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# Life Insurer Financial Distress: Classification Models and Empirical Evidence

James M. Carson
Robert E. Hoyt

## ABSTRACT

This study extends previous research on life insurer insolvency by providing empirical evidence on a large (nonmatched-pair) sample of insurers based on three alternative types of statistical models. The study utilizes 1986 through 1990 data for a sample of insurers that did or did not become financially impaired during 1989 through 1991. Empirical evidence suggests that surplus measures and leverage measures are strong indicators of insurer financial strength; however, no evidence is found for a strong relationship between state minimum capital requirements and insolvency. Classification rates for this study's large sample are generally lower than those found in previous studies examining earlier time periods and using smaller, matched-pair samples.

## Introduction

The 1991 failure of two large U.S. life insurers has drawn widespread public attention to the financial condition of life insurers. Mutual Benefit Life and Executive Life had assets of $13.5 and 10.2 billion, respectively, at year end 1990 (A. M. Best, 1991). Failures of the magnitude that these two life insurers experienced and the increased frequency of life insurer insolvency suggest that a reexamination of the risk profiles of life insurers is warranted. Detection of insurer financial distress is important to regulators, consumers, agents, and insurers. This study aims to provide empirical evidence on insurer insolvency models based on a large sample of insurers and identify significant variables in the early detection of financially distressed life insurers.

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James M. Carson is Assistant Professor of Insurance in the Department of Finance, Insurance, and Law at the Katie Insurance School, Illinois State University. Robert E. Hoyt is Associate Professor of Risk Management and Insurance in the Terry College of Business, University of Georgia.

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## Prior Research and Focus of Study

Various statistical models for the classification and prediction of financial distress have been presented in prior insolvency studies. A comprehensive review of insurer insolvency literature is given in BarNiv and McDonald (1992). More recently, Ambrose and Carroll (1994) applied logistic regression analysis to matched-pair samples of life insurers and found that financial variables combined with National Association of Insurance Commissioners Insurance Regulatory Information System ratios outperformed A. M. Best's recommendations in distinguishing between solvent and insolvent insurers. Combining all three types of predictors into one model provided the most accurate classification.

This study extends prior research in several ways. One of the most important differences here is that empirical evidence is provided based on a nonmatched-pair sample of 1,685 insurers, thus minimizing biases resulting from choice-based samples (see Palepu, 1986). Another important difference is that a more current data set and a relatively short sample period are used—data are for 1986 through 1990, for insolvencies occurring in 1989 through 1991. Finally, a relatively new methodology, recursive partitioning, is applied to life insurer insolvency classification. The recursive partitioning methodology has been applied successfully in other areas of finance (Marais, Patell, and Wolfman, 1984; Frydman, Altman, and Kao, 1985; Srinivasan and Kim, 1987), but has not been applied to the insurance industry.

## Methodology

The three empirical models used in the study are recursive partitioning, logistic regression, and multiple discriminant analysis. For discussions of multiple discriminant analysis and logit, which have been used extensively in previous insolvency studies, see BarNiv and Hershbarger (1990). Recursive partitioning is based on theoretical analyses by Friedman (1977) and Gordon and Olshen (1978). Recursive partitioning defines the classification rule as a sequence of binary partitions of the independent variables. In contrast to multiple discriminant analysis, recursive partitioning requires only a "learning" sample with subsets consisting of known, discrete, and nonoverlapping groups. The procedure recursively selects from the independent variables the variable (or linear combination of independent variables) that most reduces the expected costs of misclassification. At each step, the technique selects and separates a subset of the sample into two groups by partitioning the independent variable that most improves the homogeneity of category assignments applied separately to the two resulting groups. A limitation of recursive partitioning is that no variable coefficients are produced, and thus, convenient tests of variable significance are not easily obtained. For a more complete discussion of recursive partitioning, see Frydman, Altman, and Kao (1985).

## Data, Sample of Insurers, and Variables

### *Data and Sample Selection*

Rather than obtain data primarily from the A. M. Best Company, as the majority of insurer insolvency studies have done, this research provides empirical results based on information from the National Association of Insurance Commissioners (NAIC) data base. Not only does the NAIC data base contain a larger sample of insurers, it includes data for more smaller insurers that are not included in *Best's Insurance Reports*. This fact is especially relevant since the incidence of business failure is greater with smaller firms than with larger corporations, as discussed by Altman (1968) and Abrams and Huang (1987).

