©*The Journal of Risk and Insurance*, 1998, Vol. 65, No. 2, 275-288.

Life Insurer Financial Distress, Best's Ratings and Financial Ratios

Steven W. Pottier

ABSTRACT

This study compares the predictive ability of: (1) ratings, rating changes and total assets; (2) financial ratios; and (3) financial ratios combined with ratings and rating changes on a sample of forty-eight insolvent life insurers over the period 1990 to 1992. Based on the expected cost of misclassification, ratings, rating changes and total assets have comparable predictive ability to financial ratios combined with ratings and rating changes. However, combining ratings and rating changes with financial ratios improves predictive ability compared to financial ratios alone for most cost ratios. Another interesting finding is that adverse rating changes are important predictors of insolvency.

INTRODUCTION

Regulators, consumers and other parties interested in the financial strength of insurers must optimally allocate their resources to solvency monitoring (Klein and Barth, 1995; Lamm-Tennant, Starks and Stokes, 1996). Different sources of information are available to evaluate an insurer's insolvency risk, including financial ratios, ratings and rating changes. The large number of potential financial ratios, along with changes in important predictor variables over time, make it costly to use financial ratios compared to summary risk measures, such as ratings and rating changes (see Denenberg, 1967; Wakeman, 1981). Consequently, the cost of solvency monitoring depends on both the predictor variables used in insolvency prediction models and the party who performs the insolvency risk assessment.

This study compares the predictive ability of financial ratios to that of A.M. Best's ratings and rating changes using a range of misclassification costs in order to evaluate their efficiency as insolvency predictor variables. It is important to consider a range of misclassification costs for at least two reasons. First, the efficiency of different insolvency predictor variables might change for different misclassification costs. Second, misclassification costs are likely to differ for regulators, consumers, insurance agents and others (see Zavgren, 1983).

Although previous researchers have examined alternative insolvency predictor variables, this study is unique in four ways. First, this study examines the

---

Steven Pottier is an Assistant Professor of Risk Management and Insurance at The University of Georgia. The author thanks Patrick Brockett, David Cummins, Sandra Gustavson, Robert Hoyt, David Sommer and two anonymous reviewers for comments and suggestions.

predictive ability of rating changes along with rating levels. Existing studies that use Best's ratings do not examine the full range of Best's ratings and do not evaluate rating changes. Second, this is the first study to compare the predictive ability of financial ratios to that of ratings and rating changes using the expected cost of misclassification. The importance of considering misclassification costs has been noted by BarNiv and McDonald (1992) and others. Third, this is the first study to examine the predictive ability of ratings and rating changes on a population of rated insurers, consistent with the actual application of insolvency prediction models (Klein, 1995; Lamm-Tennant, Starks and Stokes, 1996).[1] Fourth, this is the first study on a population of life insurers to validate its results on a time-series holdout sample.

This study provides the following new evidence on the efficiency of ratings and rating changes as indicators of insurer financial distress compared to financial ratios. It finds that for some relative misclassification costs, ratings, rating changes and total assets combined produce the lowest expected cost of misclassification. However, financial ratios combined with ratings and rating changes also produces the lowest expected cost of misclassification for some (other) cost ratios. Moreover, combining ratings and rating changes with financial ratios improves predictive ability compared to using financial ratios alone for most cost ratios. Another important finding is that adverse rating changes provide early warning of insurer financial distress. Lastly, this study finds that it is particularly important to validate results on a time-series holdout sample because a naive model produces the lowest expected cost of misclassification for some cost ratios only in the holdout samples. In summary, this study documents the importance of considering misclassification costs when choosing among alternative insolvency prediction models and finds that the predictive ability of ratings and rating changes is comparable to financial ratios alone or financial ratios combined with ratings and rating changes.

