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Separating the likelihood and timing of bank failure

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Abstract

We use a split-population survival-time model to separate the determinants of bank failure from the factors influencing the survival time of failing banks. Basic indicators of a bank's condition, such as capital, troubled assets, and net income, are important in explaining the timing of bank failure. However, many of the other variables typically included in bank failure models, such as measures of bank liquidity, are not associated with the time to failure. The results also suggest that the closure of large banks is not delayed relative to the closure of small banks.

Keywords: Survival time; Bank failure; Split population

JEL classification: G21; G28

1. Introduction

While an extensive empirical literature exists on explaining the likelihood of bank failure over a fixed time horizon [see Demirguc-Kunt (1989b) for a literature review], much less attention has been given to predicting the timing of bank failure. Recent work in explaining bank failure has followed the direction set by Kane (Kane, 1986; Kane, 1989) in analyzing the incentives facing regulators in the

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bank closure decision [see Gajewski (1988), Demirguc-Kunt (1989a), Demirguc-Kunt (1991), and Thomson (1992)]. These studies represent the most recent contributions to a long list of advancements in the literature on bank failure. In contrast, Lane et al. (1986) and Whalen (1991) are the only published empirical studies of which we are aware that explicitly model the timing of bank failure.

Both of these latter studies use the Cox proportional hazards model, which offers the advantage of avoiding some of the strong distributional assumptions associated with parametric survival-time models. However, as a vehicle for examining the determinants of bank survival time, the Cox proportional hazards model suffers from a potentially severe shortcoming. In particular, the model assumes implicitly that all banks eventually fail. As a result, it cannot identify any differences that may exist between the determinants of bank failure and the factors influencing the timing of failure. If the population of banks is split into two groups, one composed of banks that ultimately fail and the other composed of banks that survive, then failure and the timing of failure might depend on different forces.

Several considerations suggest that it may be important to allow for such a split in the population of banks. By showing that bank charter value mitigates the risk-taking incentives inherent in a flat-rate deposit insurance system, Marcus (1984) predicts a tendency for banks to gravitate toward either a high-risk or low-risk posture. Ritchken et al. (1993) extend the analysis of Marcus to allow for portfolio adjustments between audit dates. While these authors find that bank portfolio decisions may not be extreme and interior solutions may be optimal, their results also suggest that the asset flexibility option increases the range of capital ratios for which the optimal portfolio decision places a bank's charter at risk. To the extent that these types of factors give rise to differences in risk-taking among banks, a period of adverse economic conditions could result in an industry shakeout, during which the high-risk institutions fail while the low-risk institutions survive. Only a relatively small proportion of banks typically fails during any particular economic downturn, suggesting that an appropriate specification should allow for a distinction between failing and surviving banks.

Given a split in the population of banks between failures and survivors, the possibility arises that failure and the timing of failure depend on different factors. An appropriate estimation vehicle in this context is the split-population survival-time model used by Schmidt and Witte (Schmidt and Witte, 1984; Schmidt and Witte, 1989). We extend the strand of literature on the timing of bank failure by using the split-population survival-time model to examine jointly both bank failure, defined here as a bank's regulatory closure or resolution, and the time to failure. [1] While standard survival-time models would require the assumption that

[1] Hunter et al. (1995) apply the split-population survival-time model to the failure of de novo thrifts, and Dahl and Spivey (1995) use the model to examine recoveries of undercapitalized banks.

all banks eventually fail, we use the split-population model to allow for the possibility that the population of banks is split between failures and survivors. The split-population model also allows the determinants of failure to differ from the determinants of survival time. This feature facilitates inference about the separate effects of a given variable on failure and the timing of failure.

Separate inference on the determinants of failure and the time to failure is important for at least two reasons. First, the survival time of failing banks arguably reflects important elements of the regulatory closure rule [see Kane (Kane, 1986; Kane, 1989)]. The existence of high regulatory costs associated with the closure of a particular bank could work to extend the bank's expected survival time. While the model used here does not incorporate explicitly the distinction between economic insolvency and closure, the inferences it enables us to generate regarding the survival time of failing banks complement the recent focus of the bank failure literature on the closure decision.

In addition, information on the factors influencing the survival time of failing banks provides insight into the process of financial deterioration. In this regard, knowledge of the types of variables that influence the timing of bank failure could facilitate regulatory triage. Based upon expected survival times, bank regulators could seek to rehabilitate those failing institutions identified as having sufficient lead time for corrective measures and enforcement actions to take effect. Similarly, failing institutions with the shortest expected survival times could be targeted for prompt closure.