The A. M. Best definition of a "financially impaired company" is the basis for determining failed and nonfailed insurers. The date of failure is that of the first official action taken by the department of insurance in the insurer's state of domicile.[1] From 1981 through 1985, 58 life insurers in the United States became financially impaired, but from 1989 through 1991, this number increased to 141. The occurrence of a relatively large number of insolvencies over a short time period allows the use of a shorter sample period; thus, the effect of changing exogenous economic conditions and temporal instability in the parameters is of less concern than for previous studies using longer sample periods.

Unlike the majority of previous insurer insolvency studies, which use a matched-pair sampling technique, this study provides empirical evidence based on a nonmatched-pair sample of 1,685 insurers, thus minimizing biases that result from the use of choice-based samples. The sample includes 1,605 solvent insurers and 80 insurers that became insolvent from 1989 through 1991. Data are from 1986 through 1990 and are ordered to allow analysis corresponding to one year and two years prior to insolvency. All life-health insurers with complete data from the NAIC are included in the study, except for insurers involved in a merger during this study's sample period, as identified by A. M. Best.

### *Variable Selection*

Important variables from previous research, variables related to an insurer's investment and underwriting operations, and other variables are included. High correlation among several of the variables warranted care in their choice, and attempts to fit a parsimonious model were made. Forward stepwise analyses (logit) based on the entire set of variables suggested the inclusion of the variables described below, while a complete listing of variables initially examined

[1] "State actions include involuntary liquidation, receivership, conservatorship, cease and desist order, suspension, license revocation, administrative order, supervision or any other action that restricted a company's freedom to conduct business normally" (A. M. Best, 1992). This definition is similar to that used by Hershbarger and Miller (1986) and several other studies; Ambrose and Seward (1988) included those insurers "for which an assessment had been made by a guaranty fund."

is given in the Appendix.[2] The dependent variable is defined as one for "financially impaired companies" and is defined as zero otherwise. The expected sign for each variable is shown in parentheses.

*Logarithm of capital and surplus (-).* The insurer may be viewed as a financial intermediary that holds title to a set of assets and sells claims against the assets to policyholders and shareholders, as discussed in Staking and Babbel (1995). Capital (surplus) provides a buffer in the event that losses are larger than expected (or investment returns are lower than expected). Capital also serves to protect policyholders against reverse moral hazard by assuring policyholders that the firm is committed to maintaining solvency without imposing costs on policyholders through a unilateral decision to increase risk.[3] Thus, higher levels of capital and surplus are expected to indicate lower likelihoods of insolvency. Further, by increasing the amount of capital, the insurer may signal its long-term commitment to not change the level of risk.

*Logarithm of mean of capital and surplus to variance of capital and surplus (-).* A firm having relatively high variability in capital and surplus is expected to be more likely to become insolvent than a firm with more stable values of capital and surplus.

*Change in asset mix (+).* This variable is the average of the percentage change in asset accounts (same as the Insurance Regulatory Information System ratio). The larger the change in the ratio, the greater the expected probability of insolvency.[4]

*Change in product mix (+).* This IRIS ratio is calculated in the same manner as the change in asset mix variable and has the same expected effect on the probability of insolvency.

*Premiums to surplus, reserves to surplus (+).* A method by which an insurer may increase firm riskiness is by increasing leverage—insurance leverage and/or financial leverage. Capital structure literature suggests that firm value increases with increased leverage up to an optimum point and then declines as leverage extends beyond this optimum level. Thus, levels of leverage beyond the optimum level suggest higher likelihoods of insolvency.

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[2] The stepwise logit procedure was used at the 0.15 level of significance for entrance into the model. Due to collinearity concerns (measured by variance inflation factors), logarithm of total assets and real estate to total assets (mean to variance) were removed from further analyses. The one-year prior model employs change in asset mix, while the two-year prior model employs change in product mix. The ordinary least squares stepwise procedure generated a large set of variables, of which the logit stepwise set of variables was a subset, and of which the recursive partitioning set of variables was the same subset. The multiple discriminant analysis model was run with alternative sets of variables; however, no set of variables significantly outperformed the variable set chosen by the logit stepwise procedure and the recursive partitioning method.

[3] Reverse moral hazard is discussed in Staking and Babbel (1991) and refers to the idea that insurers are able to change the riskiness of the insurance contract (probability of insolvency) once written, while policyholders cannot cancel past coverage, obtain a refund, and costlessly transfer past exposures to another insurer.

