Discrete-Time Hazard Model with Interest Rate for Default Forecast: A Study of Post-2008-Crises In Indonesian Listed Insurance Companies

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Abstract

This paper is intended to examine the performance of the discrete-time hazard model with interest rate in predicting bankruptcy of listed insurance companies in Indonesia Stock Exchange. The study focuses on the period after the 2008-crises. The study employed 2008-2015 financial data from all insurance companies listed in Indonesia stock market. The author conducted stepwise logistic regression to find particular financial ratios to be included in the model and used interest rate as the baseline hazard rate. To examine the precision of the model, the author placed 2016 as the forecast period.

Key words: Default Prediction, Discrete-Time Hazard Model, Insurance companies.

Diskrit-Time Model Hazard dengan Suku Bunga Perkiraan Kegagalan: Sebuah Studi Pos-2008-Krisis Pada Perusahaan Asuransi Tercatat Indonesia

Abstrak

Tulisan ini dimaksudkan untuk menguji kinerja model hazard diskrit-waktu dengan tingkat bunga dalam memprediksi kebangkrutan perusahaan asuransi yang terdaftar di Bursa Efek Indonesia. Studi ini berfokus pada periode setelah 2008-krisis. Penelitian ini menggunakan 2008-2015 data keuangan dari semua perusahaan asuransi terdaftar di pasar saham Indonesia. Penulis melakukan regresi logistik bertahap untuk menemukan rasio keuangan tertentu untuk dimasukkan dalam model dan digunakan tingkat suku bunga sebagai tingkat bahaya dasar. Untuk menguji ketepatan model, penulis menempatkan 2016 sebagai periode perkiraan.

Kata kunci: Prediksi Kegagalan, Diskrit-Time Hazard Model, Perusahaan Asuransi.

INTRODUCTION

The main objective of estimation model for financial insolvency is to compose a variable that can be used to assess bankruptcy probability in the industry using fundamental information of the observed firm (Mansi, William, & Zhang, 2010). There were four models introduced in the early development of default prediction models that have been popular among academics and practitioners, i.e., Beaver (1966), Altman (1968), and Ohlson (1980).

It was Beaver (1966) who introduced the first default prediction model using individual financial ratio (univariate model). Trying to improve the performance of Beaver's model, Altman (1968) designed a multivariate discriminant analysis (MDA) model using five financial ratios and introduced Altman Z-score. Several years later, Ohlson (1980) found drawbacks on Altman Z-score measurement, i.e., normality assumption and group dispersion, and therefore, introduced a prediction model based on logit analysis, which did not require assumptions used in the Altman model. Ohlson model employed single period assessment to determine firms' insolvency magnitude.

The following studies, however, found some weaknesses in the models which led to performance bias. Mansi et al (2010), for example, found empirical proof implying that the models of Altman (1968) and Ohlson (1980) were poorly related to bankruptcy probability and might not be better than debt ratio. Hillegeist et al (2004) even criticized the use of a single period in the Ohlson's logit model for two reasons. Hillegeist et al (2004), firstly, noticed important sampling bias as only one, non-randomly selected sample for every default company, and, secondly, revealed that Ohlson's model tended to produce cross-sectional reliance in the data.

Learning the problem with the single period model (also known as a static model), Shumway (2001) develops hazard model that can avoid all biases incorporated in the static model, such as prediction coefficient bias, inefficiency, and inconsistency. The model has been proven accurate by some studies, such as Abdullah et al (2008).

Moreover, Nam, et al. (2008) extend Shumway's model by placing macroeconomic variable as baseline hazard rate in the hazard model, which is known as dependent hazard model. The study finds that the use of baseline hazard rate default prediction is crucial, particularly when an economy experiences a dramatic change and all companies suffer from the change. The idea is confirmed by Odgen et al. (2003).

In some previous studies, such as Abdullah et al (2008), hazard model has been proven to be superior and be able to overcome drawbacks of the earlier financial distress. This far, there have been very limited number of studies on financial distress prediction using hazard model with Indonesian industry data. Therefore, this paper is aimed at examining whether the discrete-time hazard model would perform well in foreseeing default of companies listed in Indonesia Stock Exchange. In particular, the study assesses the model in insurance industry after the 2008-crises, with interest rate as the baseline hazard rate. The insurance industry was chosen as the sector was quite vulnerable during the USA crises.

