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Why Do Banks Disappear: The Determinants of U.S. Bank Failures and Acquisitions

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ABSTRACT

This paper examines the determinants of individual bank failures and acquisitions in the United States during 1984-1993. We use bank-specific information suggested by examiner CAMEL-rating categories to estimate competing-risks hazard models with time-varying covariates. We focus especially on the role of management quality, as reflected in alternative measures of x-efficiency and find the inefficiency increases the risk of failure, while reducing the probability of a bank's being acquired. Finally, we show that the closer to insolvency a bank is, as reflected by a low equity-to-assets ratio, the more likely its acquisition.

KEYWORDS: Bank failures, bank acquisitions, managerical efficiency, hazard model estimation

JEL CLASSIFICATION: G21, G34

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1. INTRODUCTION

From a post-war peak of over 15,000 banks in 1984, the number of commercial banks in the United States had declined to 10,741 ten years later, and continues to fall. Banks disappear primarily for one of two reasons: either they fail, or they are acquired by (or merge with) another bank.[1] Since 1984, the number of acquisitions has been roughly four times the number of failures, even counting acquisitions of insolvent banks only as failures. Moreover, while the number of failures has declined sharply since 1990, acquisitions continue at a record pace. The enactment of new interstate banking and branching authority portends even more acquisitions in the future, with the possibility of a radical change in the market structure of the U.S. banking industry.

Several studies have sought to identify the characteristics that cause banks to fail.[2] Apart from excessive risk-taking, or simply bad luck, banks that are poorly managed are thought to be prone to failure.[3] By contrast, the characteristics that determine whether a bank will be a takeover target have received comparatively little attention.[4] One hypothesis, discussed by Hannan and Rhodes (1987), suggests that poorly-managed banks are likely targets for acquisition by bankers who think they can enhance the target's management quality, and hence its profitability and value. Fundamentally, an acquirer will evaluate whether the expected profit stream generated by an acquisition, less any costs of consummating the takeover and reorganization, exceed the price it must pay to acquire the bank. If an acquirer expects a particular acquisition to generate high profits, or entail

[1] Throughout the paper we use "acquisitions" and "mergers" interchangeably. Acquisitions greatly outnumber mergers and our data source, the National Information Center (NIC) database, does not distinguish between acquisitions and mergers.

[2] See Thomson (1991) for a recent example and survey.

[3] See, for example, Berger and Humphrey (1992a) and Barr and Siems (1994).

[4] Several studies have examined the effect of mergers on bank performance, including Neely (1987), Berger and Humphrey (1992b), Cornett and Tehranian (1992), Linder and Crane (1992) and Akhavein, Berger and Humphrey (1996). We are aware of just two studies examining the characteristics affecting the likelihood that a bank will be taken over. Hannan and Rhodes (1987) find no relationship between a bank's performance, measured by either rate of return or rate of return relative to market competitors, and the probability of acquisition. Amel and Rhodes (1989), however, find a negative relationship between performance and acquisition.

relatively low reorganization costs, it might willingly pay a considerable premium over book value to acquire a controlling interest in another bank. When the expected profit stream is relatively modest, or significant costs of reorganization are anticipated, however, an acquirer might be unwilling to pay such a high purchase price.[5] Because of this tradeoff, we have no a priori expectation that poorly-managed banks will have a higher probability of being acquired – that is an empirical question, and one with considerable relevance for understanding the likely outcome of continued banking industry consolidation.

Management quality is difficult to measure directly because it can take several forms. A considerable literature has developed on the measurement of productive efficiency in banking, however, which conceivably reflects management quality. Researchers have found that banks in general suffer from considerable managerial, or "x-," inefficiency, as opposed to scale or scope inefficiency.[6] There are, however, a number of ways to measure managerial inefficiency. In this paper, we investigate whether managerial inefficiency, measured using two of the most common techniques, influences the probability of failure or acquisition, after controlling for bank portfolio characteristics and operating environments. Because banks may disappear through either failure or acquisition, and since occurrence of either event precludes the other, we use a competing-risks hazard model framework to identify characteristics leading to each outcome. Unlike more commonly used discrete-outcome models, hazard models make more efficient use of the data by explicitly incorporating information about the timing of alternative outcomes. Also, unlike most other banking studies, which are typically based on relatively small samples and short periods, we use quarterly data for 1984-93 on the universe of U.S. banks in existence in 1984 to examine

[5]Note that because the expected acquisition costs and profits generated by an acquisition will differ among potential acquirers, no two potential acquirers will necessarily be willing to pay the same price for controlling interest in a given bank. Just as a handyperson may be willing to buy a "fixer-upper" house at a price that other buyers would not pay, some bankers specialize in purchasing inefficient banks with the aim of improving their management and, hence, value, while other bankers might prefer to acquire well-managed banks.

[6]Berger and Humphrey (1991) is perhaps the most important article in this literature. See Berger, Hunter and Timme (1993) for a survey.

both failures and acquisitions.

Federal regulators evaluate banks on five criteria: capital adequacy, asset quality, management, earnings and liquidity (CAMEL). We base our empirical model on these criteria, and identify a number of characteristics significantly affecting the likelihood that a bank will disappear because of failure or acquisition. Not surprisingly, we find that highly-leveraged banks, banks with low earnings, low liquidity, or risky asset portfolios are more likely to fail than other banks. Holding other factors constant, we find that banks located in states that permit branching are less likely to fail, indicating perhaps the benefits of geographic diversification. And, finally, we find strong evidence that managerial inefficiency increases the likelihood of bank failure.

We also find that proximity to insolvency strongly affects the likelihood that a bank will be acquired. All else equal, the less-well capitalized a bank is, the greater the probability that it will be acquired, suggesting the acquisition of some banks just before they become insolvent. We also find that banks with low earnings, low liquidity, or relatively high non-performing loan ratios are less attractive takeover targets. Banks located in states permitting branching, as well as small banks in general, have been more likely to be acquired. And, finally, we find that inefficient banks are less likely to be acquired, controlling for leverage and other balance sheet and environmental characteristics. Managerial inefficiency could reflect excessive use of, or payment for, physical plant or labor, or excessive deposit interest cost. The cost of reorganizing an inefficient bank could thus be high.[7] Moreover, managerial inefficiency might be taken as a signal of potential problems that are themselves unobservable (e.g., bad loans or accounting irregularities). Thus, holding other portfolio and environmental conditions constant, acquirers on average apparently prefer not to purchase inefficient banks.

[7]Large layoffs of personnel or branch closings are sometimes necessary to improve a bank's efficiency. Perhaps because such actions can entail considerable cost, both monetarily and in terms of public relations, studies have generally found few cost efficiency gains associated with acquisitions and mergers of banks. Akhavein, Berger and Humphrey (1996), for example, find almost no such gains for recent mergers of large bank holding companies.

Section 2 describes productive efficiency and the measures we use. We also discuss the data used to measure efficiency and the results of the efficiency estimation in this section. Section 3 describes the hazard model and the data used to control for portfolio characteristics and other factors, while Section 4 presents the results of the hazard estimation. Conclusions are discussed in the final section.