[4] As stated in the NAIC's description of the IRIS ratios, rapid change in this ratio does not necessarily imply poor management, but may signal that the insurer is rearranging its asset mix due to solvency concerns.

*Separate account assets to total assets (+/-).* Insurance regulations require separate accounts for lines of insurance such as variable life and variable annuities, and insurers normally must report to policyholders on the investment performance of these reserve accounts. The proportion of assets in separate accounts may proxy the overall risk of the insurer, in that investments of separate account assets generally are viewed as more aggressive investments. Thus, a higher proportion of assets in separate accounts suggests a higher likelihood of insolvency. Alternatively, the investment risk of separate account assets may be largely shifted to policyholders, and the proportion of assets in separate accounts may reduce the likelihood of insolvency.

*Real estate to assets (+).* This variable measures an insurer's exposure to changes in real estate values. Given the declines in real estate during the sample period of insolvencies (1989 through 1992), it is expected that the larger this variable, the higher the probability of insolvency.

*Mutual or stock insurer (+).* The ownership form of an insurer may be related to an insurer's propensity for failure. Lamm-Tennant and Starks (1993) discuss the theoretical foundation for an expected difference in risk across ownership form, and provide empirical evidence suggesting that the risk inherent in future cash flows is higher for stock insurers than for mutual insurers, and that stock insurers write relatively more business than mutuals in lines and states having higher risk. It is expected that stock insurers will have a higher likelihood of insolvency given the different risk incentives that may exist among stock and mutual insurers.[5]

## Empirical Results

### *Empirical Models, Classification Results, and Independent Variables*

Classification results and coefficients for the eight-variable classification function for the logit and multiple discriminant analysis models one year prior to insolvency are presented in Table 1.[6] Results were validated using the Lachenbruch method, the V-fold method, and the estimation/holdout sample method.[7] Examining the results for the full sample indicates that the logit

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[5] In the empirical models, mutual equals zero, and stock equals one. A stock insurer owned by a mutual insurer is treated as a mutual insurer, as in Lamm-Tennant and Starks (1993).

[6] The models were run with and without a constant term. Results for coefficients and classification generally were similar, with somewhat higher classification rates for models with a constant term. The one-year and two-year logit models are significant at the 0.001 level (chi-square statistic). Tests of normality of the independent variables indicated that the multiple discriminant analysis assumption of multivariate normality is violated for all of the variables. The assumption of equal covariance matrices also was violated. Coefficients of the multiple discriminant analysis model will be biased, but the multiple discriminant analysis model still may be used for classification purposes. Recursive partitioning does not produce coefficients of the variables.

[7] The ratio of Type I errors to Type II errors varied from 1 to 40. Results presented here are for the ratio of 20/1. Similar changes occur in all three models for decreases and increases in the ratio of errors, in that, when the ratio is increased, fewer solvent insurers are correctly classified, and more insolvent insurers are correctly classified, and vice versa. BarNiv and McDonald (1992) also discuss the ratio of errors.

model outperforms multiple discriminant analysis, misclassifying fewer solvent and insolvent insurers. Logit and recursive partitioning perform similarly for classifying insolvent insurers, but logit classifies solvent insurers more accurately than recursive partitioning. Multiple discriminant analysis outperforms recursive partitioning in terms of solvent insurer classification, and recursive partitioning outperforms multiple discriminant analysis in terms of insolvent insurer classification. Thus, in terms of classification of this study's sample for one year prior to insolvency, logit outperforms multiple discriminant analysis and recursive partitioning. Logit outperforms multiple discriminant analysis and recursive partitioning for the estimation/holdout sample as well.

The coefficients of all variables in the logit model are significant except the coefficient on the mutual-stock variable (p-value = 0.20). The results suggest that, one year prior to insolvency, insurers having high capital and surplus, capital and surplus with a high mean and low variance, low reserves to surplus (insurance leverage), low separate accounts holdings, low holdings of real estate to assets, low average changes in asset mix, and low ratios of premium to surplus (financial leverage) have a lower probability of insolvency. The significance of the real estate variable may be highly temporal, in that it is primarily during the late 1980s and the early 1990s that problem real estate became a concern for life insurers. As in BarNiv and Hershbarger (1990), the sign and the magnitude of the various coefficients differ across the logit and multiple discriminant analysis models.

