Multiperiod Logit on Survival Analysis of Financial Distress in Manufacturing Company

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ABSTRAK

Perusahaan dituntut untuk dapat mempertahankan kelangsungan hidupnya agar tujuan perusahaan dapat tercapai dengan baik. Financial distress merupakan salah satu faktor yang menyebabkan perusahaan tidak dapat mempertahankan kelangsungan hidupnya sehingga tujuan perusahaan tidak tercapai. Faktor yang menyebabkan perusahaan berada dalam keadaan tertekan adalah faktor internal dan eksternal. Penelitian ini adalah penelitian deskriptif kuantitatif menggunakan 16 rasio keuangan, IHSG dan BI rate. Metode penelitian ini adalah metode kuantitatif dengan menggunakan data time series dengan model multiperiod logit. Penentuan sampel menggunakan purposive sampling sehingga terdapat 79 sampel yang digunakan dalam penelitian ini. Berdasarkan hasil deskripsi kurva Kaplan Meier, uji log rank, model logit multiperiod dengan pemilihan variabel, berarti perusahaan survive dan financial distress memiliki perbedaan yang menonjol pada rasio profitabilitas dan rasio market measure. Sedangkan berdasarkan hasil uji parsial 4 dari 5 rasio keuangan, hasil pemilihan variabel berpengaruh signifikan terhadap financial distress. Lima perusahaan terbaik untuk berinvestasi dengan nilai peluang hazard minimum adalah perusahaan dengan kode emiten SKBM, IGAR, PBRX, PSDN dan UNIC.

Kata kunci : Logit Multiperiod; Analisis Kelangsungan Hidup; Kesulitan keuangan; Perusahaan manufaktur

ABSTRACT

The company is required to be able to maintain its survival so that the company's goals can be achieved properly. Financial distress is one of the factors that causes the company to be unable to maintain its viability so that the company's goals are not achieved. The factors that cause the company to be in a state of distress are internal and external factors. This is descriptive quantitative research which used 16 financial ratios, IHSG and BI rate. This research method is a quantitative method using time series data with a multiperiod logit model. Determination of the sample using purposive sampling so that there are 79 samples used in this study. Based on the results of the description of the Kaplan Meier curve, log rank test, multiperiod logit model with variable selection, it means that companies survive and financial distress have prominent differences in profitability ratios and market measure ratios. Meanwhile, based on the results of the partial test 4 out of 5 financial ratios, the results of the selection of variables have a significant effect on financial distress. The five best companies to invest in with a minimum hazard opportunity value are companies with issuer codes SKBM, IGAR, PBRX, PSDN and UNIC.

Keywords : *Multiperiod Logit; Survival Analysis; Financial Distress; Manufacturing Company*

INTRODUCTION

Financial developments in Indonesia can be observed through the share of capital from the entire industry on the Indonesia Stock Exchange (IDX). The absolute number of organizations listed on the IDX is approximately 685 organizations which are separated into accompanying characterizations. The Indonesian Industry Service sees that the manufacturing business is one of the fields that basically contributes to the interests of the whole of Indonesia. According to the Minister of Industry, Airlangga Hartanto previously, “the manufacturing business area is the backbone for public finance development and is a pillar area in driving value towards a comprehensive turn of events and local government assistance” (www.kemenperin.go.id). In the attached image, the JCI information shows that of the eight areas listed on the IDX, only one area is in the green zone (positive zone), particularly the essential and synthetic business areas. While the other seven regions are in the red zone (negative zone). A particularly fragile area is the consumer goods industry.

