

The Use of Event History Analysis to Examine Insurer Insolvencies

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ABSTRACT

This study employs dynamic statistical methodology, particularly event history analysis, to examine insurer insolvencies. Various potential factors associated with insolvencies are modeled empirically for a sample of insolvent and solvent insurers from 1984 through 1990 for property-liability insurers, and from 1987 through 1990 for life insurers.

Introduction

Insolvencies in the U.S. insurance industry have recently received increased attention. Both the number and magnitude of insolvencies have been significantly increasing relative to historical trends. In the 1980s, 258 insolvencies of property-liability insurers occurred, compared to 108 insolvencies during the 1970s. While the insolvencies of the 1970s occurred almost exclusively in small insurers, the more recent cases involved large property-liability insurers such as the Mission Insurance Group, Integrity Insurance Company, and Transit Casualty Company. Traditionally, life insurers have experienced considerably fewer insolvencies than property-liability insurers. From 1975 through 1990, 140 life insurer insolvencies have occurred, over half of which occurred from 1987 to 1990; in 1989 alone, 27 insurers became insolvent.

The two major statistical models that have been used for insolvency studies are multivariate discriminant analysis and binary response regression models. Both of these methods use a sample of solvent and insolvent firms studied over a short time interval. One limitation of this type of analysis is that the output is a classification of companies into a set of distressed companies and

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the complimentary set. In contrast to classification methodologies, the principal purpose of this study is to employ a dynamic statistical methodology to the financial data of property-liability and life insurer insolvencies. Various potential factors associated with insolvencies are empirically modeled for a sample of insolvent and solvent insurers from 1984 through 1990 for property-liability insurers, and from 1987 through 1990 for life insurers.

Because a superb review of earlier work on the use of statistical methods to identify financial distress in the insurance industry has been provided by BarNiv and McDonald (1992), we forego a review of the literature.

Methodology

Event History Analysis

This study employs a dynamic statistical methodology called event history analysis to examine property-liability and life insurer insolvencies. The event history approach is not unique to the social sciences; similar methods have developed independently in such diverse areas as actuarial science, biostatistics, demography, and engineering (Amburgey, 1986; Barnett, 1990; Carroll, 1983; Freeman, Carroll, and Hannan, 1983; Stinchcombe, 1965; Tuma, 1979; and Yamaguchi, 1991). Event history analysis explicitly considers the dynamics of the factors influencing the probability of insolvency over an interval of time. In case of major fluctuations, the snapshot methodology of classification analysis, which considers a shorter interval, may provide an incomplete picture of the situation. Event history analysis explicitly incorporates information on prior history for improving the explanatory capacity of the model. Finally, since a static model can be viewed as a special case of a dynamic model, dynamic models have more implications, thereby expanding the ability to test hypotheses.

This study focuses on the events of insurer insolvencies and factors associated with these insolvencies. Because events can be defined in terms of change over time, an effective way to study events and their causes is to collect event history data that record the exact time and sequence of particular kinds of changes. Thus, the problem is to specify how the occurrence of the event (in this case, insolvency) depends on explanatory variables. The most common approach is to define a variable called a hazard rate (also referred to as a force of mortality and a failure rate) that measures the conditional probability density of the occurrence of the event as a function of time and selected explanatory variables. The method allows for the examination of the causal factors possibly related to insolvency by finding whether the explanatory variables significantly affect the hazard rate.

In a study of the duration of insurer insolvencies, the two states "solvent" and "insolvent" are distinguished. The goal is to examine both the rate of transition from the solvent state to the absorbing insolvent state and the observable variables that influence this rate. An event history describes the values of a variable, $Y(t)$, within some observation period. $Y(t)$ indicates the state at time t , and the set of all possible states is called the state space. In the present

two-state insolvency case, $Y(t)$ takes only the values 1 (insolvent) or 2 (solvent).