PRIOR RESEARCH

Various predictor variables and methodologies have been used to predict insurer insolvency. BarNiv and Hershbarger (1990) is the first study to examine life insurer insolvency. Ambrose and Carroll (1994) conclude that financial ratios combined with Best's recommendations[2] are more efficient predictors of life insurer insolvency than either financial ratios or Best's recommendations separately. The results of this study are different from theirs because this study considers a range of misclassification costs, rating changes and a more complete

[1]The large sample size makes it feasible to construct an extensive system of binary variables to measure rating levels and rating changes prior to insolvency while minimizing the potential loss of information by aggregating rating categories (see Altman, et al., 1981, p. 132). In small samples, the degrees of freedom would preclude examination of such a large number of predictor variables.
[2]Their Best's recommendations variable equals one if an insurer is rated A or higher, and zero otherwise.

specification of Best's ratings. Carson and Hoyt (1995) is the first study to use a population of life insurers.

Trieschmann and Pinches (1973), Harrington and Nelson (1986), Ambrose and Seward (1988), BarNiv (1990), Brockett et al. (1994), Cummins, Harrington and Klein (1995), and Lamm-Tennant, Starks and Stokes (1996) examine property-liability insurer insolvencies. BarNiv and McDonald (1992) discuss methodological problems related to many insolvency studies and provide a good summary of earlier studies. Lee and Urrutia (1996) use the expected cost of misclassification to compare logit and hazards models and conclude that these two models have comparable forecasting ability. BarNiv and Hathorn (1997) examine the merger or insolvency alternative in the insurance industry.

METHODOLOGY, VARIABLES AND SAMPLE

Methodology and Variables

Three insolvency prediction models are estimated for two estimation samples using stepwise logistic regression. The three models use different sets of predictor variables. The three sets of predictor variables are: (1) financial ratios (FINANCIAL); (2) Best's ratings, rating changes and total assets (RATINGS); and (3) financial ratios combined with ratings and rating changes (FINRATING). The potential predictor variables are listed in Appendix A. Best's ratings are described in Best (1990). Results are validated on two time-series holdout samples. The expected cost of misclassification is used to compare the performance of the three sets of predictors (see BarNiv, 1990; BarNiv and McDonald, 1992).[3]

Sample

The estimation and holdout samples consist of U.S. domiciled stock and mutual life insurers that were rated by Best for each of the three consecutive years prior to insolvency. The use of rating change variables motivated the requirement for three years of ratings. These criteria produced samples of 1208, 1148, and 1074 insurers in 1989, 1990, and 1991 data years, respectively. The number of insolvent insurers was 15, 24, and 9 in 1990, 1991, and 1992, respectively, yielding corresponding sample insolvency frequency rates of 1.24, 2.09, and .84 percent. These sample

[3]Insurers are classified as solvent or insolvent using the probability cutoff scores that minimize the expected cost of misclassification in the estimation sample (see Dopuch, Holthausen, and Leftwich, 1987, pp. 444-445). Observations in the holdout sample are then classified with cutoff scores that minimize the expected cost of misclassification in the estimation sample for each relative cost of type 1 and type 2 errors. The expected cost of misclassification (ECM), is: ECM=[Prob(insolvent in population) x (1 - percent insolvent correctly classified) x relative misclassification cost] + [Prob(solvent in population) x (1 - percent solvent correctly classified)]. This study uses a prior probability of insolvency of one percent. The relative misclassification cost is the ratio of the cost of type 1 errors (insolvent insurer identified as a solvent one) to the cost of type 2 errors (solvent insurer identified as an insolvent one) and ranges from 1 to 200. The optimal cutoff point (i.e., predicted probability) is high (low) when relative misclassification costs are low (high).

insolvency frequency rates are comparable to other studies using a population of insurers.[4]

EMPIRICAL RESULTS

Logistic regression results for the 1990 data year are shown in Table 1.[5] A positive (negative) slope coefficient indicates that a higher value of that independent variable increases (decreases) the predicted probability of insolvency. The coefficients of all predictor variables are significant at traditional levels. As reported in Table 1, binary variables for various ratings and adverse rating changes are significant predictors of insolvency.