2. THE MEASUREMENT OF PRODUCTIVE INEFFICIENCY

2.1 Definitions and Models

To measure productive inefficiency, one must first define an input/output mapping. Banks use a number of inputs to produce a myriad of financial services, and to study efficiency researchers are forced to employ simplified models of bank production. Typically, banks are viewed as transforming various financial resources, as well as labor and physical plant, into loans, other investments and, sometimes, deposits. One view, termed the *production* approach, measures bank production in terms of the numbers of loans and deposit accounts serviced. The more common *intermediation* approach measures outputs in terms of the dollar amounts of loans and deposits. The production approach includes only operating costs, whereas the intermediation approach includes both operating costs and interest expense, and hence is probably of more interest for studying the viability of banks. In this study we adopt the intermediation approach.[8]

Researchers have used various criteria to identify the specific inputs and outputs to include in models of bank production. Typically, various categories of loans are included as outputs, while funding sources, labor and physical plant are treated as inputs. The categorization of deposits varies across studies. Whereas non-transactions deposits are almost always treated as inputs, transactions deposits are sometimes considered to be outputs. In the absence of a consensus on the specification of an input/output mapping, we follow Kaparakis *et al.* (1994), which is somewhat representative.

[8]See Berger, Hanweck and Humphrey (1987) or Ferrier and Lovell (1990) for further discussion of these approaches.

There are various notions of productive efficiency, as well as different techniques for measuring each type of inefficiency (see Lovell, 1993 for discussion). In order to check robustness, we use a parametric stochastic frontier model to estimate cost inefficiency, as well as nonparametric distance functions to estimate input and output technical inefficiency. Although Berger and Humphrey (1991) find that technical inefficiencies comprise the vast majority of cost inefficiency in banks, the parametric and nonparametric estimation methodologies have led to very different estimates of efficiency (*e.g.*, Ferrier and Lovell, 1990). Our choice of efficiency concepts and estimation methods broadly reflects those used in bank efficiency studies.

Among parametric models used in recent banking studies, the translog specification has probably been the most common choice for variable cost functions. For the input/output specification used by Kaparakis *et al.* (1994), the corresponding variable cost function may be written as

$$\begin{aligned}\log C =& \alpha_0 + \sum_{j=1}^{4} \alpha_j \log Y_j + \sum_{k=1}^{4} \beta_k \log P_k + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \pi_{jk} \log Y_j \log Y_k \\ &+ \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \delta_{jk} \log P_j \log P_k + \sum_{j=1}^{4}\sum_{k=1}^{4} \tau_{jk} \log Y_j \log P_k + \phi_0 \log X_0 \\ &+ \sum_{j=1}^{4} \phi_j \log Y_j \log X_0 + \sum_{j=1}^{4} \psi_j \log P_j \log X_0 + \frac{1}{2}\gamma(\log X_0)^2 + \varepsilon\end{aligned} \tag{2.1}$$

where C denotes variable cost, Y_j denotes the ith output, P_k denotes the jth input price, X_0 is a fixed input, all lograrithms are natural, and α, β, γ, δ, π, ϕ, ψ and τ are parameters to be estimated. The Kaparakis *et al.* input/output mapping includes four outputs, four variable inputs, and one quasifixed input (these are discussed later). Linear homogeneity in input prices implies the restrictions $\sum_{j=1}^{4} \beta_j = 1$; $\sum_{j=1}^{4} \delta_{jk} = 0 \; \forall \; k$; $\sum_{k=1}^{4} \tau_{jk} = 0 \; \forall \; j$; and $\sum_{j=1}^{4} \psi_j = 0$. In addition, we restrict $\pi_{jk} = \pi_{kj} \; \forall \; j,k$ and $\delta_{jk} = \delta_{kj} \; \forall \; j,k$. As in Kaparakis *et al.*, we also specify a composite error structure

$$\varepsilon = v + u \tag{2.2}$$

with $v \sim N(0, \sigma_v^2)$, $u = |U|$, and $U \sim N(0, \sigma_u^2)$. The v term in (2.2) represents stochastic noise, while u captures cost inefficiency. Maximum likelihood estimates are obtained along the lines of Aigner *et al.* (1977) and Meeusen and van den Broeck (1977); the inefficiency term is estimated for each firm in the sample by computing the conditional expectation $E(u|\varepsilon = \hat{\varepsilon})$ as described by Jondrow *et al.* (1982).

To obtain nonparametric estimates of technical efficiency, we use the Shephard (1970) input and output distance functions computed (respectively) by solving the linear programs:

$$\left(\hat{D}_i^{in}\right)^{-1} = \min\{\lambda \mid \boldsymbol{y}_i \leq \boldsymbol{Y}\boldsymbol{q}_i,\ \lambda\boldsymbol{x}_i \geq \boldsymbol{X}\boldsymbol{q}_i,\ \boldsymbol{i}\boldsymbol{q}_i = 1,\ \boldsymbol{q}_i \in \mathbb{R}_+^N\} \tag{2.3}$$

and

$$\left(\hat{D}_i^{out}\right)^{-1} = \max\{\lambda \mid \lambda\boldsymbol{y}_i \leq \boldsymbol{Y}\boldsymbol{q}_i,\ \boldsymbol{x}_i \geq \boldsymbol{X}\boldsymbol{q}_i,\ \boldsymbol{i}\boldsymbol{q}_i = 1,\ \boldsymbol{q}_i \in \mathbb{R}_+^N\}, \tag{2.4}$$

where $\boldsymbol{Y} = [\boldsymbol{y}_1 \ldots \boldsymbol{y}_N]$, $\boldsymbol{X} = [\boldsymbol{x}_1 \ldots \boldsymbol{x}_N]$, with $\boldsymbol{x}_i$ and $\boldsymbol{y}_i$ denoting the $(n \times 1)$ and $(m \times 1)$ vectors of observed inputs and outputs for the ith bank $(i = 1, \ldots, N)$, $\boldsymbol{x}_j \in \mathbb{R}_+^n$ and $\boldsymbol{y}_j \in \mathbb{R}_+^m$ for all $j = 1, \ldots, N$, and where $\boldsymbol{i}$ is a $(1 \times N)$ vector of ones and $\boldsymbol{q}$ is a $(N \times 1)$ vector of intensity variables which serve to form a piecewise linear approximation of the technology.[9]

Both $\hat{D}_i^{in}$ and $\hat{D}_i^{out}$ measure the radial distance from an observed point $(\boldsymbol{x}_i, \boldsymbol{y}_i)$ to the boundary of the convex hull of the sample observations, and are invariant with respect to units of measurement. The input distance function in (2.3) measures the maximum feasible proportionate reduction in inputs, subject to the existing technology, holding outputs fixed. By definition, $\hat{D}_i^{in} \geq 1$, with $\hat{D}_i^{in} = 1$ indicating that bank i is *ostensibly* efficient.[10] Larger values of $\hat{D}_i^{in}$ indicate increasing inefficiency. Similarly, the output distance function in (2.4) measures the maximum feasible proportionate expansion of outputs, holding inputs

[9]The formulations in (2.3)–(2.4) implicitly assume that (i) the underlying production set is closed, convex; (ii) all production requires use of some inputs; and (iii) both inputs and outputs are strongly disposable. The constraint $\boldsymbol{i}\boldsymbol{q}_i = 1$ imposes variable returns to scale on the reference technology; other returns to scale may be imposed by modifying this constraint (*e.g.*, see Grosskopf, 1986).