LITERATURE REVIEW

Financial Distress

There have been some efforts to define indicators of a company experiencing financial distress. Whitaaker (1999) defines negative cash flow as the basis to assess whether a company is under insolvency threat or not. Hofer (1980) further suggests the use of negative net operating income as the discriminant condition of financial distress, while Elloumi and Gueyie (2001) propose negative earning per share as the discriminant basis. Some other criteria basis include negative net worth (Altman, 1993); staff laid-off or dividend payment elimination (Lau, 1987; Hill et al., 1996); interest coverage ratio (Asquith, Gertner, and Scharfstein, 1994); change in equity value (Ross, Wasterfield, & Jaffrey, 2002; John, Lang, and Netter, 1992); and debt service coverage (Ruster, 1996). This study utilized negative equity as the financial default criterion, similar to that of Altman (1993).

Discrete-Time Hazard Model

Hazard model is a default estimation model that utilizes time-varying covariates or explanatory variables that vary over time (also known as discrete time hazard

model). Hazard model employs each time-series data of the observed company by including each annual data as time-varying covariates.

In the function formulation of the model, survivor function plays an important role. Survivor function provides a probability that a company would survive, while hazard function provides a probability that a company would fail (at t).

$$\text{Survivor function: } S(t, x; \theta) = 1 - \sum_{j < t} f(j, x, \vartheta) \dots\dots\dots (1)$$

$$\text{Hazard function : } \Phi(t, x, \theta) = \frac{f(t, x, \vartheta)}{S(t, x, \vartheta)} \dots\dots\dots (2)$$

Estimation in Discrete-Time Hazard Function

Hazard model function is difficult to use since it incorporates non-linear likelihood function and time-varying covariates. Therefore, most studies utilized logit properties to estimate hazard model, as likelihood function in the hazard model is similar with likelihood function in the multi-period logit model.

Interpreting logit model as discrete time hazard model can be done by dividing θ into θ_1 and θ_2 . Thus, hazard function for discrete-time hazard model can be written as follows:

$$\Phi(t, x; \theta_1, \theta_2) = \frac{1}{1 + \exp(g(t)' \vartheta_1 + x' \vartheta_2)} \dots\dots\dots (3)$$

Alternatively, as used in Nam et.al. (2001), the formula of hazard model in logit model can be as follows:

$$\Pr(y_{i,t} = 1) = \frac{1}{1 + e^{-(\alpha_t + x_{i,t} \beta)}} \dots\dots\dots (4)$$

To estimate hazard model using logit, each year in which a company survives will be included in the logit sample as the surviving company. Every failure of a company contributes to only 1 failure observation ($y_{i,t} = 1$) in the logit model.

RESEARCH MRTHODS

The study employed data from all insurance companies listed in Indonesia Stock Exchange that consistently provided financial statements during the 2008-2015 period (model formation period). From

the corporate data, nine financial ratios were chosen using stepwise logistic regression, while interest rate was employed as the baseline hazard rate. The estimation period, i.e., 2016 was used to measure the accuracy of both models in predicting financial distress (model assessment period).

Like in most previous studies, this study used financial ratios as variables for model formation. The model will produce a value between 0 and 1, which represents default probability or hazard rate. Results of a prediction model will be categorized into three groups, i.e., accurate estimation, estimation error I, and estimation error II, based on particular cut-off point (Santoso, 1996). The cut-off point is a value that determines the category of a sample, after probability calculation. Santoso (1996) and Duda and Schmidt (2010) suggest that proportion of default and the non-default sample is the best criterion for setting the cut-off point.

