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Abstract

Significant numbers of U.S. commercial bank failures in the late 1980s and early 1990s raise important questions about bank performance. We develop a failure-prediction model for Connecticut banks to examine events in 1991 and 1992. We adopt data envelopment analysis to derive measures of managerial efficiency. Our findings can be briefly stated. Managerial inefficiency does not provide significant information to explain Connecticut bank failures. Portfolio variables do generally contain significant information.

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ABSTRACT

Significant numbers of commercial bank failures in the late 1980s and early 1990s raise important questions about bank performance. We develop a failure-prediction model for Connecticut banks to examine events in 1991 and 1992. We adopt data envelopment analysis to derive measures of managerial efficiency. Our findings can be briefly stated. Managerial inefficiency does not provide significant information to explain Connecticut bank failures over this time period.

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1. Introduction

The commercial banking industry recently experienced problems of bank failures not seen since the Great Depression. Almost 1,500 banks covered by the Federal Deposit Insurance Corporation (FDIC) Bank Insurance Fund failed between 1980 and 1993, including triple digit failures between 1985 and 1992 that peaked at 206 in 1989.¹ Moreover, the pattern was geographically uneven with significant failures in oil-patch (i.e., Louisiana, Oklahoma, and Texas) and farm-belt (i.e., Iowa, Kansas, Minnesota, Missouri, and Nebraska) states during the middle to late 1980s, but switching dramatically to Northeastern states in the early 1990s.² New

England had less than five failures through 1989, but experienced 16, 53, and 31 failures in 1990, 1991, and 1992, respectively before falling back to 3 failures in 1993. Focusing on 1991 and 1992, Connecticut had 27 of the 84 failures, trailing only Massachusetts with 30. Connecticut topped the list in New England in 1991 with 17 failures, followed by Massachusetts with 14.

We investigate those factors that may help to explain bank failures in Connecticut. Our failure-prediction model considers predictions at one- and two-year ahead time horizons. The Connecticut experience deserves special attention because of the large number of new bank failures. Of the 27 failures in Connecticut in 1991 and 1992, 15 were new banks chartered in 1984 or later and 3 were conversions of saving banks to stock ownership since 1983. ³

Federal regulators use an early warning system to identify problem banks that are in danger of failure. This system uses the acronym CAMEL, representing Capital adequacy, Asset quality, Management quality, Earnings ability, and Liquidity. Bank examiners score banks in each CAMEL category on a scale of 1 to 5, with 1 being the strongest rating. The overall CAMEL rating emerges from the underlying factor scores. The examiners can find ample information from bank balance sheet and income statements to assess capital adequacy, asset quality, earnings ability, and liquidity. Management quality presents the examiners with a tough nut to crack. No clear-cut measures of management quality readily emerges from the bank's financial statements. Examiners must rely on more subjective factors. Siems (1992), Barr and Siems (1993), and Barr, Seiford, and Siems (1993) suggest the use of data envelopment analysis (DEA) to measure management quality.

A substantial literature exists that develops failure-prediction models. Crucial to any such analysis is the identification of those variables that reliably predict future bank failure. Studies adopt a number of different methods, including multiple discriminant analysis, factor analysis, proportional hazard models, and logit analysis. The studies use variables that reflect asset quality, liquidity, capital adequacy, management quality, and local or regional economic conditions.

Most studies find that capital adequacy, earning ability, and asset quality, measured by the concentration of certain loan types, help to predict bank failure (e.g., Sinkey 1975, Pantalone and Platt 1987, Barr and Siems 1993, and Barker and Holdsworth 1993). For example, Barker and Holdsworth (1993) report that, on average, capital and income slowly deteriorate while past-due loans and charge offs increase as failure approaches. On the other hand, Heyliger and Holdren (1991) discover that asset quality, measured by the ratios of loan loss provisions and net charge offs to total loans, do not provide reliable indicators of bank failure.

Researchers construct various financial ratios to capture management quality. Meyer and Pifer (1970) state that "Managerial ability is like Lord Acton's elephant -- difficult to define but easy to identify. Over a period of time differences between good and poor management will be systematically reflected by the balance sheet and income data, and analysis of such data should enable prediction of failures." (p. 856) Graham and Horner (1988) evaluate the factors that

contributed to the failure of 162 national banks and conclude that more than 60 percent of failed banks experienced poor management, measured by such variables as poorly followed loan policies, inadequate problem loan identification systems, and non-existent or poorly followed asset/liability management. Barr and Siems (1993) provide the only direct measurement of management quality, using data envelopment analysis (DEA) to quantify the quality of management. They conclude that the predictive performance of their failure-prediction model improves markedly with the inclusion of the DEA efficiency variable.

