

Classifying Financial Distress in the Life Insurance Industry

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ABSTRACT

This study presents models which incorporate variables designed to identify the financial solvency of life insurers. The purposes of this article are twofold: to review the financial operations of life insurers in order to detect variables which may be helpful in monitoring their solvency, and to examine the applicability and efficiency of alternative multivariate models for solvency surveillance of life insurers. Thus, decision tools are developed based on real data, and systematic statistical frameworks are applied for evaluating the financial viability of life insurers. Three multivariate analyses have been used: Multidiscriminant Analysis (MDA), nonparametric analysis, and a logit analysis. Most IRIS tests, the decomposition measures and other financial ratios have been found to be accurate measures for classifying failures in a multivariate framework. The analyses correctly classify between 82 and 91 percent of the life insurers one and two years prior to insolvency. It appears that the nonparametric analysis and the logit model dominate the MDA. However, further analyses of these models and a prospective probability model indicate that more than one multivariate analysis may be required to measure the probability of failure.

Introduction

Prediction of financial insolvency of insurers is a major concern of insurance consumers and regulators. In the property-liability sector of the industry, over 130 firms have failed in the last decade, making insolvency a major issue for the National Association of Insurance Commissioners (NAIC), state regulators, and state and federal legislators. Life insurer failures have not been a serious problem in the past, but the number of such insolvencies has been increasing. Over 70 insolvencies have been reported since 1975; in addition, about 30 companies have been dissolved.¹ Although most

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¹ Many other life insurers voluntarily dissolved, withdrew, voluntarily withdrew, or withdrew by dissolution. The authors' inquiries concerning the differences between these terms were unfruitful.

failed life insurers have been small in terms of premium and liability volumes, the number of insolvent life insurers is a statistic worthy of attention.

During the 1970s the NAIC developed the Insurance Regulatory Information System (IRIS). Life insurers with four or more of 12 financial ratios outside specified ranges were classified as priority firms for immediate regulatory attention. In the property-liability sector the reliability of a similar 11 ratio system (see e.g., Breslin and Troxel, 1978) has been subject to considerable criticism (see Thornton and Meador, 1977, Hershbarger, 1981, Hershbarger and Miller, 1986). The authors find that the NAIC system is not a reliable predictor of insolvency for life insurers, and it does not provide early warning of financial failures. However, the IRIS ratios and additional listed financial measures have been found to be significant measures for classifying insolvencies where elaborated and more sophisticated multivariate statistical models were employed. Explanatory variables which encompass measures of profitability, liquidity, growth, decomposition of assets and liabilities, and stability of performance are used in this study. The selection of such variables is not a straightforward task. It must be operationally related to the financial characteristics of life insurers.

The models presented in this article extend previous models for solvency prediction which have been used in the property-liability industry (e.g., Trieschmann and Pinches, 1973, and BarNiv and Smith, 1987). Most of these studies have used multidiscriminant analysis (MDA) (see Trieschmann and Pinches, 1973, Harmelink, 1974, Pinches and Trieschmann, 1974, 1977, Hershbarger and Miller, 1986, and Ambrose and Seward, 1988) or a closely related zero-one regression model (see Eck, 1982). However, the use of MDA has been recently discouraged in the bankruptcy and risk rating literature (see Kaplan and Urwitz, 1979, Ohlson, 1980, Zmijewski, 1984, and Zavgren, 1985). Beginning in the late 1970s, logit and probit models were employed for solvency prediction for corporations other than insurers (e.g., Ohlson, 1980, and Zmijewski 1984) in order to reduce some of the violations of the basic assumptions of MDA. McFadden (1976) pointed out that the logit model is more robust than MDA, but according to Lo (1986), MDA may be superior to logit if distributions are approximately normal. The authors of this article also present a multivariate nonparametric discriminant model for financial distress identification. The model appears to overcome some of the shortcomings of traditional models such as the MDA and the zero-one regression model. Shaked (1985) provided a prospective probability model for measuring the probability of failure using market and financial accounting data for a sample of 31 publicly-traded large life insurers.

In this article three samples and two additional cross-validation samples of life insurers are considered. Because it appears that more than one

There were about 240 failures and voluntary retirements of life insurers from 1975 through 1985. About 25 life insurers were declared insolvent, dissolved, withdrew, or withdrew by dissolution. Twenty life insurers voluntarily withdrew or dissolved during 1986 (See Best's Reports, various issues from 1975 through 1987).

multivariate model may be required for assessing the vulnerability of failure in the life insurance industry, four different multivariate models were employed: MDA, nonparametric discriminant analysis, logit analysis, and the prospective probability model. This discussion highlights the following dual purposes of this study: to employ multivariate models on the financial data of life insurers and to compare the efficiency as well as the classification power of these models for solvency surveillance in the life insurance industry; and, to detect financial characteristics (and variables) which may be helpful in monitoring solvency of life insurers. The relative contribution of each variable to the assessment of the probability of failure is also estimated.

Relationship to Prior Research

Most previous efforts of insolvency prediction in the insurance industry have been undertaken for property-liability insurers. Early studies used descriptive analysis of financial distress for the property-liability insurance industry. Denenberg (1967) found that Best's ratings provided signals for eventual insolvency. Evans (1968) and Nelson (1971) used several kinds of financial statement analysis and found below-average performance to be associated with insolvency. These authors did not evaluate the classification power of their measures.

Multivariate models are frequently used for predicting financial distress in various industries. Beginning in the late 1960s, multidiscriminant analysis (MDA) was employed for solvency prediction. Altman's (1968) research on industrial corporations provided the foundation for studies on financial distress. Zavgren (1983) summarized the usefulness of MDA and other models for insolvency prediction.

Since the early 1970s, multivariate models have been used for prediction of insolvency in the property-liability industry. Trieschmann and Pinches (1973) and Pinches and Trieschmann (1974, 1977) used financial ratios and MDA to classify 26 solvent and 26 insolvent property-liability insurers two years prior to insolvency. The best single variable correctly classified 75 percent of the sample. Multivariate analysis improved the classification from 86 percent for a combination of univariate ratios, to 94 percent for six-variable MDA. Cooley (1975) reexamined the results of Trieschmann and Pinches while focusing on prior probabilities and misclassification costs. Harmelink (1974) also used MDA to predict the degree of solvency as measured by Best's policyholder rating. MDA or the closely related zero-one regression analysis have also been used by recent work on insolvency prediction for property-liability insurers (see Eck, 1982, Hershbarger and Miller, 1986, and Ambrose and Seward, 1988).

Different approaches for solvency surveillance in the property-liability insurance industry were recently employed. Harrington and Nelson (1986) identified insurers whose premium to surplus ratio was significantly higher than other solvent insurers in their samples. They regressed this ratio against several other financial characteristics of insurers. Residual analysis was then

used to identify 83 percent of a sample of 12 insolvent insurers, approximately similar to a contrasted performance of the NAIC-IRIS ratios. BarNiv and Smith (1987) used a mean/variance ranking method for detecting financially distressed property-liability insurers. The ranking was based on the mean and variation over time of underwriting and investment performance. The method identified between 77 and 84 percent of the property-liability insurers failing within three years prior to insolvency.

Another group of methodologies is based on modern portfolio analysis. Venezian (1983) provided a model that could be used to evaluate the effect of profit margin on insolvency. Hammond and Shilling (1978), Kross (1978), Kahane (1978), Kahane, Tapiero and Jacque (1986), and others employed portfolio analyses for measuring the solidity of property-liability insurers. Gustavson and Lee (1986) employed the capital asset pricing model to investigate the risk-return relationship for life insurers. The overall prediction of the model was weak, but a few variables were significant. The authors concluded that the search for relevant variables must continue. A major contribution of this research will be to identify such variables in the financial data of life insurers.

