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BY

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INSOLVENCY AND FAILURE IN THE SAVINGS AND LOAN INDUSTRY

By

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I. Introduction

In the six year period from 1980-1985, nearly 600 thrift institutions insured by the Federal Savings and Loan Insurance Corporation (FSLIC) failed, an annual failure rate exceeding that of the Depression years from 1930 to 1933. Currently there is an even greater concern about the insolvency and likely failure of an additional 500 or more Savings and Loan Associations (SLA). These institutions remain in operation due to the use of Regulatory Accounting Principles (RAP) and Federal Home Loan Bank Board (FHLBB) net worth certificates which allow insured SLAs to overstate their equities and more recently due to the under capitalization of FSLIC. An optimistic view of the industry indicates that there are more than 830 SLAs with RAP net worth less than 3 percent of total assets. The high incidence of insolvency in the industry is coincident with several important changes in SLA regulation; including the Depository Institutions Deregulation and Monetary Control Act (1980), the Garn-St. Germaine Act (1982), the increased use of secondary market instruments to restructure SLA portfolios, and the introduction of many new interest rate sensitive asset and liability products.

The purpose of this study is to develop an econometric model that accounts for the timing of insolvency given SLA portfolio structure. The model represents a departure from previous empirical studies of SLA failure, because it is not the closing of the SLA that is the major concern of this research. Instead, the focus taken is the portfolio management decisions made by

SLAs and whether these decisions lead to solvency or insolvency. Since the unit of analysis is the individual SLA, the strategy will lead to estimates of the probability of insolvency, or more accurately the expected residual time until insolvency. Estimated probabilities such as these would be useful as exogenous predictors in FSLIC decisions concerning which institutions to close, which to merge under supervisory mergers, and which to leave alone.

The paper is organized into five sections. A brief review of previous studies of failure in the SLA industry is presented in Section II. A model of SLA insolvency is discussed in Section III and a strategy for estimating the model is developed in Section IV. Techniques used to construct the data set and variable selection are discussed in Section V. The results of the analysis are presented in Section VI and conclusions follow in Section V.

II. Previous Research

Although there are numerous studies of failure in commercial banks (Santano and Vinso, 1977; Sinkey, 1975; Sinkey, 1978; Pettway and Sinkey, 1980; Martin, 1977; Kwast and Rose, 1982; Lane et al., 1986; Meyer and Pifer, 1970), there relatively few studies that have SLAs as their major focus. Probably the most widely cited, is a study by Altman (1977) in which SLAs were divided into three categories: serious problems, temporary problems, and no problems where problem was defined as a SLA that went into receivership or received contributions in the form of loans, purchases of assets, or straight contributions, and those that entered into a supervisory merger. Financial ratios such as the operating ratio, net worth to total assets, borrowed money to total savings were introduced as exogenous factors in a linear multiple discriminant analysis of the three states.

Several more recent studies have been completed by Barth et al (1986), Benston (1986), and Pantalone and Platt (1987). All three of these studies are empirical analyses of SLA closures rather that insolvencies. As in the Altman (1977) study, closure is estimated as a function of financial ratios that proxy for various risk classes such as capital adequacy, usually measured as net worth to total assets, profitability, usually measured as net income to total assets, credit risk, measured as some variant of loans to total assets, interest rate risk, measured as interest sensitive funds to total assets, and liquidity risk, measured as liquid assets to total assets. Similar proxies have been used to model closure in commercial banking (Martin, 1977; Sinkey, 1975; Avery and Hanweck, 1984; and Lane, et al., 1986).

The statistical techniques used in the SLA studies are multiple discriminant analysis or logit analysis. The dependent variable in these studies is a single state measure of whether the institution has exited the market, either through closure or supervisory merger, as a function of risk proxies. The timing effects of closure are not accounted for and the institutions are treated as nonfailures until they are observed to fail. Only one recent study of commercial banking (Lane et al., 1986), has better exploited the availability of panel data for regulated financial institutions. The Lane et al. study applies the Cox proportional hazards model (Cox, 1972) which accounts for the timing of closure, however, closure is again modeled as a function of constructed proxies as previously discussed.

All of the previously cited work models closure or supervisory merger without accounting for the fact that the most frequently included proxy for capital adequacy, net worth to total assets, is strictly speaking an endogenous variable. Since closure or merger can only occur through direct regulatory action, models of the market exit of financial institutions are actually models of regulatory closures rules which are exercised conditional on the solvency or insolvency of institutions. As the Barth et al. study clearly indicate (Barth et al., 1986) the more binding FSLIC's capitalization constraints the less likely that closure and economic failure are temporal equivalents. Since regulatory authorities determine closure or merger institutions from a nonrandomly selected distribution of institutions that are insolvent, models of closure must also account for the prior determination of the financial condition of the bank or thrift institutions.