The effect of local economic conditions on bank failure is unclear. Sinkey (1975), Pantalone and Platt (1987), Graham and Horner (1988), and Duwe and Harvey (1988) find that local economic conditions do not significantly affect bank failure. Looney et al. (1989), Thomson (1991), Whalen (1991), Barker and Holdsworth (1993), and Barr and Siems (1993) report that local economic conditions do help to predict bank failure. Our analysis obviates this issue by considering bank failure within a local region (i.e., Connecticut).

2. Measures of Managerial Efficiency

A number of studies apply DEA to the question of efficiency in banking, including Rangan, Grabowski, Aly, and Pasurka (1988), Grabowski, Rangan, and Rezvanian (1993), Aly, Grabowski, Pasurka, and Rangan (1990), Elyasiani and Mehdian (1990), Ferrier and Lovell (1990), Yue (1992), and Miller and Noulas (1995). And as noted above, Barr and Siems (1993), Barr, Seiford, and Siems (1993), and Siems (1992) all use DEA to measure management quality.

Several general conclusions emerge from this literature. First, inefficiency traces primarily to pure technical, rather than scale, effects. That is, if a bank has not fully exhausted economies of scale, or if it has gone too far and experienced diseconomies of scale, neither event contributes much to overall bank inefficiency. Inefficiencies link more to inefficient resource utilization rather than production scale. Second, the level of efficiency appears to rise with bank size.

We employ Call Report data. In selecting our sample, we choose all commercial banks in Connecticut that survived through the end of 1992 or failed in 1991 or 1992. We exclude banks that exited the industry through a non-FDIC assisted merger. Within the sample banks were identified as old or new based on charters before or after 1984. Our final sample included 45 surviving banks and 20 failed banks. Of the 45 surviving banks, 27 were old banks and 18 were new. Of the 20 failed banks, 6 were old and 14 were new. Thus, 60 percent of the surviving banks were old while only 30 percent of the failed banks were old.

Little agreement exists over what a bank produces or how to measure output. Two different approaches -- production and intermediation -- model bank behavior. ⁴ The production approach measures outputs by the number of accounts and considers only operating costs. The intermediation approach assumes that banks collect deposits and purchased funds with the assistance, of course, of labor and capital and intermediate these sources of funds into loans and other assets. Output

is measured by the dollar value of accounts; both operating and interest costs are included in the total cost.

The definition of inputs and outputs in bank production studies remains a most contentious issue. One point needs attention relative to our definitions. Researchers debate whether transactions deposits are inputs, intermediate outputs, or final outputs (e.g., Siems 1992). We assume that transactions deposits are inputs, since they are another source of funds like non-transactions deposits. Moreover, transactions deposits receive an interest payment, explicit and/or implicit (implicit payments measure the less than full-cost charges on the bank's administration costs associated with transactions deposits). Thus, we include transactions deposits in the set of inputs.

Our analysis measures DEA efficiency for several specifications. Our most disaggregated specification includes seven inputs -- total transactions deposits (D_T), total non-transactions deposits (D_N), purchased funds (PF), total interest expense (E_I), total non-interest expense (E_N), the number of full-time equivalent employees (labor, L), and fixed premises and fixed assets (capital, K) -- and six outputs -- commercial and industrial loans (CIL), consumer loans (CL), real estate loans (REL), investments (IN), total interest income (Y_I), and total non-interest income (Y_N). We refer to this specification as the 13 variable DEA model (V_{13}). We eliminate interest and non-interest income and expenses to generate our 9 variable DEA model (V_9). Finally, our bare-bones specification includes total loans (TL) and investments as outputs and deposits (D) (i.e., transactions and non-transactions deposits, and purchased funds), labor, and capital as inputs for our 5 variable DEA model (V_5).