State probabilities describe the probabilities of occupying each state and are defined as

$$P_y(t) = \Pr[Y(t) = y], \quad (1)$$

where y takes the values 1 and 2 in the two-state insolvency case. Unlike state probabilities, transition probabilities describe the probabilities of specific changes in Y across two points in the time interval $[t, t+\Delta t]$, conditional on the prior history. We are interested in the instantaneous probability that an event (insolvency) will occur in the interval $[t, t+\Delta t]$, given that the event has not occurred before the beginning of this interval. Let T be a positive and continuous random variable denoting the time of event transition from solvent to insolvent, and the hazard rate is defined as

$$\lambda(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | t \leq T)}{\Delta t}, \quad (2)$$

where $P(\cdot)$ is the probability of insolvency between time t and $t+\Delta t$. This probability of insolvency is a rate because it is constructed over an interval of time (Δt). It is also an instantaneous rate because it is constructed over an infinitesimal interval, defined at the limit of Δt as it approaches zero.

Other important statistical concepts of event history analysis are the integrated hazard rate and survivor function. The integrated hazard rate is defined as

$$H(t) = \int_0^t \lambda(s) ds. \quad (3)$$

The survivor function, $S(t)$, is the probability that the individual insurer has not been insolvent by time t :

$$S(t) = P(T > t). \quad (4)$$

This survivor function gives the cumulative survival probabilities to all durations and is determined by the hazard rate. These three concepts of event history analysis are closely related, since

$$S(t) = \exp[-H(t)] = \exp\left[-\int_0^t \lambda(s) ds\right]. \quad (5)$$

If one of these functions is known, the derivation of both the other functions is possible. Additionally, the relationship between $S(t)$ and $\lambda(t)$ implies that when the log of survivor function is plotted against time, the negative slope of that curve is the estimate of the instantaneous rate of insolvency.

Also, the density ($f(t)$) and distribution function ($F(t)$) of the duration T are defined by

$$F(t) = P(T \leq t) = \int_0^t f(u) du \quad (6)$$

$$f(t) = F'(t).$$

Thus, $F(t) = 1 - S(t)$.

These results permit the estimation of the probability of insolvency in the next t year by calculating $F(t)$ using the estimate of $\lambda(s)$. The effect on the probability of insolvency by changing an explanatory variable can be calculated directly. It is now possible to use finite ruin probabilities as a direct tool of management and regulation. Classical collective risk theory has produced infinite horizon ruin probabilities that depend only on initial surplus, the security loading in the premiums, and the claims amount distribution.

The hazard rate, $\lambda(t)$, as a function of time, indicates that the probability of an event's occurrence may vary with time. Previous research on organizational mortality suggests that organizational death rates vary as a function of age in a large number of populations (Freeman, Carroll, and Hannan, 1983; Carroll, 1983). However, such findings may be unsuitable to the insurance industry. Thus, this insolvency study employs the exponential model that includes the age effect variable.¹

The exponential model lends itself to convenient interpretation and is commonly applied as the basic model. It remains nonnegative, as a hazard rate is compelled to do. Thus, results are obtained from the exponential model, modeling the hazard rate of insolvency as follows:

$$\lambda(e) = \exp[\beta x(e)],$$

where β = a row vector of coefficients, and

x = a column vector of explanatory variables indexed by calendar time e . In this model, explanatory variables vary as a step function over calendar time (s) by segmenting the life of each insurer into one-year intervals in which each segment is regarded as an observation in the estimation; this allows time-dependent explanatory variables to be updated from year to year. The coefficients are estimated using all the data within the periods studied.

Hazard rate analysis does not classify companies into those bound for insolvency and those destined for survival. The usual test of a classification methodology, such as multivariate discriminant analysis or binary response regression using a logit or probit transformation, is to hold part of the data

¹ The Gompertz model, well known in studies of mortality, was also employed initially. In this model, the hazard rate rises or falls monotonically with age. A monotonically decreasing hazard rate assumes that new organizations are more likely to die than old ones. However, this model was not used because the computer program used to estimate the parameters did not converge for this model in the case

aside from the estimation procedure and then determine how well the fitted model classifies the items withheld. This procedure is not appropriate in a hazard rate analysis.