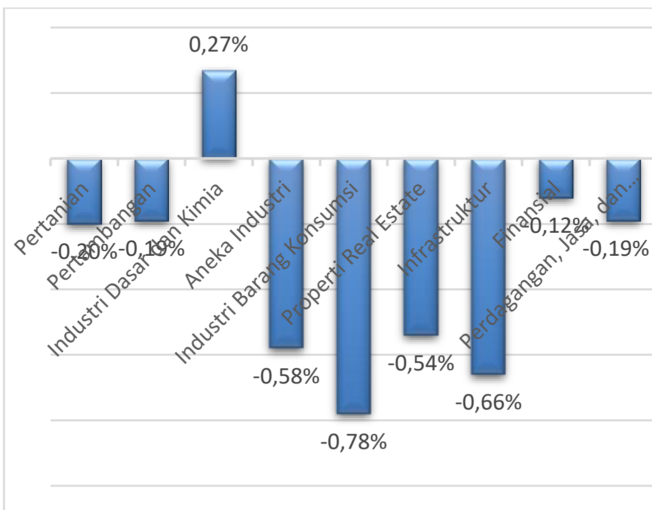

Figure 1. Stock Trading Index on the Indonesia Stock Exchange
Source: idx.com (Data processed by the author, 2020)

Based on Figure 1, it can be seen that only 1 sector rose and the rest fell. The fundamental and substance industry areas are the more down-to-earth areas, while the buyer's merchandise industry is the more vulnerable area. The decrease in stock costs can be used as an indication of a decrease in monetary execution in the regions[1]. Financial distress is a stage of decline in financial conditions that occurs before the company goes bankrupt or goes into liquidation. So this should be a concern for the company's management because it can affect sales and profits to be obtained so that later it will also have an impact on the company's operational activities.

The motivation behind establishing an organization is actually to generate benefits. These benefits are relied on to work on organizational presentations and follow the organization's business coherence in the long run. For that, the organization must compete with other competing organizations. In addition, the organization will also compete with changes in various parts of improvement in Indonesia. Similarly, high-benefit-generating organizations will attract consideration of financial backers to contribute. The financial backer will see and examine the state of the organization before making a choice to contribute. Budget summary examination serves to decide the functional performance of the organization for a period and is used to forecast the organization's accounts at a later date. If bad things happen to the organization, for example facing financial problems or financial challenges, the organization definitely knows how to deal with those problems.

In 1968, Altman directed his exploration of the liquidation of manufacturing companies in America using discriminant analysis. The review reveals that there are five factors that significantly influence the forecast for bankruptcy including working capital per total asset, retained earnings per total asset, EBIT per total asset, market value of equity per total liability and sales per total asset. Besides that, [2]. also researched about bankruptcy with logistic regression. The test shows that the factors of net income per net sales, current liabilities per total assets, current assets per current liabilities, net income per asset growth are factors that significantly affect corporate chapter 11.

The two tests above focus on using a static model that relies on information for an indefinite period of time. This review means predicting the condition of the company that fails in the accompanying period by ignoring how the condition of the organization changes after some time. [3]. offers a multiperiod logit technique that can represent this progress and is admittedly more stable than the static model. In his exploration, Shumway showed that the multi-period logit model can predict bankruptcy better than using the discriminant analysis made by Altman to estimate corporate bankruptcy on the financial data of companies on the NYSE and AMEX from 1962 to 1992. In addition,[4] provides another experimental model on the use of the multiperiod logit technique on the insolvency data of commercial banks in America from the FDIC website in 1980-1992. In their research, Cole and Wu compared the single time frame probit model and the multiperiod logit model, the consequence of this study finding the results that the multiperiod logit model gives a great hope better than the static model with the consequence of forecasting accuracy of 93.12% compared to 72.34%. in the first decile.

Based on the above description in the form of a demonstration of the bankruptcy of a manufacturing company listed on the Indonesia Stock Exchange (IDX), a survival analysis will be carried out using the multiperiod logit technique. This technique can predict several companies in financial distress. Based on research [5][6] that the hazard function needs to be refined to get the best estimation model. Using eighteen financial ratios in the company's report and two macroeconomic indicators that are suspected to affect the company's liquidation. This exploration is expected to contribute to several groups such as investors, creditors, company management, and public authorities in providing an overview to take steps that are believed to be used to survive or prevent company bankruptcy.