DEA uses the principles of linear programming theory to examine how a particular decision making unit (DMU) operates relative to the other DMUs in the sample. That is, the technique provides a benchmark for best practice technology based on the experience of those banks in the sample. It does not necessarily provide a benchmark against the most efficient technology available. DEA was introduced by Charnes, Cooper, and Rhodes (1978), based on the work of Farrell (1957). Banker, Charnes, and Cooper (1984) demonstrate that the efficiency measure described in Charnes, Cooper, and Rhodes (1978) can be divided into pure technical and scale efficiencies. DEA has proliferated in recent years; Seiford and Thrall (1990) provide a recent review of various developments.

As just noted, DEA constructs a frontier based on the actual data in the sample. Banks on the frontier are efficient, while banks inside the frontier are inefficient. Efficiency is measured by the ratio of weighted outputs (virtual output) to weighted inputs (virtual input). This ratio varies between zero and one. A ratio of one (less than one) means that the bank is efficient (inefficient). A bank that is efficient does not necessarily produce the maximum level of output from the given inputs. Rather, the bank produces the "best practice" level of output for the banks in the sample.

The Model:

Consider N banks (DMUs), each producing m different outputs using n different inputs. The efficiency of the DMU is found by solving the following linear programming problem:

$$\text{minimize } \beta_s \tag{1}$$

$$\text{subject to } \sum_{r=1}^N \phi_r y_{ir} \geq y_{is}, \quad i = 1, \dots, m \text{ and } r = 1, \dots, N;$$

$$\beta_s x_{js} - \sum_{r=1}^N \phi_r x_{jr} \geq 0, \quad j = 1, \dots, n; \quad \phi_r \geq 0; \text{ and } \beta_s \text{ free.} \tag{2}$$

The variable β_s is the overall technical efficiency and must lie between zero and one.

Results:

Table 1 reports the efficiency results. Several general observations emerge. The level of bank efficiency generally increases with the degree of disaggregation of outputs and inputs. Thus, the efficiency measure V_{13} exceeds the comparable V_9 measure. And V_9 , in turn, exceeds V_5 . In addition, average inefficiencies across the various classifications in Table 1 are small. Even in the most inefficient year (1990) for the least disaggregation in outputs and inputs (V_5), bank efficiency measures just over 87 percent for survived (S) banks and just over 80 percent for failed (F) banks. Finally, the average efficiencies for all banks do not indicate a clear pattern between survived and failed banks. Failed banks sometimes exceed the efficiency of, and sometimes fall short of, survived banks.

Table 1 also reports efficiency findings for old banks (banks that had charters before 1984) and new banks (banks that received charters during or after 1984). Here we do find some patterns between survived and failed banks. For the V_5 efficiency measure, survived old and new banks generally have a slightly higher efficiency than failed old and new banks, respectively. This pattern continues for the V_9 efficiency measure only for old banks. For new banks, the V_9 efficiency measure has failed banks higher than for survived banks. Finally, the differences between the V_{13} efficiency measures for survived and failed banks is much smaller and less consistent.

What do these results suggest? One possible implication is that bank efficiency may not provide information to distinguish between survived and failed banks. Such a conclusion must remain speculative, since it uses only average data across the categories of survived, failed and old, new banks. Multivariate logit analysis can provide a more definitive answer in section 4.

3. Portfolio Characteristics

Table 2 presents average values for a number of portfolio characteristics across survived, failed and old, new banks. All variables, save one, are relative to total assets. Focusing on the loan portfolio, a couple of general observations emerge. Total loans are generally higher for failed banks, than survived banks. And except for 1987, new banks have higher total loans than old banks. Construction and land development and commercial real estate loans were higher for

failed old banks than for survived old banks. Commercial real estate loans were lower for failed new banks than for survived new banks while construction and land development loans were nearly the same for failed and survived new banks. Commercial and industrial loans provide a consistent picture with failed banks having higher amount of these loans than survived banks. Finally, total real estate loans presents a counterintuitive finding, at least based on conventional wisdom, with failed banks having lower level of these loans than survived banks. Moreover, a convergence occurs with failed banks increasing their proportions into the range of between 40 and 50 percent real estate loans to assets for survived banks.

In sum, the real estate portfolio conveys a mixed picture. If the banking problems in Connecticut in the early 1990s trace their roots to real estate loans, then one can find some evidence to support this view, commercial and industrial and construction and land development loans. But other loan categories, total real estate loans, support the view that real estate loans did not precipitate Connecticut bank failures. Commercial real estate loans give conflicting signals with the conventional wisdom being supported for old banks.