The ultimate application of hazard rate analysis derives from equation (6). The probability of insolvency of a company during a fixed future period can be estimated by equation (6), using the fitted model and the explanatory variables for the company. For a set of solvent companies, these estimated probabilities of insolvency could be used to determine an expected number of insolvencies. After expiration of the period, the expected and observed number of insolvencies could be compared. Even this test would not be conclusive. Management could learn from an unacceptably high probability of insolvency and adapt by changing the values of the company's explanatory variables.

Such a comparison was not done in this study. All the data were used in the estimation. Ultimately, hazard rate analysis, as well as other ruin probability methodologies, should be subjected to empirical examination. Some students of risk theory would assert that ruin probabilities are useful indices of current stability despite the fact that the nonstationary business world prevents their empirical specification.

Empirical Specification

For both property-liability and life insurer insolvencies, a set of ten variables is investigated as potential explanatory variables (see the Appendix). These variables were selected based on prior research, recent concerns being expressed by regulators, and data availability.

The rate of insolvency of property-liability insurers can be specified as follows by using the exponential model:

$$\lambda(e) = \exp [\beta_0 + \beta_1 \times \text{AGE}(e) + \beta_2 \times \text{CHNPW}(e) + \beta_3 \times \text{YIELD}(e) + \beta_4 \times \text{COMBR}(e) + \beta_5 \times \text{EXP}(e) + \beta_6 \times \text{RES}(e) + \beta_7 \times \text{REI}(e) + \beta_8 \times \text{RCG}(e) + \beta_9 \times \text{UCG}(e) + \beta_{10} \times \text{EXPANSION}(e)], \quad (7)$$

where β_0 is an intercept, and e is a calendar time within the observation period. Similarly, the hazard rate of insolvency of life insurers can be specified using the exponential model as follows:

$$\lambda(e) = \exp [\beta_0 + \beta_1 \times \text{AGE}(e) + \beta_2 \times \text{CHNPW}(e) + \beta_3 \times \text{YIELD}(e) + \beta_4 \times \text{RCG}(e) + \beta_5 \times \text{UCG}(e) + \beta_6 \times \text{NOM}(e) + \beta_7 \times \text{JUNK}(e) + \beta_8 \times \text{CM}(e) + \beta_9 \times \text{RE}(e) + \beta_{10} \times \text{EXP}(e)]. \quad (8)$$

The coefficients of explanatory variables in the models are estimated by the method of maximum likelihood. This method is selected over commonly-used least squares methods for two reasons. First, maximum likelihood estimators are asymptotically consistent, efficient, and normally distributed under fairly weak conditions (see Dhrymes, 1970). Thus, maximum likelihood estimation gives good estimates of parameters in the model by several criterion for optimal estimates. Second, maximum likelihood estimation combines the censored

and uncensored observations, thus allowing one to make full use of the information available.²

Empirical investigations are always plagued by the necessity to emphasize prediction or testing in the analysis. With observational data it is frequently difficult to test hypotheses about particular explanatory variables because of complex interrelationships among the explanatory variables. The most common manifestation of the problem is the multicollinearity similar to that found frequently in linear regression models.

It is likely that the explanatory variables listed in Tables 1 and 2 are interrelated. By examining correlation matrices and by fitting various reduced models, insights into the effect of the explanatory variables will be sought. It is acknowledged that these data analysis devices will not lead to definitive statements about the impact of the various explanatory variables. For prediction of the probability of ruin in a finite time period, as explained in connection with equation (6), the interrelationships among the explanatory variables is not a serious concern. It is anticipated that the empirical-based probabilities of ruin for a finite time period will be the most significant contribution of this methodology.

