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Using Best's Ratings in Life Insurer Insolvency Prediction

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ABSTRACT

This article examines the efficiency of Best's recommendations, Insurance Regulatory Information System (IRIS) ratios, and other financial measures in their statistical ability to classify solvent and insolvent life insurers by estimating classification models for a sample of insurers for 1969 through 1986 and applying the models to a holdout sample for 1987 through 1991. The financial variables and IRIS ratios outperformed Best's recommendations in distinguishing between the two groups in a logit model. However, combining all three types of predictors into one model provided the most accurate classification of solvent or insolvent life insurers.

Introduction

Recent insolvencies of several major life insurers have generated much media attention and public concern. The usefulness of rating agencies, particularly the A. M. Best Company, as a tool for evaluating life insurers has come to the forefront. This article examines how effectively Best's ratings identify financially distressed life insurers. The predictive ability of Best's ratings is an important and timely issue; some of the recent insolvent life insurers carried Best's highest rating, prompting criticism of the rating system.

Researchers have attempted to predict the solvency status of insurers using a variety of methodologies. Most studies have focused on property-liability insurers and have used financial characteristics as predictors (Trieschmann and Pinches, 1973; Pinches and Trieschmann, 1974; Harrington and Nelson, 1986; Hershbarger and Miller, 1986; BarNiv and Smith, 1987; Ambrose and Seward, 1988; BarNiv, 1990; Barrese, 1990; and BarNiv and McDonald, 1992). Few studies have examined life insurer solvency (Shaked, 1985, and BarNiv and Hershbarger, 1990). Best's ratings have been incorporated as predictors in only

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two studies. Denenberg (1967) used Best's ratings in a descriptive way while Ambrose and Seward (1988) used a more rigorous multivariate analysis to link specific ratings with property-liability insurer insolvencies.

This study is the first to compare and combine Best's ratings with financial ratios to determine their ability to predict life insurer insolvency. A logit model is estimated for a sample of life insurers over the period 1969 through 1986 and then is used to predict insolvencies in a holdout sample for the period 1987 through 1991.

Sample Description and Methodology

In compiling both the estimation and holdout samples, an insurer was considered insolvent if the domiciliary state insurance commissioner declared the insurer insolvent or placed it in receivership, conservatorship, or liquidation.[1] A list of 111 such insurers was compiled from *Best's Insurance Reports: Life and Health Edition* from 1969 through 1986 for the estimation sample. Of these, 26 had sufficient financial information and ratings and were ultimately included in the sample. Each insolvent insurer was then matched with a randomly chosen solvent insurer according to the size of policyholder surplus in year t, where t is defined as the year prior to insolvency. The estimation sample therefore comprises 52 life insurers—26 insolvent and 26 solvent.[2] The holdout sample was chosen in a similar manner for the period 1987 through 1991 and comprises 34 insurers—17 insolvent and 17 solvent. A complete list of all insurers in the samples is presented in Appendix A.

Two types of variables are used as predictors in this analysis: financial ratios and dummy variables representing Best's recommendation status. The dummy variables take a value of one if the insurer is recommended in a particular year, zero if not. An insurer is considered recommended if it received a Policyholder Recommendation prior to 1976 or an A or A+ rating after 1975.[3] An explanation of all variable names and symbols is presented in Appendix B.

Because the dependent variable is dichotomous (one if insolvent, zero if not), this study employs the logit technique to predict insolvency. Logit is the preferred method in this case as some important distributional assumptions

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[1] This definition excludes insurers that were voluntarily liquidated, completely reinsured, or merged into another company. Because information was not available for these insurers, any insurer dissolved for these reasons was not included in the sample.

[2] This choice-based sampling causes insolvent insurers to be overrepresented compared to the population. Depending on the methodology used, biased coefficients may result. Palepu (1986), BarNiv (1990), and BarNiv and McDonald (1992) propose a correction for this problem. However, with logit (the methodology emphasized here) the coefficients of the explanatory variables are not affected by the unequal sampling rates. It is only the constant term that is biased. This causes the probability of insolvency to be underestimated (see Maddala, 1991, for a discussion and correction of this problem). Because the adjustment to minimize misclassification costs relies on knowing the true population proportions of solvent and insolvent insurers, misclassification costs are assumed equal.