A review of the prior research in the area of life insurance insolvency reveals that only limited attention has been directed to this topic. Gold (1979) and De Heuck (1981) indicated that deterioration of financial viability of life insurers increased during the late 1970's. Radcliffe (1982) pointed out that all the margins of life and health insurers have disappeared. The profitability of stock life insurers was presented by Pritchett and Wilder (1986). Belth (1984) argued that it is possible for large life insurers to get into financial distress, and that the consequence of such failures would be disastrous, especially in terms of a loss of public confidence in life insurers. Changing economic conditions and industrial factors (such as increasing demand for policy loans) have been cited by these researchers as possible causes of crises. Granger, Mason and Garrison (1987) used decomposition analysis with a sample size of 12 life insurers to conclude that asset and balance sheet decomposition measures were good indicators of failure for life insurers one year prior to insolvency. They concluded that additional research needs to be done using larger sample sizes. Cheong and Skipper (1988) presented a preliminary research scheme for life insurer insolvency prediction. They employed MDA as the multivariate framework for insolvency prediction and factor analysis for variable selection.

A rigorous technique for measuring probabilities of insolvency and its applications to the life insurance industry was presented by Shaked (1985). His findings indicated that large life insurers are reasonably safe, but the distribution of failure probabilities is skewed to the right. thus, a few life insurers posed greater insolvency risk than others in his sample.²

²Shaked (1985) assumes that the assets returns of life insurers are log normally distributed, and modifies the option pricing model while deriving the prospective probability of insolvency.

Because the first working draft was written in 1987, this study is the first to use multivariate analyses for solvency surveillance of life insurers. An investigation of a large set of financial measures, as well as an estimation of the significant contribution of these variables in multivariate frameworks, is conducted. In contrast to previous studies, this article also compares the classification power and efficiency of different multivariate models and employs several samples for estimation and cross validation.

Data and Sample Selection

In this study, insolvent insurers are defined as those companies which were declared insolvent by their respective state insurance commissioners and reported by the A.M. Best Company (Best's Reports, 1975 through 1986). Life insurance companies which were listed as "dissolved" are not included in this study since this term may include voluntary dissipation. Therefore, the sample includes 28 life insurers that failed from 1975 through 1985 for which the required data were available (approximately 40 percent of Best's list of insolvencies). There were an additional 42 insolvencies for which data were not available (60 percent of Best's list), most of which were very small in terms of premium and total asset volumes. A.M. Best included data on life insurers only if they met minimum premium volume requirements.

The solvent companies studied were grouped into two sets. The first set consists of 28 companies which were chosen to match the insolvent firms. This paired-matching was based on: state of domicile; size of assets; and time, using the calendar year prior to insolvency as the first year of data for the matched solvent firm. The second set is a random sample of 49 companies selected from a population of companies listed in Best's Reports (1986) with total assets of less than \$60 million, which is the approximate asset size of the largest insolvent insurer. Also, for every year of required data, there are at least the same number of solvent companies as insolvent ones. A third set was used as a holdout sample. This set consists of 31 solvent companies with data on Compustat.³ A fourth set consists of 31 life insurers identified as priority companies by the NAIC-IRIS during the period 1979 through 1980. This cross-validation sample provides evidence on variables and models which might be useful in identifying insurers in danger of becoming insolvent.

Financial data for all of the life insurers were available from either the A.M. Best Company or the National Association of Insurance Commissioners (NAIC). Although the NAIC does not furnish the IRIS tests for the general

³This sample was also used by Shaked (1985). In our study the sample is used to assess the probability of insolvency among large life insurers based on the coefficients obtained in the analyses. The accounting records were obtained from Best's Reports (1976 through 1982), and only life insurance data were used. An attempt was made to control for potential impact of nonlife insurance affiliates (see e.g., Harrington, 1981). For example, data for the largest life insurer in a holding group were used. However, the inclusion of holding companies that operate in the property-liability lines (e.g., Aetna and Travelers) pose some approximations for evaluating the financial strength of these companies.

public, the IRIS annual reports and data regarding the sampled insurers were obtained from state insurance departments for the years 1973 through 1978 and from Best's Trend Reports (1982 through 1986) for the years 1977 through 1985.

Methodology

Four major empirical models for predicting financial distress are used in this study: MDA; probabalistic logic model; nonparametric multivariate model; and prospective probability model. The discussion in this section focuses on these models and univariate characteristics.

Multidiscriminant Analysis (MDA) and Probabalistic Logit Model

MDA and logit or probit analyses have been the most widely used methods for classifying distressed and sound firms. In general, discriminant functions are based on linear combinations of independent variables that discriminate between two groups. These functions are of the form:

$$Z_j = B_1X_1 + B_2X_2 + \dots + B_kX_k \quad (1)$$

where $(X_1 \dots X_k)$ represents the variables (e.g., financial ratios).

The MDA classification rule for the case of two groups is optional under certain restricted assumptions: the multivariate probability distributions are multivariate normal within each group; the covariance matrices of the two groups are equal; and the vectors of means and the common covariance matrix are known. This traditional classification rule for the case of two groups is assigned an observation with a profile vector x to group 1 (e.g., the insolvent group) if:

$$x' \Sigma^{-1} (\mu_1 - \mu_2) \geq \frac{1}{2} (\mu_1 - \mu_2)' \Sigma^{-1} (\mu_1 + \mu_2) \quad (2)$$

where μ_1 , μ_2 and Σ^{-1} are group means and the inverse of the common covariance matrix, respectively.

The basic assumptions of the MDA are usually violated where financial data and dummy variables are employed. Zavgren (1985), Frydman, Altman and Kao (1985), and others have commented on or criticized misapplication, misinterpretation and biases of MDA in distress prediction models. Ohlson (1980), Zavgren (1985), and others have suggested the use of a probabilistic model of bankruptcy in order to reduce the problems and violations of the basic assumptions of MDA; they employed a multivariate logit model to predict bankruptcies among industrial firms.⁴ Zmijewski (1984) examined estimation biases related to the distress prediction probit model.

⁴For a theoretical discussion of the logit model see McFadden (1974) and Maddala (1983); a comparison with MDA and probit analysis is provided by Amemiya (1981) and others. MDA focuses on the distribution of the profile vector x (explanatory variables) conditional on the dichotomous discrete variable y . In contrast to MDA, logit analysis always involves the distribution of y conditional on x which is assumed to be logistic.

The coefficients of the independent variables are derived by conditional probability models through a dichotomous dependent variable, y_i . The cumulative distribution might be derived by either the logit or the probit models. The logit model is expressed by a cumulative logistic distribution function $F(z)$:

$$F(z) = \frac{1}{1 + e^{-z}} \quad (3)$$

where z is a linear combination of the independent variables. The ex post logit empirical prediction model in a general form is:

$$p(y_i = 1) = \frac{1}{1 + e^{-z}} \quad (4)$$

In practice, logit and probit models overcome some of the basic shortcomings of MDA, but these models are parametric in nature (i.e., x is assumed to be logistic or probit).

NonParametric Multivariate Models

A nonparametric recursive partitioning analysis was employed by Frydman, Altman and Kao (1985) for classifying financially distressed firms. This approach overcomes some shortcomings and problems of the parametric techniques; however, it cannot be used for scoring observations within the same group (i.e., the method does not assign a score to each observation). BarNiv and Raveh (1989) present a nonparametric discriminant model (NPD) which also provides a continuous scoring system. Since the NPD is a new model which has only been developed recently, it will be discussed in more detail.

The nonparametric discriminant model is based on a search for an optional (linear) combination which yields minimum overlapping between two or more groups of observations. The scores of the insolvent group (of n_1 observations) are denoted by Z_i , $i = 1, \dots, n_1$, and the scores for the solvent group by Z_j , $j = 1, \dots, n_2$; n_1 and n_2 do not have to be equal. A search is conducted for an optimal linear combination which yields minimum overlapping between the two groups of scores. The zone of overlap between the two groups of scores obtained by the NPD is always smaller than the overlap obtained by MDA and the model minimizes the number of misclassifications. Thus, an index of separation $IS(B)$ is obtained with the objective of maximizing the following index:

$$IS(B_k) = \frac{\bar{Z}_1 - \bar{Z}_2}{\frac{1}{n_1 n_2} \sum_i \sum_j |Z_i - Z_j|} \quad (5)$$

where $\bar{Z}_1$ and $\bar{Z}_2$ are the mean scores of the insolvent group and the solvent group, respectively. The condition $-1 \leq IS(B_k) \leq +1$ is always maintained.