The results of our study provide evidence that a broader range of variables are important for predicting bank failure than for predicting the survival time of failing banks. We find that only a limited number of the variables typically used to explain bank failure are significant in explaining bank survival time. These results have important implications for bank regulators, bank investors, and other parties concerned with assessing the expected survival time of financially impaired banks.

Our study is organized as follows. Because the split-population model has not been used widely, we provide a brief overview of this methodology in the next section. In the third section, we describe the data used in the analysis. Estimation results are presented in the fourth section, followed by a brief summary and concluding remarks.

2. The split-population survival-time model

The split-population survival-time model has been used in finance and economic studies only rarely. Survival-time models that do not allow for a split population have been used somewhat more frequently, but even they have found only limited application.

Survival-time models explain duration, or, in our context, the time until failure, over a given observation period. The likelihood function for the standard parametric survival-time model can be written as

$$L=\prod_{i=1}^{N}\left[f(t_i)\right]^{Q_i}\left[S(t_i)\right]^{(1-Q_i)}, \tag{1}$$

where $f(t)$ is the density function of the time to failure and $S(t)$ is the survival function, which equals $P(T \geq t)$, the probability that the random duration T equals or exceeds the value t. The indicator variable Q equals one for an uncensored observation and equals zero otherwise. Here, Q equals zero both for banks that left the sample for reasons other than failure and for banks that survived over the entire sample period. The number of banks in the sample is denoted as N. [2]

The standard model given in Eq. (1) may be inappropriate in the context of bank failure. Because $S(t)$ approaches zero as time at risk becomes large, the standard survival-time model assumes implicitly that each bank ultimately fails. This assumption results in a misspecification if risk differences among banks imply that only a limited number of banks actually fail. Moreover, the model given by Eq. (1) does not distinguish between the determinants of failure and the factors influencing the timing of failure. Semiparametric models, such as the Cox proportional hazards model, also do not separate the determinants of failure from the determinants of the time to failure.

A useful generalization of the standard model allows the probability of eventual failure to be less than one. Let

$$P(F=1)=\delta, \tag{2}$$

where F is a binary variable that equals one for banks that ultimately fail and zero otherwise. The appropriate density for a failure in period t is equal to $\delta f(t)$, where $f(t)$ now is understood to be the density function of the time to failure conditional on $F=1$. Similarly, the probability attached to a censored observation is equal to the sum of the probability of survival, $(1-\delta)$, and $\delta S(t)$, where, again, $S(t)$ now is defined conditional on $F=1$. The likelihood function in Eq. (1) then is generalized as

$$L=\prod_{i=1}^{N}\left[\delta f(t_i)\right]^{Q_i}\left[(1-\delta)+\delta S(t_i)\right]^{(1-Q_i)}, \tag{3}$$

where the probability of failure, δ, is a parameter to be estimated. [3]

[2] For a detailed discussion of survival-time models, see Lancaster (1990).

[3] Note that the restriction $\delta = 1$ applied to Eq. (3) results in the standard survival-time model given by Eq. (1). Because this restriction is on the boundary of the parameter space, the associated likelihood ratio test statistic does not possess the usual chi-squared (χ^2) distribution.

The split-population model given in Eq. (3) is made operational by specifying a particular distribution for $f(t)$ and $S(t)$. A useful selection criterion is the hazard function, $h(t)=f(t)/S(t)$, which gives, for banks that ultimately fail, the probability of failure in period t conditional on survival to that period. In the present context, the log-logistic distribution is a likely candidate, because it can generate a hazard which first rises and then falls, as might be expected during a period of banking difficulties. The log-logistic specification is given by

$$S(t) = 1/\left[1 + (\lambda t)^{p}\right], \text{and} \tag{4}$$

$$f(t) = \lambda p(\lambda t)^{p-1}/\left[1 + (\lambda t)^{p}\right]^{2}, \tag{5}$$

where $\lambda > 0$ and $p > 0$ are the defining parameters. Substitution into Eq. (3) gives the specific likelihood function.

In addition, both the probability of eventual failure and the timing of failure can be made to depend on bank-specific characteristics. In this regard, it is convenient to introduce covariates by specifying

$$\lambda = e^{-\beta' X}, \text{and} \tag{6}$$

$$\delta = 1/(1 + e^{\alpha' X}). \tag{7}$$

Eq. (6) allows $f(t)$ and $S(t)$ to depend on a vector of bank characteristics, X, such that a positive coefficient implies a direct relationship between a given characteristic and survival time. Similarly, Eq. (7) specifies a logistic model for the probability of eventual failure, which is equivalent to the standard logit model applied to the probability of survival. In Eq. (7), a positive coefficient indicates a direct relationship between a given characteristic and the probability of survival. Substitution of Eq. (4) through Eq. (7) into Eq. (3) results in the complete likelihood function.