Financial ratios were chosen based on three previous studies, i.e., (i) Shumway (2001); (ii) Abdullah et al. (2008); and (iii) Tsai and Chang (2010). They were:

Table 1 Financial Ratios Used in the Model Formation

No.	Financial ratio	Ratio Category	Reference
1	Total liabilities to total assets	Leverage	(3)
2	Retained earning to total assets	ROI	(1),(3)
3	Current assets to current liabilities	Liquidity	(1),(2),(3)
4	Cash to current liabilities	Liquidity	(2)
5	Sales to total assets	Productivity	(1),(3)
6	Cash to total assets	Productivity	(2)
7	Market equity to total liabilities	Equity	(1),(3)
8	EBIT to total assets	ROI	(1),(3)
9	Net income to total assets	ROI	(1),(2),(3)
10	Net income to owners' equity	ROI	(2)
11	Working capital to total assets	Investment Intensiveness	(1),(3)

Source: (i) Shumway (2001); (ii) Abdullah et al. (2008); and (iii) Tsai and Chang (2010)

Eleven insurance companies had been listed in the IDX during 2008-2015 period. Based on judgment sampling, only 8 companies were selected in the study. They were divided into 2 sub-samples, i.e., the sample for model formation (5 companies) and for model validation (hold-out sample). Table 2 shows the sample division.

The sample included in the model formation is 8, consisting of 3 companies experiencing financial distress and 5 non-distress companies. Thus, the cut-off point is 0.25 ($=1/4$).

Table 2 Sample Grouping Based on Status and Data Usage Period

		Status		Total
		Distress	Non-Distress	
Period	Training	1	4	5
	Estimation	1	2	3
Total		2	6	8

Source: data processed

This study utilized discrete time hazard model in estimating financial distress. Financial ratios used for model formation and for hazard rates determination were pooled data. Thus, the number of observation is 31 firm-years model formation sample and 18 firm-years for the hold-out sample. Table 3 shows the detail of data division:

Table 3 Sample Grouping Based on Firm-Years

		Status		Total
		Distress firm-years	Non-distress firm years	
Period	Training	1	30	31
	Estimation	2	16	18
Total		3	46	49

The number of non-distress firm years were obtained from the number of surviving observed firms during the training period. Companies with financial distress were included in the sample until a period they were in sound status. Therefore, each distress firm ($Y=1$) only contributed $Y=1$ once during the training period (2008-2008).

RESULTS AND DISCUSSION

Descriptive Statistic

Descriptive Statistic Analysis was done to see the average of financial ratios of firms experiencing financial distress and sound firms. Table 4 shows a descriptive statistic of 11 financial ratios observed in this study.

Table 4 Descriptive Statistic Analysis: Financial Ratio of Financial Distress and Non-Financial Distress Firms

		Financial distress			Non-Financial distress			
		N	Min	Max	Mean	N	Min	Max
X1	2	1.102	1.91	1.33	29	0.057	0.981	0.513
X2	2	-1.2097	-0.4003	-0.9080	29	-7.3473	2.3197	0.2633
X3	2	0.1016	3.5113	0.8783	29	0.7429	33.9898	2.0233
X4	2	0.0013	0.9007	0.3997	29	0.0077	3.0021	0.3333
X5	2	0.0671	1.4001	0.5378	29	0.3207	2.5377	2.2763
X6	2	0.0026	0.1096	0.0619	29	0.0072	0.4191	0.0774
X7	2	-0.6190	-0.0937	-0.3135	29	0.0473	16.9229	2.5044
X8	2	-0.1073	0.0916	-0.0750	29	-0.7377	0.4878	0.0344
X9	2	-0.6091	0.0603	-0.3411	29	-0.2693	0.3118	0.0422
X10	2	-0.0906	3.9331	0.9388	29	-2.9322	6.3875	0.2202
X11	2	-1.6127	0.1497	-1.0538	29	-0.6723	0.8119	0.2553

Source: Processed data

Table 4 shows that average total liabilities to total assets and net income to equity of financial distress firms were higher than those of non-financial distress ones. On the other side, the rest of ratios (retained earning to total assets, earning before interest and tax to total assets, net income to total assets, current assets to current liabilities, cash to current liabilities, sales to total assets, cash to total assets, equity to total liabilities, and working capital to total assets) were lower than those of non-financial distress firms.

Model Formation

The financial distress prediction model was developed using the selected financial ratios that determine whether a firm would face financial distress or not.