$IS(B_k) = 1$ implies there is no overlapping between the two distributions of scores of the two groups; i.e., there is maximum separation.

The NPD function of k variables with the coefficients $B_k^* = (B_1^*, \dots, B_k^*)$ is found by maximizing the separation index IS . The maximization index is solved by the Zangwill (1967/8) algorithm which is a modification of the known Powell algorithm. The Zangwill modification requires an initial guess of the k coefficients and is restricted to local maxima. Initial guesses might be based on the data properties, for instance. Other possible initial guesses are the coefficients obtained by the MDA, logit or probit or their signs multiplied by 1.0. Another initial guess might be the uniform vector $B_k' = (1, \dots, 1)$ or $(-1, \dots, -1)$.

Univariate Characteristics

Most previous studies on insolvency prediction for corporations, including property-liability insurers, used financial ratios. Pinches and Trieschmann (1974, 1977) and Harmelink (1974) used a six-ratio MDA and seven-ratio MDA, respectively, to examine property-liability insurers' solvency. Most of these ratios were underwriting-profitability and leverage ratios. Eck (1982) used a zero-one regression model based on financial ratios that would detect dishonesty. Ambrose and Seward (1988) recently employed MDA with Best's ratings (dummy variable) and other financial ratios, including several IRIS tests. A sample of insolvent property-liability insurers from the NAIC early warning system was examined by Thornton and Meador (1977), who concluded that the system was not a reliable predictor of insolvency. Hershbarger and Miller (1986) examined failed property-liability insurers and additional samples of sound and priority companies. They found that the system had very little ability to distinguish between failed and sound insurers.

In this study, financial ratios which are relevant for the life insurance industry are employed. Variables measuring the variability and stability of balance sheet items over time are used. Measures of rapid growth, size and profits are also utilized. The IRIS tests, additional leverages and profitability financial ratios and growth ratios are employed. Thirty-one variables are employed in the various multivariate analyses according to forward stepwise procedures one and two years prior to insolvency. Among these, the 21 most important may be grouped in the following subsets: all 12 IRIS tests; the ratio of net gains from operations and investments to premiums; the log of growth rate of assets and premiums; the premiums to surplus and assets to surplus (leverage ratios); the size of surplus and net gain from operations; and the decomposition measures on both the liabilities and the assets size. A complete list of the 31 variables is presented in Appendix 3.

Measures of ratio stability require data over long periods of time (see e.g., Dambolena and Khoury, 1980, and BarNiv and Smith, 1987). However, data for many insolvent life insurers were limited to three years. The decomposition measures are based on information theory and are also designed to measure the stability and performance over time. They are useful for measuring stability over relatively short intervals, e.g., two years, and therefore are

employed in this study. Lev (1971, 1974), Booth (1983), BarNiv and Raveh (1989), and others provide evidence that decomposition measures are useful in predicting financial distress and demonstrate remarkable results in classifying bankrupt and nonbankrupt industrial firms.

The Decomposition Measures (DM) are computed on the liability size (DM_L) or on the assets size (DM_A). The New Decomposition Measures (NDM) are the absolute value of the decomposition measures. For example, the new liabilities decomposition measure is defined as:

$$NDM_L = \sum_{i=1}^n Q_i \left| \ln \frac{Q_i}{P_i} \right| \quad (6)$$

where i is a component, or a type of liability (including surplus),

$i = 1, \dots, n$. In this study $n = 2$, or $n = 4$.

Q_i = the relative proportion (share) of component i to total balance sheet for a current year;

P_i = the relative proportion (share) of component i to total balance sheet for a previous year. $0 \leq P_i, Q_i \leq 1$,

and the previous year is one year before the current year (which is one year prior to insolvency in the case of the present study). NDM_A are the new assets decomposition measures.⁵

The following liability accounts were used: surplus (equity), which included capital and surplus; net policy reserve; policy claims and policyholders' dividend-accumulated coupons; and all other liabilities. The liabilities were also divided into two components: surplus and all other liabilities. The asset accounts were divided into four components: bonds; common and preferred stocks; mortgage loans and policy loans; and all other assets. Other partitions of liability accounts and asset accounts also were employed, but they are not reported in this article because they were less significant and highly correlated with the reported decomposition measures.

The major significant variables used in the analyses and the expected direction of their effect on the probability of insolvency are as follows:

I_2 -Net gain to Total Income (-): This IRIS ratio is a measure of profitability. Both net gain and income include underwriting and investment measures. Generally, this ratio estimates the overall managerial effectiveness and efficiency. The larger the ratio, the smaller the expected probability of insolvency.

I_3 -Commission and Other Expense to Premium (+): This IRIS ratio is a measure of operating efficiency. The larger the ratio, the greater the expected probability of insolvency.

I_5 -Nonadmitted to Admitted Assets (+): This IRIS ratio is a measure of the degree to which the company invests either in nonproductive or risky

⁵ The NDM differs from DM, which does not have the absolute value. Based on characteristics of the logarithmic function, substantially different measures were obtained where DM and NDM were computed using the same data.

assets. The larger the ratio, the greater the expected probability of insolvency.

I_{10} -Change in Product Mix (+): This IRIS ratio represents the average change in the percentage of total premium from each product line during the year. For a substantial shift in the ratio, it is generally true that the bigger the change, the greater the expected probability of insolvency.

I_{11} -Change in Asset Mix (+): This IRIS ratio is calculated in the same manner as the change in product mix (I_{10}) and has the same effect on the probability of insolvency.

DM and NDM-Decomposition Measures (+): These variables were discussed above and are listed in Appendix 3. The larger the decomposition measures, the greater the expected probability of insolvency.

Size Variables (-): Appendix 3 lists these variables. Surplus and assets were occasionally significant. It is expected that large companies are less vulnerable to insolvency, since regulators may be less likely to liquidate large insurers. Thus the smaller the size (especially surplus), the greater the probability of insolvency.

$\text{Ln}(\text{GRA})(+)$: This ratio is measured by the natural log of total assets in the current year divided by total assets in the previous year. Rapidly growing companies are more vulnerable to financial distress. Above a certain range it is expected that the larger the ratio, the greater the expected probability of insolvency.

GP-Gains to Premium, and Other Measures of Gains (such as I_4) (-): These few variables measure the investment and underwriting gains. The smaller the variables, the greater the probability of insolvency.

P/S-Premium to Surplus (+): This ratio is a common measure of solvency in the property-liability industry. Its relationship to default risk has been extensively documented (e.g., Trieschmann and Pinches, 1974, Hammond and Shilling, 1978, and Harrington and Nelson, 1986). The larger the ratio, the greater the expected probability of insolvency.

Shaked (1985) estimated several variables which differ from those above. This model was termed the prospective probability of insolvency (prospective). Parameters required for estimating the probability of insolvency were calculated from accounting and market data.⁶ Estimation of the variance of asset returns (σ_A) was calculated using three months of daily market data for the 31 life insurers. However, market data for almost all United States life

⁶Shaked (1985) assumed that life insurers remained solvent at time t if $A_t > L_t e^{gt}$, where A_t are the assets to time t , and L_t the current liabilities. The probability that this inequality is satisfied is,

$$N\left(\frac{\ln(A_0) - \ln(L_0) + (\mu - \delta - c - g)t}{\sigma_A \sqrt{t}}\right).$$

Shaked estimated the gross expected rate of return (μ), the dividend payout rate (δ), the cost rate per unit of assets for underwriting expenses (c), and the expected nonstochastic promised rate on liabilities (g).

insurers are not available. Although Shaked suggested estimation of an individual standard deviation for each asset category along with the covariance (e.g., for mutual insurers), such an estimation requires strict assumptions and may yield biased estimates.⁷

Empirical Results

Univariate Analysis

The NAIC system failed to provide early warning of financial insolvency. Only 16 life insurers (57 percent of the insolvent sample) had four or more ratios outside the acceptable ranges one year prior to insolvency. Seven (25 percent) and six (21 percent) had four or more ratios outside the acceptable ranges two and three years prior to insolvency, respectively. Approximately 220 of the 1300 life insurers who reported data to the NAIC were classified as priority companies in 1980. In addition, the IRIS also appears to include a few tests which have little ability to discriminate between solvent and insolvent firms.