3. Data

The majority of the data used in this study comes from statements filed by FDIC-insured commercial banks in the quarterly Report of Condition and Income ('call report'). Specifically, we use data from the December 1985 call report to predict survival times during the period from the first quarter of 1986 through the second quarter of 1992. This period covers the majority of the recent banking downturn. The maximum survival time is censored at 26 quarters. We identify bank failures using FDIC press releases. For multibank holding companies, we include only the lead (largest) bank. This sample restriction allows us to avoid the unwieldy task of attempting to model bank failures precipitated by the insolvency of a multibank holding company's lead bank. We also exclude from the sample banks established during 1985 because measurement of the earnings and expense

Table 1
Definitions of variables used to explain the survival and survival time of FDIC-insured commercial banks

Variable	Definition	Expected sign	
		Survival	Survival time
Capital:	ratio of equity capital and loan loss reserves to gross assets.	+	+
Troubled Assets:	ratio of loans past due 90 days or more, nonaccrual loans, and other real estate owned to gross assets.	−	−
Net Income:	ratio of net income to average net assets.	+	+
Securities:	ratio of investment securities to gross assets.	+	+
Large CDs:	ratio of large certificates of deposit ($100,000 and greater) to gross assets.	−	−
C&I Loans:	ratio of commercial and industrial loans to gross assets.	−	+ / −
Agricultural Loans:	ratio of agricultural production loans to gross assets.	−	+ / −
Commercial Real Estate Loans:	ratio of construction loans and loans secured by multifamily, nonresidential, or farm real estate to gross assets.	−	+ / −
Residential Real Estate Loans:	ratio of loans secured by 1–4 family real estate to gross assets.	−	+ / −
Consumer Loans:	ratio of consumer loans to gross assets.	−	+ / −
Other Loans:	ratio of all other loans to gross assets.	−	+ / −
Insider Loans:	ratio of insider loans to gross assets.	−	+ / −
Salary Expense:	ratio of salaries and employee benefits to average net assets.	−	−
Premises Expense:	ratio of expenses of premises and fixed assets to average net assets.	−	−
Other Noninterest Expense:	ratio of other noninterest expense to average net assets.	−	−
Asset Size:	logarithm of gross assets ($ thousands).	+	+
Holding Company:	one for holding company banks, zero otherwise.	+	+
Oil:	growth in state nonagricultural employment resulting from a $5 reduction in oil prices [Brown and Hill (1988)].	+	+ / −
Rural:	one for rural counties, zero otherwise.	+ / −	+ / −

Data sources: FFIEC Report of Condition and Income; Board of Governors of the Federal Reserve System, Bank Structure Data Base.

variables used in the analysis requires that each bank operated for that entire year. The resulting sample consists of 10,843 banks, of which 811, or 7.5 percent, failed during the sample period.

In Table 1, we identify explanatory variables appearing in the model along with the expected sign of each variable's relationship with both the probability of survival and expected survival time. A number of variables are included in the model to capture the effects of a bank's financial condition, including measures of capital adequacy, asset quality, earnings, and liquidity. These variables represent the four financial components of the CAMEL rating system and reflect areas of primary concern to bank regulators. Additional variables related to managerial decision-making (the fifth CAMEL component), efficiency, bank structure, and economic conditions also are included in the model.

We measure capital adequacy by the ratio of equity capital and loan loss reserves to gross assets. Because capital serves as a buffer between losses experienced by a bank and losses imposed on the deposit insurance fund, this ratio is expected to be positively related to both the likelihood of survival and expected survival time.

Asset quality difficulties are measured by the ratio of loans past due 90 days or more, nonaccrual loans, and other real estate owned to gross assets. Banks reporting large troubled asset ratios typically must provide for losses on a significant portion of these assets, which reduces net earnings and, ultimately, capital. Therefore, the troubled asset ratio is hypothesized to be negatively related to both the probability of survival and expected survival time.

We measure the effects of earnings using the return on bank assets. Strong earnings enable a bank to boost capital and signal to regulators that a bank is viable. As a result, the ratio of net income to average net assets is expected to be positively related to both the probability of survival and expected survival time.