[3] Best changed their rating system to include minus as well as plus ratings beginning in reporting year 1987.

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under multivariate discriminant analysis (MDA) are violated (see Ohlson, 1980, and Maddala, 1983, for a complete discussion of these limitations). MDA estimators are inconsistent if the independent variables are not normally distributed, as is the case when dummy variables are used.[4] A stepwise procedure is used for the selection of independent variables.

The stepwise logit considered various subsets of the variables identified in Appendix B. These subsets included the seven Best's recommendation dummy variables, the financial ratios for the year prior to insolvency, financial ratios for two years prior to insolvency, and financial ratios for both years. Also tested were subsets of the financial ratios, such as eight of the IRIS ratios and groups of ratios focusing on such areas as profitability, efficiency, and leverage. By partitioning the variables into these subsets and by using the stepwise selection technique, the effect of the small sample size is minimized.

Results

Table 1 presents descriptive statistics by solvency status for the holdout and estimation samples for each variable ultimately chosen in the models. For the most part, solvent and insolvent insurers differ significantly in the values of each of the predictors for the estimation sample. This is to be expected since the estimation sample was used in the stepwise logit process to develop the predictive model. In the holdout sample, on the other hand, no significant differences are observed between solvent and insolvent insurers for any of the predictors; however, when these variables are considered jointly in a multivariate context, their ability to distinguish between solvent and insolvent insurers is generally good, as indicated by the classification accuracies presented below.

Statistical Analysis of Best's Recommendations

Following Denenberg (1967), six years of Best's recommendations (or converted ratings, post-1975) were collected for each insurer in the sample. In the estimation sample, solvent insurers had a slight edge in the proportion of insurers recommended by Best in four of the six years examined. Insolvent insurers had a higher percentage of recommendations in two of the six years and showed no obvious deterioration in recommendation status as the year of insolvency approached.

A formal analysis of the seven Best's recommendation dummy variables described in Appendix B is carried out through the use of the stepwise logit procedure. Table 2 presents a summary of the coefficients of the variables chosen and the classification accuracies and statistics for model fit.[5] From the prior six years of the Best's recommendation dummy variables and the change

[4] If the primary purpose is to develop a discriminating device, a violation of assumptions may not be critical to the ultimate result. In fact, BarNiv and McDonald (1992) indicate, among other things, that MDA seems robust if the objectives are simply to classify and predict solvent and insolvent firms.

[5] The cut-off point for classification is 50 percent probability of insolvency.

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Table 1
Estimation and Holdout Sample Summary Statistics

	Solvent Insurers		*Insolvent Insurers*		*Test Statistics*	
	Mean	*S.D.*	*Mean*	*S.D.*	*T-test*[a]	*Wilcoxon Z*[b]
Estimation Sample						
BRT	0.1923	0.4019	0.0769	0.2717	1.2127	-1.1917
NIITI	0.2351	0.1900	0.0966	0.0814	3.3918*	-3.5779*
CHAMIX	0.0017	0.0026	0.0067	0.0103	-2.3922**	2.3151**
NOGNPW	0.0874	0.1479	-0.0358	0.1688	2.7986*	-2.9739*
CHRES	-28.6193	89.1631	-2.9379	13.1836	-1.4529	2.5347**
CHCS	0.0522	0.1716	-0.0460	0.3057	1.4269	-1.8393***
CHNPW	0.0058	0.3160	0.4339	1.0142	-2.0546**	0.6223
Holdout Sample						
BRT	0.2353	0.4372	0.0588	0.2425	1.4552	1.4031
NIITI	0.4435	0.6921	0.2056	0.2140	1.3543	1.4122
CHAMIX	0.0040	0.0059	0.0238	0.0531	-1.5296	-0.9644
NOGNPW	0.0033	0.2117	-0.0692	0.3292	0.7634	1.6709*
CHRES	-0.0032	0.2123	15.0058	62.0543	0.8460	0.8611
CHCS	0.0394	0.1575	-0.1324	0.8222	-0.7849	0.5855
CHNPW	-0.0059	0.2797	0.3658	1.9322	0.4435	0.3100