The insolvent insurers were small firms. The average values of premiums for the insolvent insurers (excluding one firm) were \$4.1 million and \$3.3 million, respectively, one and two years before insolvency. Summary statistics of significant univariate variables for the sample of insolvent life insurers, as well as for the matched and the random samples of solvent life insurers, are shown in Table 1. The mean and standard deviation for each of these three groups are presented for one and two years prior to insolvency.⁸ Significant differences between the groups of solvent life insurers and the group of insolvent ones are also shown in the table. Wilcoxon and Mann-Whitney normal approximation statistics and the parametric t-statistics were used to test whether the univariate variables differed in centers.

The average values of profitability characteristics, such as net gain to total income (I_2 investment yield (I_4), net gain to premium (GP) and net gain from operation (NGFO) were significantly larger for the solvent firms studied than those average values of the insolvent companies. The average values of premium to surplus (P/S) for the insolvent insurers were 2.85 and 2.63, for one and two years prior to insolvency, respectively. These values were significantly larger than the average values for the solvent samples, approximately within the range of 1.73 to 1.9. Thus, insolvent firms operated

⁷Technically these biases are more severe than those assumed by Shaked (1985, p. 66). For example, each asset category of an individual insurer is changed over time. (The asset-mix and the fraction of each investment in total assets are changed even for short time intervals). Moreover, aggregating returns of asset category may obscure significant subnormal return or even negative returns on a specific portfolio of the individual insurer. Thus, estimates based on aggregate asset class (e.g., corporate bonds or stocks) may yield biased estimates.

⁸A complete list of all 31 variables is presented in Appendix 3. A short explanation for each of these variables is available there. Insignificant variables are not presented in Table 1. More detail on the calculation of the IRIS test is provided by the NAIC (see National Association of Insurance Commissioners, 1986).

Table 1.

Summary Statistics: Means and Standard Deviations of Significant Independent Variables

Variables	Insolvent Insurers	Solvent (Matched) Insurers	Solvent (Random) Insurers
One year prior			
I ₂	-1.64 (20.55)	12.57 (15.13)	5.51 (20.55)
I ₃	114.43 (239.75)	40.89 (19.10)	45.83 (19.49)
I ₄ *	6.33 (3.32)	7.91 (1.66)	7.39 (1.67)
I ₆	43.60 (118.31)	15.32 (27.46)	17.97 (28.70)
I ₇	27.57 (74.11)	7.11 (18.18)	14.34 (23.56)
I ₈	8.75 (28.52)	2.75 (7.31)	9.65 (25.86)**
I ₁₀ *	2.41 (3.10)	1.07 (1.14)	1.10 (1.42)
I ₁₁ *	3.18 (2.95)	1.27 (1.25)	1.32 (1.27)
I ₁₂	-15.79 (32.78)	-17.04 (31.22)**	-6.18 (30.92)
NDM _{LS} *	.2450 (.3242)	.0502 (.0498)	.0746 (.1294)
NDA _A	.4278 (.6235)	.2952 (.4324)	.4139 (.7984)
GP*	-3.29 (14.96)	15.9 (22.41)	8.36 (.2023)
P/S	2.85 (4.28)	1.90 (3.06)	1.73 (1.57)
Ln (GRA)	-1.191 (1.393)	-1.154 (.952)**	-1.417 (.652)
Ln (GRP)	.259 (1.439)	.061 (.359)	-.0073 (.570)
Surplus	1825† (11533)	3034 (2436)	3378 (2255)
NGFO*	-211† (4964)	325 (531)	337 (564)
Two Years Prior			
I ₂	7.82 (21.79)	11.43 (10.73)	5.76 (10.73)
I ₃	129.43 (254.14)	70.18 (114.99)	45.00 (15.25)
I ₄	6.65 (5.21)	7.55 (2.16)	7.10 (1.47)
I ₅	3.89 (5.29)	17.50 (78.37)	2.55 (4.45)**
I ₆	24.60 (73.38)	11.64 (29.19)	12.79 (27.02)
I ₇	17.64 (37.69)	3.93 (13.49)	12.93 (25.70)
I ₉	111.00 (244.20)	20.50 (51.45)	29.60 (100.68)
I ₁₀ *	1.70 (1.92)	.989 (.991)	1.63 + (2.32)**
I ₁₁	2.13 (2.34)	2.014 (2.409)**	1.90 (1.85)
NDM _{LS} *	.1698 (.2529)	.119 (.3502)	.0696 (.1055)
NDM _A	6.6968 (30.48)	1.7401 (3.856)	1.2787 (1.3848)
GP*	1.62 (15.89)	13.24 (17.79)	8.22 (16.89)
P/S	2.63 (2.797)	1.83 (2.614)	1.87 (1.86)
Ln (GRA)	-1.036 (1.084)	-1.088 (.954)**	-1.341 (.732)
Ln (GRP)	.392 (.910)	.099 (.645)	.199 (.505)
Surplus	1831 (2945)	2850 (2165)	3163 (2383)
NGFO*	-217 (632)	241 (418)	306 (598)

Notes:

(1) IRIS ratio I₁ to I₁₂, and GP are in percentages; the variables surplus and NGFO are in thousand dollars.

(2) Standard deviations are in parentheses.

* Highly significant in the multivariate analyses; see, Table 2 and Table 3.

** Insignificant differences. The parametric t-test and the Wilcoxon-Mann-Whitney nonparametric statistics tested whether the univariate variables for the solvent and insolvent insurers differed in centers.

† The average value excludes one outlier.

with larger leverages. The average growth of premium, $\ln(\text{GRP})$, for the insolvent insurers was significantly larger than the average values for the solvent sample, indicating that insolvent companies have more rapid growth than solvent ones. Commission and expense to premium (I_3) ratio were significantly larger for the insolvent firms. Also, insolvent insurers invested more in real estate relative to surplus (I_6), and their rates of change of product mix (I_{10}) were significantly larger than those rates for solvent firms. Finally the new decomposition measures (NDM_{LS} and NDM_A) for the insolvent firms were significantly larger than those of solvent companies. This study shows, therefore, that the asset and liability accounts of insolvent firms revealed considerable instability, while asset and liability accounts for solvent firms were relatively stable over time. The variables which were highly significant in the multivariate analyses (discussed below) are also indicated with an asterisk (*) in Table 1.

The best single univariate variable, GP, correctly classified 73 percent of the life insurers. The second best univariate variable, I_{10} , correctly classified 72 percent of the firms. Also NDM_{LS} and I_2 correctly classified 72 percent and 71 percent of the firms, respectively, one year prior to insolvency.

Multivariate Analysis

The following eight-variable classification functions are employed for one year prior to insolvency:

$$\begin{aligned} Z(\text{MDA}) &= .970 + .004 I_6 + .0077 I_7 + .2583 I_{10} + .0147 I_{12} \\ &\quad + 2.8521 \text{NDM}_{\text{LS}} - 3.7596 \text{GP} + 1.7416 \text{NDM}_L - .5644 \text{NDM}_A \\ Z(\text{NPD}) &= .0048 I_6 + .0117 I_7 + .2429 I_{10} + .0111 I_{12} + 3.6983 \text{NDM}_{\text{LS}} \\ &\quad - 5.2418 \text{GP} + 1.4695 \text{NDM}_L + .672 \text{NDM}_A \\ Z(\text{Logit}) &= .0040 I_6 + .0312 I_7 + .4967 I_{10} + .0382 I_{12} + 6.32717 \text{NDM}_{\text{LS}}^{**} \\ &\quad - 18.6127 \text{GP}^* - .4754 \text{NDM}_L - .2458 \text{NDM}_A \end{aligned}$$

where, * is significant at .01, and ** is significant at .05. The eight coefficients and variables for two years prior to insolvency are available upon request.