Sample and Data Source

The sample comprises 82 property-liability insurers that failed from 1984 through 1990 for which the data were obtainable from *Best's Insurance Reports* and the *NCIGF Special Report*. An additional 123 insolvent property-liability insurers were eliminated from consideration because data were not available from *Best's* mainly because of their small size. Similarly, a sample of 42 life insurers involved in insolvency for the period 1987 through 1990 was collected. There were an additional 33 life insurers for which data were not available. A seven-year period, 1984 through 1990, was used for the study of property-liability insurer insolvency and a four-year period, 1987 through 1990, for the study of life insurer insolvency. These dates were selected because of large increases in the numbers of insolvency cases in 1984 in the property-liability insurance industry and in 1987 for the life insurance industry.

In addition, 82 additional solvent property-liability insurers and 42 solvent life insurers were chosen in a random sampling from the population of insurers listed by *Best's Insurance Reports*. Many previous studies have employed a nonrandom equal-matching process, by which an equal number of solvent insurers are selected from the population of insurers by matching some characteristics of insurers such as the size of assets, organizational form, and state of domicile. However, Manski and Lerman (1977) found that the maximum likelihood estimators of the coefficients from this procedure are generally inconsis-

² Estimating the parameters from the samples used here requires the analysis of risks when not all units experience the event by the end of the sample period. This problem is known as "right censoring." The maximum likelihood estimates of the coefficients of variables and the asymptotic standard errors of these coefficients are obtained by RATE, a FORTRAN computer program.

tent. Moreover, it is difficult to determine which firms are most suitably matched. As a correction, they proposed a weighted maximum likelihood estimator which they demonstrated to be consistent. Manski and Xie (1989) suggested weighted maximum likelihood estimators for general models based on response-based samples. By weighting the observation properly, this procedure makes the estimates from the response-based sample consistent and asymptotically unbiased as if it were a random sampling.³

Event history analysis allows estimates of coefficients of causal factors to incorporate estimates of both cross-sectional and time series data. Therefore, while most previous studies gathered data for the last year prior to the date of insolvency or for a short term before insolvency, this study includes data of insurers for several years before insolvency or right censoring within the observation period.

Empirical Results

Property-Liability Insurer Insolvencies

Equations are developed for the hazard rate of insolvency on which the effects of independent financial variables are analyzed. We estimate six versions of the exponential model. The first version uses all available data including the loss reserve variable but excludes the realized capital gains variable, the reinsurance variables, and the expansion variables because of high interrelationships among these four variables probably due to the common denominator of surplus in all four variables.⁴ Similarly, the second, third, and fourth versions each in turn exclude one of the other of these variables. The fifth version incorporates all four variables into one equation for comparison with the separate variable findings. The sixth version examines the effect of the expense variable separately from the underwriting results variable. Thus, this version excludes the underwriting results variable from the fifth version of the model because of high correlations between these two variables. The expense variable was excluded from the first five versions of the model due to the high correlation.

Table 1 reports the estimated parameters from the six versions of the exponential model for property-liability insurers. The model is estimated on 164 cases and 878 firm-year observations over the seven-year period 1984 through 1990. The RATE program calculates the log likelihood for the model with covariates. In comparing the model without covariates to the model with

³ The principle of the weighted maximum likelihood estimator can be explained as follows: Suppose that the sample is intentionally drawn so that it consists of 50 percent insolvent insurers and 50 percent solvent insurers. The true proportion of insolvent and solvent insurers are one percent and 99 percent. To get the right mix in the sample, one can scale down the proportion of insolvent insurers by a factor of $0.01/0.50 = 0.02$ and scale up the proportion of solvent insurers by a factor of $0.99/0.50 = 1.98$. This is done by simply weighting the observations with weighting variables.

⁴ The matrix of correlation coefficients is available from the authors.