LITERATURE REVIEW

A. Survival Analysis

Survival analysis is a statistical method where the variable to be observed is the time duration until the occurrence of an event[7], [8]. In this study, the event in question is a condition of Financial distress. The time that is the focus of survival analysis is called survival time (T) because it shows the time an individual "survive" in a certain observation period. While the event can be considered as a failure (*d*). An event is denoted by the symbol d to define the status of the event whether it is failure or censored. The value of *d=1* indicates failure and *d=0* indicates censored. In general, the purpose of survival analysis is as follows.

a. Estimate and interpret survival function and/or hazard function from survival data.
b. Compare survival and/or hazard functions.
c. Knowing the effect of predictor variables on survival time.

B. Survival Function dan Hazard Function

In the endurance test, there are two basic quantities that are commonly used, namely the survival function referred to as S(t) and the hazard function indicated by h(t). The survival function is characterized as the probability that an individual can survive more than a certain time, while the hazard function is characterized as the rate at which an event occurs after the individual survives for a certain period of time. It tends to be numerically expressed as follows.

$$\boldsymbol{S(t) = P(T > t)} \tag{1}$$

Where T is the time of occurrence as an arbitrary nonstop variable, the survival function is the complement of the cumulative distribution function. Where the cumulative distribution function is characterized as the probability value of the random variable T that is incorrect or equivalent to time t written as $F(t) = P(T \leq t)$, so the survival function can be expressed as follows.

$$\boldsymbol{S(t) = P(T > t) = 1 - P(T \leq t) = 1 - F(t)} \tag{2}$$

When expressed in a survival probability density function (PDF) the results are obtained as follows.

$$\boldsymbol{S(t) = P(T > t) = \int_{t}^{\infty} f(u)du} \tag{3}$$

The second fundamental quantity, especially the hazard function, is defined as the rate at which a single event experiences an event in the time span t to $t + \Delta t$ if it is realized that the individual is still alive up to time t. Mathematically the hazard function can be denoted as follows.

$$\boldsymbol{h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}} \tag{4}$$

The relationship between the survival function and the hazard function can use the conditional probability theory $P(A|B) = \frac{P(A \cap B)}{P(B)}$, where A is the hazard function and B is the survival function. In addition, $P(A \cap B)$ is the probability of a joint event between A and B. The conditional probability value of the meaning of the hazard function is as follows.

$$\frac{P(t \leq T < t + \Delta t)}{P(T > t)} = \frac{F(t + \Delta t) - F(t)}{S(t)} \tag{5}$$

where F(t) is the distribution function of T, then we get

$$h(t) = \lim_{\Delta t \to 0} \left\{ \frac{F(t + \Delta t) - F(t)}{\Delta t} \right\} \frac{1}{S(t)} \tag{6}$$

So, the relationship between the survival function and the hazard function is as follows.

$$h(t) = \frac{f(t)}{S(t)} \tag{7}$$

C. K-Nearest Neighbour Multiple Imputation

Missing data is one of the problems that are often encountered in the use of big data. Therefore, we need a special method to deal with missing data. McGraw Hill Finance (2015) in their work report states that the k-nearest neighbor (KNN) method is better for imputing financial ratio data. The KNN imputation method is one method to overcome missing data without the need for the formation of a prediction model for each item that experiences missing data, but only uses a distance measure[9].

1. The procedure for imputing missing data using the KNN method is as follows: Determine the value of K, which is the number of closest observations that will be used to estimate the missing data.
2. Calculate the distance between observations containing missing data on the jth variable and other observations that do not contain missing data on variables other than j (denoted by j') using the following formula.

$$d(x_a, x_b) = \sqrt{\sum_{\substack{j'=1 \\ j' \neq j}}^{m} \left(x_{aj'} - x_{bj'}\right)^2}$$

where:

$d(x_a, x_b)$ = distance between observations x_a and observations x_b on variables other than variable j

x_{aj} = the value of the j^{th} variable in the target observation x_a

x_{bj} = the value of the j^{th} variable on the target observation x_b

3. Find the closest K observations based on the smallest distance value. The value of the variable in the nearest K observations will be used for the imputation process in the observations that contain missing values.
4. Calculate the weight (weight) on each K closest observation. The closest observation will get the biggest weight.
5. Calculate the average value of the nearest K observations that do not contain missing values with the weighted mean estimation procedure, which is with the following formula.

$$\hat{x}_j = \frac{1}{w}\sum_{k=1}^{K} w_k v_{kj}$$

where vkj is the value of the j[th] variable at the k[th] observation, k=1,2,…,K dan $W = \sum K \sum_{k=1}^{K} w_k v_{kj}$ is the k-th nearest neighbor observation weight, where $w_k = \frac{1}{(x,v_k)^2}$

6. Perform the imputation process of missing data on observations that contain missing values with the average value obtained in stage 5.