The ratios of investment securities to gross assets and large certificates of deposit to gross assets serve as indicators of bank liquidity. Liquid assets enable a bank to respond quickly to unexpected demands for cash, so that the ratio of investment securities to gross assets should increase both the probability of survival and expected survival time. For troubled banks, large certificates of deposit, of which portions are not insured explicitly, are a less stable and potentially more expensive funding source than retail deposits. As a result, the ratio of large certificates of deposit to gross assets is expected to reduce both the likelihood of survival and the expected survival time of failing banks.

In an attempt to capture the effects of managerial decision-making on the likelihood and timing of bank failure, we include in the analysis information on seven categories of bank loans, as shown in Table 1. Insofar as a high proportion of assets in any of the lending categories reflects high credit risk, we expect the loan portfolio variables to reduce the probability of survival during the economic and banking downturn that occurred during the sample period. However, predicting the relationship of the lending variables with bank survival time is more complicated. The credit risk associated with bank lending could shorten the expected life of a failing bank. At the same time, certain peculiarities of bank lending and the institutional arrangements surrounding it could work to extend, rather than reduce, expected survival time.

The role of banks as delegated monitors implies that banks possess information about the financial condition of their borrowers superior to that available to other parties [see Diamond (1984)]. In this regard, the importance to the regulatory process of on-site bank examinations can be viewed as deriving from the efforts of regulators to mitigate their informational disadvantage relative to banks. In the event of an impending default by its borrowers, a bank could exploit the information asymmetries associated with its lending activities by concealing knowledge of the borrowers' true financial condition from regulators. The success of this strategy would be enhanced to the extent that resource constraints or other institutional features hampered the efforts of regulators to obtain accurate information about the market value of the bank's loans. To the extent that such a strategy were successful, a high proportion of assets invested in a certain category of loans could extend a troubled bank's expected survival time. As a result, the expected effect of the lending variables on bank survival time is ambiguous.

An additional complication arises in the interpretation of the effects of the loan variables on survival time. The estimated effects of the loan variables may reflect differences in the timing of economic downturns across industries. For example, a high proportion of assets in agricultural production loans could reduce expected survival time if the effects of the downturn in the agricultural sector were most pronounced in the early part of the sample period. Such considerations suggest that, in this particular regard, the estimation results should be interpreted in the context of the events peculiar to our sample period.

To capture the potential effects of a bank's cost structure, we include in the model three measures of noninterest expense, each expressed relative to average net assets. Because excessive overhead costs reduce a bank's competitive position, we expect high levels of salaries and employee benefits, expenses of premises and fixed assets, and other noninterest expense to reduce both the probability of survival and expected survival time.

Effects of bank structure are captured by the inclusion of bank size and holding company affiliation. We expect larger banks to be more likely to survive, everything else equal, both because they possess more flexibility in financial markets and because they are better able to diversify credit risk. Among large banks that do fail, relative flexibility in the short-term funding market may extend survival time. Moreover, the complications and costs associated with the regulatory resolution of large failing banks also could lengthen their time to failure. We include in the model the logarithm of gross assets as a measure of size to test and control for these effects.

Similarly, to the extent that holding company affiliation enhances the financial resources available to a subsidiary bank, we also expect holding company affiliation to increase both the probability of survival and expected survival time. Moreover, any complications and costs associated with the resolution of a subsidiary bank could work to increase the time to failure. We include in the model a dummy variable for holding company affiliation to capture these effects.

Finally, we include in the model two additional variables to control for the effects of economic conditions. During the sample period, states with oil-dependent economies ranked among the highest in terms of the bank failure rate. To control for the lingering effects of the oil-price shock that occurred in 1986, the predicted growth in state nonagricultural employment resulting from a $5 oil-price decline, as calculated by Brown and Hill (1988), is included in the model. [4] While we expect this measure of the economic effects of the oil-price shock to be positively related to the probability of survival, its relationship with survival time is unclear. To the extent that adverse economic conditions shorten a failing bank's expected survival time, banks in regions hurt by the shock might be expected to fail relatively early. However, for regions where the economic impact of the shock was the most severe, the associated large number of failing banks may have overwhelmed the resources available to regulators, resulting in closure delays.

In addition to the oil-price variable, a dummy variable for banks in rural counties also is included in the model to help control for differences in economic conditions. Because many rural counties were relatively unaffected by the real estate boom and bust that occurred during the sample period, and because rural banks may enjoy a degree of monopoly power in their limited markets, banks in rural areas may have had a higher probability of survival than urban banks. However, problems in the farm sector during the mid-1980s may have worked in the opposite direction to lower the probability of survival for rural banks. Both of these factors also would be expected to shape the effect of a rural location on survival time.