Table 1
Exponential Models of the Rate of Property-Liability Insurer Insolvencies

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-6.108* (0.3671)	-5.929* (0.3693)	-5.955* (0.3659)	-5.998* (0.3736)	-6.260* (0.3881)	-6.266* (0.3878)
Organizational Age Effect	-0.00153* (0.0003865)	-0.001406* (0.0003727)	-0.001494* (0.0003837)	-0.001439* (0.0003714)	-0.001552* (0.0003922)	-0.001546* (0.0003917)
Premium Growth	0.004737* (0.00206)	0.004755* (0.001801)	0.004799* (0.001932)	0.004892* (0.001693)	0.004680* (0.001594)	0.004684* (0.001587)
Investment Performance	-0.2815* (0.04571)	-0.2824* (0.04651)	-0.2852* (0.04611)	-0.2898* (0.04576)	-0.2768* (0.04666)	-0.2770* (0.04658)
Underwriting Results	0.004265* (0.001004)	0.006186* (0.0004875)	0.006181* (0.0004886)	0.006181* (0.0004886)	0.0043* (0.00101)	
Expense						0.004354* (0.0009855)
Loss Reserves	0.004945* (0.001203)				0.004971* (0.001207)	0.009334* (0.0006129)
Reinsurance			0.00008287* (0.00003811)		0.00002374 (0.00004433)	0.00002334 (0.00004435)
Realized Capital Gains		-0.0007303* (0.0001568)			-0.0006127* (0.0002838)	-0.0006146* (0.000284)
Unrealized Capital Gains	-0.002733* (0.0005905)	-0.002869* (0.0005982)	-0.001944 (0.001163)	-0.002839* (0.0006031)	-0.002706* (0.0007164)	-0.002707* (0.0007161)
Expansion to Other States				0.00488 (0.005831)	0.00564 (0.006043)	0.005743 (0.006042)
X ²	129.44	117.92	114.54	110.82	138.59	139.19
df	6	6	6	6	9	9
Insolvencies	82	82	82	82	82	82
Censored Cases	82	82	82	82	82	82
Total One-Year Spells Used in Estimation	878	878	878	878	878	878

Note: Standard errors are in parentheses.

* $\alpha < 0.05$.

covariates, based on a likelihood ratio test, an X^2 value is obtained. Both the X^2 value and the value of degrees of freedom are given for each version of the model. The estimates of the coefficients and their asymptotic standard errors are shown for each financial variable. Note that, since the dependent variable is the hazard rate of insolvency, those variables with positive coefficients indicate that higher values of those variables are associated with insolvency; those variables with negative coefficients indicate that lower or negative values are associated with insolvency.

Age effect. The estimated coefficient for the age effect variable is negative and significant at the $\alpha = 0.05$ level for all six versions of the model. This finding is consistent with Stinchcombe's (1965) liability of newness thesis that new organizations suffer a higher failure rate than older organizations. The age variable may be correlated with firm size, thus picking up the effects of size as well as age.

Premium growth. The empirical result supports rapid growth of premium volume as one of the causal factors in insolvency. The coefficients of the premium growth variable are positive and significant at the $\alpha = 0.05$ level for all six versions of the model.

Investment performance. When interest rates began to soar in the late 1970s, cash flow underwriting spread in the property-liability insurance industry. We found a significant and negative effect from investment performance on the rate of insolvency at the $\alpha = 0.05$ level in all six versions of the model. This empirical result relates to the ongoing discussion of the economic reality of cash flow underwriting.

Underwriting results. The estimated coefficients of the underwriting results variable are positive and significant at the $\alpha = 0.05$ level for the five versions of the model in which this variable is included. A significantly higher rate of insolvency can be inferred for the higher combined ratio since a higher combined ratio indicates a higher proportion of losses and expenses relative to premiums, resulting in lower or negative underwriting profits.

Expense. Some previous studies (Kramer, 1990; A. M. Best, 1991; U.S. Congress, 1990) have commented on poor management practices and fraud as causal factors associated with property-liability insurer insolvencies. However, because these factors are hard to measure, estimating their magnitude is difficult. The expense ratio is used here because it may indicate inefficient and fraudulent management. From Model 6 in Table 1, the estimated coefficient of the expense variable is positive and significant at the $\alpha = 0.05$ level, which supports the existence of the effects of management problems on the rate of insolvency.