Table 2 shows the MDA, nonparametric and logit coefficients, and the separation index for each model for both the insolvent group of insurers and matched solvent insurers. The coefficients for four-variable discriminant functions, as well as the classification results, for all models are presented for one and two years prior to insolvency. The three different analyses illustrate that the sign and the magnitude of various coefficients differ across the three models. The separation indices generally improved and were close to one when nonparametric models were employed.⁹ In addition, the logit coefficients and their significance level are presented in Table 2. The X^2 indices indicate that the logit models were very significant. The number of correct classifications is

⁹The initial coefficients for the nonparametric analysis were those obtained by the MDA. Other initial guesses might improve the classification results obtained by the nonparametric approach.

Table 2

Classifications Based on Multidiscriminant (MDA), Nonparametric (NPD) and Logit Analyses for Insolvent and Matched Samples

Model	One Year Prior to Insolvency			Two Years Prior to Insolvency		
	MDA	NPD	Logit	MDA	NPD	Logit
Panel A: Four-Variable Functions						
Classification (%) ¹						
Solvent	92.9%	82.1%	89.3%	89.3%	92.8% ⁴	89.3%
Insolvent	71.4%	85.7%	92.9%	64.3%	67.8%	82.1%
Overall	82.1%	83.9%	91.1%	76.8%	80.4%	85.7%
Total Number ²	46	47	51	43	45	48
Index ³	.639	.954	42.3*	.643	.949	47.2*
Panel B: Eight-Variable Functions						
Classification (%) ¹						
Solvent	92.9%	89.3%	89.3%	78.6%	85.7% ⁴	82.1%
Insolvent	85.7%	89.3%	92.9%	85.7%	89.3%	85.7%
Overall	89.3%	89.3%	91.1%	82.1%	87.7%	83.9%
Total Number ²	50	50	51	46	49	47
Index ³	.970	.976	48.8*	.909	.990	52.78*

The four-variable classification functions (one year prior to insolvency) are:

$$Z(\text{MDA}) = -.789 + .193 I_{10} + 2.589 \text{NDM}_{\text{LS}} - 3.970 \text{GP} + .890 \text{NDM}_A$$

$$Z(\text{NPD}) = .106 I_{10} + 4.456 \text{NDM}_{\text{LS}} - 4.287 \text{GP} + .776 \text{NDM}_A$$

$$Z(\text{LOGIT}) = .366 I_{10} + 3.838 \text{NDM}_{\text{LS}} - 18.551 \text{GP}^* + 1.165 \text{NDM}_A$$

The four-variable classification function (two years prior to insolvency) are:⁴

$$Z(\text{MDA}) = .343 -.002 I_3 -.470 I_{10} + .00022 \text{Surplus} + .0016 \text{NGPO}$$

$$Z(\text{NPD}) = 2.717 I_3 + 49.894 I_{10} -.436 \text{Surplus} - 8.463 \text{NGPO}$$

$$Z(\text{LOGIT}) = .004 I_3 + 1.320 I_{10}^* -.0004 \text{Surplus} -.155 \text{NGPO}^*$$

Notes:

¹Percentage of insurers correctly classified.

²Total number of insurers correctly classified.

³Index of separation IS; χ^2 for the logit

⁴Converged based on specific initial guess.

*Significant at .01

also presented for each model.¹⁰ The four-variable analysis correctly classifies 82.1 percent, 83.9 percent, and 91.1 percent of the life insurers for the MDA, nonparametric and logit model, respectively, one year prior to insolvency. The eight-variable analysis correctly classifies 89.3 percent for the MDA and the nonparametric analyses, as well as 91.1 percent for the logit analysis.

Table 2 also presents the results of the analyses for two years prior to insolvency. The eight-variable analysis correctly classifies 82.1 percent of the

¹⁰The paired matched sample technique also enables a comparison between the results of paired comparisons. For each insolvent life insurer a solvent matched life insurer is selected and the scores are matched and classified. Results for this analysis are available from the authors upon request.

Table 3

Classifications Based on Multidiscriminant (MDA), Nonparametric (NPD) and Logit Analyses for Insolvent and Random Samples¹

Model	One Year Prior to Insolvency			Two Years Prior to Insolvency		
	MDA	NPD	Logit	MDA	NPD	Logit
Panel A: Four-Variable Functions						
Classification (%) ²						
Solvent	91.8%	89.8%	95.9%	93.9%	91.8%	93.9%
Insolvent	64.3%	71.4%	64.3%	64.3%	78.6%	82.1%
Overall	81.8%	83.1%	84.4%	87.0%	89.6%	89.6%
Total Number ³	63	64	65	64	67	69
Index ⁴	.849	.863	33.59*	.930	.977	55.43*
Panel B: Eight-Variable Functions						
Classification (%) ²						
Solvent	91.8%	93.9%	91.8%	87.8%	89.8%	89.8%
Insolvent	75.0%	78.6%	71.4%	78.6%	85.7%	85.7%
Overall	85.7%	88.3%	84.4%	84.4%	88.3%	88.3%
Total Number ³	66	68	65	65	68	68
Index ⁴	.827	.926	40.61*	.934	.982	63.19*

The four-variable classification functions (one year prior to insolvency) are:

$$Z(\text{MDA}) = .333 - .031 I_2 + .005 I_3 - .191 I_4 + .383 I_{11}$$

$$Z(\text{NPD}) = .037 I_2 + .020 I_3 - .210 I_4 + .497 I_{11}$$

$$Z(\text{LOGIT}) = -.034 I_2 + .008 I_3 - .341 I_4^* + .647 I_{11}$$

The four-variable classification function (two years prior to insolvency) are:

$$Z(\text{MDA}) = .827 + .004 I_3 - .152 I_4 + .007 I_{12} - .001 \text{NGFO}$$

$$Z(\text{NPD}) = .0375 I_3 - .183 I_4 + .039 I_{12} - .0025 \text{NGFO}$$

$$Z(\text{LOGIT}) = .0275 I_3 - .378 I_4^{**} + .058 I_{12}^* - .0037 \text{NGFO}^{**}$$

Notes:

¹The insolvent and random samples include 28 and 49 life insurers, respectively.

²Percentage of insurers correctly classified.

³Total number of insurers correctly classified.

⁴Index of separation IS; χ^2 for the logit

*Significant at .01

**significant at .05

life insurers for the MDA, and 87.5 percent and 83.9 percent of the life insurers for the nonparametric analysis and the logit model, respectively. The three models demonstrate similar results, but the nonparametric and the logit analyses slightly dominates the MDA.

In the preceding analyses, estimates for the new decomposition measures indicate a significant positive relationship between these variables and the probability of insolvency. The effects were expected *ex ante* and were usually the same across the multivariate analyses. The estimates for GP were negative and significant in all functions. Estimates for other profitability measures (I_2 , I_4) were also in the expected direction, but often not significant. NGFO were sometimes significant in the negative direction. The estimates for the change in product mix (I_{10}) were also positive in the expected direction but were often

insignificant. In conclusion, the estimates show that several variables had a relatively significant contribution to the multivariate estimated probability of insolvency.

Table 3 shows the four-variable functions and classification results for the insolvent group vis-a-vis the random sample of solvent insurers one and two years prior to the event. The four-variable analysis correctly classifies 81.8 percent, 83.1 percent, and 84.4 percent of the life insurers for the MDA, nonparametric and logit analyses, respectively, one year prior to insolvency. The eight-variable analysis correctly classifies 85.7 percent, 88.3 percent and 84.4 percent of the insurers for the MDA, nonparametric and logit analyses, respectively. Results for two years prior to insolvency are also summarized in Table 3. The four-variable analysis correctly classifies 87 percent and 89.6 percent of the life insurers for the MDA, nonparametric (and logit) analyses, respectively. The results improved slightly for the MDA and nonparametric analyses when the eight-variable functions are employed.