The level of past due and non-accruing loans was generally higher for failed banks than for survived banks. That is, larger past due and non-accruing loans make bank earnings worse, other things constant. Moreover, past due and non-accruing loans increased dramatically over the 1987 to 1990 period for all banks. As a result, we also observe that net income generally falls for all banks and that failed banks have lower net income than survived banks. Finally, net income is generally negative for new banks whether they survived or failed; survived banks just have lower losses than failed banks.

Failed old banks had a higher level of purchased funds than survived banks except in 1990. On the other hand, failed new banks had lower purchased funds than survived banks. Survived banks had higher levels of checkable deposits than failed banks. Purchased funds are usually a higher cost and more volatile deposit source. A higher reliance on purchased funds should, other things constant, indicate a riskier portfolio. In addition, new banks generally had lower checkable deposits than old banks.

Finally, while the total equity was about the same for survived and failed banks in 1987, the failed banks had a lower equity position for every subsequent year in Table 2. ⁵ The old failed banks actually achieved a negative equity position by 1990 while the new failed banks still had an equity to total loan ratio, on average, of just over 6 percent.

These results can be summarized as follows. The failed banks generally have higher total loans to total assets (TL/TA), construction and land development loans to total assets (CLD/TA), commercial and industrial loans to total assets (CIL/TA), and past due 90 days or more and non-accruing loans to total assets (PDNA/TA) than survived banks. The survived banks generally have higher real estate loans to total assets (REL/TA), net income to total assets (NI/TA), total deposits to total assets (DD/TA), and total equity to total loans (TE/TL) than failed banks.

4. Determinants of Bank Failure: A Failure-Prediction Model

The previous discussions, while informative, cannot provide definitive assessments of the determinants of bank failures in Connecticut. What is needed is a multivariate analysis. The variable that we are interested in explaining is discrete -- the bank either fails or survives. Thus, we adopt logit analysis to consider the issue where the dependent variable (F/S) is coded one for failed banks and zero for survived banks. We consider banks that survived and failed during 1991 and 1992. We employ information about the banks either one-year ahead (i.e., 1989 and 1990) or two-years ahead (i.e., 1988 and 1989). That is, when considering bank failures that occurred sometime in 1992, we use explanatory variables from 1990 for the one-year ahead and from 1989 for the two-year ahead failure-prediction models. ⁶

Our preliminary analysis of the data suggests that there may be a fundamental difference between old and new bank behavior. ⁷ That is, the determinants of old and new bank failures may be significantly different. Thus, we introduce a dummy variable coded one for new banks and zero for old banks. We include the dummy variable in our logit regressions by itself and interactively with each of the independent variables. As such, we can test to see if significant differences exist between the determinants of bank failure for the old and new banks. We find that the interactive terms involving the independent variables and this dummy variable are generally not significant. Thus, we do not report these findings. The inclusion of the dummy variable by itself occasionally leads to significant differences in the failure rates. Note that these differences must reflect factors not already contained in the list of independent variables. We return to this point shortly.

In sum, we attempt to construct failure-prediction models for Connecticut bank failures in 1991 and 1992, using balance sheet and income statement data for 1988, 1989, and 1990. The 1988 and 1989 data are used in our two-year ahead failure-prediction model while the 1989 and 1990 data are used in the one-year ahead model.

We begin our inquiry by adopting the specification that Barr and Siems (1993) employ in their failure-prediction model for a national sample between 1986 and 1989. After considering a number of different variables to capture each of the component parts of the CAMEL rating scheme, they settle on equity capital to total loans (Capital Adequacy), non-performing loans to total assets (Asset Quality), the DEA efficiency measure (Management), net income to total assets (Earnings), and large dollar deposits to total assets (Liquidity). Since they employ a national sample, they also include the change in statewide housing starts to reflect local economic conditions. We do not include such a variable, since our analysis examines only bank failures in Connecticut.

The first and third columns of Table 3 report the logit results for the Barr and Siems (1993) specification; column one reports the one-year ahead model and column three, the two-year ahead model. All specifications use the V_5 efficiency measure; the inclusion of the V_9 and V_{13}

measures do not alter the findings appreciably. A positive coefficient means that a higher value of the variable associates with a higher probability of failure; a negative value, a lower probability. Several conclusions emerge. First, the bank efficiency measure is rarely significant, suggesting that this measure is not important in explaining bank failures in Connecticut in 1991 and 1992. While the V_5 measure is significant in one instance, it has the wrong sign (i.e., higher efficiency associates with a higher probability of failure).