Thus, an important research task that has not been adequately addressed is the determination of SLA insolvency as a function of the portfolio decisions of the institutions. Such a model should account for the timing of insolvency since interest rate risk and duration mismatch are functions of the shape of the yield curve. The model should also account for the credit worthiness of the portfolio and its on and off balance sheet activity. Specification and estimation of SLA profitability is the necessary first step in modeling closure rules accounting for the financial conditions of the institutions and their likelihood of survival. This task is addressed in the following three sections.

III. A Model of Thrift Profitability

A difficult and as it turns out currently intractable problem in analyzing SLA economic performance is that the income that the SLA earns from supplying intermediation services is codetermined with the capital gains and losses on its portfolio of assets and liabilities. At least conceptually it is possible to distinguish the various product lines of an institution and thereby identify specific sources of risk. As Hess (1987) and Santomero (1987) have shown, the single period intermediation income (Y_t) accruing to an institution's equity holders can be stated as

$$(1) \quad Y_t = \Sigma\, \Sigma\, r^a_{ni} A_{ni} - \Sigma\, \Sigma\, r^l_{nj} L_j + \Sigma\, F_q - C(A_i, L_j, F_q)$$

where r^a_{ni} and r^l_{nj} are defined for each maturity n as the uncertain returns to asset i and liability j, A_{ni} and L_{ni} are the beginning of the period market values of assets and liabilities, respectively, F_q is fee income per period, and C(.) is the cost function.

The profit function can be further dissected into four activity types:

$$
\begin{aligned}
(2)\quad Y_t = {} & \Sigma\, \Sigma\, (r^a_{ni} - r^l_{ni})\, A_{ni} - C(A_i \mid L_j, F_q) && \text{Credit Risk} \\
& && \text{(Default Intermediation)} \\
& + \Sigma\, \Sigma\, (r^m_{nj})(A_{ni} - L_{nj}) && \text{Interest Rate Risk} \\
& && \text{(Maturity Intermediation)} \\
& + \Sigma\, \Sigma\, (r^m_{ni} - r^l_{nj})\, L_{nj} - C(L_j \mid A_i, F_q) && \text{Transactions} \\
& && \text{(Denomination Intermediation)} \\
& + \Sigma\, F_q - C(F_q \mid A_i, L_j) && \text{Fee Income}
\end{aligned}
$$

where r^m_{ni} is the market's risk free price for funds to finance asset i for maturity term n. The cost function appears as conditional in each of its terms given there may be economies of scale or scope arising from jointness in production.

Assuming that assets and liabilities remain on the books, the market value of the thrift, V_e, is the discounted present value of the expected income stream

$$(3)\qquad V_e = \sum_{i=0}^{\infty} B^i\ E(Y_{t+i})$$

where B^i is the market discount rate, E(.) is the mathematical expectations operator, and Y_t is net intermediation income as defined above. If the ratio of V_e to total assets is greater than 3%, the limit previous to Garn-St.Germain, then the institution continues operations. If V_e to total assets is less than or equal to 3%, the deposit insurer would be expected to take one of two actions. If the ratio is greater than zero the SLA has going concern value and the insurer might supervise a merger or sell the thrift. If the term is less than or equal to zero the thrift does not have going concern value and it should be closed. It is important to notice here that it is the future expected profits not past expected profits that determine the market value of thrift net worth.

Although conceptually this is the process leading to market exit, in fact thrift assets and liabilities do not mark to market and thus accurate measurement of the going concern value and liquidation value of gains and losses is not currently available. The regulatory evaluation of the financial performance of thrifts occurs through the analysis of accounting income. A serious problem with this strategy is that the going concern value of the thrift cannot be distinguished from the capital gains and losses due to interest-rate and credit surprises. Because accounting income always moves inversely to market interest rates, given the duration imbalance between assets and liabilities, accounting and intermediation income measures would be expected to provide very different indications of performance.

Accounting net income before taxes in period t can be represented as

$$(4) \qquad Y(ACC)_t = \Sigma\,\Sigma\, r^a_{ni}\, BA_{ni} - \Sigma\,\Sigma\, r^l_{nj}\, BL_{nj} + \Sigma\, F_q - C(BA_i, BL_j, F_q) - \delta\, K.$$

Here BA and BL are the book values of assets and liabilities by maturity class at period t, δ is the rate at which depreciation is charged against earnings, and K the gross book value of physical capital. As Hess (1987) has demonstrated accounting and intermediation measures of financial performance will differ to the degree that the institution has not successfully hedged the duration imbalance in its portfolio. One further problem with the accounting measure of profitability is that it does not enable one to identify the various sources of risk in the product line management of the institution. These risk elements are now embedded in valuation techniques used to measure assets and liabilities and in the imputed rates of return for each asset and liability class.