The following eight-variable equations were employed for estimation of the scores (MDA and nonparametric) and the probability of insolvency (logit) one year prior to insolvency:¹¹

$$Z(\text{MDA}) = .517 - .035 I_2 - .005 I_3 - .204 I_4 + .143 I_5 + .241 I_{11} + .000007 \text{ Assets} + .158 \text{ P/S} + .359 \text{ Ln (GRA)}$$

$$Z(\text{NPD}) = 3.009 I_2 + 1.618 I_3 - 18.065 I_4 + 10.728 I_5 - .432 I_{11} + .00066 \text{ Assets} + 31.079 \text{ P/S} + 41.889 \text{ Ln (GRA)}$$

$$Z(\text{Logit}) = -.0469 I_2 + .0146 I_3 - .4596 I_4^* + .0809 I_5 - .4289 I_{11}^{**} + .000012 \text{ Assets}^{***} + .2846 \text{ P/S} + .3270 \text{ Ln (GRA)}$$

The equations and coefficients for two years prior to insolvency are available upon request.

In these comparisons, the separation indices, $IS(B)$, usually improved when the nonparametric analysis was applied. It also appears that variables entering the models change across various analyses because of the latitudinal nature of the study necessitated by the limited number of insolvencies in a given year and exogenous economic conditions, which may create inconsistencies in the order that variables enter the analysis.

The findings indicate that three multivariate analyses perform quite well for insolvency classification in the life insurance industry. The nonparametric model slightly outperforms the MDA in terms of correct classifications and separated indices. Similar classification results are obtained by the nonparametric and the logit models. Both the logit and the NPD slightly dominated the MDA, but results were significant only for most four-variable functions. Although the classification results often improved when the eight-variable analyses are employed, differences between eight-variable and four-variable functions appear to be insignificant for most comparisons.

¹¹ * Significant at .01

** Significant at .05

*** Significant at .10

Thus, it appears that four-variable multivariate analyses are significant measures of financial distress in the life insurance industry.

Probabilities of Insolvency and Scores for Publicly-Traded Life Insurers

Rather than limiting the conclusions to small and medium life insurers, the validity of the multivariate models is also examined on the publicly-traded life insurers. No large life insurer has collapsed during the research period. Coefficients for four-variable and eight-variable analyses are used to calculate the scores and the probability of insolvency of publicly-traded life insurers for 1979 and 1980. These 31 large life insurers (see also footnote 5) are listed in Table 4, panels A and B. The table presents for each insurer the scores obtained by the MDA and the nonparametric models, the estimated probability of insolvency as measured by the logit model, and the prospective probability of insolvency as measured and presented by Shaked (1985).¹²

Panel A of Table 4 includes the results for 1980 and one year prior to insolvency. All the 31 life insurers are correctly classified as solvent companies by the logit, MDA and nonparametric models. The probability of insolvency as measured by the logit model was comparatively low for all these life insurers. The results for 1979 and two years prior to insolvency are presented in panel B of the table. All 31 life insurers are correctly classified as solvent companies. The estimated probabilities of insolvency obtained by the prospective model are also presented for both panels. Further results are available upon request.

Table 5 presents several comparisons between the logit, MDA, nonparametric and the prospective model. In 1980, half of the publicly-traded life insurers had a probability of insolvency of less than .01 and .0001 for the logit and the prospective model, respectively. In 1979 the median probabilities were .015 for the logit model and .002 for the prospective model. The results indicate that most of these large life insurers were reasonably safe. However, skewness can be observed by comparing the mean with the median and by the coefficient of skewness. Skewness is observed for the prospective model in both years and for the logit model in 1979. Thus, a few publicly-traded life insurers exhibited larger probabilities of insolvency. Skewness, however, is not observed by the nonparametric model for both years. Also it appears that the probabilities of insolvencies was substantially reduced from 1979 to 1980.

Table 5 also presents the cross-sectional correlation matrices of the various models. The MDA and the nonparametric model are significantly correlated. The logit model was significantly correlated with both in 1979. However, the prospective model was uncorrelated with all the other models. The correlation was insignificant for the prospective model for 1979 versus 1980. Thus, intertemporal instability of the prospective model is demonstrated. The

¹²One may argue that these 31 large life insurers may have a below average risk of insolvency because they have survived over long periods and are regulated by several bodies (e.g., NAIC, state insurance departments, and the SEC). However, the collapse of such a large insurer might be disastrous (see e.g., Belth, 1984, p. 31).

Table 4

Probability of Insolvency and Scores for Publicly Traded Life Insurers

		Probability Logit	MDA	Z Scores Nonparametric	Prospective Probability 1979	Probability 1980
Panel A - 1980						
<u>Life Insurer</u>						
Aetna Life and Cas.	01	0.0222	-1.1203	-1.4107	0.0008750	0.0039620
American General	02	0.0290	-0.7939	-0.7937	0.0027658	0.0001122
American National	03	0.0071	-0.9478	-0.7508	0.0000000	0.0000000
Business Mens Ass.	04	0.0720	-0.5791	-0.5517	0.0117471	0.0000097
Capital Holding Co.	05	0.0004	-1.2788	-1.2534	0.0004215	0.0046840
Colonial Life and Acc.	06	0.0109	-0.8687	-0.6395	0.0041009	0.0055777
Colonial Penn. Group	07	0.0044	-0.8992	-0.6521	0.0432801	0.0823638
Connecticut Gen'l	08	0.0108	-1.3803	-1.6946	0.0000000	0.0000003
Gov't. Employees Life	09	0.0017	-0.9564	-0.8750	0.0041962	0.0000011
Gulf United Co.	10	0.0142	-0.5494	-0.4765	0.0366522	0.0000051
Independent L + Acc.	11	0.0189	-0.7175	-0.4206	0.0000028	0.0000000
Jefferson-Pilot Co.	12	0.0007	-1.3434	-1.4788	0.0002962	0.0005681
Kansas City Life	13	0.0041	-0.9467	-0.9937	0.0000000	0.0000000
Lamar Life Co.	14	0.0009	-1.3166	-1.4105	0.0000000	0.0000000
Liberty Co.	15	0.0033	-1.2240	-1.1665	0.0267977	0.0070174
Liberty Nat'l. Li.	16	0.0032	-0.5727	-0.3344	0.0000108	0.0003578
Lincoln National	17	0.0197	-1.0243	-1.1278	0.0002381	0.0004688
Monarch Capital Co.	18	0.0018	-1.0845	-1.1158	0.0021574	0.0000052
Monumental Co.	19	0.0182	-0.8905	-0.5202	0.0017899	0.0000057
NLT Co.	20	0.0094	0.1700	0.4752	0.0022131	0.0449365
Natl. Old Line	21	0.0011	-1.0543	-0.9945	0.0380441	0.0000000
Northwestern Natl.	22	0.0202	-1.0109	-1.1704	0.0045892	0.0000000
Pencorp Financial	23	0.0278	-0.6383	-0.2913	0.0483419	0.0145384
Protective Life Co.	24	0.0093	-0.9746	-1.1185	0.0000004	0.0000023
Provident L + Acc.	25	0.0435	-0.8910	-0.9975	0.0029934	0.0084083
Republic National Li.	26	0.0412	-0.7599	-0.8701	0.0730852	0.0000566
Southland Financial	27	0.0107	-1.0524	-1.1362	0.0000002	0.0017898
Travelers Co.	28	0.0204	-1.3433	-1.7206	0.0006787	0.0067292
United Services Li.	29	0.0047	-0.8704	-0.9174	0.0078318	0.0000000
U.S. Life Co.	30	0.0188	-1.0466	-1.0508	0.0018659	0.0083661
Washington Nat'l. Co.	31	0.0314	-0.7457	-0.7117	0.0183866	0.0304904

significant correlations among the logit, MDA and nonparametric models are consistent with the theoretical arguments by Amemiya (1981), Maddala (1983) and others. The prospective model was derived based on different assumptions and data sets; it is not surprising that it was not significantly correlated with the other models. In conclusion, all 31 of these larger life insurers are correctly classified as solvent companies by most analyses. These results appear to be consistent with the estimated probabilities of insolvencies derived by the prospective model, but the cross sectional correlations between the prospective model and the three other multivariate models were insignificant.