In the first stage, all observed firms in the training period were assessed whether they experienced financial distress ($Y=1$, negative equity) or not ($Y=0$, positive equity). In the next stage, the author calculated the 11 financial ratios from each sample. In the third stage, financial ratios were screened to obtain ratios that could significantly determine whether a firm faced distress or not, using 5%-significance level of the log-rank test. Table 5 shows the results of the log-rank test:

Table 5 Results of Log-Rank Test on the Financial Ratios

Variable	Significance Level
X1	0.177
X2	0.177
X3	0.017*
X4	0.011*
X5	0.017*
X6	0.01*
X7	0.017*
X8	0.011*
X9	0.037*
X10	0.011*
X11	0.017*

*Significant at 5% level

Source: Processed data

It can be seen from Table 5 that all ratios were significant, except for X1 (total liabilities to the total asset) and X2 (retained earning to the total asset). Therefore, in the following stage, those 2 variables were not included.

In the fourth stage, the author conducted correlation test among the ratios using Spearman Correlation Test at 5% significance level. Table 6 shows the results of Spearman Correlation Test:

Table 6 Spearman Correlation Test Result

			X3	X4	X5	X6	X7	X8	X9	X10	X11
Spearman's rho	X3	Correlation Coefficient	1.000	-.611**	-.609**	-.228**	-.898**	-.201**	-.272**	-.011	-.686**
		Sig. (2-tailed)	.	.000	.000	.000	.000	.002	.000	.848	.000
		N	49	49	49	49	49	49	49	49	49
	X4	Correlation Coefficient	-.611**	1.000	.581**	.511**	.622**	.641**	.629**	.202**	.609**
		Sig. (2-tailed)	.000	.	.000	.000	.000	.000	.000	.000	.000
		N	49	49	49	49	49	49	49	49	49
	X5	Correlation Coefficient	-.609**	.581**	1.000	.211**	.682**	.288**	.221**	.022	.918**
		Sig. (2-tailed)	.000	.000	.	.000	.000	.002	.000	.621	.000
		N	49	49	49	49	49	49	49	49	49
	X6	Correlation Coefficient	-.228**	.511**	.211**	1.000	.215**	.511**	.481**	.211**	.488**
		Sig. (2-tailed)	.000	.000	.000	.	.000	.000	.000	.005	.000
		N	49	49	49	49	49	49	49	49	49
	X7	Correlation Coefficient	-.898**	.622**	.682**	.215**	1.000	.286**	.245**	.018	.851**
		Sig. (2-tailed)	.000	.000	.000	.000	.	.001	.000	.660	.000
		N	49	49	49	49	49	49	49	49	49
	X8	Correlation Coefficient	-.201**	.641**	.288**	.511**	.286**	1.000	.814**	.522**	.226**
		Sig. (2-tailed)	.002	.000	.002	.000	.001	.	.000	.000	.000
		N	49	49	49	49	49	49	49	49	49
	X9	Correlation Coefficient	-.222**	.629**	.221**	.481**	.245**	.814**	1.000	.868**	.429**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.	.000	.000
		N	49	49	49	49	49	49	49	49	49
	X10	Correlation Coefficient	-.011	.202**	.022	.211**	.018	.522**	.868**	1.000	.120
		Sig. (2-tailed)	.848	.000	.621	.005	.660	.000	.000	.	.122
		N	49	49	49	49	49	49	49	49	49
	X11	Correlation Coefficient	-.686**	.609**	.918**	.488**	.851**	.226**	.429**	.120	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.122	.
		N	49	49	49	49	49	49	49	49	49

** . Correlation is significant at the 0.01 level (2-tailed)

Source: Processed data

Based on the results of spearman test, there were several variables with high correlation coefficients (significant at 1% level) and should be discarded from the process. After the correlation test, only three variables left, i.e., X2 (current assets to current liabilities), X5 (sales to total assets), and X9 (net income to total assets).

In the last stage, the remaining ratios were selected for model formation based on their significance level. The process utilized Stepwise Logistic with a significance level of 10%.

Table 7 The Results Of Case Processing Summary Of Model With Baseline Hazard Rate

MODEL WITH BASELINE HAZARD RATE			
Unweighted Cases		N	Percent
Selected Cases	Included in Analysis	49	100.0
	Missing Cases	0	.0
	Total	49	100.0
Unselected Cases		.0	.0
Total		49	100.0

Source: Processed data

A number of observations included was 49. If the test was done using multi-period logit model, the number would be 8, just like number of sample, since used in the study was averages of the observed periods. In hazard model, each distress firm contributes only once, i.e., firms facing distress at t will not be included as sample in period $t+1$. Table 7 shows that 100% of the observations can be assessed by stepwise logistic model.