[10]If $\hat{D}_i^{in} = 1$, then bank i lies on the boudary of the convex hull of the sample observations; this may or may not correspond to the *true* boundary of the underlying production set.

fixed. By definition, $\hat{D}_i^{out} \leq 1$ with $\hat{D}_i^{out} = 1$ indicating that bank i is ostensibly efficient; smaller values of $\hat{D}_i^{out}$ indicate increasing inefficiency.

The distance functions in (2.3)–(2.4) resemble other linear-programming-based efficiency measures which are collectively referred to as Data Envelopment Analysis (DEA) in the literature.[11] DEA methods have been widely applied in banking (*e.g.,* see Ferrier and Lovell, 1990; Barr *et al.,* 1993; and Wheelock and Wilson, 1995) as well as other areas (*e.g.,* Färe *et al.,* 1994). The measures we have chosen are representative of those used in the banking literature.

While cost and technical inefficiency are closely related concepts, the techniques used to measure them are quite different and involve several tradeoffs. The cost function in (2.1) requires specification of specific funtional forms for the cost function itself as well as for the distributions of noise and inefficiency; specification error, which would lead to biased and inconsistent estimation, is an ever-present possibility with this approach. Among parametric forms, the translog form in (2.1) is typically regarded as being rather flexible, although its use would be problematic in small samples. Moreover, parametric assumptions required on the densities of u and v in (2.2) may be restrictive.

Because no parametric assumptions are required, the DEA approach offers more flexible forms of the technology and distributions of inefficiency than does estimation of the translog cost function. The DEA methods do not allow for noise, however, and thus, when DEA measures are used, any noise in the underlying data-generating process will be confused with inefficiency. Apart from this problem, DEA methods give consistent estimates of inefficiency under appropriate assumptions about the underlying data-generating process, but suffer from the usual statistical inefficiency problems incurred in nonparametric estimation (Kneip *et al.,* 1996).[12]

[11] Shephard (1970) and Färe (1988) give further details on the measures in (2.3)–(2.4), while Lovell (1993) discusses DEA methods in general.

[12] This implies that even if the data-generating process does not involve a noise process as in (2.1), DEA methods may yield noisy, imprecise estimates of inefficiency in finite samples due to sampling variation (we return to this point in Secton 4). On the other hand, inconsistency due to misspecification of the

2.2 The Data

Our data are taken from the quarterly Statements of Income and Condition (call reports) filed by commercial banks. We use end-of-quarter data from 1984(3) through 1993(4), giving a total of 38 quarters. Following Kaparakis *et al.* (1994), we specify four outputs, four variable inputs, and one quasi-fixed input. The outputs are: loans to individuals for household, family, and other personal expenses (Y_1); real estate loans (Y_2); commercial and industrial loans (Y_3); and federal funds sold, securities purchased under agreements to resell, plus total securities held in trading accounts (Y_4). The variable inputs are: interest-bearing deposits except certificates of deposit greater than \$100,000 (X_1); purchased funds (certificates of deposit greater than \$100,000, federal funds purchased, and securities sold plus demand notes) and other borrowed money (X_2); number of employees (X_3); and book value of premises and fixed assets (X_4).

The quasi-fixed input (X_0) consists of noninterest-bearing deposits. Kaparakis *et al.* argue that since, by definition, banks cannot attract more of these deposits by offering interest, they can be regarded as exogenously determined as a first approximation. Although banks might offer various services or other incentives to attract non-interest bearing deposits, we assume that banks take the quantity of these deposits as given. Because no explicit price exists for this input, it must either be omitted from the cost function altogether, or its quantity rather than price must be included in the cost function. Following Kaparakis *et al.*, we opt for the latter.

Input prices are computed as follows: average interest cost per dollar of X_1 (P_1); average interest cost per dollar of X_2 (P_2); average annual wage per employee (P_3); and average cost of premises and fixed assets (P_4). Our computation of input prices is identical to that of Kaparakis *et al.* and others.[13] As is typical, we compute the dependent variable (C) in

technology or the distribution of inefficiency does not appear to be a problem when DEA methods are used.

[13]Computing input prices in terms of average expense for each input may result in measurement error. Kaparakis *et al.* discuss alternative specifications for some price variables, but these are also likely to introduce significant measurement error.

(2.1) as the total cost of the variable inputs; *i.e.*,

$$C = \sum_{i=1}^{4} P_i X_i. \tag{2.8}$$

The Call Reports contain information on banks whose business does not involve the traditional banking operations reflected in our input/output mapping (*e.g.*, credit-card banks), and nonparametric efficiency measures in particular are sensitive to outliers in the data. We therefore employ several selection criteria to limit our sample to a group of relatively homogenous banks. In particular, we omit banks with foreign branches, banks with nonpositive values for inputs, outputs, or prices, and banks reporting assets of less than $50,000 (1986 dollars). Since some remaining observations contain values for P_1 and P_2 that are suspect, we omit observations when either of these variables exceeded 0.45.[14] Finally, we include only those banks operating in 1984(3), the beginning of our sample period. The number of observations in each quarter ranges from 2967 to 5530.

2.3 Efficiency Estimation Results

Estimation of the frontier cost function represented in (2.1) is straightforward.[15] We estimate a series of cross-sectional relationships rather than a panel data model to allow for the possibility that inefficiency varies over time. The parameter estimates for the cost function in (2.1) vary a great deal over the 32 quarters in which convergence was achieved, suggesting that the technology shifted over time.[16]

The nonparametric measures of efficiency are obtained by solving the linear programs (2.3)–(2.4). Although time-consuming, the linear programs have a solution in each instance

[14]We arrived at this criteria by examining the distributions of the price variables; the distributions were somewhat continuous up to some point below 0.45, with a few (clearly implausible) large outliers in the right tail.

[15]We used procedures contained in LIMDEP version 6.0 to compute the cost function estimates; see the *LIMDEP Version 6.0 User's Manual and Reference Guide*, Econometric Software, Inc., Bellport, NY (1992). Nonparametric estimates were computed using Fortran code written by the authors.

[16]We omit the parameter estimates to conserve space; the actual values are available on request. In the six quarters where convergence was not achieved, initial ordinary least squares estimation (to obtain starting values) yielded residuals skewed in the correct direction; hence, failure to acheive convergence in these quarters may reflect poor starting values rather than specification problems (see Greene, 1993).

and hence we are able to obtain efficiency estimates for each period. To compute both the input and output distance function measures of efficiency, (2.3)–(2.4) are each solved once for each bank in each cross section. Each time the equations are solved, efficiency for the ith bank at time t is measured relative to the convex hull of observations on the N_t banks observed at time t.