Note: S.D. = standard deviation. BRT = a dummy variable for Best's recommendation at time t, equal to one if recommended in year t and 0 if not recommended in year t; NIITI = the ratio of net investment income to total income; CHAMIX = change in asset mix; NOGNPW = the ratio of net operating gain to net premiums written; CHRES = change in reserves; CHCS = change in capital and surplus; and CHNPW = change in net premiums written.
[a] F-tests indicated that t-tests using unequal variances were appropriate.
[b] Wilcoxon two-sample test.
* Significant at the 1 percent level.
** Significant at the 5 percent level.
*** Significant at the 10 percent level.

in recommendation variable, the stepwise logit procedure chose only the recommendation in the year prior to insolvency, implying that, from a statistical point of view, little advance warning of insolvency is given by relying on Best's recommendation alone.[6] Although this single variable classifies insolvent insurers extremely well, with 92.3 percent accuracy in the estimation sample and 94.1 percent accuracy in the holdout sample, the overall correct classification percentages suffer from the poor performance on solvent firms (slightly above 55 percent).

Statistical Analysis of Financial Ratios

Because the Best's models poorly discriminate between solvent and insolvent insurers, we sought better predictors among financial ratios. The results

[6] Dummy variables representing the actual letter rating for the post-1975 period were also used in this study as predictors—that is, A+ = 1, 0 otherwise; A = 1, 0 otherwise; B+ = 1, 0 otherwise, etc. Far better predictive ability was achieved with the recommendation dummy variable results presented here.

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Table 2
Logit Predictor Coefficients and Classification Accuracies

Predictor	*Best's Ratings*	*Financial Variables*	*IRIS*
Logit Predictor Coefficients for Estimation Sample			
BRT	-1.0498		
NIITI	-7.4324***		
NOGNPW	-3.6767	-4.7109***	
CHAMIX	128.8000	138.7000	
CHNPW	1.0746		
CHCS	-1.7353	-1.7646	
Model Fit[a]	1.486	15.745*	12.810*
Pseudo-R^2	2.12%	28.60%	24.30%
Classification Accuracies for Estimation and Holdout Samples (%)			
Estimation Sample			
Correct Solvent	19.23	73.08	73.07
Correct Insolvent	92.31	80.77	57.69
Correct Total	55.77	76.92	65.38
Holdout Sample			
Correct Solvent	23.53	82.35	58.82
Correct Insolvent	94.12	64.71	58.82
Correct Total	58.82	73.53	58.82

Note: BRT = a dummy variable for Best's recommendation at time t, equal to one if recommended in year t and 0 if not recommended in year t; NIITI = the ratio of net investment income to total income; CHAMIX = change in asset mix; CHNPW = change in net premiums written; and CHCS = change in capital and surplus.
[a] Chi-square statistic.
* Significant at the 1 percent level.
*** Significant at the 10 percent level.

presented are based on the stepwise selection process using the subset of financial variables for year t (the year prior to insolvency) and the subset of eight IRIS ratios.[7] These particular subsets produced higher classification accuracies compared to any of the previously discussed subsets, including those that contained variables from two years prior to insolvency. Table 2 summarizes the coefficients and classification accuracies of the models.

[7] This set of financial variables excludes ratios of expenses to total premiums, expenses to net premiums written, expenses to total income, expenses to insurance in force, and the lapse ratio—which were missing for half the estimation sample—and the organizational form, general agency, and branch office dummy variables—which were never selected by the model in any subset. Only eight of the twelve IRIS ratios for life insurers could be calculated with the data base available: change in capital and surplus, ratios of net operating gain to net premiums written, expenses to total premiums, net investment income to liquid assets, real estate to capital and surplus, change in net premiums written, change in product mix, and change in asset mix. Change in asset mix is calculated using five rather than ten asset classes. The ratio of expenses to total premiums was often dropped, because it was unavailable for half of the insurers in the estimation sample.