Table 2 displays classification rates for the 1990 estimation sample and 1991 holdout sample.[6] The low frequency of insolvent insurers in the population and the use of time-series holdout samples might explain why classification rates in the holdout samples for insolvent insurers are lower than reported in prior research. Assuming equal relative misclassification costs, no insolvent insurers are correctly classified in the holdout samples. If all insurers are predicted to be solvent (i.e., naive model), then 97.91 and 99.16 percent would be correctly classified in the 1990 and 1991 holdout samples, respectively. When relative misclassification costs are equal (cost ratio = 1), the hypothesis that the three alternative sets of insolvency predictor variables have the same predictive ability cannot be rejected using a chi-squared test (see BarNiv, 1990; Conover, 1971, pp. 140-149).[7] When misclassification costs are not equal, the relative performance of ratings and financial ratios is compared based on expected misclassification costs.[8]

The expected cost of misclassification (ECM) associated with the three sets of predictor variables (FINANCIAL, FINRATING and RATINGS) and a naive model is presented in Table 3 for various cost ratios in the range of 1 to 200. Figures 1 and 2 graphically present these results. The most prominent result is that the relative performance (ranking by ECM) of the three alternative sets of predictor variables varies depending on the assumed cost ratio, which clearly demonstrates the importance of considering misclassification costs when choosing among

[4]The insolvency frequency rates in Lamm-Tennant, Starks and Stokes (1996) range from .26 to 1.4 percent.

[5]Logistic regression results for the 1989 data year are available from the author upon request. The primary difference is that significant predictors within each set differ between estimation samples because a stepwise logistic procedure is used. However, the initial three sets of potential predictors considered by the stepwise procedure do not change between estimation samples.

[6]Tables showing classification results and the expected cost of misclassification for the 1989 estimation sample and 1990 holdout sample are available from the author upon request.

[7]The null hypothesis is that the overall classification rates from each of the three sets of predictors are equal. The chi-squared statistics (2 degrees of freedom) are below one for each of the four samples, and therefore, the overall classification rates are not significantly different.

[8]In general, minimizing the expected cost of misclassification is not equivalent to maximizing the overall classification rate. These criteria are equivalent when relative misclassification costs are equal (cost ratio = 1) and the sample proportions of solvent and insolvent insurers equal their prior probabilities in the ECM formula. This result is easily derived from the definition of ECM given in footnote 3.

alternative insolvency prediction models. In addition, in both estimation samples, the three sets of predictors outperform a naive model for all cost ratios. However, in the 1990 and 1991 holdout samples, the naive model produces the lowest ECM for 11 and 2 cost ratios, respectively, all below 20.[9]

Table 1
Predictor Coefficients: 1990 Estimation Sample
(1990 data year, 1991 insolvencies)

	Model		
Predictor Variables	FINANCIAL	FINRATING	RATINGS
Financial Ratios:			
Real Estate to Capital and Surplus	0.0130***		
Change in Asset Mix	0.2430***	0.2839***	
Non-admitted Assets to Total Assets	0.0099*		
Benefits Paid to Net Premiums Written	0.0016*		
Non-Investment Grade Bonds to CSMSVR	0.0065***	0.0073***	
Delinquent and Foreclosed Mortgages to CSMSVR	-0.0171***	-0.0066*	
Separate Account Assets to Total Assets	0.0357***	0.0352**	
Life Exposure to CSMSVR	0.4091***	0.3463***	
Accident & Health Exposure to CSMSVR	0.2999***	0.2610***	
Other Exposure to CSMSVR	-0.6344**	-0.5676**	
Log of total admitted assets			0.4184***
Ratings and Rating Changes:			
D Rating		2.8934***	4.4431***
NA3 Rating			3.3949***
NA4 Rating			3.6817***
NA5 Rating			3.4216***
NA9 Rating			3.6873***
Letter Downgrade, 1			2.4625***
Letter Downgrade, 2		2.1801***	2.4226***
Letter to NA Rating, 1		1.5726*	
NA to other NA Rating, 2		2.2961**	
Constant	-7.1131***	-7.7782***	-14.372***
Number of Independent Variables	10	11	7
Logistic R^2	.4389	.5095	.3551
Likelihood Ratio Statistic	102.3***	118.8***	82.8***
Number of Solvent Insurers	1124	1124	1124
Number of Insolvent Insurers	24	24	24

Note: ***, ** and * indicate significance at the .01, .05 and .10 levels, respectively.

[9]A naive model also produces a lower expected cost of misclassification for some cost ratios in Lee and Urrutia (1996).