Mean values of the cost inefficiency estimates from (2.1) are shown in Table 1. For each quarter in which the data needed to compute efficiency are available, mean cost inefficiencies of all banks that neither failed nor were acquired at any time before 1994(2) are reported in the column labeled "Survived." The number of observations changes from quarter to quarter because two successive Call Reports are needed to compile cost figures for each bank, and many banks have missing data for one or more of the necessary variables in any given quarter. Mean cost inefficiency for banks that failed (defined here as closure by regulators) within one year after the given quarter are reported in the column labelled "Failed," and means for banks that were acquired within one year after the quarter are reported in the column labeled "Acquired." For each period, we use the bootstrap procedure described by Atkinson and Wilson (1995) with 1000 replications to test for significant differences in mean efficiency measures for failed versus survived banks and acquired versus survived banks. Asterisks in Tables 1–3 indicate differences in means that are significant at 95 percent.[17]

Consistent with Berger and Humphrey (1992a) and others, we find that failing banks almost always were more cost-inefficient than surviving banks, though in several periods the differences in mean inefficiency are not statistically significant. By contrast, acquired banks were, on average, almost always less inefficient than survivors, and the differences in mean inefficiency between acquired and surviving banks are almost always statistically significant. There may well be other important characteristics that affect the likelihood

[17]Small numbers of observations for failed banks in each quarter, together with nonnormality of the efficiency scores, precludes use of conventional t-ratios.

that a bank will be acquired, but it appears that inefficient banks are less likely to be acquired than efficient banks.

Tables 2 and 3 report means for the nonparametric measures of technical inefficiency (in Table 3 we report means of the *inverse* output efficiency measure to facilitate comparison with the other efficiency measures). In contrast to the cost inefficiency results, failing banks often appear less technically inefficient than surviving banks. Of course, this analysis does not control for other possible determinants of failure, but from this comparison failing banks do not appear consistently more technically inefficient than surviving banks. As with the cost inefficiency estimates reported in Table 1, we find that acquired banks were less technically inefficient than surviving banks, regardless of whether technical inefficiency is measured using the input orientation or the output orientation. Thus, whereas the parametric cost inefficiency measure and the nonparametric technical inefficiency measures provide estimates of the relationship between managerial inefficiency and bank failure that are inconsistent with one another, both measures indicate that, at least during 1984–93, banks that were acquired were generally *less* inefficient than banks that failed or survived the decade.

We next investigate whether the relationships between efficiency, failure and acquisition suggested by comparison of means continue to hold once other likely characteristics affecting the probability of failure or acquisiton are controlled for.

3. MODELING THE TIME-TO-DISAPPEARANCE

We wish to examine the hazard, or risk, of banks disappearing due either to acquisition or to failure, which we refer to as *events* in the following discussion. We assume that the causal processes for acquisitions and failures are different. As shown below, our empirical results support this assumption.

Either acquisition or failure removes a bank from risk of the other event; this has been labelled *competing risks* in the duration model literature. Conceivably, failure and acquisiton times may be dependent on one another, for example if banks are acquired just before they would otherwise have failed. However, without additional information, any dependent competing risks model is observationally equivalent to an independent competing risks model.[18] Fortunately, our data contain additional information which allow us to handle this problem. By including a key indicator of failure—the ratio of equity to assets—in the acquisition hazard, we provide a test of whether proximity to failure affects the likelihood of a bank's acquisition. This is the approach suggested by Kalbfleisch and Prentice (1980, pp. 175–177).

We analyze the disappearance of banks using Cox (1972) proportional hazards models with time-varying covariates, which are estimated by maximizing the partial likelihood function. Our estimation is thus semiparametric, since we do not specifiy the baseline hazards. This approach is standard in most applied work (*e.g.,* see Katz and Meyer, 1990). In modelling the failure hazard, acquired banks are treated as censored at the date of acquisition; in modelling the acquisition hazard, banks that failed are treated as censored at the failure date. This approach assumes that censoring does not provide any information about latent failure times beyond that available in the covariates.

Our sample consists of banks operating in 1984(3), the beginning of our sample period. We update the data on these banks over the next 38 quarters, through December 31, 1993, in the hazard estimation. Through time, failure, acquisition, or simply missing data cause banks to disappear. Banks are treated as censored when they are missing from the Call Reports for more than three consecutive quarters, but have not failed or been acquired.[19] Since the balance sheets of failing banks may change drastically in the months before

[18]In other words, dependent hazards can be modelled using appropriate multivariate distributions, but the data are unable to distinguish between dependent and independent models; *i.e.,* for each dependent model, there will be a corresponding independent model which yields the same likelihood value. Without additional information, one cannot test the null hypothesis of independence, nor test hypotheses regarding the structure of the dependence. See Elandt-Johnson and Johnson (1980) and Lancaster (1990) for proofs; Kalbfleisch and Prentice, (1980, pp. 172–175) provide an example.

[19]These banks are treated as censored on the day before the date of the first Call Report from which they are missing.

failure, by treating banks with missing data as censored, we avoid biasing the results by using information from the distant past to describe characteristics of banks at the time of their failure.[20]

Each bank i in the sample is observed at J_i different times $t_{i1} < t_{i2} < \ldots < t_{iJ_i}$, with either failure, acquisition, or censoring occurring at time t_{iJ_i}. Time is measured by calendar time since the first observation date, which is identical for all banks in the sample, so that $t_{i1} = 0 \; \forall \; i$. The data 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 estimated model is time-varying in that the covariates in z are assumed constant for intervals of time $[t_{ij}, t_{i(j+1)})$, but may vary across intervals. Thus for the ith bank there are $(J_i - 1)$ censored observations whose contribution to the likelihood is given by $[S(t_{i(j+1)}|z, \theta) - S(t_{ij}|z, \theta)]$, where $S(\cdot)$ is the survivor function; again, the J_ith observation represents either failure, acquisition, or censoring.

In choosing covariates for the hazard models, we attempt to account for capital adequacy, asset quality, management, earnings, liquidity, and miscellaneous factors. Specifically, we define the following variables:[21]

1. Capital adequacy:
   $CAPAD$ = total equity/total assets.

2. Asset quality:
   $A1$ = total loans/total assets.
   $A2$ = real estate loans/total loans.
   $A3$ = other real estate owned/total assets.
   $A4$ = income earned, but not collected on loans/total assets.

[20]Unfortunately, many banks do not submit Call Reports for several quarters before their failure dates; our scheme treats these as censored observations. Of 1392 banks closed by the FDIC due to failure during 1984(3)–1993(4), we observe only 281 banks in the Call Report data within three quarters prior to the date of failure. Our approach is conservative; to the extent we treat failed banks as censored, significance levels will be reduced when we estimate the failure hazard. Data on 4061 banks are used in the hazard models. Of these banks, 1387 are observed to be acquired between 9/30/84 and 3/31/94, while 281 are reported as failing during the same period. While efficiency estimates could be obtained for a larger number of banks, additional data requirements in the hazard models reduced the number of banks.