Priority Firms

In order to provide evidence that the variables and models are useful in identifying distressed insurers that are in danger of becoming insolvent, the authors randomly sampled 31 life insurers flagged as priority companies by the NAIC-IRIS in 1979 and 1980. All these 31 insurers were still active in 1985. Eight (26 percent), six (19 percent), and five (16 percent) of these companies were identified as insolvent by the eight-variable MDA, NPD and

		Probability Logit	Z Scores MDA Nonparametric		Prospective 1979	Probability 1980
Panel B - 1979						
<u>Life Insurer</u>						
Aetna Life and Cas.	01	0.0339	-0.5023	-1.5096	0.0008750	0.0039620
American General	02	0.0100	-1.0358	-1.9994	0.0027658	0.0001122
American National	03	0.0176	-0.8353	-1.3527	0.0000000	0.0000000
Business Mens Ass.	04	0.0656	-0.2897	-0.8057	0.0117471	0.0000897
Capital Holding Co.	05	0.0080	-1.0423	-2.0360	0.0004215	0.0046848
Colonial Life and Acc.	06	0.0045	-1.1922	-2.2965	0.0041009	0.0055777
Colonial Penn. Group	07	0.0219	-0.5819	-1.1661	0.0432801	0.0023638
Connecticut Gen'l	08	0.0068	-1.0238	-2.5000	0.0000000	0.0000003
Gov't. Employees Life	09	0.0232	-0.6163	-1.4003	0.0041962	0.0000011
Gulf United Co.	10	0.0132	-0.8084	-1.9921	0.0366522	0.0000051
Independent L + Acc.	11	0.2637	0.1005	0.6644	0.0000028	0.0000000
Jefferson-Pilot Co.	12	0.0024	-1.3272	-3.0196	0.0002962	0.0005681
Kansas City Life	13	0.0161	-0.8077	-1.7089	0.0000000	0.0000000
Lamar Life Co.	14	0.0217	-0.6525	-1.4886	0.0000000	0.0000000
Liberty Co.	15	0.1296	-0.1508	-0.0735	0.0267977	0.0070174
Liberty Nat'l. Li.	16	0.0063	-1.1051	-2.1304	0.0000108	0.0003578
Lincoln National	17	0.0118	-0.8946	-1.9623	0.0002381	0.0004688
Monarch Capital Co.	18	0.0508	-0.3378	-0.9403	0.0021574	0.0000052
Monumental Co.	19	0.0070	-1.1327	-1.7540	0.0017899	0.0000057
NLT Co.	20	0.1107	-0.2164	-0.0421	0.0022131	0.0449365
Natl. Old Line	21	0.0903	-0.2460	-0.3534	0.0380441	0.0000000
Northwestern Natl.	22	0.0020	-1.3670	-3.2521	0.0045892	0.0000000
Pencorp Financial	23	0.0154	-0.9384	-1.4217	0.0483419	0.0145384
Protective Life Co.	24	0.0414	-0.8236	-1.1877	0.0000004	0.0000023
Provident L + Acc.	25	0.0020	-1.2959	-3.3197	0.0029934	0.0084083
Republic National Li.	26	0.1674	-0.1047	-0.2408	0.0730852	0.0000566
Southland Financial	27	0.0147	-0.7901	-1.8154	0.0000002	0.0017898
Travelers Co.	28	0.0025	-1.2893	-3.2696	0.0006787	0.0067292
United Services Li.	29	0.0058	-1.0045	-2.5748	0.0078318	0.0000000
U.S. Life Co.	30	0.0082	-0.9840	-2.1758	0.0018659	0.0083661
Washington Nat'l. Co.	31	0.0103	-0.8912	-2.0027	0.0183866	0.0304904

Note:

The sample and the prospective probabilities were used by Shaked (1985, Tables 1-A and 1-B).

logit models, respectively, for both years (1979 and 1980). The NAIC-IRIS failed to provide an early warning system for insolvent companies, and flagged many solvent insurers. The models outperformed the NAIC-IRIS, by identifying most of the 31 insurers as solvent. Thus, in addition to minimizing the misclassification of insolvent life insurers, the models also reduced the number of misclassified solvent insurers. This illustration should be interpreted cautiously because the definition of flagged companies as insurers that were in danger of becoming insolvent might be wrong. Additionally, a major problem in this analysis is to identify *ex ante* criteria for selecting insurers in danger of becoming insolvent; however, the models might ease the problem of errors in identification. The number of designated insurers for immediate regulatory attention, as well as the number of misclassified insolvent insurers, would be substantially reduced if the models were used by regulators.

Empirical results also indicate most NAIC-IRIS tests perform well in combinations with other financial measures (e.g., decomposition measures and additional financial ratios), where multivariate frameworks are employed. These findings are in contrast with previous findings in the property-liability

Table 5

Summary Statistics and Correlation Matrices for the 31 Publicly-Traded Life Insurers

	<u>Logit</u>		<u>MDA</u>		<u>Nonparametric</u>		<u>Prospective</u>	
	1980	1979	1980	1979	1980	1979	1980	1979
<u>Panel A Summary Statistics</u>								
Mean	0.0154	0.0382	-0.9262	-0.7802	-0.9087	-1.6493	0.00711	0.01075
Median	0.0108	0.0147	-0.9478	-0.8353	-0.9937	-1.7540	0.00011	0.00216
Standard Dev.	0.0158	0.0585	0.3084	0.3974	0.4523	0.9834	0.01701	0.01835
Skewness	1.807	2.563*	1.355	0.542	0.711	0.333	3.521*	2.030**
<u>Panel B Correlation Matrices</u>								
<u>1980</u>	Logit		MDA		Nonparametric		Prospective	
Logit	1.000							
MDA	0.310**		1.000					
Nonparametric	0.173		0.942*		1.000			
Prospective	0.225		0.220		0.237		1.000	
<u>1979</u>	Logit		MDA		Nonparametric		Prospective	
Logit	1.000							
MDA	0.837*		1.000					
Nonparametric	0.829*		0.944*		1.000			
Prospective	0.005		0.138		0.160		1.000	
Prospective 1980/1979:	0.301							

* Significant at .01

** Significant at .05

industry (e.g., Thornton and Meador, 1977, and Hershberger and Miller, 1986), which indicate that the NAIC-IRIS system had very little ability to classify solvent and failed property-liability insurers even in a multivariate framework. As presented, financial measures computed by the NAIC-IRIS, as well as decomposition measures and other financial measures, are found to be accurate for classifying failures in multivariate frameworks one and two years prior to insolvency.

Summary and Conclusions

In reviewing the findings and conclusions of this study one is able to see several implications. First, several of the IRIS tests which were developed by the NAIC for life insurance companies seem to be more efficient in the multivariate framework than those developed for the property-liability companies. Since the IRIS ratios are predominantly financial ratios, and life insurers function more closely as intermediaries and less as risk takers, one is not surprised by this conclusion.

A second implication is that the Change in Product Mix (I_{10}) variable appears in all of the analyses for insolvent and matched sample companies. The staying power of this variable in the analysis indicates that management of life insurers should be cautious about abrupt changes in their product mix.

Professionals in the industry argue that large and frequent changes in product mix may increase the annual cost of underwriting business, because the cost of new policies is often larger than premiums collected for the first year. However, managers of a troubled life insurer may correct the situation by infrequent and moderate changes in the product and asset mixes, both of which improve the financial strength of the insurer.

Third, in all panels analyzing the variables for two years prior to insolvency, the net gains from operations (NGFO) and gain to premium or total income surfaced. An implication of this result is that life insurers need absolute and relative gain (including investment yield) in order to remain solvent. Hence, during their review of companies to be placed on the surveillance roster, insurance regulators should consider these variables in addition to IRIS ratios.