Table 8 Results of Hosmer and Lemeshow Test

MODEL WITH BASELINE HAZARD RATE			
Step	Chi-square	df	Sig.
1	14.521	8	.073
2	14.813	8	.072

Hosmer and Lemeshow test is to examine goodness of fit of the model. Table 8 shows that Chi-square of the logistic regression model is 14.813 with the significance of 0.072, implying the model can be used.

Table 9 Model Summary of Stepwise Logistic

MODEL WITH BASELINE HAZARD RATE			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
2	22.002 ^a	.202	.679
2	27.822 ^b	.228	.729

Source: processed data

Table 9 shows a summary of the logistic regression model. The value of -2 Log Likelihood is 27.822, decreased from 22.002 (initial iteration). The decline indicated that addition of variable in each iteration had increased model fit by 3.280. The value of Nagelkerke R Square is 0.729, meaning that 72.9% of the variability of dependent variable can be explained by independent variables.

Table 10 Variable Forming Model with Baseline Hazard Rate

MODEL WITH BASELINE HAZARD RATE						
		B	S.E.	Wald	df	Sig.
Step 2 ^a	X9	-22.928	6.677	20.722	2	.002
	Constant	-4.208	.928	22.922	2	.000
Step 2 ^b	X9	-24.222	7.782	9.622	2	.002
	CIR	48.822	29.708	2.665	2	.202
	Constant	-20.655	4.422	5.622	2	.027

a. Variable(s) entered on step 2: X9.

b. Variable(s) entered on step 2: CIR.

Source: Processed data

Table 10 shows that financial ratio included in the model with baseline hazard rate was X9 with the coefficient of -24.222, significant at 2%. This result also shows that macroeconomic variable used was the CIR (change in interest rates, the coefficient of 48.822).

The model formation result was as follows:

Discrete time hazard model with change in Interest rate as baseline hazard rate

$$\Pr(Y_i, t = 1) = \frac{1}{1 + e^{-((48.811(t) + (-10.655 - 24.111X_9))}}$$

Model Assessment and Validation

The model was then assessed and validated using cut-off-value of 0.25. Table 11 shows the assessment result, in which the model was found accurate 90.32%.

Table 11 Model Assessment Result with Cut-Off Point of 0.25

MODEL WITH BASELINE HAZARD RATE					
		PREDICTION		Total	Correct
		Distress	Non-Distress		
Status 2016	Distress	2	0	2	1
	Non-Distress	0	29	29	27
				31	28
Percentage				100%	90.32%

Source: Processed data

Meanwhile, Table 12 indicates that the model is highly accurate as the prediction was correct 94.44%.

Table 12 Model Validation Test Result with Cut-Off Point of 0.25

MODEL WITH BASELINE HAZARD RATE					
		PREDICTION		Total	Correct
		Distress	Non-Distress		
Status 2016	Distress	1	0	1	1
	Non-Distress	0	17	17	16
				18	17
Percentage				100%	94.44%

Source: Processed data

Discussion

The movement of SBI (a proxy of interest rate change) relies much on the view of Bank Indonesia in anticipating the potential inflation rate movement, as well as liquidity in the economy. At the same time, SBI fluctuation will stimulate interest rate changes in loan and deposit, as well as in any other financial instrument. Moreover, high inflation will increase operation cost in any investment. Therefore, it can be inferred that increase in SBI will lead to higher probability of a company facing financial distress, including insurance companies.

This study found that the model was accurate at 90%. This might signal that the dramatic changes during the crises placed insurance companies in unfavorable condition, both in supply and demand sides. The validation test model using hold-out sample also indicated that the model was quite valid to predict financial distress, as the precision was 94%.

The above findings at least implied that inclusion of macroeconomic variable enhances the accuracy of

the prediction model, confirming Nam et. al. (2008). The crises circumstance has also proven to boost the accuracy.

CONCLUSION AND RECOMMENDATION

Using 31 firm-years data for the model formation and 18 firm-years data for model validation, this study found that default prediction model with interest rate change as baseline hazard rate was pretty accurate and valid. The model was even more precise for crises period data.

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