D. Kaplan Meier Curve and Log Rank Test

In the survival analysis, the Kaplan-Meier curve was used to estimate the survivor function[7]. The Kaplan-Meier curve is a curve that describes the relationship between survivor function estimation and survival time. If the probability of Kaplan-Meier is denoted by $\hat{S}(t(j))$ then the general Kaplan-Meier equation is as follows.

$$\hat{S}(t(j)) = \hat{S}(t(j\text{-}1)) \times \hat{P}r(T > t(j)|\, T \geq t(j))$$

$$\hat{S}(t(j-1)) = \prod_{i=1}^{j-1} \hat{P}r(T > t(j)|\, T \geq t(j))$$

So that $\hat{S}(t(j))$ can be formulated as follows.

$$\hat{S}(t(j)) = \prod_{i=1}^{j} \hat{P}r(T > t(j)|\, T \geq t(j))$$

The Kaplan-Meier survival curve can be illustrated through Figure 2.2 below.

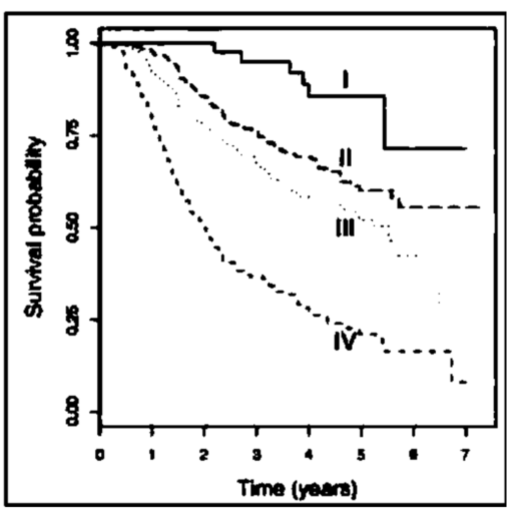

Figure 2 Illustration of Kaplan-Meier Curve

The Kaplan-Meier curve illustration in Figure 2 shows that in a period of 7 years, the survival curve of group I individuals is above the survival curve of group II, III and IV individuals. This shows that individuals belonging to group I have a higher probability of surviving for 7 years when compared to individuals of other groups. On the other hand, group IV individuals have the lowest probability of surviving for 7 years when compared to individuals belonging to other groups. In addition to the Kaplan-Meier curve, there is also a log rank test that is used to compare survival curves in different groups[7]. The hypothesis used in the log rank test for two or more is as follows.
H_0: there is no difference in the survival curve between different groups
H_1: there is at least one difference in the survival curve between different groups

E. Variable Selection

The hazard model using many independent variables will cause problems, namely the occurrence of multicollinearity cases. Therefore, a method is needed to select independent variables that can produce the best model and avoid multicollinearity cases. Variable selection methods that can be used in the hazard model are forward, backward and stepwise methods. The forward method is a variable selection method that works by inserting independent variables into the model gradually, the backward method is a variable selection method that works by inserting all independent variables first, then independent variables that do not have a significant effect in the model will be removed from the model, while the stepwise method is a method that combines forward and backward methods. In these three methods, it is important that a variable is not measured based on the AIC value (Akaike Information Criterion)[10].

$$\boldsymbol{AIC = -2L + 2(p + 1)} \tag{8}$$

where:
L: log-likelihood model
p: many parameter estimates in the model

The steps of variable selection using the forward method are as follows.