Table 2
Classifications Results
1990 Estimation Sample and 1991 Holdout Sample
(percent correct)

Model	Estimation sample Insolvent N=24	Estimation sample Solvent N=1124	Estimation sample Overall N=1148	Holdout sample Insolvent N=9	Holdout sample Solvent N=1065	Holdout sample Overall N=1074
	Cost ratio=1			*Cost ratio=1*		
FINANCIAL	29.17	100.00	98.52	0.00	99.91	99.07
FINRATING	29.17	100.00	98.52	0.00	99.91	99.07
RATINGS	8.33	100.00	98.08	0.00	100.00	99.16
	Cost ratio=20			*Cost ratio=20*		
FINANCIAL	66.67	96.71	96.08	33.33	96.71	96.18
FINRATING	87.50	94.48	94.34	55.56	95.49	95.16
RATINGS	62.50	93.51	92.86	33.33	93.15	92.64
	Cost ratio=100			*Cost ratio=100*		
FINANCIAL	83.33	89.68	89.55	33.33	91.74	91.25
FINRATING	91.67	93.59	93.55	66.67	95.02	94.79
RATINGS	95.83	86.39	86.59	77.78	85.07	85.01
	Cost ratio=200			*Cost ratio=200*		
FINANCIAL	100.00	62.81	63.59	77.78	65.63	65.74
FINRATING	91.67	93.59	93.55	66.67	95.02	94.79
RATINGS	95.83	86.39	86.59	77.78	85.07	85.01

Table 3
Expected Cost of Misclassification
1991-1992 Insolvencies

	Model			
	FINANCIAL	FINRATING	RATINGS	NAIVE
Cost ratio	*Panel A: 1990 estimation sample (1990 data year, insolvent 1991)*			
1	0.0071	0.0071	0.0092	0.0100
5	0.0306	0.0305	0.0410	0.0500
10	0.0577	0.0498	0.0746	0.1000
20	0.0993	0.0796	0.1393	0.2000
50	0.1855	0.1051	0.1556	0.5000
100	0.2688	0.1468	0.1764	1.0000
150	0.3426	0.1884	0.1973	1.5000
200	0.3682	0.2301	0.2181	2.0000
	Panel B: 1991 holdout sample (1991 data year, insolvent 1992)			
1	0.0109	0.0109	0.0100	0.0100
5	0.0528	0.0454	0.0482	0.0500
10	0.1028	0.0871	0.0732	0.1000
20	0.1659	0.1335	0.2012	0.2000
50	0.4151	0.2159	0.2589	0.5000
100	0.7485	0.3826	0.3700	1.0000
150	0.8582	0.5493	0.4811	1.5000
200	0.7847	0.7159	0.5922	2.0000

Figure 1
Expected Cost of Misclassification
1990 Estimation Sample
(1990 data year, 1991 insolvencies)

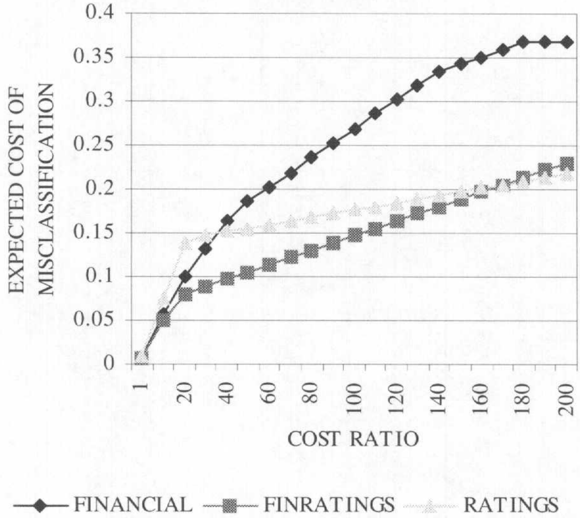
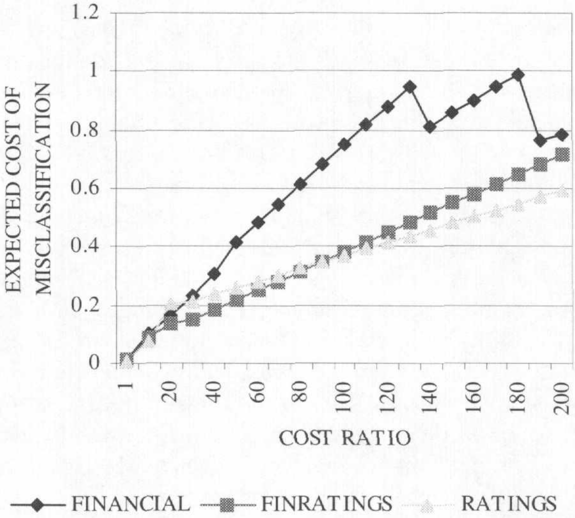