Loss reserves. The empirical finding from Models 1, 5, and 6 supports loss reserve exposure as one of the causal factors in insolvency. The coefficients of the loss reserve variables are positive and significant at the $\alpha = 0.05$ level.

Reinsurance. Model 3 indicates a significantly positive estimate of the reinsurance variable coefficient at the $\alpha = 0.05$ level, which supports the idea that the more a primary insurer has to rely on (or is exposed to) its reinsurance recoverables, the more it is exposed to the adverse financial impact of a rein-

surer failure. It should be noted that the significant result may have been produced due to collinearity of the reinsurance variable with omitted variables.⁵ The estimated coefficients of the reinsurance variable in Models 5 and 6 are not significant. Thus, there is no clear evidence to support reinsurance recoverables as a percentage of surplus as one of the factors associated with insolvency.

Realized capital gains and unrealized capital gains. The empirical findings support both realized and unrealized capital losses as determinants of insurer insolvencies. The coefficients of the unrealized capital gains variable are negatively and significantly related to the rate of insolvency at the $\alpha = 0.05$ level for all six versions of the model except Model 3. The estimated coefficient of the realized capital gains variable in Models 2, 5, and 6 are negative and significant at the $\alpha = 0.05$ level.

Expansion to other states. When an insurer expands into new territories without adequate resources to support expansion, problems can develop due to a loss of control over insurance operations. Yet Models 4, 5, and 6 indicate no significant effect from expansion to other states on the rate of insolvency.

Life Insurer Insolvencies

As in the case of property-liability insurer insolvencies, our analysis of life insurer insolvencies uses event history analysis to develop equations for a dependent hazard rate of insolvency on which the effects of financial variables are examined. The exponential model of event history analysis is used on 84 cases and 280 firm-year observations over the four-year period 1987 through 1990. Unlike property-liability insurer insolvencies, there were not high correlations among variables in life insurer insolvencies. The model has two versions. The first version includes all independent variables including the expense variable. The second version includes both the expense variable and its square in order to examine the effect of this variable more closely. Table 2 reports the empirical results from the insolvency hazard rate model for life insurers.

Age effect. The coefficient of the age effect variable shows a negative and significant effect on the rate of insolvency at the $\alpha = 0.05$ level. This result supports the age dependence of life insurer failures. As with property-liability insurers, age might be correlated with firm size and might pick up the effects of size as well as age.

Premium growth. The premium growth variable is not statistically significant for either version of the model. Thus, the results do not support the hypothesis that rapid premium growth has a significant effect on the rate of life insurer insolvency.

Investment performance. With higher interest rates and the introduction of interest-sensitive life insurance and annuity products, greater importance has

⁵ Correlation coefficients of reinsurance with loss reserves is 0.825, with realized capital gains -0.680, and with expansion to other states 0.739.

Table 2
Exponential Models of the Rate of Life Insurer Insolvencies

<i>Independent Variables</i>	<i>Model 1</i>	<i>Model 2</i>
Constant in B	-4.365* (0.5207)	-4.974* (0.5234)
Organizational Age Effect	-0.001756* (0.0008273)	-.0002317* (0.0008796)
Premium Growth	-0.0004268 (0.0003398)	-0.001776 (0.0003207)
Investment Performance	-0.2576* (0.06059)	-0.2916* (0.06216)
Realized Capital Gains	0.02191* (0.007434)	0.02563* (0.006910)
Unrealized Capital Gains	0.01515* (0.003405)	0.01670* (0.003155)
Net Operating Margin	-0.02812* (0.008828)	-0.01850* (0.007575)
Junk Bond	-0.001775 (0.002109)	-0.0007848 (0.002353)
Commercial Mortgage	-0.001638 (0.002113)	-0.002118 (0.002137)
Real Estate	0.005779* (0.003001)	0.005344* (0.002691)
Expense	-0.007513* (0.003016)	0.04434* (0.01431)
(Expense) ² /100		-0.0002637* (0.00008478)
X ²	68.45	83.46
df	10	11
Insolvencies	42	42
Censored Cases	42	42
Total One-Year Spells Used in Estimation	280	280

Note: Standard errors are in parentheses.