[21]This specification attempts to account for the principal components of the CAMEL ratings assigned by regulators in their evaluations of individual banks. Note that balance sheet items are reported as book values; we convert all dollar figures to 1986 dollars using the quarterly gross national product deflator.

$A5$ = commercial and industrial loans/total loans.

3. Management:
   $M1$ = cost inefficiency.
   $M2$ = input distance function measure of technical inefficiency.
   $M3$ = 1/output distance function measure of technical inefficiency.

4. Earnings:
   $EARN$ = net income after taxes/total assets.

5. Liquidity:
   LIQ = (federal funds purchased − fed funds sold)/total assets.

6. Miscellaneous factors:
   $SIZE$ = log of total assets.
   $HOLD$ = 1 if 25% or more of equity is held by a multi-bank holding company; 0 otherwise.
   $BR1$ = 1 if bank is located in a state allowing limited branching; 0 otherwise.
   $BR2$ = 1 if bank is located in a state allowing unlimited branching; 0 otherwise.

In estimating the failure hazard, we expect the coefficient on $CAPAD$ to have a negative sign, indicating that banks with higher equity as a percentage of total assets should be less likely to fail. Obviously, the less equity a bank has, the less protection it has against loan losses or other declines in the value of its assets.

Loans are typically the least liquid and most risky of bank assets. Thus, we expect that the more concentrated a bank's assets are in loans, the greater the likelihood of failure, and hence we expect a positive coefficient on $A1$. In the absence of direct information about the riskiness or quality of a bank's loan portfolio, we include two measures of loan concentration by category, and two measures of loan portfolio performance. We include the ratios of real estate loans to total loans and of commercial and industrial loans to total loans to test whether concentration in either category affects the probability of failure. The variables $A3$ and $A4$ are indicators of asset quality. "Other real estate owned" reflects foreclosed property, and higher values could indicate problem loans. Similarly, a high level of earned, but uncollected loan income might also indicate that a bank's loan portfolio quality is low. Thus, the coefficients on $A3$ and $A4$ are expected to be positive.

We use the various measures of inefficiency (*M1–M3*) to reflect management quality; each is constructed so that larger values reflect greater inefficiency. From the discussion in Section 2, we expect the coefficients on each to be positive in the failure hazard. For the quarters in which the cost function (2.1) could not be estimated, M1 is set equal to its value in the previous quarter. Although this may introduce measurement error, no alternative is evident if parametric efficiency estimates are to be used.[22]

Banks with greater earnings are, presumably, less likely to fail, and hence we expect a negative coefficient on *EARN*. Positive values of *LIQ* indicate net purchases of federal funds, which might indicate illiquidity. If illiquid banks are more likely to fail, the coefficient on *LIQ* should be positive.[23]

We use the log of total assets to measure bank size. Casual empiricism suggests that small banks may be more likely to fail. If this remains true after controlling for other factors, the coefficient on *SIZE* should be negative. We include *HOLD* to test whether membership in a multi-bank holding company affects the probability of failure. For example, if a parent company injects cash into a weak subsidiary, holding company membership might lessen the chance of failure. On the other hand, the failure of a lead bank in a holding company has sometimes led regulators to close all holding company members. Although we are uncertain about the likely sign on *HOLD,* including it in the hazard model should lead to more precise estimates of the coefficients of the remaining variables. Finally, we include branching dummy variables to test whether the opportunity to branch enhanced geographic diversification and thereby lessened the chance of failure. If so, the coefficients on *BR1* and *BR2* should be negative.

In estimating the hazard models, we define bank failure two different ways. First, we treat only those banks that were closed by the FDIC as failed. Some banks, however,

[22] This is entirely within the spirit of time-varying covariates hazard models, since we update variables whenever new information becomes available.

[23] Unfortunately, missing data for many banks prevented use of a broader measure of liquidity including currency, coin and US Treasury securities, as well as net fed funds purchased.

were allowed to remain in operation for quite some time after becoming insolvent, in some cases operating for several quarters with negative equity. Because of regulatory action, the precise timing of failure is sometimes arbitrary. Hence, our second definition of bank failure expands the first to also include banks with total equity capital less goodwill divided by total assets of less than two percent. For these banks, the failure date is taken as the earlier of (1) the reported date of closure or (2) the day before the Call Report on which the equity ratio is observed below two percent.[24]

We are unaware of any studies that attempt to estimate acquisition hazards. As a starting point, we use the same variables as in our failure hazard specifications. Casual observation again suggests that small banks are more likely takeover targets, and so we expect a negative sign on *SIZE*. With respect to the management variables, buyers may look for poorly-managed banks whose values could be enhanced by superior management. Inefficient banks represent such opportunities, so we might expect a positive sign on *M1–M3* in the acquisition hazards. Indeed, Berger and Humphrey (1992) find that in a sample of large bank holding company acquisitions, the acquirer was typically more efficient than the acquired firm. The acquisition of inefficient banks may entail substantial costs of reorganization, however, and inefficiency may signal other problems, such as bad loans, and thus discourage potential acquirors. Hence the effect of managerial inefficiency on the acquisition hazard is an empirical question.[25]

Our data on bank acquisitions come from the National Information Center (NIC) database, which is maintained by the Federal Reserve System. The data include information on the type of acquisition, banks involved, date of acquisition, and whether the acquisition was arranged by the FDIC in the case of failed banks. For purposes of estimating the

[24] 51 additional banks are identified as failed under this expanded definition, although the timing of other failures is affected. We choose 2 percent as our criteria since the Federal Deposit Insurance Corporation Improvement Act of 1991 requires regulators to close or impose prompt corrective action on any bank whose equity ratio falls below 2 percent.

[25] Some acquisitions result from holding company reorganizations. To the extent that these reorganizations have little to do with efficiency of the "acquired" bank, we would expect the statistical significance of the efficiency variables *M1–M3* and perhaps that of other variables to be reduced.

acquisition hazard, we define an acquisition as the purchase of one bank by another bank, without the purchase being arranged by the FDIC, with the charter of the purchased bank being discontinued, and that of the purchasing bank continuing to exist. For some acquired banks, failure may have been imminent; however, when we use our second, expanded definition of bank failure, we treat such banks as failed if their equity ratio falls below the two percent level before the reported date of acquisition. Consequently, in the acquisition hazard, such banks are treated as censored.

4. HAZARD ESTIMATION RESULTS

4.1 Time-to-Failure

The results of the hazard model estimation for time-to-failure are reported in Table 4. Results for three pairs of equations are shown, corresponding to the three measures of inefficiency. Within each pair, two definitions of failure are used: (1) closure by the FDIC, and (2) an equity/asset ratio below .02. Equations *I–II* include cost inefficiency (*M1*); equations *III–IV* include input technical efficiency (*M2*), while *V–VI* include the output technical efficiency measure (*M3*).