Figure 2
Expected Cost of Misclassification
1991 Holdout Sample
(1991 data year, 1992 insolvencies)



The ECM from each set of predictors is compared in Table 4. This comparison is performed for three different ranges of cost ratios because the relative performance of the three sets of predictors differs across these three ranges of cost ratios, as discussed below. The Friedman chi-squared test (see BarNiv, 1990; Conover, 1971, pp. 265-270) is used to test the hypothesis that the ECM from two different models differs in medians.[10] As shown in Table 4, the RATINGS model is significantly better than the FINRATING model for cost ratios 1 to 20. The RATINGS model is significantly better than the FINANCIAL model for cost ratios 1 to 100. The FINRATING model is significantly better than the two other sets of predictors for cost ratios 1 to 100. While in the 1990 holdout sample, for cost ratios 101 to 200, FINRATING and FINANCIAL are significantly better than RATINGS; in the 1991 holdout sample, RATINGS is superior to the other two models. Consequently, the two holdout samples produce remarkably similar results for cost ratios below 100, but inconclusive results regarding the performance of RATINGS compared to either FINANCIAL or FINRATING for cost ratios above 100. Ratings and rating changes add incremental predictive ability to financial ratios for most cost ratios in both holdout samples (as a result, FINRATING is significantly better than FINANCIAL for cost ratios 1 to 200).[11] However, because the relative performance of the three sets of predictors changes across the range of

[10] Since the primary interest of this study is in predictive ability, statistical tests are not reported for the estimation samples. Results from the estimation samples are available upon request from the author.
[11] In the holdout samples, FINANCIAL produces a lower ECM than FINRATING only six times.

cost ratios, this study concludes that the three sets of predictors have comparable predictive ability.

SUMMARY AND CONCLUSIONS

The purpose of this study is to evaluate the efficiency of Best's ratings and rating changes compared to financial ratios as predictors of life insurer insolvency. The expected cost of misclassification of using financial ratios, ratings and rating changes, and financial ratios combined with ratings and rating changes is compared over a broad range of relative misclassification costs. This study provides evidence that using ratings, rating changes and total assets combined is more efficient than using financial ratios combined with ratings and rating changes (or financial ratios alone) for some cost ratios in both holdout samples. However, using financial ratios combined with ratings and rating changes is more efficient for some other cost ratios. Also, combining ratings and rating changes with financial ratios improves predictive ability compared to financial ratios alone for most cost ratios, but ratings and rating changes do not consistently outperform financial ratios. Consequently, this study concludes that the three sets of insolvency predictors have comparable forecasting ability. Another important finding is that adverse rating changes are significant predictors of insurer insolvency even when combined with financial ratios suggesting that rating changes should be incorporated into insolvency prediction models.

A limitation of the study is that prior research provides little guidance on the appropriate relative misclassification cost considering that the relative performance of the three sets of predictors changes over the range of cost ratios. The actual cost ratio also is likely to differ for regulators, consumers, insurance agents and others (see Zavgren, 1983).

This study extends prior insolvency research by examining rating changes and a more complete specification of ratings. Other important extensions to prior research are considering how the predictive ability of ratings, rating changes and financial ratios change under different assumptions about misclassification costs and using a population of insurers. The evidence that ratings and rating changes are more efficient predictors of insolvency over some ranges of relative misclassification costs might support the use of ratings and rating changes rather than financial ratios by consumers, insurance agents and other parties who might rely exclusively on ratings to evaluate insurers because of the higher information cost of financial ratio analysis.