Although interest rate risk and credit risk are hopelessly intermingled, in equation (4), the equation does demonstrate that the appropriate measure of financial performance requires the estimation of the fully specified accounting function. The common use of proxies for the various risk classes in early warning studies of SLA failure (Barth et. al., 1985; Pantalone and Platt, 1987; Benston, 1985; Altman, 1977) also intermingle credit and interest rate risk as long as book value measures are used to define these proxies. Additionally, by not estimating the fully specified accounting profit function, proxies will reflect the effects of omitted assets and liabilities in addition to the joint effects of credit and interest rate risk.

Since the interest here is insolvency and only accounting measures of assets and liabilities are available, it is also important to determine the relationship between the book value of net worth and the market value of net worth defined in equation (3) above. A perfect forecast present value for V_e at time t can be defined as

$$(5) \qquad V_{et}^{*} = V_{et} + u_t$$

where u_t is the forecasting error which under rational expectations would be "white noise". The book value of net worth, $V(ACC)_{et}$ is equal to

$$(6) \qquad V(ACC)_{et} = (1/B)\ V(ACC)_{t-1} + (1/B)Y(ACC)_{t-1},$$

again if assets and liabilities remain on the books. Given (3) and (5) and assuming that market net worth and book net worth are the same when the assets and liabilities are entered on the books at time T, market net worth can be defined as

$$(7) \qquad V_{et} = V(ACC)_{et} - \sum_{j=0}^{\infty} B^{-j}\ u_{t-j}.$$

implying that the book and market-value measures of performance differ by a "white noise" error term reflecting unanticipated and unrealized capital gains and losses. Equation 7 holds, of course, only under the assumption that the two measures were equal at the time of origination which may not be true if the value of such intangibles as goodwill or customer relations are not included in measures of book net worth (Maisel, 1979).

It is clear from this comparison of accounting and mark-to-market measures of profitability that past profits may be a poor indicator of the market value of net worth. If expectations change at some future time, market and book value measures of net worth would be expected to diverge systematically. Additionally, statistical estimations of SLA profitability using accounting income will always blur the effects of interest rate and credit risk in the portfolio structure. Finally, estimation of firm insolvency using book value net worth as shown in equation (7) can at best only measure the liquidation value of the thrift and not its going concern value which is a serious limitation of current accounting practices and the data available to those interested in evaluating profitability.

IV. Estimation of Thrift Insolvency

As previously discussed most empirical studies of the performance of an intermediation institution's performance analyze accounting income. In these statistical cost accounting studies imputed rates of return are estimated for the balance sheet as a function of net income (Hester and Zoellner, 1966; Gendreau, 1983). These studies usually estimate an equation of the general form of equation (4) with the exclusion of the off balance sheet activity represented by F_q, fee income. The usual form of these models is

$$(8) \qquad Y_{ACC}^{*} = \beta_0 + \Sigma\, \beta_{it}\, Z_{it} + \varepsilon_{it}$$

where β_0 reflects net fixed revenue, Z_{it} are the book values of the i^{th} asset or liability class, and the β_{it}'s are the net imputed rates of return obtained by the statistical allocation of overhead, losses, revenues, and costs to the institution's balances. Because of the balance sheet identity one asset or liability must be deleted for equation (8) to be in an estimable form. Since data are not currently available on the maturities of various assets and liabilities by class, equation (4) is estimated as a function of the gross book value of asset and liability classes thus further blurring the effects of interest rate versus credit risk. The parameter estimates in these models are interpreted as net rates of return.

From equation (6) above, the book value of net worth is a function of past book net worth and past cash accounting profits. Thus within the statistical cost accounting framework the book net value of the thrift can be represented by returns on the one period previous book values of asset and liability classes.

Thus, by substitution the book net worth can be represented as

$$(9) \qquad V(ACC)_{et} = \Gamma_i\, \Sigma\, \beta_{i\,t-1} Z_{i\,t-1} + V(ACC)_{t-1} + e_{it}$$

Under the current regulatory structure, thrifts would be considered to be GAAP solvent if at time t the value of $V(ACC)_{et}$ was greater than zero. Thus, the unconditional probability that a thrift institution is solvent at time t is

$$\Pr\ (\ V(ACC)_{et}\ >\ 0\ ). \tag{10}$$

From a regulatory perspective, there are advantages in predicting severe weakness in an institutions well in advance of failure. A desirable characteristic of a weakness prediction model would be that it determines not only that an institution, given its portfolio structure, has an elevated probability of becoming insolvent but also indicates the timing of likely insolvency for problem firms. With such a model FSLIC could predict from a fixed evaluation date not only which firms would be unlikely to survive a given horizon date but the timing of insolvency in the problem population. With such information FSLIC could better sequence its interventions.

