AN APPLICATION OF DISCRIMINANT ANALYSIS IN CLASSIFICATION OF FINANCIAL DISTRESS OF NON-LIFE INSURANCE COMPANIES

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ABSTRACT

The purpose of this research is to study factors affecting financial distress of Non-life Insurance Companies and classify their financial distress into solvent and insolvent insurers using discriminant analysis. The validity of the proposed model is measured by the accuracy rate of classifications. The model gives 88.30 % correctly classified with 6.38 % type I error and 14.44 % type II error. Hence, it can be claimed that the model performs reasonable well in classifying financial distress.

KEYWORDS : Discriminant Analysis, Insolvent Insurer and Solvent Insurer, Financial Distress, Fisher's Linear Discriminant Analysis, Stepwise Procedures.

1. INTRODUCTION

Non-life insurance business plays a number of significant roles in Thai modern's economy. The non-life insurance industry provides vital financial intermediary services and transfers funds to capital investment. Some examples of line of businesses involve with fire, marine & transportation and automobile insurance services. Enterprises require insurance to protect them against risks in doing their businesses.

The financial condition of the non-life insurers has increasing received attention for several parties including consumers/ insurance buyers, agents and insurers. The number of success and failure of these firms will be affected to public and economic system of the country. It is therefore necessary for stakeholders and policymakers to examine the risk profiles of these companies. As such, it would be of grate benefit for the department of insurance and relevant agencies to have a useful tool in order to determine what criteria or financial ratios are related to success and failure in the non-life insurances and early identify the status of them at risk. This will help to pinpoint warning symptoms of firm's failure beforehand.

In the literature, there is a number of models for classification and prediction of financial distress [1, 2]. Such prominent and well-known approach is discriminant analysis. Discriminant analysis has been widely used in many disciplines such as social sciences, biology and business. In financial area, Bajgier and Hill [3] presented an experimental comparison of three linear programming approaches and the Fisher procedure for the discriminant problem. The linear programming approaches were MMD (maximize minimum distance), OSD (optimize sum of distances) and MIP (mixed-integer linear goal programming). Each test problem consisted of a 30-case estimation sample and a 1,000-case holdout sample. The results showed that the linear programming approaches were statistically more effective than the Fisher procedure.

Altman [1] applied multivariate discriminant analysis (MDA) to the use of financial ratios for predicting bankruptcy of manufacturing firms. On the original sample of firms, the model gave a correct classification for 95%.

Pinches and Trieschmann [4] applied multivariate discriminant analysis (MDA) to financial data to identify property-liability insurers with a high potential for financial distress. The research

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showed that multivariate discriminant models were superior to univariate models in identifying firms with a high probability of distress.

BarNiv and Hershbarger [5] compared nonparametric analysis, multivariate discriminant analysis (MDA) and the logit model for the solvency prediction the property-liability industry using data from Best's Insurance Reports from 1975 through 1985. The results showed that the nonparametric analysis and the logit model slightly dominated MDA.

In this paper, discriminant analysis is employed to classify the financial distress of non-life insurance companies over the period 2002-2003 into solvent and insolvent insurers. The proposed model will help relevant agencies to identify significant criteria in the early detection of financially distressed non-life insurance companies.

The paper is organized as follows. In the following section, we briefly introduce linear discriminant analysis and identify dependent and independent variables. Next, the results of the discriminant analysis are consequently displayed. We then concluded the study by evaluating the strongness of the classification power of the approach and possible research improvement.

2. MATERIALS AND METHODS

2.1 Discriminant Analysis

Discriminant analysis is a multivariate statistical technique use to classify an observation into a original group dependent upon observation's individual characteristic. It is used primarily to classify or predict groups in classifications problem. Simultaneously, it also determines on what characteristics make these groups differ. Therefore, the first step is to establish explicit group classifications. The number of original groups can be two or more. Fisher's linear discriminant analysis (FLDA) is employed in this study, since this method is the most widely used for discriminant analysis [6]. Likewise, this method can be used in categorical data [7].