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There was significant overlap in the variables chosen by the stepwise procedure from both the financial ratio and IRIS subsets. The ratio of net operating gain to net premiums written, change in asset mix, and change in capital and surplus are common to both models, but the inclusion of a fourth variable, the ratio of net investment income to total income, in the financial ratio model produced better classification results for the estimation sample (76.9 percent correct) than did the selection of the change in net premiums written in the IRIS model (65.4 percent correct). The financial ratio model does a better overall job of classification, particularly in identifying insolvent insurers (80.8 percent correct). This general finding that additional financial variables must be considered in conjunction with IRIS ratios is consistent with Barrese (1990) and BarNiv and Hershbarger (1990).

When the models developed from the estimation sample were applied to the holdout sample, classification results were somewhat less accurate, with one exception. The financial variable logit model performed comparably for the estimation and holdout samples (76.9 percent and 73.5 percent total correct, respectively). However, better accuracy in predicting solvent insurers came at the expense of accuracy in predicting insolvent insurers for the holdout sample.

One explanation for this decreased predictive accuracy lies with the possible systematic change over time in the variables chosen as model predictors. Such change could be attributable to differences within the industry as well as in the economy between the estimation sample time period of 1969 through 1986 and the holdout sample time period of 1987 through 1991. A Wilcoxon matched-pairs sign-ranks test was applied to the data to detect changes in the predictors between the estimation and the holdout sample periods. For solvent insurers, all chosen variables except the change in net premiums written were significantly different at conventional levels across the two time periods. Variables for the insolvent insurers were more stable; only change in asset mix, the ratio of net operating gain to net premiums written, and the ratio of net investment income to total income were significantly different from the estimation to the holdout periods. In a multivariate context, the chosen variables still discriminate with reasonable accuracy for the holdout sample.

Combining Best's Recommendations with Financial Ratios

To capture nonfinancial as well as the more detailed financial information contained in Best's recommendations, Best's dummy variables should be combined with financial ratios into one model. Incorporating the Best's information could be done using a Bayesian approach, where, in a financial variable model, the prior probabilities of solvency and insolvency are altered according to Best's classification results (see Ambrose and Seward, 1988). However, given the poor fit of the Best's model, the Best's dummy variables are simply considered as predictors simultaneously with financial ratios.

From this set of variables—which included the full six years of Best's recommendation variables, the change in recommendation variable, and the financial ratios from one year prior to insolvency—the stepwise logit procedure selected three variables chosen in previous models (the ratio of net investment

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income to total income, the ratio of net operating gain to net premiums written, and change in asset mix) and also selected the time t Best's recommendation dummy variable and the change in reserves variable.[8] This predictor combination produced the most successful classification of any other models considered, with a total accuracy of 80.8 percent using logit on the estimation sample (see Table 3). It performed particularly well in identifying insolvent insurers (88.5 percent correct).[9] Although the logit model including the time t Best's recommendation dummy variable performed equally as well overall as the financial variables model on the holdout sample, it classified insolvent insurers more successfully.

To highlight the marginal contribution of the Best's recommendation dummy variable, we conducted the same test using the same four financial variables omitting the Best's variable (see Table 3).[10] Although the model fit and pseudo-R^2 statistics are slightly improved, classification accuracy for insolvent insurers suffers when the Best's variable is omitted. When applied to the holdout sample, the marginal contribution of the Best's variable is more pronounced. The total percentage correct dropped from 73.5 percent to 66.7 percent.

Conclusions

The primary purpose of this study is to formally incorporate Best's recommendations into a life insurer insolvency prediction model. Using the recommendation in the year prior to insolvency as the predictor correctly identifies over 90 percent of insolvent insurers but performs poorly in identifying solvent insurers. These results imply that ratings below A or A+ do not necessarily indicate a high probability of insolvency and that parties who rely on these ratings may find that they provide insufficient advance warning of possible financial distress.