The Proportional Hazard Model has been used extensively in the biomedical and demographic literature because it does account for both the occurrence and the timing of failure (Cox,1972; Kalbfleisch and Prentice, 1980). Increasingly the model is appearing in economic research involving analysis of panel data sets (Keifer, 1988; Heckman, 1981) where interest is in the duration of economic phenomena. A central concept of the hazard models is that the conditional probability of survival is estimated (e.g. the probability of insolvency at time t given that the institution has survived to t-1) rather than the unconditional probability of insolvency (e.g. the probability that an institution becomes insolvent in exactly t periods). Briefly, T is defined in these models as a continuous nonnegative random variable representing the survival time of an individual SLA and Z is a vector of book values of assets and liabilities, $Z(t) = \{z(t),\ 0<\tau<t\}$ as defined above. A survivor function $S(t|Z)$ can be defined as

$$(12) \qquad S(t|Z) = \mathrm{Prob}(T \geq t|\ Z),$$

where $S(0) = 1$ and $S(\infty) = 0$. The distribution function of time to failure is defined as $F(t|Z) = 1 - S(t|Z)$ and the density function is, $f(t|Z) = S'(t|Z)$. The conditional density of the institution's failure at T = t given that the thrift has survived up to time t is called the hazard rate and is defined as

$$(13) \qquad h(t|Z) = \frac{f(t|Z)}{S(t|Z)} .$$

Under the proportional hazard model hypothesis, the conditional probability of insolvency is a function of two multiplicative factors; a "baseline" hazard representing the proportion of the population that would fail under stationary and homogeneous conditions and a second factor which is greater than or less than one depending on whether elements of the portfolio make insolvency more or less likely. Thus, it is assumed that the hazard rate above is separable and proportional (Kalbfleisch and Prentice, 1980) and can be written as

$$(14) \qquad h(t|Z) = \Phi(Z)\, h_0(t),$$

where the $h_0(t)$ is the "baseline" hazard corresponding to $\Phi(.)=1$ and $\Phi(Z)$ is some function of Z such that $\Phi(0)=1$. By defining all SLA's exogenous variables as deviations from the sample mean, a thrift with Z=0 is a thrift with book value balances of assets and liabilities at the sample mean. Thus, $h_0(t)$ is interpretable as the hazard function for the "average" thrift in the sample. This strong underlying assumption of the proportional hazards model implies that the effect of the exogenous variables is to multiply the hazard of an average thrift, by some function $\Phi(Z)$ of the deviations of the explanatory variables from their mean values.

Cox's model (1972) assumes that $\Phi(z)$ is of the form, $\Phi(Z)=\exp(\Gamma'Z)$, where Γ is a vector of regression coefficients and the β's have been suppressed to simplify notation. The hazard function is defined as

$$(15) \qquad h(t|Z) = \exp(\Gamma'Z)\, h_0(t).$$

The model is semiparametric in the sense that the hazard $h_0(t)$ is assumed to be arbitrary and no distributional assumptions are required to estimate either Γ or $h_0(t)$. The model in exponential form implicitly contains two assumptions. First, the ratio of the hazard functions for two institutions with different sets of covariates does not depend upon time. Second the model is the log-linear effect of the covariates upon the hazard function.

Estimation of the conditional probability that an institution with covariate vector, z_i, will fail at time t_i given that a single failure occurs at t_i, is the ratio of the hazard for the individual institution divided by the sum of the hazards for all the institutions who could have become insolvent at time t_i:

$$\exp(\Gamma' z_i) / \Sigma \exp(\Gamma' z^j). \tag{16}$$

The likelihood is formed as the product of the individual contributions. The likelihood in the case of ties among the times of failure was proposed by Breslow (1974) and appears as:

$$L(\Gamma) = \pi \{ \exp(\Gamma' s_i) / [(\Sigma \exp(\Gamma' z_j)]^{m^i} \} \tag{17}$$

where m^i is the number of failures at time t_i and s_i is the vector sum of the m_i institutions.

V. Sample and Variables

Data for this analysis were obtained from the Federal Home

Loan Bank Semi-annual and Quarterly Financial reports beginning June of 1980 through March of 1987. Insolvent SLAs for the purposes of this analysis included all those institutions with reported GAAP net worth of less than or equal to zero, all the institutions that were closed during the period, and all institutions that were merged and had GAAP net worth of less than or equal to zero at the time of merger.