The 19 explanatory variables shown in Table 1 cover the major categories of factors that typically receive attention in bank failure studies. While it is not difficult to envision alternative measures of the factors we consider, some degree of parsimony is necessary to maintain tractability. In most cases, alternative measures of a particular factor are highly correlated, so that multicollinearity considerations prevent us from nesting within a single model every alternative measure that might apply to our study.

A few guiding principles have been used to help narrow down the particularly lengthy list of potential explanatory variables. First, we rule out the use of financial ratios that employ as their denominator some measure other than total assets. Many alternative deflators, such as total loans or total equity capital, have values that are very small or zero for a significant number of the banks in our sample. As a result, a ratio that uses one of these variables as its denominator is

[4] In the practical context of forecasting, one typically lacks knowledge of the timing and nature of catastrophic events. By including the oil-price variable, we have benefitted from hindsight, since its appropriateness obviously is specific to our sample period. Our purpose, in this regard, is not only to assess the importance of the oil-price shock in affecting both bank failures and the survival time of failing banks during the time period we examine, but also to help achieve accurate inferences on the other factors included in the model.

Table 2
Sample means of variables used to explain the survival and survival time of FDIC-insured commercial banks

Variable [a]	Survival		Survival time	
	Survivors	Failures	Early failures [b]	Late failures [b]
Capital	9.71 [c]	8.26	7.58 [c]	9.31
Troubled assets	1.93 [c]	5.39	6.87 [c]	3.11
Net income	0.79 [c]	−1.24	−1.92 [c]	−0.19
Securities	29.81 [c]	14.45	14.38	14.55
Large CDs	9.33 [c]	20.90	20.97	20.78
C&I loans	11.54 [c]	20.88	21.15	20.46
Agricultural loans	6.81 [c]	6.48	8.82 [c]	2.86
Commercial real estate loans	8.05 [c]	12.17	11.19 [c]	13.69
Residential real estate loans	10.54 [c]	9.11	8.72	9.70
Consumer loans	11.90 [c]	13.83	13.17 [c]	14.85
Other loans	2.18	2.31	2.38	2.21
Insider loans	0.59 [c]	1.62	1.73	1.47
Salary expense	1.75 [c]	2.04	2.02	2.07
Premises expense	0.53 [c]	0.81	0.81	0.81
Other noninterest expense	1.21 [c]	1.69	1.73 [c]	1.64
Asset size	10.56 [c]	10.40	10.30 [c]	10.55
Holding company	54.50	53.88	53.46	54.55
Oil	0.05 [c]	−1.07	−1.12	−0.99
Rural	60.59 [c]	40.69	47.36 [c]	30.41

[a] Each variable is multiplied by 100, with the exception of asset size.
[b] Early failures are those occurring during the period from the first quarter of 1986 through the first quarter of 1989, whereas late failures are those occurring during the period from the second quarter of 1989 through the second quarter of 1992.
[c] Indicates that the Wilcoxon rank-sum test statistic for a shift in the location parameter between the two groups is significant at the 1-percent level.

undefined for many banks and, for the remaining banks, has a distribution that is highly skewed by extremely large values. Second, when variables from both the balance sheet and the income statement are available as measures of a particular factor, we tend to rely on balance-sheet data. To the extent that substantial differences exist between the two types of measures, balance-sheet data arguably provide a superior indication of the cumulative effect of recent events on a bank's current financial condition. [5] These considerations suggest that the set of explanatory variables discussed above provides a reasonable basis for detecting differ-

[5] For example, the troubled asset ratio measures the proportion of existing assets recently affected by credit difficulties. An alternative measure of asset quality problems that utilizes data from the income statement is the rate of net charge-offs on loans. However, this variable indicates only the proportion of loans charged off in the current period, which, during a period of severe banking difficulties, can be small relative to the total proportion of loans that are troubled.

ences between the determinants of failure and the determinants of the timing of failure.