1. Calculate the value of $AIC0$, where the value is the AIC value for the model with intercept only.
2. Select the independent variable included in the model by calculating the value of $AIC(0)$ for the model containing the variable x_j. Suppose x_j is an independent variable with j = 1, 2, … , p. The selected independent variable is the variable in the model with the independent variable x_{e1} that has the smallest $AIC(0)$.
3. Test $AIC(0)$ with $AIC0$. If $AIC(0)$ is smaller than $AIC0$ then the independent variable x_{e1} can enter the model.
4. Calculate the value of $AIC(1)$ which expresses the AIC value of the model containing the variables x_{e1} and x_j. Suppose the model containing independent variables $xe1$ and $xe2$ is the model that has the smallest AIC value of $\mathrm{AIC}_{e_{ij}}^{(1)}$and $\mathrm{AIC}_{e_{ij}}^{(1)}$ is smaller than $AIC(0)$ then the independent variable $xe2$ can enter the model.
5. The iteration stops when there is no model with the addition of a new variable that has an AIC value smaller than the AIC value of the previous model.

The steps of variable selection using the backward method are as follows

1. Enter all independent variables into the model and calculate the value of $AIC(0)$.
2. Calculate the value $\text{AIC}_{e_{ij}}^{(1)}$ which expresses the AIC value of the model containing the variable xej . The most suitable variables to leave the model are variables with the smallest value of $\text{AIC}_{e_{ij}}^{(1)}$. If this variable is expressed as x_{r1} .
3. Calculate the value of $\text{AIC}_{-e_{r1}}^{(2)}$ which expresses the AIC value of the model without variables x_{r1}. If the value of $\text{AIC}_{-e_{r1}}^{(2)}$ is less than the value of $AIC(0)$ then $-er1$ continue reducing the independent variable as in step 2.
4. The iteration stops when there is no model with the elimination of a new variable that has an AIC value smaller than the AIC value of the previous model.

While the stepwise method is a method that combines forward and backward. So the step to use the stepwise method is to perform selection using forward and backward in each stage to obtain the smallest AIC value.

F. Multiperiod Logit

Multiperiod Logit model is a logit model estimated by using survival data with autonomous perception between objects. The multiperiod logit model is comparable to the hazard function model in discrete time with a function form

$$h(t_i, x_i; \theta) = P(T \leq t | y_i = 1)$$

with y = {1; there is an event and 0; others}, so that the multiperiod logit model can be described as a hazard function model[3].

The relationship between the multiperiod logit model and the hazard model can be described as follows. Because the multiperiod logit model is estimation data taken from independent observations, the likelihood function is as follows[3].

$$L = \prod_{i=1}^{n} \left(F(t_i, x_i; \theta)^{y_i} \prod_{j<t_i} [1 - F(j, x_i; \theta)] \right)$$

As a probability distribution function, the value of F will be between zero and one $(0 \leq F \leq 1)$, with $F(0) = 0$ and $F(\infty) = 1$. The value of F always depends on *t*, so that F can be interpreted as a hazard function $h(t)$

$$L = \prod_{i=1}^{n} \left(h(t_i, x_i; \theta)^{y_i} \prod_{j<t_i} [1 - h(j, x_i; \theta)] \right)$$

defined the likelihood of the survival function as follows.

$$S(t, x; \theta) = \prod_{j<t_i} [1 - h(j, x_i; \theta)]$$

If the above survival function is substituted into the hazard function equation, the likelihood function is obtained as follows.

$$L = \prod_{i=1}^{n} \left(h(t_i, x_i; \theta)^{y_i} S(t, x; \theta)\right)$$

The likelihood function is equivalent to the likelihood function produced by the hazard model which was first introduced by Cox and Oakes in 1984 [11]. So that the model obtained from the Multiperiod Logit method is equivalent to be used as a hazard function.

METHODS

A. Data Types and Sources

This type of research is quantitative research. While the data used in this review is optional data obtained from the organization's quarterly fiscal reports on the Indonesia Stock Exchange website IDX and ICMD from the first quarter of 2001 to the third quarter of 2021. In the manufacturing sector, eight sub-areas were selected for observation, more specific, food, drink, and food. pets, ceramics, glass and porcelain, synthetic materials, footwear, plastics and bundling, mash and paper, and apparel materials and articles. This data is data from the organization's financial statements so that calculations are completed first to obtain financial proportion information that will be used as a predictor variable.