The qualitative results appear robust across both the different efficiency measures and the failure definitions; signs and significance levels are similar in all six equations. The financial variables affect the probability of failure largely as anticipated. For example, the less well-capitalized a bank was, the more likely it was to fail. By the same token, failure was more likely for banks with larger ratios of loans to assets, other real estate owned to total assets, uncollected loan income to assets, and commercial and industrial loans to total assets.

Not surprisingly, failure probability was negatively related to earnings. The coefficient on the liquidity variable is counter to expectations, however, perhaps indicating that it is a poor proxy. We find no robustly significant relationships between size or holding company membership and the probability of failure, but we do find that failure was less likely in states permitting either limited or state-wide branching. Apparently, the geographic diversification afforded by branching reduced the likelihood of failure, holding individual bank characteristics fixed.

The cost inefficiency variable *M1*, and the input technical inefficiency variable *M2* both have positive and statistically significant coefficients. The positive signs indicate that, holding capital adequacy, asset quality, earnings, liquidity and other factors constant, the more inefficient a bank was, the more likely it was to fail. The t-ratios for *M2* are lower than those for *M1*, and are insignificant for *M3*, reflecting at least in part the incorporation of noise into the nonparametric efficiency scores as discussed earlier. Our results support previous research, as well as intuition, however, that managerial inefficiency increases the likelihood that a bank will fail.

4.2 Time-to-Acquisition

Next, we investigate whether the same variables that explain time-to-failure can also explain time-to-acquisition. Table 5 reports these results. Again, we distinguish among alternative types of inefficiency, as well as definitions of failure (failures are treated as censored observations in the model of acquisition).

In general, we find that the lower a bank's equity/asset ratio, the more likely it was to be acquired. As the results in Table 4 illustrate, banks with little equity relative to assets are at significantly greater risk of failure than other banks. Indeed, insolvency, *i.e.*, an equity/asset ratio of zero, is the economic definition of failure, and would be the practical definition as well were it not for regulator determination of bank closure.[26] Thus, finding a negative relationship between the equity/asset ratio and the probability of acquisition could be interpreted as the closer a bank is to failure, the more likely it is to be acquired. This does not, however, imply that failure is imminent for all banks that are acquired,

[26] Apart from the cost of acquiring information about the true financial condition of a bank, with deposit insurance, depositors have little or no incentive to run on an insolvent bank and thus force closure at the time of insolvency. Bank closure has thus been left to regulators who monitor "problem" banks and determine when a bank has failed.

though it may be for some. Especially skillful managers might be able to operate banks safely with little capital, and such banks might be highly profitable or desirable takeover candidates for other reasons. Nevertheless, thinly capitalized banks are generally at greater risk of failure, and, apparently also of being acquired.

Our results also indicate that banks with higher ratios of real estate loans to total loans had a higher probability of being acquired. Banks with suspect loans, as reflected by high ratios of interest earned but not collected to total assets were, unsurprisingly, less likely to be acquired. On the other hand, a lower rate of return on assets increased a bank's likelihood of being acquired, as did a low ratio of net fed funds purchased to assets.

Holding other variables constant, smaller banks were more likely to be acquired than larger banks. Members of holding companies were also more likely to be acquired, as were banks located in state-wide branch banking states.

Finally, we find that cost inefficiency reduced the probability of being acquired, all else equal. Not only might the acquisition of an inefficient bank entail higher costs of reorganization than for an efficient bank, but inefficiency might be taken by potential acquirers as a signal of hidden problems with the bank's operations. Indeed, for given financial characteristics and key environmental variables, our results indicate that managerial inefficiency reduces the attractiveness of banks to acquirers.[27] Acquisition appears unrelated to technical inefficiency, however, at least as measured by the input and output distance functions. Given that cost inefficiency and technical inefficiency are in theory similar, related concepts, the insignificance of technical inefficiency in the acquisition hazard may reflect noise in these measures.[28]

[27]This might also explain why Akhavein *et al.* (1996) find little improvement in cost efficiency following the merger of very large banks, despite the observed potential for large improvement.

[28]DEA methods are sensitive to outliers. While methods exist to detect outliers in DEA models, they are difficult to employ with large sample sizes. In addition, as noted earlier, the slow convergence rates of nonparametric efficiency estimators such as these implies that estimates from small samples will have high variance due to sampling variation. To the extent that variables in the hazard models contain noise, we would expect an attenuation effect as with other measurement-error problems that would reduce significance levels.

5. CONCLUSIONS

The U.S. banking system is in a period of transition. From the mid-1930s through the 1970s, banking markets were insulated, bank profits were stable, and the regulatory and technological environment in which banks operated changed little. Since 1980, however, significant changes have increased competition and begun to alter the market structure of the banking industry. The number of U.S. banks has fallen sharply since 1985, initially because of failures, but more recently because of high numbers of acquisitions and mergers. We have sought to identify the characteristics of banks exiting the industry through either failure or acquisition, focusing especially on how managerial inefficiency might affect the likelihood of either outcome.

We find, not surprisingly, that less-well capitalized banks are at greater risk of failure, as are banks with high ratios of loans to assets, evidence of poor quality loan portfolios and banks with low earnings. Given bank-specific characteristics, we find that banks located where branching is permitted had a lower probability of failing, supporting the claim that enhanced freedoms to branch would afford banks greater diversification and thereby reduce their vulnerability to localized economic shocks.

We also find that, after controlling for other determinants, the lower a bank's capitalization, the greater the probability that it would be acquired. This is consistent with the acquisition of failing banks prior to insolvency, but also with the purchase of banks with skillful managers who are able to operate successfully with high leverage. We find, however, that the probability of acquisition declined with higher return on assets. The likelihood of acquisition also was higher for banks located in states permitting state-wide branching, suggesting that industry consolidation will likely follow as branching restrictions continue to fall.

Finally, we find that the probability of failure was higher for managerially inefficient banks, as reflected in measures of both cost and technical inefficiency. The likelihood of acquisition, however, declined with cost inefficiency, and we detect no clear relationship of acquisition with technical inefficiency. Although inefficient banks might be ripe for takeover by owners who could enhance their management quality, and thereby their value, we find that, on average, high cost inefficiency has lowered the probability that a bank will be acquired. Indeed, other studies have found little cost efficiency gain associated with large bank acquisitions (e.g., Akhavein, Berger and Humphrey, 1996). Apparently, the costs of reorganizing an inefficient bank and the potential for other hidden problems that inefficiency might signal, tend to discourage the acquisition of inefficient banks.