Table 2 presents the sample means of the explanatory variables. The first two columns contrast the means for banks that survived throughout the sample period with the means for banks that failed. We use the Wilcoxon rank-sum test to identify statistically significant location shifts across the two groups. In most cases, differences in the sample means correspond to expectations, and, with the exception of the variables representing miscellaneous loans and holding company affiliation, the Wilcoxon rank-sum test indicates that the differences are statistically significant at the 1-percent level. Banks that failed during the sample period had lower capital ratios, higher troubled asset ratios, lower earnings-to-assets ratios, lower securities-to-assets ratios, and higher ratios of large certificates of deposit to assets than banks that survived. Among the seven loan portfolio variables, failing banks had higher ratios of commercial and industrial loans, commercial real estate loans, consumer loans, and insider loans, but lower proportions of agricultural production loans and residential real estate loans. In addition, failing banks had higher ratios of salary expense, premises and fixed asset expense, and miscellaneous noninterest expense. Failing banks also were smaller, more vulnerable to a reduction in oil prices, and less rural.

The third and fourth columns of Table 2 present the sample means for banks that failed in the first and last halves of the observation period. While statistically significant location shifts occur across failing and surviving banks for 17 of the 19 explanatory variables, location shifts across early and late failures are significant for only nine variables. This result suggests that only a restricted set of the total list of explanatory variables is relevant for predicting the timing of bank failure. Early failures had lower capital ratios, higher troubled asset ratios, and lower earnings-to-assets ratios. Evident in the lending categories is the timing of the agricultural loan crisis that occurred during the mid-1980s. Based on the sample means, early failures had ratios of agricultural production loans to assets more than three times those of late failures. Also, early failures held lower proportions of commercial real estate loans and consumer loans than late failures, incurred relatively high ratios of miscellaneous noninterest expense, were smaller than late failures, and were located disproportionately in rural areas. There are no significant location shifts across early and late failures for the variables representing securities, large certificates of deposit, commercial and industrial loans, residential real estate loans, miscellaneous loans, insider loans, salaries and employee benefits, expenses of premises and fixed assets, holding company affiliation, and oil-price dependence.

4. Estimation results

An important first step in estimating the split-population model is to evaluate the appropriateness of the distributional assumptions employed. This is accom-

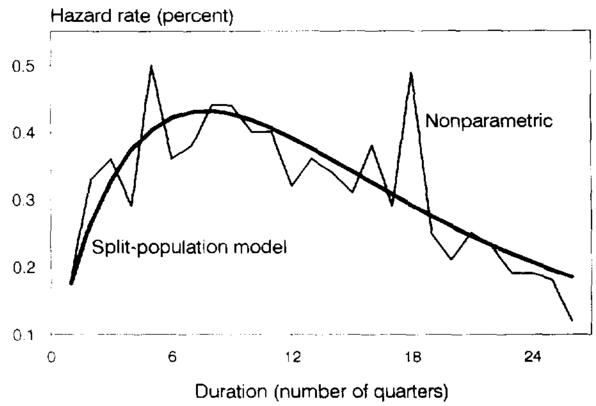

Fig. 1. Estimated hazard rate for bank failure, 1986QI–1992QII.

plished by estimating the model without covariates and comparing the predicted hazard to a nonparametric estimate. The nonparametric hazard estimate used here is the number of failures in period t divided by the number of banks at risk in period t, where the number of banks at risk is equal to the number of banks that neither failed nor were censored in prior periods. The predicted hazard used from the split-population model is not $h(t)$, defined conditional on $F = 1$, but rather

$$h^*(t) = \delta f(t) / [(1 - \delta) + \delta S(t)], \tag{8}$$

which gives the unconditional hazard. The inclusion of δ facilitates the generation of the steeply declining hazard rates implied by the split-population model.

Fig. 1 shows the nonparametric hazard estimate and the hazard estimate based on the split-population log-logistic model without covariates. The nonparametric hazard rises and then declines fairly rapidly, consistent with the split-population model's assumption that, as time went by, an increasing proportion of the sample consisted of banks that would not fail. Due to the peculiar shape of the hazard, standard survival time models do not fit the data well. However, as shown in Fig. 1, the hazard predicted by the split-population model tracks the shape of the nonparametric hazard closely, indicating an adequate parametric specification.

Notes to Table 3:

[a] Indicates significance at the 1-percent level.

[b] Indicates significance at the 5-percent level.

Column 1 presents results obtained using a logit model to estimate the determinants of bank survival, while column 4 presents results obtained using the Cox proportional hazards model to estimate the determinants of bank survival time. Columns 2 and 3 present results obtained using a split-population model to estimate jointly the determinants of bank survival and bank survival time. For each variable, the first row presents the parameter estimate, and the second row presents, in parentheses, the standard error associated with that parameter estimate.