Similar to regression equations, discriminant function score for a case is predicted from the sum of the series of independent variables, each independent variables weighted by coefficient. FLDA will give discriminant function score for each group [7]. By discriminant function score, the new observation is assigned to the group that has maximum score. A linear discriminant function score can be written as:

$$Z = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_p x_p \tag{1}$$

where Z = Discriminant Function Score
b_i = Discriminant Coefficients for $i = 0, 1, \ldots, p$
x_i = Independent Variables for $i = 1, 2, \ldots, p$

FLDA requires two assumptions i.e. (1) multivariate normality of the independent variables and (2) variance – covariance matrix of the independent variables in all groups are equal. However, Barbara and Linda [8] suggest that it is not necessary to worry about multivariate normality assumption if sample sizes are large. Likewise, the assumption about variance- covariance matrix of the independent variables can be relaxed if sample sizes in each group are equal or the p-value is less than 0.001 when using Box's M test.

Discriminant coefficients are found in the same manner as coefficients for canonical discriminant function coefficients. After the groups for specific, FLDA attempts to derive a linear combination of these characteristics which "best" discriminates between the groups by minimizing the classification error rate. This study is concerned with two groups i.e. solvent and insolvent insurers.

Discriminant analysis computes the discriminant coefficients that maximize the difference between groups relative to the difference within group while the independent variables are the actual values. We use SPSS (Version 12.0) to analyze this problem. The stepwise procedure is used to find important variables [6]. Empirical cross validation method [8] is also employed in the analysis.

Once the values of the discriminant coefficients are estimated, it is possible to calculate discriminant scores for each observation in the sample, or any insurers, and assign the observations to one of the groups based on this score. In this manner, the insurer is assigned to the group it most closely resembles. Prediction is also enhanced if the base rates or prior probabilities of group membership are known [9]. The actual group membership is equivalent to a priori groupings and the model attempts to classify correctly these insurers. The apparent accuracy rate can be calculated from the classification chart, which shows actual versus predicted group membership. The classification chart is demonstrated in Table 1. The H 's represents correct classifications, whereas the M_1 and M_2 represent misclassifications. The M_1 stands for a Type I error, whereas the M_2 stands for a Type II error in classification [1]. The sum of the diagonal elements is equal to the total correct classification. The success of the discriminant analysis in classifying insurers is measured by the percent of insurers correctly classified.

2.2 Data Sample

Twelve independent variables which are very important to examine and analyze the overall performance of each insurer are selected to this study. These variables are as follows:

X_1 : The ratio of Losses Incurred to Earned Premiums;

X_2 : The ratio of Underwriting Expenses plus Commissions of Brokerages to Net Written Premiums;

X_3 : The ratio of Net Profit Current Year to Total Capital Funds;

X_4 : The ratio of Net Investment Income to Net Written Premiums;

X_5 : The ratio of Change in Capital's Funds (Current year minus Previous year) to Capital's Funds Previous year;

X_6 : The ratio of Change in Net Written Premiums (Current year minus Previous year) to Net Written Premiums Previous year;

X_7 : The ratio of Net Written Premiums to Earned Premiums;

X_8 : The ratio of Uncollected Premiums to Net written Premiums;

X_9 : The ratio of Technical Reserves to Net Written Premiums;

X_{10} : The ratio of Technical Reserves to Liquidity Asset;

X_{11} : The ratio of Capital Funds to Total Asset;

X_{12} : The ratio of Total Liabilities to Total Asset.

The research utilized these financial data from the Department of Insurance during the period 2002 - 2003. The numbers of solvent and insolvent insurers over the period of specific time are 90 and 47, respectively. Table 2 summarizes the independent variables included in the analysis and their formula.

3. RESULTS

Independent variables mean (X_1 to X_{12}) of each group and test of significance are presented in Table 3. The table shows that X_3, X_4, X_{10}, X_{11} and X_{12} are significant at the .05 level, indicating extremely significant differences in these variables between groups. Variables X_1, X_2, X_5, X_6, X_7, X_8 and X_9 do not show a significant difference between groups and the reason for its inclusion in the variables profile is not clear as yet.

Table 4 shows the final independent variables and discriminant coefficients. Thus, the final linear discriminant function score is presented as follow:

Discriminant function score for solvent insurers is

$$Z = -13.470 + 0.575X_3 - 0.212X_{10} + 29.408X_{11} + 19.178X_{12} \qquad (2)$$

Discriminant function score for insolvent insurers is

$$Z = -12.497 - 0.568X_3 + 0.246X_{10} + 20.674X_{11} + 22.026X_{12} \qquad (3)$$

Table 5 presents the summary of the discriminant classification accuracy for the separation of two groups. The table indicates that the model is extremely accurate in classifying 88.30 % of the total sample. The type I error proved to be only 6.40 %, while the type II error was even better at 14.40 %. Hence, it can be claimed that the level of prediction accuracy of the model is very accurately.