[8] The lack of significance of any of the variables at the 10 percent level or less arises because the default level of significance for a variable to enter or stay in the model is set at 15 percent in the SAS procedure.

[9] Because choice-based sampling causes the probability of being classified as insolvent to be underestimated and since misclassification of insolvent firms is more costly, alternative cutoff probabilities were considered. At a 60 percent cutoff point in the model including the time t Best's recommendation dummy variable, total correct percentages dropped to 75 percent and 70.6 percent for the estimation and holdout samples, respectively. In both cases, the decrease came entirely from more misclassified solvent insurers. At a 70 percent cutoff point, the percentage correct insolvent was still 88.5 percent, but the percentage correct solvent dropped to 50 percent, for a total percent correct of 69.2 percent for the estimation sample. For the holdout sample, the total correct percentage stayed the same at 73.5 percent, with a gain in the percent correct for insolvent to 88.2 percent but a drop for solvents to 64.7 percent correct.

[10] Differences between the variables selected and classification accuracies in the financial variable model shown in Table 2 and the four-variable model without the Best's variable in Table 3 stem from the stepwise logit procedure choosing from different variable selection sets.

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Table 3

	Financial Ratios With Best's Recommendations	*Financial Ratios Without Best's Recommendations*
Logit Predictor Coefficients for Estimation Sample		
BRT	-0.2047	
CHRES	0.0160	0.0169
NIITI	-6.0640	-6.0020
NOGNPW	-3.9054	-4.0615
CHAMIX	124.7000	127.5000
Model Fit[a]	15.870*	16.192*
Psuedo-R^2	27.52%	28.88%
Classification Accuracies for Estimation and Holdout Samples (%)		
Estimation Sample		
Correct Solvent	73.07	73.07
Correct Insolvent	88.46	84.62
Correct Total	80.77	78.85
Holdout Sample		
Correct Solvent	76.47	70.59
Correct Insolvent	70.59	62.50
Correct Total	73.53	66.67

Note: BRT = a dummy variable for Best's recommendation at time t, equal to one if recommended in year t and 0 if not recommended in year t; CHRES = change in reserves; NIITI = the ratio of net investment income to total income; NOGNPW = the ratio of net operating gain to net premiums written; and CHAMIX = change in asset mix.

[a] Chi-square statistic.

* Significant at the 1 percent level.

The IRIS ratios considered here do not sufficiently distinguish between solvent and insolvent insurers, achieving at best a 75 percent correct classification rate. Additional financial variables in conjunction with IRIS ratios provide significant improvement in predicting solvency status.

Further improvement in classification occurs by combining the IRIS ratios and other financial variables with Best's recommendations. This five-variable logit model correctly classifies a total of 80.8 percent of insurers in the estimation sample and 73.5 percent in the holdout sample. More importantly, it is particularly effective in identifying insolvent insurers, with 88.5 percent correct in the estimation sample. This model achieves a higher overall correct classification percentage than any other model considered, providing weak evidence that Best's ratings contain additional information for insolvency prediction within the multivariate framework.

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Appendix A

Sample Life Insurers

Holdout Sample

Solvent

Arcadia National Life Insurance Company
B'nai Zion
Catholic Knights of America
Colonial Security Life
Connecticut Mutual Life
Employers Life Insurance Company of Alabama
Financial Security Life
First American Southwest Life Insurance Company
First Catholic Slovak Union
Gulf and Western Life Insurance Company of Arizona
Life Assurance Company of America
Monitor Life Insurance Company of New York
Mountain States Life Insurance Company
National Home Life and Accident Insurance Company
National Life Insurance Company
Transamerica Occidental
Universal Assurors Life Insurance Company

