2.21)	(2.30)	(2.20)	(2.27)	
INSAFT	−0.3356	−0.3380	−0.3402	−0.3323	—
	(−0.76)	(−0.76)	(−0.77)	(−0.75)	
INS	—	—	—	—	0.1629
					(0.41)
LIAB	−0.4953	−0.3479	−0.5567	−0.9406	−0.4573
	(−0.54)	(−0.39)	(−0.64)	(−0.99)	(−0.50)
CAPRAT	−13.01**	−12.79**	−12.97**	−12.12**	−14.02**
	(−2.73)	(−2.62)	(−2.73)	(−2.50)	(−2.97)
BNDRAT	−6.535	−6.357	−6.749	−8.084*	−5.919
	(−1.41)	(−1.38)	(−1.50)	(−1.83)	(−1.28)
LOANRT	−3.846	−3.364	−4.120	−5.728**	−3.631
	(−1.22)	(−1.09)	(−1.44)	(−2.05)	(−1.11)
CSHDEP	−7.484**	−7.681**	−7.696**	−9.520**	−7.479**
	(−2.63)	(−2.75)	(−2.90)	(−3.62)	(−2.61)
DEPRAT	−0.2297	−0.5559	−0.2490	−0.8461	−0.07851
	(−0.07)	(−0.17)	(−0.08)	(−0.26)	(−0.03)
LIABRT	6.289*	6.525*	6.203*	5.961	7.541**
	(1.72)	(1.74)	(1.71)	(1.60)	(2.23)
LLF	−131.053	−132.564	−131.074	−134.104	−134.545

NOTE: Asterisk (*) denotes parameter estimates with t-ratios significant at .1 (two-sided); double asterisk (**) denotes estimates with t-ratios significant at .05 (two-sided).

FIGURE 1
Measuring Technical Efficiency