* $\alpha < 0.05$.

been assigned to higher yield investments. The estimated coefficient of the investment performance variable is negative and significant at the $\alpha = 0.05$ level for both versions of the model, thus indicating that the lower investment yields increase the rate of insolvency.

Realized capital gains and unrealized capital gains. The estimated coefficients of the realized capital gains and unrealized capital gains variables are positive and significant at the $\alpha = 0.05$ level. Thus, unlike property-liability insurers, life insurers with larger (not lower or negative) capital gains exhibit an increased rate of insolvency. For realized capital gains, the positive relation may be explained by a desperate insurer that is forced to liquidate investments to meet cash flow needs. Because an insurer would be expected to liquidate those investments with the most favorable realized capital gains, a positive

relation could be present with realized capital gains and a financially troubled insurer.

This explanation seems especially plausible in recent years, when life insurers marketed higher-yielding policies such as single premium deferred annuities, universal life, and guaranteed investment contracts (GICs). Specifically, GICs guaranteed very competitive rates of return on large, lump-sum transfers of pension funds. Therefore, large realized capital gains in life insurers may indicate that the life insurer needs more cash to pay promised higher returns to policyholders. Critical cash flow shortages may force troubled life insurers to use realized capital gains generated by the liquidation of investments to meet current cash requirements. The explanation for the positive relation of life insurer insolvency with unrealized capital gains is more perplexing. The authors suggest this finding to be a stimulus for future research.

Net operating margin. The empirical results shown in Table 2 offer support for small or negative profit margins as one of the determinants of life insurer insolvencies. The coefficient of the net operating margin variable is negatively and significantly related to the rate of insolvency at the $\alpha = 0.05$ level for both version of the model.

Junk bond. In the competitive life insurance industry, life insurers seek higher investment returns which also bring higher risk investments such as junk bonds. The coefficient of the junk bond variable is not statistically significant, indicating that junk bonds do not appear to affect the rate of insolvency based on our analysis.

Commercial mortgage and real estate. Two other potential troublesome investments for the life insurance industry are commercial mortgages and real estate. The coefficient of the commercial mortgage variable is not statistically significant, but the coefficient of the real estate variable is positive and significant at the $\alpha = 0.05$ level for Model 2. The results thus support the hypothesis that real estate holdings may have a significant effect on the rate of life insurer insolvency.

Expense. The expense variable has a significant but negative coefficient in the first version of the model. Thus, the second version of the model is used to test the effect of the expense variable by adding the squared expense variable. The coefficient of the squared expense variable is negative and significant at the $\alpha = 0.05$ level, but the coefficient of the expense variable becomes positive and significant. This indicates that, at low levels of expense ratio, an increase in the expense ratio increases the rate of insolvency, but at high levels, the increase of this ratio decreases the rate of insolvency as the squared term dominates. Overall, the relation of expense ratios to life insurer insolvency is unclear.

Summary

The analysis of property-liability and life insurer insolvencies was performed using event history analysis—a form of dynamic statistical methodology. This methodology offers certain advantages over the classification statisti-

cal methods, like multivariate discriminant analysis and logit models, which have largely been used in previous studies of insurer insolvencies. To our knowledge, this is the first study of insurer insolvencies that has employed this methodology.

The examination of various factors associated with property-liability and life insurer insolvencies reveals several statistically significant relationships. For property-liability insurers, statistically significant factors with consistent signs in various versions of the exponential model included organizational age, premium growth, investment yields, underwriting results, expense ratios, loss reserve exposure, and realized and unrealized capital gains. For life insurers, statistically significant factors with consistent signs in the exponential model included organizational age, investment yields, realized capital gains, unrealized capital gains, income performance, real estate holdings, and expense ratios.