Insolvent

Amalgamated Labor Life Insurance Company
American Guaranty Life Insurance Company
American Standard Life and Accident
American Sun Life Insurance Company
American Trustee Life Insurance Company of America
California Pacific Life Insurance Company
Colony Charter Life Insurance Company
Executive Life
Farm and Ranch Life Insurance Company
First Capital Life Insurance Company
First Farwest Life Insurance Company
Mutual Benefit Life
Old Southern Life Insurance Company
Professional Investors Life Insurance Company
The Midwest Life Insurance Company
University Security Life Insurance Company
World Life and Health Insurance Company of Pennsylvania

Estimation Sample

Insolvent

American Savings Life Insurance Company
American Travelers Life Insurance Company
California Life Insurance Company
Community Life Insurance Company
Continental Bankers Life Insurance Company of the South
Equity Educators Assurance Company
Farmers National Life Insurance Company
Federated American Life Insurance Company
First National Credit Life Insurance Company
First National Life Insurance Company
Georgetown Life Insurance Company
Imperial General Life Insurance Company
Independent Liberty Life Insurance Company
International Bankers Life Insurance Company
Iowa State Travelers Mutual Assurance Company
Life Insurance Company of America
Los Angeles Life Insurance Company
Mercury National Life Insurance Company
National Assurance Life Insurance Company
National Bankers Life Insurance Company
Northeastern Life Insurance Company of New York
Southwest Capital Life Insurance Company
Southwestern Security Life Insurance Company
Standard Life and Accident Insurance Company
Underwriters National Assurance Company
Universal Security Life Insurance Company
Western American Life Insurance Company of New Mexico

Solvent

Atlantic Coast Life Insurance Company
Bankers Life Insurance Company of America
Central Plains Life Insurance Company, Inc.
Congressional Life Insurance Company
Degree of Honor Protective Association
First Pyramid Life Insurance Company of America
Foley Reserve Life Insurance Company
GIC Life Insurance Company
Great Equity Life Insurance Company
Guaranty National Life Insurance Company
Hill Country Life Insurance Company
Independence Life and Accident Insurance Company
Kennedy National Life Insurance Company of America
Liberty Investors Life Insurance Company
National Farm Life Insurance Company
North America Life Insurance Company
North Coast Life Insurance Company
Old Colony Life Insurance Company
Ozark National Life Insurance Company
Reserve National Life Insurance Company
Standard Life and Casualty Insurance Company
State Life Insurance Company of Colorado
States General Life Insurance Company
World Insurance Company

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Appendix B

Variable Definitions

Financial Ratios

CHCS	Change in Capital and Surplus
NOGNPW	Net Operating Gain to Net Premiums Written
EXTP	Expenses to Total Premium
NIILA	Net Investment Income to Liquid Assets
NIITI	Net Investment Income to Total Income
REPHS	Real Estate to Capital and Surplus
CHNPW	Change in Net Premiums Written
CHPMIX	Change in Product Mix
CHAMIX	Change in Asset Mix
PHSTL	Capital and Surplus to Total Liabilities
PHSIIF	Capital and Surplus to Insurance in Force (in thousands)
AATL	Admitted Assets to Total Liabilities
TLLA	Total Liabilities to Liquid Assets
EXPNPW	Expenses to Net Premiums Written
EXPTI	Expenses to Total Income
EXPIIF	Expenses to Insurance in Force (in thousands)
CHIIF	Change in Insurance in Force
CHAA	Change in Admitted Assets
GRPCT	Group Net Premiums Written to Net Premiums Written
AHPCT	Accident and Health Net Premiums Written to Net Premiums Written
PCONC	Product Line Concentration
IFCONC	Insurance in Force Concentration
NPWPHS	Net Premiums Written to Capital and Surplus
RESPHS	Reserves to Capital and Surplus
CHRES	Change in Reserves
COMNPW	Commissions to Net Premiums Written
COMIIF	Commissions to Insurance in Force (in thousands)
LAPS	Lapse Ratio
FORM	Organizational form dummy: 1 = stock, 0 = mutual
GA	General Agency dummy: 1 = general agency, 0 = other
BO	Branch Office dummy: 1 = branch office, 0 = other

Note: All financial ratios were calculated for both year t and year t-1, where t is the year prior to insolvency and t-1 is two years prior to insolvency. Listed above are the variable names for year t only. Year t-1 variables are designated by adding a 1 at the end of each variable name. For instance, CHCS1 is Change in Capital and Surplus Year t-1.