Barr and Siems (1993) find that the ir DEA efficiency measure is highly significant in explaining bank failure. What may explain this difference? Barr and Siems (1993) use a national sample; we use a Connecticut sample. Banks in a local market may imitate their competitors more closely and produce a more homogeneous portfolio mix. If so, then DEA efficiency measures based on a sample of local banks may show less variability than similarly constructed measures based on a national sample.

Second, of the other explanatory variables, both net income to total assets and total equity to total loans are both significant at the 1-, 5-, or 10-percent levels. Higher net income and equity associate with a lower probability of bank failure. Net income has a more significant effect in the one-year ahead model than in the two-year ahead model. Exactly the opposite occurs for total equity to total loans, where it has a more significant effect in the two-year ahead model.

Third, the dummy variable for new and old banks is only significant in the two-year ahead model. Here newer banks have a significantly higher probability of failure than old banks. While the sign of the coefficient of the dummy variable in the one-year ahead model has the same sign, the coefficients are not significant at the 10-percent level.

The preliminary analysis of the data in Table 2 suggests that certain other portfolio variables may provide valuable information for a failure-prediction model. Thus, we add to the basic Barr and Siems (1993) specification commercial and industrial loans to total assets, commercial real estate loans to total assets, and construction and land development loans to total assets.⁸

The inclusion of these additional variables makes only one change in the qualitative results for the variables already included in the basic Barr and Siems (1993) specification. To wit, the new and old bank dummy variable is no longer significant in the two-year ahead model, suggesting that the dummy was capturing the effect of these newly included variables previously.

Both commercial and industrial loans to total assets and construction and land development loans to total assets have significant positive effects on the probability of bank failure in both the one-year and two-year ahead models at either the 1-, 5-, or 10-percent levels. Commercial real estate loans to total assets is only significant in the one-year ahead model and has a negative sign.

5. Conclusion

We have examined a number of variables that may help to explain commercial bank failures in Connecticut in 1991 and 1992. Our results indicate that the probability of bank failure negatively relates to capital adequacy and earnings performance. On the other hand, increasing a bank's exposure to commercial and industrial, and construction and land development loans positively affects the probability of bank failure. Our DEA efficiency measure designed to capture management quality did not provide significant information in explaining the probability of bank failure, unlike the study by Barr and Siems (1993).

Barr and Siems (1993) use a nationwide sample of banks; we focus on Connecticut. It may be that within the state market, banks tend to be more uniform in their actions and portfolio composition. If so, then our efficiency measure may be higher than it would be if the analysis was done on a national sample. That is, banks may match what their local competition does. If so, then the regulators role becomes much more important in identifying troubling trends in bank portfolio composition.

Finally, we find little evidence that failure is related to the newness of the bank charter. That is, our dummy variable capturing banks chartered from 1984 onward generally does not affect the failure probability significantly. Significant effects from the new bank dummy variable disappear when we add additional portfolio variables, such as the ratio of construction and land development and commercial and industrial loans to total assets, and commercial real estate loans to total assets. Moreover, the effect of holding a higher proportion of commercial real estate loans to total assets reduces the probability of a bank failure, probably against the conventional wisdom.

Endnotes:

Table 1: Bank Efficiency Measures Using Data Envelopment Analysis

Banks	Old Banks		New Banks		All	
	S	F	S	F	S	F
V₅						
1987	0.877	0.899	0.866	0.866	0.903	0.924
1988	0.935	0.931	0.926	0.920	0.953	0.939
1989	0.888	0.857	0.856	0.843	0.933	0.903
1990	0.872	0.809	0.856	0.744	0.893	0.829
V₉						
1987	0.977	0.978	0.974	0.948	0.984	1.000
1988	0.979	0.975	0.976	0.960	0.984	0.986
1989	0.970	0.966	0.967	0.915	0.969	0.985
1990	0.978	0.979	0.967	0.921	0.990	0.997
V₁₃						
1987	0.995	0.998	0.993	0.996	1.000	1.000
1988	0.994	0.995	0.996	1.000	0.991	0.992