B. Variables

The response variable is in the form of a dummy variable, where the company's status will have a value of 1 if the company experiences financial distress and a value of 0 for others.
While the predictor variables consist of 16 company financial ratios and the JCI and the BI rate which are used as macroeconomic indicators.
The stages of data analysis to be carried out in this study are as follows.

1. Collect financial data for manufacturing companies listed on the Indonesia Stock Exchange (IDX) from the first quarter of 2001 to the third quarter of 2021. Financial data is obtained from the publication of quarterly issuer financial reports on www.idx.go.id (IDX website) as well as from www.icamel.id (IDX electronic library)
2. Pre-processing the company's financial data using the progress report, namely: working on the company's financial reports, converting data into discrete form, handling missing qualities and anomalies. The company's financial ratios are determined using the equation of financial ratios in general. Then, at that point, the missing data is associated using the k-Closest Neighbor technique. From there, exclusions are controlled using the 2.5% quantile for the upper and lower quantiles.
3. Describe the quality of financial ratio information by using a clear measurable strategy as mean, middle, minimum and maximum. As well as showing the difference in the

circumstances of the sample surviving and failing (facing bankruptcy) using the Kaplan-Meier curve.

4. Create a multiperiod log model with progress attached to it.
   a. Selecting variables by utilizing forward, backward and gradual strategies.
   b. Form a multiperiod logit model by utilizing indicator factors from the best model results from the three strategic choices above.
   c. Estimating the parameters of the multiperiod log model
   d. Performing a significance test of the parameters of the multiperiod logit model using simultaneous testing (likelihood ratio) and partial testing (Wald test)
   e. interpret the Multiperiod Logit model and then calculate the probability value of the hazard function, survival, and probability of financial distress in each sampled company.
5. Make a conclussions

RESULT AND DISSCUSSION

This chapter examines the characteristics of manufacturing companies listed on the IDX from 2001 to the third quarter of 2021. There are 79 companies in the manufacturing sector, out of these 79 companies 73 have survived, 4 financial distress companies and 2 Relisting companies. Companies that are categorized as experiencing financial distress are companies that survive and financial distress. The Relisting Company will not be used in the analysis because the survival model used is not a repeating model. The two Relisting companies will be discussed in a separate sub-chapter. The data consists of 16 financial ratios and 2 macroeconomic indicators. In addition, there are also EPS and PBV variables contained in the data, but these two variables are not financial ratios, so statistical descriptions will only be carried out and not included in the modeling.

In the next stage, multiperiod logit modeling is carried out. Modeling begins with selecting variables to get the best model. Then to find out the factors that influence the bankruptcy of companies, simultaneous and partial testing of the best model obtained from the selection of variables is carried out. The interpretation of the model will be carried out at the end of the discussion.

A. Pre-Processing Data

The risk of using big data in analysis is that there are outliers and missing data. In this sub-chapter, we will discuss methods for overcoming the problem of missing data and outliers.

B. Missing Data

The financial ratio data used is data that still contains missing data (missing value). Comparison of observations which are complete data and contain missing data is shown in the following figure.

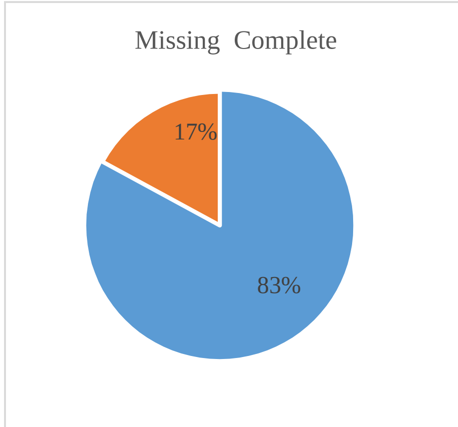

Figure 3. Complete Data Comparison with Missing Data

From the picture above it appears that 17% of the total data is in the form of incomplete time-observation or contains missing values. Eliminating missing data means deleting one observation (company) because the data used is panel data which are independent of one another. It should also be noted that 17% of the missing data comes from almost all companies. So deleting lost data is not a workable solution.