The intervals of analysis for the study were twelve month periods. A ten percent sample of institutions was drawn from the December financial report for each year from 1980 through 1987. The sampled institutions were then followed until the following December. Those institution that became GAAP insolvent at some point in the interval and never moved out of that status during the eight period of analysis were considered to be failed institutions. Those institutions that did not become GAAP insolvent over the interval were considered to be survivors. These survivors or solvent SLAs were then treated as censored observations because within the interval all that is known about these firms is that they were solvent until the end of the twelve month period.

The sample frequencies for each of the twelve month intervals are reported in Table 1. The sample is quite representative of the actual population of institutions over each time interval. The sampling strategy yielded a total sample size of 2,270 firms of which 76 are insolvent. Forty four of the failed institutions are mutuals and 32 of them are stock corporations.

The variables included in the analysis and their mean values are reported in Table 2. The notable differences between the portfolio structures of solvent and insolvent SLAs is the greater relative risk of the asset and liability allocations of the two classes of institutions. The insolvent SLAs hold riskier types of mortgages in the form of more 5 plus dwelling unit mortgages and mortgages on undeveloped land. The mean levels of foreclosed assets are higher for the insolvent SLAs and they hold more substantial equity holdings in service corporations and subsidiaries.

The asset holdings of secondary mortgage instruments also differs between the solvent and insolvent SLAs. The solvent SLAs hold more conventional and insured mortgage pass-through securities than the insolvent institutions. The differences between the two classes of firms is less apparent on the liability side of the balance sheet, although the insolvent firms have more fixed maturity deposits and not surprisingly more FHLB advances. Insolvent firms also hold substantially larger proportions of their liabilities in other borrowings such as commercial loans, mortgage backed bond issues, and reverse repurchase agreements.

The variables comprise all the asset and liability classes, with the exception of goodwill, that appear on the balance sheet plus non operating income from prepayments, sale of foreclosed real estate, and mortgage servicing and sale activity, as specified by equation (9). Because regional economic effects were thought to effect insolvency rates data were also obtained from the Salomon Brothers Real Estate Research division for employment and unemployment growth over the analysis period. These data were then merged with the master files by state of charter. This strategy, in retrospect, seriously ignored the network structure and regional diversification of many SLAs which increasingly operate across several states.

Most statistical cost accounting studies "deflate" the balance sheet variables by total assets to correct for heterskedasticity caused by scale effects. In principle violations of homoskedasticity are testable at least in the ordinary least squares framework. Preliminary analyses of the profit function, in the ordinary least squares framework, indicated violations of homoscedasticity assumptions. For this reason total assets were used to deflate all the balance sheet variables and all the variables are entered in percentage form.

VI. Estimation Results

The results from the estimation of the proportional hazard model are presented in Table 3. The reported results predict to the probability that a given institution will survive until period t given that it has survived until period t-1. The survival time is defined as the time (in months) from the initial December observation of the SLA until the institution becomes insolvent or the 12 month interval ends. All solvent SLAs have the same censored survival times. The sampling framework is intended to provide results similar to those of other early warning models of institutional failure. The framework allows for an estimation of the conditional probability that a firm given its balance sheet characteristics at the beginning of the evaluation period will fail at some specific time in the next 12 months.

As previously discussed, an important assumption of the proportional hazards model is that the $\Phi(.)$ factor in equation (14) does not depend on duration t. Under the assumption that this function is defined as $\Phi(\Gamma'Z) = \exp(\Gamma'Z)$, the partial derivative of the log of the hazard function with respect to the Z vector of exogenous variables is simply the parameter vector Γ. The vector of coefficients can therefore be interpreted as the constant proportionality effect of the exogenous balance sheet characteristics on the conditional probability of completing a 12 month interval. The proportionality assumption implies that the values of the independent variables remain constant for each thrift over the 12 month time interval. The exogenous factors for each firm are the December financial statement proportions at the beginning of the twelve month interval for the sample in which the firm was drawn.

A positive coefficient in the proportional hazard model indicates that an increase (decrease) in the variable is associated with a decrease (increase) in the conditional probability of solvency. Given that the function estimated is the profit function it would be expected that assets should reduce the likelihood of insolvency, since they should increase profits, and liabilities should on average decrease the conditional probability of insolvency since as they decrease profits. As shown in Table 3, a number of the asset classes have positive signs implying that higher proportions of these assets would decrease the conditional probability of solvency. The assets that have a statistically significant effect on the hazard function and have positive signs are Unimproved Land Mortgages, holdings in Service Corporations and subsidiaries, Foreclosed Real Estate, and Fixed Capital Assets used in the operation of the institution such as buildings. This result for service corporations is consistent with recent Senate hearings which have lead to restrictions on these investments by insured thrift institutions.