Models for two years prior to insolvency also were constructed. Results were similar to those for the one-year prior models, except that the mutual-stock variable was significant and positive (p-value = 0.08), suggesting a greater risk of insolvency among stock insurers compared to mutual insurers. As with previous research, classification accuracy decreased with the two-year prior model.

### *Comparison with Prior Research*

The percentages of insurers correctly classified in the above models are lower than classification rates from previous research. Potential reasons for the lower classification rates include the use of different time periods and different variables, and this study's use of a larger, nonmatched-pair sample. To test the stability of significant variables over time, and to provide a comparison of classification rates with prior research, the four-variable, two-year prior logit model of BarNiv and Hershbarger (1990) was applied to the two-year prior data set here. The four-variable model includes commissions and expenses to premiums, change in product mix, surplus, and net gain from operations.[8]

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[8] BarNiv and Hershbarger obtained reasonably accurate classification rates two years prior to insolvency for a matched-pair sample of 56 insurers. This four-variable model was chosen for comparison since it is the model in BarNiv and Hershbarger's study for which all of the variables were available here. Their study also showed, using an alternative four-variable model, high classification rates for the same set of insolvent insurers combined with a random sample of 48 solvent insurers.

**Table 1**
Validated Classification Results and Predictor Coefficients:
One-Year Prior Multiple Discriminant Analysis, Logit, and
Recursive Partitioning Eight-Variable Models
Number and Percent of Correctly Classified Insurers

| *Classification* | *Multiple Discriminant Analysis* *N* | *%* | *Logit* *N* | *%* | *Recursive Partitioning* *N* | *%* | *Sample Size* *N* |
|---|---|---|---|---|---|---|---|
| *Full Sample*[a] | | | | | | | |
| Solvent | 1,124 | 70 | 1,172 | 73 | 1,011 | 63 | 1,605 |
| Insolvent | 58 | 72 | 65 | 81 | 65 | 81 | 80 |
| Overall | 1,182 | 70 | 1,237 | 73 | 1,076 | 64 | 1,685 |
| *Estimation Sample*[b] | | | | | | | |
| Solvent | 951 | 79 | 1,023 | 85 | 1,024 | 85 | 1,204 |
| Insolvent | 45 | 75 | 52 | 86 | 49 | 82 | 60 |
| Overall | 996 | 79 | 1,075 | 85 | 1,073 | 85 | 1,264 |
| *Holdout Sample*[c] | | | | | | | |
| Solvent | 273 | 68 | 289 | 72 | 261 | 65 | 401 |
| Insolvent | 13 | 67 | 16 | 80 | 14 | 70 | 20 |
| Overall | 286 | 68 | 305 | 72 | 275 | 65 | 421 |

| *Predictor Variable*[d] | *Multiple Discriminant Analysis*[e] | *Logit* |
|---|---|---|
| Intercept | -37.26 | -2.38 |
| Logarithm of Capital and Surplus | 7.68 | -0.11** |
| Logarithm of Mean of Capital and Surplus to Variance of Capital and Surplus | 1.06 | -0.01* |
| Reserves to Surplus | 0.74 | 0.04* |
| Separate Account Assets to Total Assets | -0.46 | 2.05** |
| Real Estate to Assets | 1.79 | 13.30* |
| Change in Asset Mix | 3.76 | 17.04* |
| Premium to Surplus | 2.66 | 0.05*** |
| Mutual or Stock | 3.83 | 0.69 |
| Pseudo-$R^2$ | 25.02% | |

[a] Results were validated using the Lachenbruch (jackknife) method for multiple discriminant analysis and logit, and the V-fold method for recursive partitioning. For a discussion of recursive partitioning and the V-fold validation method, see the Appendix and Frydman, Altman, and Kao (1985).
[b] The estimation sample comprises 75 percent of the full sample. The variables and coefficients of this model, while somewhat different, were similar to the full sample model. The model developed from the estimation sample was then applied to the holdout sample to provide validated results.
[c] Classification results are based on the model developed from the estimation sample above, as applied to the remaining 25 percent of firms.
[d] Coefficients for multiple discriminant analysis and logit are based on the full sample. The recursive partitioning procedure does not produce coefficients.
[e] For the multiple discriminant analysis model, adjusted discriminant coefficients are shown, as in Trieschmann and Pinches (1973).
* Significant at the 0.01 level.
** Significant at the 0.05 level.
*** Significant at the 0.10 level.