Table 3
Determinants of the survival and survival time of FDIC-insured commercial banks

Variable	Logit survival model	Split-population model		Cox proportional hazards model
		α Survival	β Survival time	
Constant	2.711 [a]	3.186 [a]	2.115 [a]	–
	(0.837)	(1.004)	(0.508)	
Capital	13.185 [a]	7.407 [a]	6.405 [a]	−12.878 [a]
	(1.974)	(2.453)	(0.924)	(1.500)
Troubled assets	−18.221 [a]	−15.336 [a]	−6.238 [a]	12.464 [a]
	(1.567)	(1.661)	(0.571)	(0.862)
Net income	12.135 [a]	13.066 [a]	5.657 [a]	−9.674 [a]
	(2.784)	(2.824)	(0.950)	(1.611)
Securities	2.259 [a]	2.238 [a]	−0.066	−2.196 [a]
	(0.669)	(0.738)	(0.379)	(0.545)
Large CDs	−3.891 [a]	−4.097 [a]	−0.264	3.070 [a]
	(0.478)	(0.594)	(0.243)	(0.337)
C&I loans	−5.706 [a]	−5.281 [a]	−0.975 [b]	4.773 [a]
	(0.740)	(0.803)	(0.381)	(0.583)
Agricultural loans	−6.539 [a]	−5.639 [a]	−2.902 [a]	5.921 [a]
	(0.792)	(0.842)	(0.418)	(0.638)
Commercial real estate Loans	−6.427 [a]	−7.330 [a]	−0.037	5.276 [a]
	(0.829)	(0.972)	(0.439)	(0.643)
Residential real estate loans	−1.167	−1.854	0.238	1.178
	(0.847)	(0.987)	(0.505)	(0.699)
Consumer loans	−4.303 [a]	−5.193 [a]	0.093	3.645 [a]
	(0.728)	(0.859)	(0.420)	(0.567)
Other loans	−5.502 [a]	−5.287 [a]	−1.200	4.619 [a]
	(1.351)	(1.643)	(0.736)	(1.030)
Insider loans	−8.616 [a]	−4.905 [a]	−2.786 [a]	1.204
	(2.584)	(1.244)	(1.025)	(0.725)
Salary expense	9.116	13.006	5.053	−5.322
	(10.78)	(13.65)	(5.910)	(8.214)
Premises expense	−30.635 [b]	−47.746 [b]	−0.173	28.319 [a]
	(14.19)	(19.28)	(6.771)	(9.530)
Other noninterest expense	−3.121	−15.512	2.284	0.537
	(7.490)	(9.283)	(3.564)	(5.523)
Asset size	0.224 [a]	0.209 [a]	0.051	−0.179 [a]
	(0.056)	(0.067)	(0.036)	(0.046)
Holding company	0.047	−0.084	0.140 [b]	0.030
	(0.101)	(0.123)	(0.058)	(0.080)
Oil	48.810 [a]	42.001 [a]	7.823 [a]	−42.588 [a]
	(3.520)	(4.529)	(2.136)	(2.698)
Rural	0.338 [a]	0.326 [b]	0.106	−0.221 [b]
	(0.120)	(0.156)	(0.076)	(0.095)

Because the probability of survival and expected survival time are specified separately, the split-population model used here can distinguish between the determinants of survival and the determinants of survival time. Table 3 presents the estimation results. The second column contains the estimates of the elements of α and their associated standard errors, while the third column of Table 3 contains the estimates of the elements of β, along with their standard errors.

The results explaining bank survival largely confirm the findings of the Wilcoxon rank-sum tests in Table 2, as well as the results of previous bank failure studies. As shown in the second column of Table 3, only two variables – salary expense to assets and holding company affiliation – do not have the hypothesized sign, and neither is significant at the 5-percent level. Only two additional variables – the ratios of residential real estate loans to assets and of miscellaneous noninterest expense to assets – lack statistical significance at the 5-percent level. The lack of statistical significance for residential real estate loans is consistent with the view that the boom-to-bust lending pattern evident in the commercial real estate sector did not carry over to the residential sector. In contrast, the variable measuring the effects of the oil-price shock is highly significant, underscoring the pernicious and pervasive effects of declining oil prices on the financial health of the banking industry.

For purposes of comparison, we also estimate a standard logistic regression model of the probability of survival. As shown in the first and second columns of Table 3, the results for the standard logit model applied to bank survival (in column 1) are similar to those obtained from the survival equation of the split-population model (in column 2). With the exception of holding company affiliation, which is insignificant in explaining bank survival, the signs of the variables are identical across the two models. Moreover, each of the variables that is statistically significant in one model also is significant in the other. These findings suggest that accounting for the survival time of failing banks does not alter substantially inferences on the factors influencing bank survival.