The National Association of Insurance Commissioners currently relies on private rating services to rate certain insurer investments, such as bonds. Other regulatory bodies, such as the Securities and Exchange Commission have required financial ratings for many years (Cantor and Packer, 1995). The results of this study suggest that regulators should consider whether ratings should be relied upon more to monitor insurer solvency. A final implication of this study is that future research on insurer insolvency should consider a broad range of relative misclassification costs when comparing different insolvency predictor variables.

Table 4
Comparison of Expected Cost of Misclassification
1991 Holdout Sample (Insolvent 1992)

Models Compared	Cost ratio 1-20	1-100	101-200
FINANCIAL vs. RATINGS:			
FINANCIAL lower than RATINGS	1	6	0
RATINGS lower than FINANCIAL	19	94	100
Chi-squared statistic	**16.2**	**77.4**	**100.0**
FINRATING vs. RATINGS:			
FINRATING lower than RATINGS	6	74	0
RATINGS lower than FINRATING	14	26	100
Chi-squared statistic	**3.2**	**23.0**	**100.0**
FINANCIAL vs. FINRATING:			
FINANCIAL lower than FINRATING	5	5	0
FINRATING lower than FINANCIAL	15	95	100
Chi-squared statistic	**5.0**	**81.0**	**100.0**

Note: This tables shows the number of times (frequencies) one model produces a lower ECM than another model for three different ranges of relative misclassification costs (cost ratio). The Friedman chi-squared test (see BarNiv, 1990; Conover, 1971, pp. 265-270) is used to test the hypothesis that the ECM from two different models differs in medians. Chi-squared statistics, shown in bold, are significant at traditional levels (.10 level or better).

APPENDIX A

Independent Variables Considered

IRIS:
Change in CS
Net Income to Total Income
Adequacy of Investment Income
Non-Admitted Assets to Total Assets
Real Estate to CS
Affiliated Investments to CS
Commissions and Expenses to Premiums and Deposits
Change in Premiums
Change in Product Mix
Change in Asset Mix
Change in Reserving Ratio
Surplus Relief

LIQUIDITY:
Quick Liquidity
Current Liquidity
Non-Investment Grade Bonds to CSMSVR

LEVERAGE:
Assets to CS
CS to Liabilities
Direct Premiums Written to CS
NPW to CS
Life Exposure to CSMSVR
Annuity Exposure to CSMSVR
Accident and Health Exposure to CSMSVR
Other Exposure to CSMSVR

PROFITABILITY
Benefits Paid to NPW
Commissions & Expenses to NPW
Net Operating Gain to Total Assets
Net Investment Yield
Return on Equity
Net Operating Gain to NPW
Pretax Operating Income to Total Revenue

Delinquent and Foreclosed Mortgages to CS	Accident and Health Combined Ratio
Common Stock to CS	<u>OTHER:</u>
Property Occupied by Company to CS	Natural Log of Total Admitted Assets
Bond Portfolio weighted average maturity	Years in Business
Separate Account Assets to Total Assets	Group affiliate binary variable
Cash Inflow to Cash Outflow	Organizational form binary variable
Ordinary Lapse Ratio	

<u>RATINGS:</u>	
A+(Superior)	=1, if rating A+ for data year, 0 otherwise
A(Excellent)	=1, if rating A for data year, 0 otherwise
A-(Excellent)	=1, if rating A- for data year, 0 otherwise
B+(Very Good)	=1, if rating B+ for data year, 0 otherwise
B(Good)	=1, if rating B for data year, 0 otherwise
B-(Good)	=1, if rating B- for data year, 0 otherwise
C+(Fair)	=1, if rating C+ for data year, 0 otherwise
CC-(Marginal)	=1, if rating C or C- for data year, 0 otherwise
D(Below Minimum Standards)	=1, if rating D for data year, 0 otherwise
NA2(Less Than Minimum Size)	=1, if rating NA2 for data year, 0 otherwise
NA3(Insufficient Operating Experience)	=1, if rating NA3 for data year, 0 otherwise
NA4(Rating Procedure Inapplicable)	=1, if rating NA4 for data year, 0 otherwise
NA5(Significant Change)	=1, if rating NA5 for data year, 0 otherwise
NA9(Company Request)	=1, if rating NA9 for data year, 0 otherwise
<u>RATING CHANGES:</u>	
Letter Downgrade, t	=1, if letter rating downgraded in t year before data year, 0 otherwise
Letter Upgrade, t	=1, if letter rating upgraded in t year before data year, 0 otherwise
Letter to NA, t	=1, if letter rating changed to NA in t year before data year, 0 otherwise
NA to Letter, t	=1, if NA rating changed to letter in t year before data year, 0 otherwise
NA to other NA, t	=1, if change within NA category in t year before data year, 0 otherwise