The problem of insolvencies in the insurance industry has dramatically increased in recent years and is receiving substantial attention in regulatory, government, industry, and consumer circles. The time periods of analysis, 1984 through 1990 for the property-liability insurance industry and 1987 through 1990 for the life insurance industry, represent significant increases in insolvencies relative to previous periods. New and expanded analysis of these recent insolvencies are needed if solutions to the problem are to be found.

Appendix

Variables Analyzed in Property-Liability Insurance Insolvencies

$$\text{Age Effect (AGE)} = \text{YEAR} - \text{START}$$

where YEAR = Year of Observation
START = Year Insurer Began Operations

$$\text{Premium Growth} = \frac{(\text{NPW}_t - \text{NPW}_{t-1})}{\text{NPW}_{t-1}}$$

where NPW = Net Premium Written

$$\text{Investment Performance} = \frac{\text{NII}_t}{\text{AIA}_t}$$

where NII = Net Investment Income
AIA_t/AIA = Average Invested Assets

$$\text{Underwriting Results} = \left[\frac{\text{LOSS}_t + \text{LAE}_t}{\text{NPE}_t} + \frac{\text{EXP}_t}{\text{NPW}_t} \right]$$

where LOSS = Incurred Losses
NPE = Net Premium Earned
LAE = Loss Adjustment Expenses
EXP = Expenses Incurred

$$\text{Expense} = \frac{\text{EXP}_t}{\text{NPW}_t}$$

where EXP = Expenses Incurred

$$\text{Loss Reserves} = \frac{\text{RES}_t}{\text{SUR}_t}$$

where RES = Loss Reserves
SUR = Surplus

$$\text{Reinsurance} = \frac{\text{REI}_t}{\text{SUR}_t}$$

where REI = Total Reinsurance Recoverable

$$\text{Realized Capital Gains} = \frac{\text{RCG}_t}{\text{SUR}_t}$$

where RCG = Realized Capital Gains

$$\text{Unrealized Capital Gains} = \frac{\text{UCG}_t}{\text{SUR}_t}$$

where UCG = Unrealized Capital Gains

$$\text{Expansion to Other States} = \frac{\text{EXPANSION}}{\text{SUR}_t}$$

where EXPANSION = Number of States in Which Insurer Is Licensed

Variables Analyzed in Life Insurance Insolvencies

$$\text{Age Effect (AGE)} = \text{YEAR} - \text{START}$$

where YEAR = Year of Observation
START = Year Insurer Began Operations

$$\text{Premium Growth} = \frac{(\text{NPW}_t - \text{NPW}_{t-1})}{\text{NPW}_{t-1}}$$

where NPW = Net Premium Written

$$\text{Investment Performance} = \frac{\text{NII}_t}{\text{AIA}_t}$$

where NII = Net Investment Income
AIA = Average Invested Assets

$$\text{Realized Capital Gains} = \frac{\text{RCG}_t}{\text{SUR}_t}$$

where RCG = Realized Capital Gains
SUR = Surplus

$$\text{Unrealized Capital Gains} = \frac{\text{UCG}_t}{\text{SUR}_t}$$

where UCG = Unrealized Capital Gains

$$\text{Net Operating Margin} = \frac{\text{NOG}_t}{\text{NPW}_t}$$

where NOG = Net Operating Gain

$$\text{Junk Bond} = \frac{\text{JUNK}_t}{\text{SUR}_t}$$

where JUNK = Junk Bonds

(continued)

(continued)

$$\text{Commercial Mortgages} = \frac{CM_t}{SUR_t}$$

where CM = Commercial Mortgages

$$\text{Real Estate} = \frac{RE_t}{SUR_t}$$

where RE = Real Estate

$$\text{Expense} = \frac{EXP_t}{NPW_t}$$

where EXP = General Expense

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