The results from the split-population model pertaining to the relationship between the explanatory variables and bank survival time are of particular importance, because they provide new evidence on the factors influencing the timing of bank failure. As shown in the third column of Table 3, the signs of the estimated coefficients correspond to expectations in all cases for which the expected sign is unambiguous, with the notable exceptions of investment securities, salary expense, and miscellaneous noninterest expense, each of which lacks statistical significance. Interestingly, while capital, troubled assets, and net income all are significant in explaining bank survival time, the ratios of investment securities and large certificates of deposit are not. These results highlight our conclusion that the types of variables typically used to model bank failure may not be useful in explaining the survival time of failing banks.

Among the lending variables, only C&I loans, agricultural production loans, and insider loans are statistically significant. The coefficient of each is negative, suggesting that these types of credit risk reduce the expected survival time of a failing bank. The high level of significance for the ratio of agricultural production loans to assets also reflects the occurrence of the agricultural loan crisis early in our sample period. No evidence is found to suggest that higher concentrations of assets in lending categories leads to increased regulatory forbearance. Similarly, none of the three variables measuring overhead costs are significant in explaining bank survival time.

The results also suggest that the closure of large failing banks is not delayed relative to the closure of small banks, as the coefficient on the variable measuring asset size is positive, but insignificant. This finding indicates that any regulatory costs associated with the resolution of large bank failures have not been allowed to extend the survival time of large failing banks.

In contrast to the result for asset size, holding company affiliation does extend the survival time of failing banks, although this result is significant only at the 5-percent level. Given the large number of observations used in the estimation, we interpret this result as providing weak evidence for the view that holding company affiliation either enhances the financial resources available to bank affiliates or increases the costs of their regulatory resolution, or both.

Finally, the variable measuring the economic impact of the oil-price shock is significantly positive, suggesting that banks in states hurt by the energy recession failed relatively early in the sample period. In contrast, the distinction between a rural and urban location is not significant in explaining the survival time of failing banks.

The estimation results for the split-population survival-time model indicate that, while 15 of the 19 variables we have selected are useful in explaining bank survival, only eight of these are useful in explaining survival time. This finding suggests that the estimation vehicle used in previous studies – the Cox proportional hazards model – may provide a distorted view of the determinants of bank survival time.

To help assess further the importance of allowing for a split in the population of banks between failures and survivors, we apply the Cox proportional hazards model to our data and compare the results with those of the split-population model. The fourth column of Table 3 contains the coefficient estimates and standard errors obtained using the Cox model. [6] Interestingly, according to those results, 14 of the 19 variables are statistically significant in explaining bank survival time. That assessment differs sharply from the results on bank survival time provided by the split-population model, which indicate that only eight of the variables included in the model actually are related to survival time.

[6] Note that, in contrast to the specification used for the split-population model, a positive coefficient in the Cox model implies an indirect relationship between a given characteristic and survival time. As a result, the expected signs for the Cox model are reversed from the signs shown in Table 1.

Further examination reveals that the results produced by the Cox model in explaining bank survival time resemble the results generated by both the logit model and the split-population survival-time model in explaining bank survival. As shown in the first, second and fourth columns of Table 3, the 14 variables that are significant in the Cox model also are significant in explaining survival in both the logit and split-population models. It appears that, because the Cox model does not allow for a distinction between failing and surviving banks, it confounds the determinants of survival and the determinants of survival time. This finding indicates that the failure to allow for a split population among banks represents an important misspecification with serious implications for inference on the determinants of the timing of bank failure.

5. Summary and conclusions

We use a split-population survival-time model to examine the determinants of bank survival and bank survival time. In contrast to the Cox proportional hazards model used by researchers in the past, the split-population model used here separates the determinants of bank failure from the determinants of survival time. Our results indicate that only a select group of the variables commonly used to predict bank failure actually help explain survival time. We find that basic indicators of a bank's condition, such as capital, troubled assets, and net income, are related significantly to the timing of bank failure. However, we do not find that variables often included in failure models as measures of bank liquidity – such as investment securities and large certificates of deposit – are important determinants of bank survival time. The results also suggest that the survival time of failing banks is not related to bank asset size.

The split-population methodology used here should facilitate further investigation into the determinants of bank survival time. We have focused on influences that varied across banks within a particular banking downturn. It also would be interesting to use the model to assess the importance of potential influences that are not bank specific and vary over time, such as elements of the regulatory environment.

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