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TABLE 1
Mean Cost Inefficiency

Quarter	Survived Obs.	Survived Mean	Failed Obs.	Failed Mean	Acquired Obs.	Acquired Mean
1984(3)	2433	0.1825	9	0.1645	113	0.1507*
1984(4)	1424	0.1835	3	0.1550*	68	0.1520*
1985(1)	2233	0.1923	6	0.2433*	97	0.1562*
1985(2)	1701	0.1854	4	0.1401	76	0.1667
1985(3)	1653	0.1966	6	0.2652*	59	0.1714*
1985(4)	1476	0.1656	8	0.1984*	45	0.1556
1986(1)	2228	0.1894	17	0.2292*	100	0.1619*
1986(2)	1789	0.1963	5	0.2472	72	0.1578*
1986(3)	1492	0.2013	4	0.2760*	101	0.1577*
1986(4)	1491	0.1929	4	0.1662	100	0.1457*
1987(1)	2166	0.1798	13	0.2012	190	0.1476*
1987(2)	1558	0.1919	15	0.2101	159	0.1621*
1987(3)	1412	0.1944	42	0.2136*	138	0.1616*
1987(4)	1412	0.1583	39	0.1504	133	0.1301*
1988(3)	1530	0.1999	28	0.2593*	60	0.1496*
1988(4)	1387	0.2047	22	0.2786*	40	0.1780
1989(1)	2062	0.1879	20	0.2195*	86	0.1633*
1989(3)	1632	0.2079	15	0.2174	77	0.1574*
1989(4)	1625	0.1768	12	0.1776	71	0.1335*
1990(1)	2135	0.1896	26	0.1828	74	0.1422*
1990(2)	1590	0.1878	16	0.1953	58	0.1512*
1990(4)	1420	0.2066	13	0.1876	47	0.1700*
1991(1)	2097	0.1971	21	0.1793	100	0.1682*
1991(2)	1433	0.2225	15	0.2116	72	0.1813*
1991(3)	1546	0.2073	11	0.1510*	64	0.1602*
1992(1)	2050	0.1967	27	0.2400*	87	0.1564*
1992(3)	1353	0.2121	11	0.1765	87	0.1813*
1992(4)	1492	0.1618	7	0.1872*	83	0.1298*
1993(1)	1980	0.1963	9	0.2329*	107	0.1702*
1993(2)	1448	0.1874	2	0.2375	75	0.1534*
1993(3)	1334	0.1733	7	0.2069*	87	0.1532*
1993(4)	1344	0.1459	4	0.1575	75	0.1280*

TABLE 2
Mean Input Technical Inefficiency

	Survived		Failed		Acquired	
Quarter	Obs.	Mean	Obs.	Mean	Obs.	Mean
1984(3)	2433	1.3187	9	1.1657*	113	1.2875
1984(4)	1424	1.3150	3	1.2032	68	1.2839
1985(1)	2233	1.3550	6	1.1602*	97	1.3203
1985(2)	1701	1.3314	4	1.1463	76	1.3387
1985(3)	1653	1.3502	6	1.3618	59	1.3474
1985(4)	1476	1.3490	8	1.4112	45	1.3390
1986(1)	2228	1.3904	17	1.3245	100	1.3675
1986(2)	1789	1.3642	5	1.3321	72	1.2873*
1986(3)	1492	1.3668	4	1.1735	101	1.2548*
1986(4)	1491	1.3776	4	1.1469*	100	1.2336*
1987(1)	2166	1.4269	13	1.3082	190	1.3524*
1987(2)	1558	1.3899	15	1.3406	159	1.2987*
1987(3)	1412	1.4006	42	1.2058*	138	1.2841*
1987(4)	1412	1.3618	39	1.1272*	133	1.2167*
1988(1)	2129	1.4436	49	1.2209*	141	1.2796*
1988(2)	1592	1.4098	48	1.1992*	85	1.3064*
1988(3)	1530	1.3932	28	1.4917*	60	1.2891
1988(4)	1387	1.3847	22	1.3576	40	1.3786
1989(1)	2062	1.4547	20	1.7238*	86	1.4106
1989(2)	1588	1.4431	20	1.4942	75	1.3247*
1989(3)	1632	1.4216	15	1.3374	77	1.3129*
1989(4)	1625	1.4091	12	1.4394	71	1.2313*
1990(1)	2135	1.4523	26	1.4233	74	1.3435*
1990(2)	1590	1.4222	16	1.3053	58	1.4087
1990(3)	1563	1.4239	12	1.2948	61	1.3936
1990(4)	1420	1.4125	13	1.2315*	47	1.3319*
1991(1)	2097	1.4528	21	1.2096*	100	1.4324
1991(2)	1433	1.4292	15	1.1763*	72	1.3757
1991(3)	1546	1.4527	11	1.1091*	64	1.3420*
1991(4)	1263	1.4484	11	1.2695	42	1.3754
1992(1)	2050	1.4774	27	1.5644*	87	1.3542*
1992(2)	1417	1.4399	24	1.3684	73	1.2982*
1992(3)	1353	1.5021	11	1.4059	87	1.3912*
1992(4)	1492	1.4375	7	1.4782	83	1.2330*
1993(1)	1980	1.4932	9	1.5408	107	1.3371*
1993(2)	1448	1.4633	2	1.5926*	75	1.2822*
1993(3)	1334	1.4628	7	1.6090*	87	1.3266*
1993(4)	1344	1.4494	4	1.5350	75	1.3319*

TABLE 3
Mean (Inverse) Output Technical Inefficiency

	Survived		Failed		Acquired	
Quarter	Obs.	Mean	Obs.	Mean	Obs.	Mean
1984(3)	2433	1.4398	9	1.2864	113	1.3632*
1984(4)	1424	1.4471	3	1.3298	68	1.3427*
1985(1)	2233	1.4949	6	1.2001*	97	1.4017*
1985(2)	1701	1.4450	4	1.1882*	76	1.3962
1985(3)	1653	1.4934	6	1.6691	59	1.4293
1985(4)	1476	1.4844	8	1.4661	45	1.3840*
1986(1)	2228	1.5477	17	1.4506	100	1.4221*
1986(2)	1789	1.4966	5	1.3570	72	1.3156*
1986(3)	1492	1.5077	4	1.2153*	101	1.3019*
1986(4)	1491	1.5180	4	1.2653*	100	1.2639*
1987(1)	2166	1.6032	13	1.3290*	190	1.3984*
1987(2)	1558	1.5347	15	1.3902	159	1.3551*
1987(3)	1412	1.5563	42	1.2059*	138	1.3436*
1987(4)	1412	1.5057	39	1.1278*	133	1.2762*
1988(1)	2129	1.6249	49	1.2283*	141	1.3427*
1988(2)	1592	1.5727	48	1.2072*	85	1.3816*
1988(3)	1530	1.5508	28	1.5409	60	1.3602*
1988(4)	1387	1.5367	22	1.4270	40	1.4379
1989(1)	2062	1.6375	20	1.9817	86	1.4721*
1989(2)	1588	1.6085	20	1.5278	75	1.3753*
1989(3)	1632	1.5861	15	1.3903	77	1.3742*
1989(4)	1625	1.5915	12	1.4604	71	1.2542*
1990(1)	2135	1.6284	26	1.4592*	74	1.3857*
1990(2)	1590	1.5811	16	1.3606*	58	1.4510*
1990(3)	1563	1.5756	12	1.3833	61	1.4514*
1990(4)	1420	1.5750	13	1.2787*	47	1.3577*
1991(1)	2097	1.6353	21	1.2550*	100	1.4626*
1991(2)	1433	1.5799	15	1.2382*	72	1.4097*
1991(3)	1546	1.6438	11	1.1699*	64	1.3873*
1991(4)	1263	1.6461	11	1.4427	42	1.4521*
1992(1)	2050	1.6675	27	1.7381	87	1.4447*
1992(2)	1417	1.6026	24	1.4121*	73	1.3079*
1992(3)	1353	1.7223	11	1.4984	87	1.4898*
1992(4)	1492	1.6214	7	1.5147	83	1.2626*
1993(1)	1980	1.6909	9	1.5966	107	1.4133*
1993(2)	1448	1.6479	2	1.7659	75	1.3393*
1993(3)	1334	1.6559	7	1.7376	87	1.4234*
1993(4)	1344	1.6390	4	1.6407	75	1.4386*