Less risky mortgage asset classes such as mortgages on 1-4 dwelling units and mortgage backed securities have the correct sign but they are not statistically different from zero at the .05 level. The results are equally disappointing for the other asset classes. Although Consumer Loans, Commercial Loans, and Real Estate Held for Development all have positive signs, suggesting higher proportions of these assets increases the conditional probability of solvency they are not statistically different from zero at the .05 level. Thus, higher proportions of these relatively less risky mortgages do not apparently have a statistically important effect on remaining solvent. The asset class, Other Investment Securities, is a catchall category including Collateralized Mortgage Obligations, U.S. government agency securities and stock for the stock corporations. Although the parameter estimate for these securities is positive it is also not statistically different from zero.

The liabilities all have the expected sign, however, only NOW, Super NOW and Transaction Accounts and FHLB Advances are statistically significant at the .05 level. Fixed Maturity Deposits and Other Borrowings are statistically significant at the .1 level, which is a rather weak result given the sample size. These results are appealing, however, since there is considerable evidence that weaker institutions have expanded their market share on deposit accounts by paying relatively higher rates and by actively bidding for brokered money. The result for the FHLB advances is also as expected, in that higher levels of borrowing from the Federal Home Loan District Banks reflects shortfalls in other areas of the portfolio and thus would be expected to decrease the conditional probability that the institution would remain solvent.

The one period previous Gaapnet worth, the magnitude of non-operating income from prepayments and sales of mortgages, and relative employment growth in the institutions state all have the anticipated signs, however, none of them are statistically significant at the .05 level. The ^{2} likelihood ratio test of the significance of the overall model was rejected at $p \leq .0001$

and R statistic of goodness of fit based on the Akaike information criterion (Atkinson, 1980) was .325. Plots of the generalized residuals for the fitted model against the value of the cumulative hazard function were essentially straight lines through the origin, suggesting an adequate level of fit for the model. Proportionality assumptions were graphically evaluated for the exogenous variables. There were two possible violations of proportionality found one for the service corporation variable and the other for year of failure. Both graphs indicated crossovers in the log survival function, however, reestimation on subsamples determined by these variables did not lead to major differences in the parameter estimates.

As discussed previously, it is difficult to interpret the parameter estimates for an indication of the sources of risk in SLA portfolios. The estimates reflect a blending of interest rate and credit risk. As suspected, however, the results appear more suggestive of credit risk mismanagement given the statistical significance of clearly riskier assets such as mortgages for the acquisition and development of land and the proportion of the foreclosed real estate in the portfolio. The effects of interest rate risk may be reflected in the results found for the liability classes. For example, the NOW and Super NOW accounts reprice with the market and thus may expose the institution to considerable interest rate risk if the mortgages held in portfolio are not adjusting to market prices at the same rate. Unfortunately, it was not possible to break the mortgage classes down into their constituent contract classes, because the early eighties data does not include this information. The interest rate risk exposure reflected in the asset holdings of these firms is completely obscured.

IV. Classification Results

A desirable byproduct of an early warning statistical model is that it successfully classifies institutions as problem and nonproblem firms over some exogenously determined evaluation horizon. An advantage of the proportional hazard model is that it provides estimates of the expected residual length of survival for firms for any given time over the evaluation horizon. This additional information on the timing of failure has the potential to provide regulators a mechanism to better evaluate the costs and sequencing of closure decisions. Thus, residual failure times from a model such as the model presented here and relative closure costs for firms could be used to estimate closure rules.

The classification rule proposed is similar to those used for logit and probit analysis of closure (Martin, 1977; Avery and Hanweck, 1985) and in a previous Cox regression analysis of commercial bank failure. A survivor function as in Equation (12) is calculated for each institution in the sample. Given the specification for the $\Phi(.)$ factor as discussed above, the survivor function for a firm at t is simply the integrated baseline hazard at t multiplied by the conversion factor $(\exp(\Gamma' zi)$ for each firm. If the calculated survivor probabilities are less than some threshold value, the institution is classified as a probable failure. Determination of threshold values has been considered in Martin (1977) and Lane et al. (1986) and in the logit and probit literature (Ben Akiva and Lerman, 1985). The common strategy is to use a value that implies a better classification than that obtainable by chance using sample or population proportions of the possible events. Thus, in this case the threshold value is the sample proportion of solvent institutions or 96.7%, so any prediction of survival that is less than this value is considered as a failure or an insolvent institution.