Best's Recommendation Dummy Variables

BRT	1 = recommended year t	0 = not recommended year t
BRT1	1 = recommended year t-1	0 = not recommended year t-1
BRT2	1 = recommended year t-2	0 = not recommended year t-2
BRT3	1 = recommended year t-3	0 = not recommended year t-3
BRT4	1 = recommended year t-4	0 = not recommended year t-4
BRT5	1 = recommended year t-5	0 = not recommended year t-5
CHBR	+1 = change from not recommended to recommended year t-1 = change from recommended to not recommended year t, 0 = no change	

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References

A. M. Best Company, annual, *Best's Aggregates and Averages: Life-Health Edition* (Oldwick, N.J.: A. M. Best).

A. M. Best Company, annual, *Best's Insurance Reports: Life and Health Edition* (Oldwick, N.J.: A. M. Best).

Ambrose, Jan Mills and J. Allen Seward, 1988, Best's Ratings, Financial Ratios and Prior Probabilities in Insolvency Prediction, *Journal of Risk and Insurance,* 55: 229-244.

BarNiv, Ran, 1990, Accounting Procedures, Market Data, Cash-Flow Figures, and Insolvency Classification: The Case of the Insurance Industry, *Accounting Review,* 65: 578-604.

BarNiv, Ran and Robert A. Hershbarger, 1990, Classifying Financial Distress in the Life Insurance Industry, *Journal of Risk and Insurance,* 57: 110-136.

BarNiv, Ran and James B. McDonald, 1992, Identifying Financial Distress in the Insurance Industry: A Synthesis of Methodological and Empirical Issues, *Journal of Risk and Insurance,* 60: 543-574.

BarNiv, Ran and Michael L. Smith, 1987, Underwriting, Investment and Solvency, *Journal of Insurance Regulation,* 5: 409-428.

Barrese, James, 1990, Assessing the Financial Condition of Insurers, *CPCU Journal,* 43: 37-46.

Denenberg, Herbert S., 1967, Is "A-Plus" Really a Passing Grade?, *Journal of Risk and Insurance,* 34: 371-384.

Harrington, Scott E. and Jack M. Nelson, 1986, A Regression-Based Methodology for Solvency Surveillance in the Property Liability Insurance Industry, *Journal of Risk and Insurance,* 53: 583-605.

Hershbarger, Robert A. and Ronald K. Miller, 1986, The NAIC Information System and the Use of Economic Indicators in Predicting Insolvencies, *Journal of Insurance Issues and Practices,* 9: 21-43.

Maddala, G. S., 1983, *Limited-Dependent and Qualitative Variables in Econometrics,* Econometric Society Monographs in Quantitative Economics (Cambridge: Cambridge University Press).

Maddala, G. S., 1991, A Perspective on the Use of Limited-Dependent and Qualitative Variables Models in Accounting Research, *Accounting Review,* 66: 788-807.

Ohlson, James A., 1980, Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research,* 18: 109-131.

Palepu, Krishna G., 1986, Predicting Takeover Targets: A Methodological and Empirical Analysis, *Journal of Accounting and Economics,* 8: 3-35.

Pinches, George E. and James Trieschmann, 1974, The Efficiency of Alternative Models for Solvency Surveillance in the Insurance Industry, *Journal of Risk and Insurance,* 41: 563-577.

Shaked, Israel, 1985, Measuring Prospective Probabilities of Insolvency: An Application to the Life Insurance Industry, *Journal of Risk and Insurance,* 52: 59-80.

Trieschmann, James S. and George E. Pinches, 1973, A Multivariate Model for Predicting Financially Distressed P-L Insurers, *Journal of Risk and Insurance,* 40: 327-338.

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