TABLE 4
Failure Hazard
(t-ratios in parentheses)

Failure Criteria	*I* Closure	*II* Equity≤ 2%	*III* Closure	*IV* Equity≤ 2%	*V* Closure	*VI* Equity≤ 2%
CAPAD	−81.15**	−89.61**	−82.07**	−91.48**	−82.88**	−91.70**
	(−23.27)	(−21.83)	(−23.39)	(−22.27)	(−23.70)	(−22.34)
A1	2.395**	3.384**	2.296**	2.694**	1.246*	1.903**
	(3.11)	(4.84)	(2.85)	(3.56)	(1.74)	(2.84)
A2	0.3726	0.7942	0.1617	0.6656	0.2035	0.6240
	(0.64)	(1.56)	(0.28)	(1.29)	(0.34)	(1.20)
A3	5.035**	8.245**	6.176**	9.810**	5.336**	9.060**
	(3.16)	(6.33)	(3.73)	(7.20)	(3.33)	(6.92)
A4	111.2**	96.04**	120.9**	102.4**	120.2**	101.2**
	(6.88)	(7.53)	(7.64)	(8.15)	(7.62)	(8.08)
A5	0.7694	2.436**	0.7945	2.715**	0.6108	2.484**
	(1.20)	(4.47)	(1.20)	(4.77)	(0.93)	(4.41)
M1	3.226**	4.254**	—	—	—	—
	(4.17)	(6.54)				
M2	—	—	0.7978**	0.6440**	—	—
			(3.51)	(2.42)		
M3	—	—	—	—	−0.03370	0.06189
					(−0.08)	(0.16)
EARN	−1.747	−6.538**	−1.782*	−6.328**	−1.846*	−6.423**
	(−1.62)	(−5.33)	(−1.67)	(−5.14)	(−1.74)	(−5.24)
LIQ	−5.078**	−5.213**	−5.823**	−5.218**	−4.713**	−4.417**
	(−8.41)	(−9.40)	(−8.22)	(−8.03)	(−7.78)	(−7.99)
SIZE	−0.01653	−0.1285	0.1105	0.03554	0.1606*	0.06398
	(−0.17)	(−1.40)	(1.22)	(0.43)	(1.88)	(0.81)
HOLD	−0.08057	−0.2305	−0.1645	−0.2678*	−0.1494	−0.2921**
	(−0.49)	(−1.56)	(−0.99)	(−1.82)	(−0.90)	(−1.99)
BR1	−0.5102**	−0.2181	−0.5276**	−0.1695	−0.5206**	−0.1827
	(−2.89)	(−1.36)	(−2.94)	(−1.05)	(−2.92)	(−1.14)
BR2	−0.6694**	−0.6016**	−0.5192**	−0.4144**	−0.5775**	−0.4868**
	(−2.63)	(−2.87)	(−2.07)	(−1.98)	(−2.29)	(−2.34)
LLF	−1134.809	−1532.376	−1132.680	−1539.646	−1137.017	−1542.280
R^2	0.3920	0.3290	0.3890	0.3230	0.3870	0.3220

NOTE: Single asterisk (*) denotes significance at .1; double asterisk denotes significance at .05.

TABLE 5
Acquisition Hazard
(t-ratios in parentheses)

Failure Criteria	*VII* Closure	*VIII* Equity≤ 2%	*IX* Closure	*X* Equity≤ 2%	*XI* Closure	*XII* Equity≤ 2%
CAPAD	−7.294**	−8.079**	−7.147**	−8.059**	−7.128**	−8.067**
	(−4.62)	(−4.87)	(−4.43)	(−4.74)	(−4.43)	(−4.75)
A1	−0.2692	−0.2106	0.6999**	0.7765**	0.7469**	0.7724**
	(−0.93)	(−0.72)	(2.36)	(2.57)	(3.00)	(3.07)
A2	0.4488**	0.4753**	0.4864**	0.5083**	0.4940**	0.5217**
	(2.09)	(2.20)	(2.28)	(2.36)	(2.30)	(2.41)
A3	−0.4022	−0.5524	−0.1115	−0.1595	−0.05282	−0.1030
	(−0.16)	(−0.20)	(−0.04)	(−0.06)	(−0.02)	(−0.04)
A4	−67.54**	−66.10**	−71.95**	−70.12**	−72.02**	−70.07**
	(−5.58)	(−5.42)	(−5.95)	(−5.76)	(−5.96)	(−5.76)
A5	−0.3639	−0.3949	−0.2730	−0.3012	−0.2682	−0.2930
	(−1.29)	(−1.38)	(−0.97)	(−1.05)	(−0.95)	(−1.03)
M1	−3.138**	−3.065**	—	—	—	—
	(−6.93)	(−6.67)				
M2	—	—	−0.03886	−0.003699	—	—
			(−0.33)	(−0.03)		
M3	—	—	—	—	0.07426	0.1044
					(0.43)	(0.61)
EARN	−7.151**	−7.266**	−6.773**	−6.895**	−6.766**	−6.878**
	(−6.66)	(−6.36)	(−6.21)	(−5.91)	(−6.20)	(−5.89)
LIQ	−3.334**	−3.384**	−3.762**	−3.855**	−3.789**	−3.828**
	(−15.11)	(−15.12)	(−14.63)	(−14.78)	(−17.65)	(−17.61)
SIZE	−0.08337**	−0.07844**	−0.1604**	−0.1519**	−0.1628**	−0.1528**
	(−2.28)	(−2.13)	(−4.33)	(−4.05)	(−4.44)	(−4.13)
HOLD	1.544**	1.537**	1.584**	1.577**	1.586**	1.578**
	(20.22)	(19.80)	(20.68)	(20.25)	(20.70)	(20.26)
BR1	0.1272*	0.1465*	0.09639	0.1188	0.09740	0.1203
	(1.70)	(1.93)	(1.28)	(1.56)	(1.29)	(1.58)
BR2	0.4365**	0.4457**	0.4091**	0.4214**	0.4111**	0.4218**
	(5.02)	(5.07)	(4.69)	(4.79)	(4.73)	(4.81)
LLF	−9977.873	−9793.731	−9899.691	−9713.783	−9899.654	−9713.608
R^2	0.0650	0.0660	0.0630	0.0630	0.0630	0.0630

NOTE: Single asterisk (*) denotes significance at .1; double asterisk denotes significance at .05.