1989	0.992	0.997	0.987	1.000	1.000	0.996
1990	0.995	0.999	0.990	1.000	1.000	0.999

NOTE: DEA efficiency specification V_{13} includes seven inputs -- total transactions deposits (D_T), total non-transactions deposits (D_N), purchased funds (PF), total interest expense (E_I), total non-interest expense (E_N), the number of full-time equivalent employees (labor, L), and fixed premises and fixed assets (capital, K) -- and six outputs -- commercial and industrial loans (CIL), consumer loans (CL), real estate loans (REL), investments (IN), total interest income (Y_I), and total non-interest income (Y_N). We eliminate interest and non-interest income and expenses to generate our 9 variable DEA model (V_9). Finally, our bare-bones specification includes total loans (TL) and investments as outputs and deposits (D) (i.e., transactions and non-transactions deposits and purchased funds), labor, and capital as inputs for our 5 variable DEA model (V_5).

Table 2: Bank Portfolio and Income Measures

Banks	Old Banks		New Banks		All	
	S	F	S	F	S	F
						TL/TA
1987	0.683	0.727	0.691	0.718	0.665	0.734
1988	0.734	0.791	0.717	0.758	0.767	0.815
1989	0.734	0.764	0.726	0.724	0.745	0.779
1990	0.734	0.817	0.712	0.768	0.761	0.831
CLD/TA						
1987	0.042	0.057	0.049	0.106	0.023	0.020
1988	0.050	0.075	0.049	0.097	0.052	0.058
1989	0.041	0.059	0.038	0.088	0.045	0.049
1990	0.029	0.048	0.025	0.073	0.035	0.040
CREL/TA						
1987	0.146	0.120	0.151	0.173	0.134	0.081
1988	0.165	0.137	0.164	0.169	0.167	0.114
1989	0.173	0.155	0.156	0.222	0.197	0.131
1990	0.185	0.170	0.158	0.242	0.218	0.148
CIL/TA						

1987	0.161	0.297	0.140	0.232	0.210	0.345
1988	0.163	0.309	0.142	0.236	0.206	0.364
1989	0.170	0.294	0.147	0.228	0.202	0.318
1990	0.167	0.277	0.138	0.219	0.202	0.295
REL/TA						
1987	0.400	0.282	0.423	0.289	0.346	0.276
1988	0.456	0.364	0.456	0.333	0.456	0.387
1989	0.451	0.379	0.469	0.348	0.426	0.390
1990	0.465	0.449	0.480	0.423	0.448	0.457
PDNA/TA						
1987	0.0060	0.0067	0.0074	0.0114	0.0028	0.0032
1988	0.0107	0.0133	0.0114	0.0165	0.0092	0.0110
1989	0.0217	0.0255	0.0184	0.0610	0.0264	0.0128
1990	0.0354	0.0830	0.0326	0.1264	0.0390	0.0697
NI/TA						
1987	0.0052	-0.0036	0.0091	0.0087	-0.0039	-0.0128
1988	0.0080	0.0034	0.0089	0.0030	0.0063	0.0037
1989	0.0022	-0.0127	0.0051	-0.0204	-0.0027	-0.0099
1990	-0.0082	-0.0474	-0.0026	-0.0600	-0.0150	-0.0436
PF/TA						
1987	0.158	0.188	0.130	0.197	0.225	0.181
1988	0.161	0.171	0.137	0.166	0.213	0.174
1989	0.151	0.175	0.139	0.209	0.170	0.163
1990	0.140	0.116	0.121	0.113	0.163	0.117
DD/TA						
1987	0.149	0.110	0.170	0.154	0.100	0.076
1988	0.139	0.104	0.160	0.136	0.096	0.080
1989	0.108	0.084	0.135	0.120	0.072	0.072
1990	0.098	0.077	0.119	0.101	0.071	0.069

Table 2: (continued)

<u>Banks</u>	<u>All</u>					
	S	<u>Old Banks</u>		<u>New Banks</u>		TE/TA
		F	S	F	S	F
1987	0.155	0.163	0.112	0.106	0.257	0.205
1988	0.122	0.104	0.109	0.090	0.147	0.114
1989	0.134	0.110	0.103	0.061	0.175	0.127
1990	0.113	0.047	0.100	-0.004	0.128	0.062

NOTE: Old banks received charters before 1984; new banks, during or after 1984. Variables are defined as follows: TA is total assets, TL is total loans, CLD is construction and land development loans, CREL is commercial real estate loans, CIL is commercial and industrial loans, REL is real estate loans, PDNA is past due 90 days and non-accruing loans, NI is net income, PF is purchased funds, DD is transactions deposits, and TE is total equity. See the Appendix for further details.