The results of this classification scheme are reported in Table 4. As shown, the errors are broken down into two types, Type I errors, the misclassification of an insolvent firm and Type II errors, the misclassification of a solvent firm. Thirty percent of the insolvent firms were predicted to be solvent at their actual time of insolvency. The Type I error, however, falls to eighteen percent misclassification in the prediction of the eventual failure (before the end of the 12 month interval) for the failed firms. Eighteen percent of the solvent firms were incorrectly classified as insolvent by the end of the 12 month interval.

Generally, to be useful as an early warning mechanism, a model should lead to fewer Type I errors which are the more serious error given the costs to the industry and to FSLIC of leaving an insolvent thrift in operation. Weighting the importance of these errors suggests that the present models fails to attain sufficient precision in accurately predicting the actual time of insolvency. Using the Korobow and Stuhr (1985) strategy of evaluating the efficiency of early warning models a weighted efficiency of the model was calculated. The weighted efficiency measure accounts for the percentage of institutions classified correctly (PCC) and then weights this value by the percentage of institutions that failed the threshold test and actually failed (PAF) and the percentage of the insolvent institutions correctly classified by the model (PCF),

$$WE = (PCC)\ (PAF)\ (PCF). \tag{18}$$

A perfect model would lead to a WE of 100 percent. The measure is sensitive both to the percentage of failed institutions that were classified incorrectly and the percentage of these in the threshold segment. The value for this model is 9.4%. This value reflects the finding that while 82% of the sample was classified correctly only 14% of the failed classifications actually failed. The model compares favorably to previous early warning models (Sinkey, 1975; Pantalone and Platt, 1987; Lane et al., 1986; Martin, 1977; Barth et al., 1986) in terms of accurate prediction of failed institutions, however it compares less favorably to Sinkey (1975) and Lane et al. (1986) in terms of weighted efficiency.

As a further test of the predictive efficiency of the model a random sample of firms not included in the original sample was drawn for the 1986 12 month interval. In this sample there were seven firms that were insolvent and 228 firms that were solvent at the end of the interval. Twenty nine percent of the insolvent firms were misclassified as solvent firms at the actual date of insolvency. Eventual insolvency was misclassified for only one firm, a 14% misclassification rate. The magnitude of the Type II errors was comparable to the within sample results with 20% of the firms incorrectly classified as failures.

One limitation with the proportional hazard model as a classification tool is that extrapolation outside the time interval used to estimate the model is not legitimate. Thus it is not possible to predict the survival probability for month thirteen given the estimated conditional probability from within a 12 month interval. For this reason, it is difficult to predict, given portfolio data for December 1985, whether firms that are mistakenly predicted as insolvent in the 1986 twelve month interval are in fact firms which became insolvent in periods outside the twelve month interval and into 1987 or 1988.

As a final indication of the types of survival analysis possible with a proportional hazards model, plots of the survival functions of the mean vector of portfolio characteristics for solvent and insolvent institutions for the in sample averages are shown in figure 1. The survivor functions for the insolvent institutions drop sharply indicating a less than 88% chance of the average such institutions remaining solvent past the eleventh month of a twelve month evaluation interval. The value of this information is that it affords regulators further flexibility in planning for and funding mergers or firm closure.

VI. Conclusions and Extensions

Given the present data constraints in the analysis of the SLA industry, empirical studies are limited to book value analyses of classes of assets and liabilities with inadequate information on the interest rates and maturities of these portfolio entries. Under these circumstances, empirical results will necessarily confound the effects of interest rate risk and credit risk. Conclusions are thus limited to indications about the gross effects of classes of assets and liabilities on the probability of insolvency. With these limitations and qualifications, it does appear to be important to accurately model the profit functions of the firms to avoid misspecification bias and to account for the timing of insolvency. The results of these analyses indicate that there are differences across the types of assets and liabilities included in the portfolio of insolvent and insolvent SLAs. In particular, it appears that insolvent SLA are much more heavily involved in riskier assets which at least given interest rate movements in the last three years have proven to be a less successful strategy than larger holdings of conventional mortgages on 1-4 dwelling units or mortgage backed securities. This finding is particularly interesting because the analysis period includes 1980 through 1982, which is considered to be a period when interest rate risk mismanagement was the cause behind most thrift insolvency and when at least theoretically 1-4 dwelling unit mortgages, which were primarily fixed, overly exposed institutions to interest rate risk.