Specifically, BarNiv and Hershbarger's four-variable model produced classification rates for solvent insurers of 89 percent, insolvent insurers 82 percent, and the overall sample 86 percent; using the same four variables in a logit model, the respective percentages found here were 49 percent, 69 percent, and 50 percent. The lower classification rates for the later time period and larger sample illustrate the nature of the insolvency classification problem. Changes in economic conditions, insurer investments, products, regulations, and distribution systems necessitate continuous revision of classification models. Consistent with studies examining property-liability insurers, evidence is found that shifts in important variables related to life insurer solvency may occur over time.[9] Further, results suggest that classification of the population of insurers may be less successful than implied by the classification rates based on matched-pair samples.

## Conclusion

The majority of prior research has employed the matched-pair sample technique, pooling insolvencies over a period of from five to 20 years. In contrast, the analysis here included all life-health insurers with complete data (solvent and insolvent) over a relatively short time period, made possible by the recent occurrence of a relatively large number of life insurer insolvencies. NAIC data were used, allowing the sample to approach the universe of U.S. insurers.

Empirical models for classifying solvent and insolvent firms were significant at the 0.001 level (chi-square statistic). Several variables were significantly related to the probability of insolvency, especially variables including capital and surplus and two measures of leverage. These variables were different, however, from significant variables found in prior studies, indicating a possible shift in important variables over time. In terms of classification rates, the logit model generally outperformed multiple discriminant analysis and recursive partitioning. The lower classification rates of this study likely are due at least somewhat to the larger sample employed here, in which the distinction between solvent and insolvent insurers is less clear than that for matched-pair samples.[10]

The dangers of holding relatively high proportions of assets in real estate were highlighted, given that distressed insurers carried significantly larger holdings of their assets in real estate. The temporal nature of this variable was illustrated, however, given that the real estate variable in BarNiv and Hershbarger (1990) was not significant. Also, the two leverage measures, in-

[9] For example, although most of this study's significant variables (or close proxies) were used in BarNiv and Hershbarger's eight-variable model, no overlap of significant variables exists with the one-year prior, eight-variable model of our study.

[10] That is, the matched-pair approach of constraining the solvent sample to insurers that can be paired with insolvent insurers, based on some matching criteria, likely results in a solvent sample with less intragroup variation than would be expected in a sample containing close to the full population of solvent insurers. Carson and Hoyt (1995b) provide preliminary evidence that this may be the case.

surance leverage (reserves to surplus) and financial leverage (premiums to surplus), show that leverage is associated with a higher propensity for failure. While the organizational form variable was not significant in the one-year prior logit model, it was significant and positive in the two-year prior logit model.

Part of the unexplained variation in insolvency models that rely on financial data likely arises because the causes of many insurer insolvencies, such as the effect of insurance contract provisions, cannot be measured by extant financial statement data.

Empirical models such as those presented here would benefit from future research exploring the costs of Type I errors (misclassifying an insolvent insurer as solvent) and Type II errors (misclassifying a solvent insurer as insolvent). Insurer insolvency literature also would benefit from examination of holding company affiliation and insolvency, and the role of executive compensation for insurers. In addition, models segregated by insurer size or product line also may yield additional insights into the problem of insurer insolvency.

## Appendix

Variables Used in the Empirical Models and
Initial Set Used in the Search for Significant Variables

| |
|---|
| Logarithm of Capital and Surplus |
| Insurance Leverage Reserves to Surplus |
| Financial Leverage Premiums to Surplus |
| Separate Account Assets to Assets |
| Real Estate to Assets |
| Change in Product Mix[a] |
| Change in Asset Mix[b] |
| Mutual or Stock Insurer (0,1) |
| |
| Liabilities to Current Assets |
| Change in Capital and Surplus |
| Logarithm of Assets |
| Capital and Surplus to Liabilities |
| Net Gain from Operations |
| Net Gains from Operations to Surplus |
| Commissions and Expenses to Premium |
| Age of Insurer |
| Minimum State Capital Requirement |
| Business Line Concentration[c] |
| Business State Concentration[d] |
| Reinsurance to Assets |

[a] Change in product mix is the average of the absolute value of percentage changes in premium for all lines of insurance (same as IRIS ratio). This variable was important in the two-year prior models only.
[b] Change in asset mix is the average of the absolute value of the percentage changes in assets for line items number one through ten (same as IRIS ratio).
[c] This variable is a Herfindahl measure of the squared percentages of premium for each line of business.
[d] This variable is a Herfindahl measure of the squared percentages of premium written in each state.

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