4. CONCLUSION

This paper suggests an overview of discriminant analysis. An illustrate example of how this powerful technique can be helped to determine what criteria or financial ratios are related to success and failure in the non-life insurances companies. The model derives from discriminant analysis can identify the status of non-life insurances companies into two groups. The findings presented in this study suggest that the error rate of classification was only 11.70 %, which means that the model is extremely suitable and performs reasonably well in classifying financial distress. It is also found that the ratio of Net Profit Current Year to Total Capital Funds (X_3), the ratio of Technical Reserves to Liquidity Asset (X_{10}), the ratio of Capital Funds to Total Asset (X_{11}) and the ratio of Total Liabilities to Total Asset (X_{12}) are significant variables for predicting the financial distress of the non-life insurance companies. The use of discriminate function in this manner will be benefit for government officers and relevant agencies to early detect and concentrate on the insurers who are at risk in financial problems more technically.

There are a number of possible directions can be further extended. Such improvements include the use of a longer sample period and a greater sample size of insurers. Other methods, for instance, a neural network model and nonparametric approach may be employed to compare the classification performance with the linear model.

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Table 1: Classification chart

Actual Group Membership	Predicted Group Membership		Total
	Insolvent Insurers	Solvent Insurers	
Insolvent Insurers	H	M_1	$H + M_1$
Solvent Insurers	M_2	H	$M_2 + H$

Table 2: Independent variables included in the analysis

Variable	Formula
X_1	$X_1 = \frac{Losses\ Incurred}{Earned\ \ Premiums}$
X_2	$X_2 = \frac{Underwriting\ Expenses + Commissions\ or\ Brokerages}{Net\ Written\ Premiums}$
X_3	$X_3 = \frac{Net\ Profit\ Current\ Year}{Total\ Capital\ Funds}$
X_4	$X_4 = \frac{Net\ Investment\ Income}{Net\ Written\ Premiums}$
X_5	$X_5 = \frac{Change\ \ in\ Capitals's\ Funds(Current\ year - Previous\ year)}{Capital's\ Funds\ Previous\ year}$
X_6	$X_6 = \frac{Change\ in\ Net\ Written\ Premiums(Current\ year. - Previous\ year)}{Net\ Written\ Premiums\ Previous\ year}$
X_7	$X_7 = \frac{Net\ Written\ Premiums}{Earned\ Premiums}$
X_8	$X_8 = \frac{Uncollected\ Premiums}{Net\ Written\ Premiums}$
X_9	$X_9 = \frac{Technical\ \ Reserves}{Net\ Written\ Premiums}$
X_{10}	$X_{10} = \frac{Technical\ \ Reserves}{Liquidity\ Asset}$
X_{11}	$X_{11} = \frac{Capital\ Funds}{Total\ Asset}$
X_{12}	$X_{12} = \frac{Total\ Liabilities}{Total\ Asset}$

Table 3: Independent variables mean of each group and test of significance

Variable	Insolvent Insurers Group Mean	Solvent Insurers Group Mean	p-value
X_1	0.598	0.490	0.068
X_2	1.483	1.444	0.964
X_3	-0.245	0.085	0.001*
X_4	0.025	0.265	0.005*
X_5	2.392	-0.012	0.575
X_6	0.322	0.143	0.158
X_7	1.089	1.217	0.484
X_8	0.295	0.491	0.130
X_9	0.832	0.842	0.840
X_{10}	2.022	0.325	0.000*
X_{11}	0.199	0.588	0.000*
X_{12}	0.856	0.432	0.000*

*Significant at the .05 level

Table 4: Discriminant coefficients

Variable	Discriminant Coefficient	
	Solvent Insurers	Insolvent Insurers
Constant	-13.470	-12.497
X_3	0.575	-0.568
X_{10}	-0.212	0.246
X_{11}	29.408	20.674
X_{12}	19.178	22.026

Table 5: Classification results

Actual Group Membership	Predicted Group Membership		Correct Classification
	Insolvent Insurers	Solvent Insurers	
Insolvent Insurers	44	3	93.60%
Solvent Insurers	13	77	85.60%
Overall correct classification = 88.30%			