As was shown in this analysis the proportional hazards model allows for relatively efficient prediction of firm insolvency. Given the assumption about the form of the conversion factor in the hazard function, the estimated coefficients were shown to have partial derivative interpretations similar to ordinary least squares parameter estimates. The estimation results for the SLA profit functions and GAAP net worth were generally reasonable and interpretable. The model was relatively efficient in accurately predicting insolvency and it provides important timing information which should be extremely useful to regulators charged with identifying and acting upon problem institutions. As estimated the proportional hazards model does have several important shortcomings in analyses such as these. First, the estimation results are extremely sensitive to prior assumptions, such as the form of the conversion factor. Second, in fact most of the asset and liability classes held in SLA portfolios should be accounted for as duration dependent which suggests that these models should be estimated with time varying explanatory variables. Unfortunately, maturity and interest rate data are not currently available, so that explicit representations of the effect of time on important explanatory variables cannot be assessed. Despite these constraints, predictions from timing models such as this do provide at least preliminary information useful for regulatory closure and merger policies.

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TABLE 1

RANDOM SAMPLE FREQUENCIES FOR EACH TWELVE MONTH INTERVAL

	TWELVE MONTH INTERVALS						
	80/81	82/82	82/83	83/84	84/85	85/86	86/87
SOLVENT SLAs	357	330	344	306	316	265	276
INSOLVENT SLAs	5	19	16	8	14	9	5

TABLE 2

VARIABLE DEFINITIONS AND BALANCE SHEET PROPORTIONS

VARIABLE	MEAN PROPORTION OF TOTAL ASSETS (PORTFOLIO AT INTERVAL START DATE)	
	SOLVENT (n=2194)	INSOLVENT (n=76)
MORTGAGE ASSETS		
1-4 Dwelling Unit Mortgages	.593	.506
5 Plus Dwelling Unit Mortgages	.110	.141
Unimproved Land Mortgages	.015	.056
Mortgage Backed Securities	.066	.045
NONMMORTGAGE ASSETS		
Consumer Loans	.034	.051
Commercial Loans	.007	.011
Real Estate Held for Development	.002	.004
Foreclosed Real Estate	.004	.021
Other Investment Securities	.134	.131
Service Corporations	.006	.017
Fixed Assets	.021	.023
LIABILITIES		
Fixed Maturity Deposits	.604	.586
NOW, Super NOW and Transaction Accounts	.024	.039
Money Market Deposit Accounts	.051	.040
Passbook Accounts	.148	.089
FHLB Advances	.041	.070
Other Borrowings	.067	.159
GAAPNET	.057	.010
TOTAL NON-OPERATING INCOME	.001	.002
EMPLOYMENT GROWTH	.021	.016

TABLE 3

COX PROPORTIONAL HAZARD ESTIMATES
OF THE RATE OF SLA SOLVENCY
DECEMBER, 1980 - MARCH, 1987
(SOLVENCY = GAAPNET > 0)

	PARAMETER ESTIMATE	STD. ERROR
MORTGAGE ASSETS AT INITIAL PERIOD		
1-4 Dwelling Unit Mortgages	-1.860	1.954
5 Plus Dwelling Unit Mortgages	.478	1.991
Unimproved Land Mortgages	3.497	1.727
Mortgage Backed Securities	-3.700	2.517
NONMORTGAGE ASSETS AT INITIAL PERIOD		
Consumer Loans	-2.783	3.674
Commercial Loans	-3.274	6.638
Real Estate Held for Development	-4.491	8.842
Foreclosed Real Estate Assets	7.976	3.412
Other Investment Securities	.363	2.304
Service Corporations	30.311	6.434
Fixed Assets	19.394	9.280
Deferred gains/losses on Mort. Sales	13.322	8.631
LIABILITIES AT INITIAL PERIOD		
Fixed Maturity Deposits	28.608	16.313
NOW, Super NOW and Transaction Accounts	34.453	17.332
Money Market Deposit Accounts	26.978	17.427
Passbook Accounts	23.385	16.162
FHLB Advances	33.219	16.348
Other Borrowings	29.465	16.217
OTHER		
Gaapnet	-10.906	16.798
Non-Operating Income	22.619	30.354
Employment Growth	-4.761	7.588

SUMMARY STATISTICS

Log of the Likelihood = -488.72

^{2}, 21 = 343.22

TABLE 4

CLASSIFICATION RESULTS

	WITHIN SAMPLE (1980-1987) INSOLVENT = 76 SOLVENT = 2194	OUTSIDE SAMPLE 1986 INSOLVENT = 7 SOLVENT = 228
TYPE I ERROR[a]		
At Failure Time	30%	29%
Eventual Failure (End of 12 Month Interval)	18%	14%
TYPE II ERROR[b]	18%	20%

[a] Misclassification of an insolvent institution.

[b] Misclassification of a solvent institution.

FIGURE 1

PREDICTED SURVIVOR FUNCTIONS FOR
SAMPLE AVERAGE FOR SOLVENT AND INSOLVENT INSTITUTIONS

(A=Solvent, B=Insolvent)