Fourth, the decomposition measures were found to be significant variables in a few analyses. The decomposition measures reflect changes in components of the financial statements caused by effects external and internal to the life insurer. The new decomposition measures of the insolvent companies are larger than those of the solvent companies, especially those computed on the liabilities side. Thus, decomposition measures and the new decomposition measures can supplement traditional monitoring tools (e.g., the IRIS tests) in the life insurance industry.

Fifth, the proposed methodologies have important implications for regulators. Additional financial ratios and the decomposition measures should be added to the NAIC-IRIS tests. The NAIC-IRIS has recently designated 220 life and health insurers for immediate regulatory attention; in addition, 140 life and health insurers are on the list of additional scrutiny (Best's Review, 1986, p. 6). In this study the NAIC-IRIS did not provide early warning of financial failures. Therefore, multivariate frameworks should be adopted by regulators. The proposed models facilitate mix-strategies for regulators. For example, the riskiest designated life insurers might be these identified by all four models (logit, MDA, nonparametric, and prospective). The minimal cost of data gathering and processing justifies the adoption of these models.

This article compares the performance of failed and sound life insurers from 1975 through 1985 in order to identify variables which will assist predicting insolvency of life insurers one or two years prior to insolvency. Also, the performance of various multivariate models for prediction of insolvency was compared systematically. The NAIC-IRIS did not provide early warning of financial failures, and designated many life insurers as priority companies. In this study, methods suggested in the literature for property-liability insurers and corporations other than insurers, are applied to life insurance data. The primary models used were MDA, nonparametric analysis, and logit analysis. The NAIC-IRIS tests, financial leverage ratios, growth ratios, other measures of income and profitability, and decomposition measures are used as variables in the analysis.

The use of MDA has been recently discouraged in the bankruptcy and risk rating literature. The findings of this article indicate that the nonparametric and logit analyses performed quite well and slightly dominated the MDA for

insolvency classification in the life insurance industry. It also appears that four-variable multivariate analyses have significant discriminatory power. The results and their applications outlined in detail above resulted in the following conclusion: several financial measures computed by the NAIC-IRIS, as well as decomposition measures and a few other financial variables, were found to be accurate measures for classifying failures in a multivariate framework one and two years prior to insolvency. Cross-sectional validation on 31 publicly-traded life insurers indicates these insurers are reasonably safe. Further statistics and correlation analyses indicate that more than one multivariate approach may be necessary for measuring the failure prospectively.

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Appendix 1

Life Insurers, Matched-Pairs*

<u>Insolvent</u>	<u>Solvent</u>
Alexander Hamilton Life Insurance (MI)**	Confederation Life Insurance Company, U.S. (MI)
American Saving Life (AZ)	Admiral Life Insurance (AZ)
BU Life Insurance (OH)	Celina National (OH)
Capital Fidelity Life (FL)	United Sun Life (FL)
Commodore Life (TX)**	Bankers Life of America (TX)
Community Life Insurance (PA)	Columbia Life Insurance Company (PA)
Dearborn Life Insurance (AZ)	HBA Life (AZ)
Farmers National Life (FL)	Conger Life Insurance Company (FL)
Federated American Life (WA)	Pemco Life (WA)
First National Credit (SC)	Companion Life (SC)
Georgetown Life Insurance (IL)	American Union (IL)
Independent Liberty Life (MI)	Auto Club Life (MI)
International Life Insurance (KY)	Mammoth Life and Accident (KY)
Iowa State Travelers (Iowa)	AID Life Insurance (Iowa)
Life Insurance Company of America (AL)	Old Southern Life (AL)
Mercury National Life (OK)	Century Life Insurance (OK)
National American Life (LA)	Saving Life Insurance Company (LA)
National Assurance Life (OK)	Member Service (OK)
National Bankers Life (IN)	Churchmembers Life (IN)
Omaha National Life (AZ)	Womens Life Insurance Company (AZ)
Peoples Standard Life (DE)	Pilgrim Life Insurance Company (DE)
Sandia Life Insurance (NM)	Early American (NM)
Seaboard Life (FL)	National Standard (FL)
Security Guaranty Life (AL)	Bankers Credit (AL)
Southwest Capital Life (OK)	Continental National Life (OK)
Southwestern Security Life (OK)	Wichita National (OK)
State Security Life (IN)	Laymen Life Insurance Company (IN)
Trans America Life (TX)	International Investors (TX)

*Matched by state, size and years

**Liquidated into and/or reinsured

Appendix 2**Solvent Life Insurers: A Random Sample***

AAA Life Insurance (DC)
Alliance Life Insurance Company (KS)
American Diversified (OH)
American Health Life (NY)
American Investors (AL)
American Union (IL)
Andrew Jackson (MS)
Bankers Life Insurance Company (TX)
Capital Reserve (MO)
Central Security (TX), 1980
Central Security (TX), 1983
Citizens Security (KY)
Citizen & Southern (GA)
Commercial Travelers (NY)
Continental Life & Accident (IN)
Family Benefit Life (MO)
Financial Security (IL)
First National (AL)
Great Fidelity (IN)
Grinnel Mutual of Iowa (Iowa)
Gulf Atlantic (TX)
HBA Life Insurance (AZ)
Integrity National (PA)
International Life (NJ)
Investment Life Trust (SC)
Investors Heritage (OH)
Life Insurance Company of Alabama (AL)
Lincoln Benefit (ME)
Members Life Insurance Company (TX)
Milwaukee Life (WI)
Missouri National (MO)
Modern Income (IL)
Monumental National Life (NY)
National Producers (AZ)
NLIC of America (PA)
New Jersey Life Insurance Company (NJ)
Oxford Life Insurance Company (AZ)
Pacific Empire (IN)
Pennsylvania National (PA)
Peoples Life (SC)
Public Saving (SC)
Saving Life (LA)
Sovereign Life (CA)
Statesmen National (TX)
Summit National (OH)
Wichita National (OK)
World Life & Health Insurance (PA)
Wright Mutual Insurance (MI)
United Agents Life (LA)

*Matched approximately by size and years

Appendix 3**A List of Variables****NAIC-IRIS**

(I ₁)	Change in Capital & Surplus
(I ₂)	Net Gain to Total Income
(I ₃)	Commissions & Expenses to Premiums
(I ₄)	Investment Yield
(I ₅)	Nonadmitted Assets to Assets
(I ₆)	Real Estate to Capital & Surplus
(I ₇)	Investments in Affiliate to Capital & Surplus
(I ₈)	Surplus Relief
(I ₉)	Change in Premium
(I ₁₀)	Change in Product Mix
(I ₁₁)	Change in Asset Mix
(I ₁₂)	Change in Reserving Ratio

Size

(Surplus)	Capital & Surplus
(Premium)	Total Premiums
(Assets)	Total Admitted Assets

Financial Leverage Ratios

(A/S)	Total Assets/Surplus
(P/S)	Premiums/Surplus
(L/S)	Liabilities/Surplus

Growth Ratios

(GRS)	Growth in Surplus, Surplus t/Surplus t-1
Ln (GRS)	Ln of Growth in Surplus, Ln(Surplus t/Surplus t-1)
Ln (GRP)	Ln of Growth in Premium, Ln (Premium t/Premium t-1)
Ln (GRA)	Ln of Growth in Assets, Ln(Assets t/Assets t-1)

Other Measures of Income

(NII)	Net Investment Income
(NGFO)	Net Gain from Operations After Tax & Dividends
(GP)	Gains/Premiums

Decomposition Measures

(DM _{LS})	Decomposition Measures on the Liability Size, Two Components
(NDM _{LS})	New Decomposition Measures on the Liability Size, Two Components
(DM _L)	Decomposition Measures on the Liability Size, Four Components
(NDM _L)	New Decomposition Measures on the Liability Size, Four Components
(DM _A)	Decomposition Measures on the Assets Size, Four Components
(NDM _A)	New Decomposition Measures on the Assets Size, Four Components

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