Table 3: One-Year and Two-Year Ahead Failure Prediction Models

	One-Year Ahead		Two-Year Ahead		CONSTANT
	F/S	F/S	F/S	F/S	
					-1.97
PDNA/TA	(-0.55)	(-0.34)	(-0.65)	(-0.65)	(-1.62)
	-21.18	-17.06	-22.26	-22.26	-17.20
NI/TA	(-1.43)	(-0.90)	(-1.02)	(-1.02)	(-0.66)
185.15**	-55.20*	-60.28**	-106.19**	-106.19**	-
TE/TL	(-2.82)	(-2.46)	(-2.24)	(-2.24)	(-2.41)
68.82**	-17.65***	-24.80***	-48.38*	-48.38*	-
PF/TA	(-1.89)	(-1.96)	(-2.92)	(-2.92)	(-2.49)
16.03***	5.51	5.75	-7.84	-7.84	-
CIL/TA	(1.50)	(1.25)	(-1.66)	(-1.66)	(-1.87)
		5.91***			11.44*
		(1.75)			(2.71)
CREL/TA		-19.52**			-10.89
		(-2.42)			(-1.62)

CLD/TA		44.01*		
31.86**		(2.86)		(2.61)
V ₅	0.99	0.66	8.53	
19.72**	(0.22)	(0.12)	(1.38)	(1.94)
NEWBANK	1.03	1.40	2.50*	1.22
	(1.40)	(1.39)	(2.72)	(1.07)

NOTE: Logit results calculated with TSP, version 7.0. F/S is a dummy variable coded one for failed banks; zero otherwise. See the Appendix for definitions of variables.

- * Significantly different from zero at the 1-percent level.
- ** Significantly different from zero at the 5-percent level.
- *** Significantly different from zero at the 10-percent level.

Table 3: Variable Averages for the Logit Model				
Variable	One Year Ahead		Two Years Ahead	
	Survivors	Failures	Survivors	Failures
PDNA/TA	0.0285	0.0381	0.0167	0.0181
NI/TA	-0.0029	-0.0251	0.0048	0.0009
TE/TL	0.1236	0.0864	0.1286	0.1085
PF/TA	0.1453	0.1708	0.1553	0.1577
CIL/TA	0.1685	0.2905	0.1669	0.3136
CREL/TA	0.1791	0.1531	0.1695	0.1552
CLD/TA	0.0353	0.0513	0.0451	0.0683

V5	0.8824	0.8638	0.9121	0.9136
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1. Data as reported in Nielsen and Sindt (1992) through 1991 and supplemented by FDIC Annual Reports (1991, 1992).

2. Texas continued to lose banks at a high rate through 1992 and 1993, comprising almost 25 percent of the total for the nation as a whole. In addition, California jumped from single digit failures throughout this period to 12 and 19 failures in 1992 and 1993, respectively.

3. Some analysts suggest that bank charters were sought in the mid-1980s not to enter the banking business but rather to capture the anticipated increase in charter values once interstate banking was authorized. We note that a flurry of charter activity occurred between 1984 and 1989.

4. Humphrey (1985) provides an extended discussion of the issues involved in this debate.

5. This is the one variable not deflated by total assets. We deflate by total loans instead to provide closer consistency with the work by Barr and Siems (1993). See the next section for further discussion.

6. Data for 1990 represent end-of-year balance sheet data (e.g., loan to asset ratio) or cumulative income statement (e.g., non-interest income to total assets). As such, the time lead involved varies from 12 to 24 months when predicting bank failure in 1992 using 1990 data. In the same manner, the 1989 data leads from 24 to 36 months when predicting bank failure in 1992.

7. This observation is consistent with the view noted above that bank charters were sought in the mid-1980s in anticipation of capital appreciation on such charters once interstate banking became a reality.

8. In regressions not reported, we included total real estate loans to total assets instead of commercial real estate loans to total assets and construction and land development loans to total assets. This variable did not provide significant information for the failure prediction model.