To handle missing data, imputation is carried out using k-nearest neighbor. This imputation method uses the data around the missing data as a reference to fill in the missing data.

C. Outliers in Financial Ratios

In addition to problems regarding missing data, outliers are also a problem encountered in the use of financial ratio data. This is due to the long observation interval which reaches 84 quarters or nearly 21 years, and the diversity of companies' financial conditions which can be very different from one another.

As an illustration, the following is a description of the data before handling the outliers.

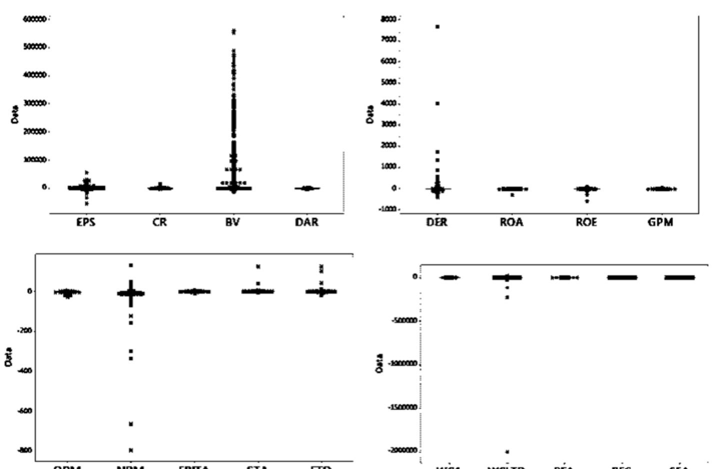

Figure 4. Box-Plot of Financial Ratios Variable

Based on the picture above, it can be seen how the outliers are in each financial statement variable. The distribution of financial ratio data is very wide. Even the shape of the box-plot is not very visible because the range compared to the quartiles is very large. Normally financial ratio data will spread between zero and one. However, in reality, several financial ratio variables are spread very wide.

D. Kaplan Meier Curve and Log Rank Test

The probability that a company can maintain its shares listed on the IDX is shown in the following figure.

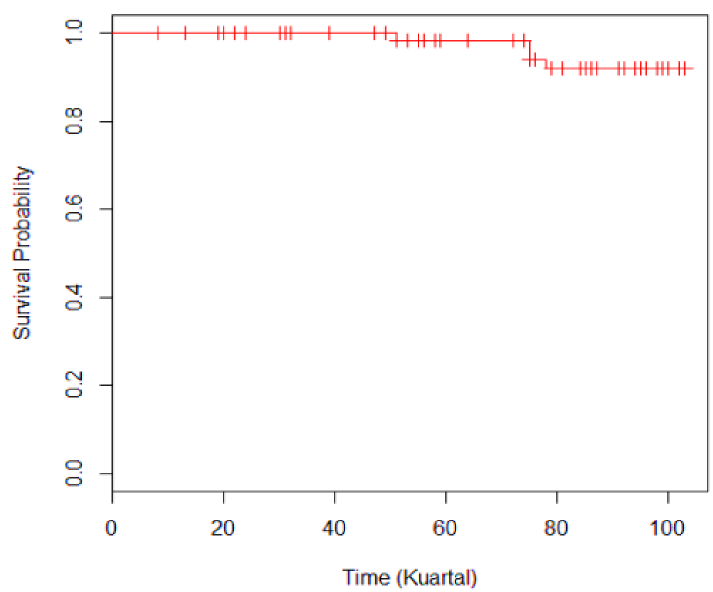

Figure 4. Kaplan-Meier Survival Curve for All Companies in the Manufacturing Sector Listed on the IDX

Figure 4 shows the survival curve of all manufacturing companies listed on the IDX. With the limited data on delisted companies used, there is no significant decrease in survival probability. Based on data used by manufacturing sector companies listed on the IDX, they were able to maintain their shares on the IDX for 103 quarters, which were relatively the same, namely above 80%. This also shows that the effectiveness of the company's business in the manufacturing sector is able to provide a sense of security to investors quite well.