Note: CS = Capital and Surplus, CSMSVR = Capital and Surplus including Mandatory Security Valuation Reserve; NPW = Net Premiums Written.

Note: Since this study considers two years of rating changes, t=1 or 2. Consequently, there are ten potential rating change variables.

REFERENCES

Altman, Edward I., R.B. Avery, R.A. Eisenbeis, and J.F. Sinkey. 1981. *Application of Classification Techniques in Business, Banking and Finance.* Greenwich, CT: JAI Press.

Ambrose, Jan M., and Anne M. Carroll. 1994. "Using Best's Ratings in Life Insurer Insolvency Prediction." *Journal of Risk and Insurance*, 61: 317-327.

Ambrose, Jan M., and J. Allen Seward. 1988. "Best's Financial 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 John Hathorn. 1997. "The Merger or Insolvency Alternative in the Insurance Industry." *Journal of Risk and Insurance* 64: 89-113.

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* 59: 543-574.

Best, A.M. 1990. *Best's Insurance Reports, Life/Health.* Oldwick, NJ: A.M. Best Co., Inc.

Brockett, Patrick L., William W. Cooper, Linda L. Golden, and Utai Pitaktong. 1994. "A Neural Network Method for Obtaining an Early Warning of Insurer Insolvency." *Journal of Risk and Insurance* 61: 402-424.

Cantor, Richard, and Frank Packer. 1995. "The Credit Rating Industry." *Journal of Fixed Income* 5: 10-34.

Carson, James M., and Robert E. Hoyt. 1995. "Life Insurer Financial Distress: Classification Models and Empirical Evidence." *Journal of Risk and Insurance* 62: 764-775.

Conover, W.J. 1971. *Practical Nonparametric Statistics.* New York, NY: John Wiley & Sons, Inc.

Cummins, J. David, Scott E. Harrington, and Robert Klein. 1995. "Insolvency Experience, Risk-Based Capital, and Prompt Corrective Action in Property-Liability Insurance." *Journal of Banking and Finance* 19: 511-527.

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

Dopuch, Nicholas, Robert W. Holthausen, and Richard W. Leftwich. 1987. "Predicting Audit Qualifications with Financial and Market Variables." *Accounting Review* 62: 431-454.

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.

Klein, Robert W. 1995. "Solvency Monitoring of Insurance Companies: Regulators' Role and Future Direction." In *The Financial Dynamics of the Insurance Industry*. New York, NY: Business One-Irwin.

Klein, Robert W., and Michael M. Barth. 1995. "Solvency Monitoring in the Twenty-first Century." *Journal of Insurance Regulation* 13: 256-301.

Lamm-Tennant, Joan, Laura Starks, and Lynne Stokes. 1996. "Considerations of Cost Tradeoffs in Insurance Solvency Surveillance Policy." *Journal of Banking and Finance* 20: 835-852.

Lee, Suk Hun, and Jorge L. Urrutia. 1996. "Analysis of Insolvency Prediction in the Property-Liability Insurance Industry: A Comparison of Logit and Hazard Models." *Journal of Risk and Insurance* 63: 121-130.

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.

Wakeman, L.M. 1981. "The Real Function of Bond Rating Agencies." *Chase Financial Quarterly* 1: 18-25.

Zavgren, Christine V. 1983 "The Prediction of Corporate Failure: the State of the Art." *Journal of Accounting Literature* 2: 1-35.