While the probability that a company can maintain its shares listed on the IDX is grouped based on three sectors, namely the basic chemical industry sector, the various industrial sectors and the consumer goods industry sector as shown in Figure 4.6 as follows.

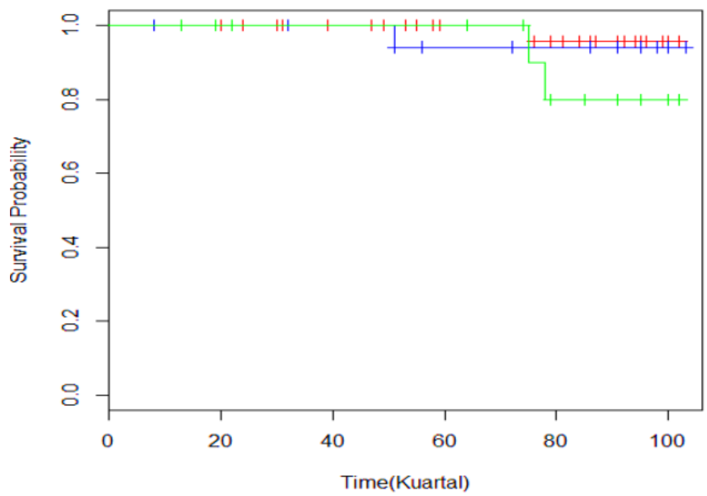

Figure 5. Kaplan-Meier Survival Curve of All Manufacturing Sector Companies Listed on IDX by Sub-Sector

Figure 5 shows that the red plot is the survival curve for companies in the basic chemical industry sector, the blue plot is the survival curve for various industrial companies and the green plot is the survival curve for companies in the consumer goods industry sector. The picture above can be interpreted that the probability of survival in the three sectors has a relatively equal probability of being able to maintain its shares on the IDX for 21 years, namely above 75% and still close together. The curves for the basic chemical industry and various industries coincide and are constant from the beginning of the observation to the end of the observation, but in the 50th quarter companies in the various industrial sectors experienced a decrease in the probability of survival, while the basic chemical industry sector experienced a decrease in the probability of survival in the 74th quarter. For the food and beverage industry sector, there was a sharper decline than the other two sectors, starting in the 74th quarter and dropping again in the 80th quarter.

To strengthen the conclusion that the survival chances of the three sub-sectors are not different, a log rank test was carried out which produced a log rank test statistical value of 2.2 and a p-value of 0.340. If a 90% confidence level is used, a failure to reject H0 is obtained, which means that there is no difference in the survival curves between the three manufacturing sub-sectors. So it can be concluded that companies in the three manufacturing sub-sectors have the same probability of staying on the stock exchange for 84 quarters.

E. Manufacturing Company Financial Distress Modeling on IDX Multiperiod Logit

With variables that always change over time. Then the static model will be difficult to be able to describe the status of the company will continue to survive or experience financial distress. The use of multiperiod logit is expected to give better results than the static model. Because the shape of the likelihood function is the same, the multiperiod logit estimator can be calculated using the logit program. The predictor variable used in modeling the financial distress of manufacturing companies on the IDX is a predictor variable that has gone through a variable selection process. Parameter estimation values and standard errors of the multiperiod logit method are shown in the following table.

Table 1. Estimator Value and Standard Error

Variable	Estimate	Std. Error	VIF
(Intercept)	-6,7649	5,2845	
CR	0,2784	0,129	1,1727
GPM	6,1418	3,1744	1,3412
SFA	-5,335	2,7433	1,0687
BI Rate	-1,9689	0,882	1,2223

Based on Table 4.1 it can be seen that there are no VIF values that are more than ten, so there is no longer multicollinearity in the model. The hazard model is also obtained which is shown in the following equation.

$$h(t_i, x_i) = \frac{a}{1+a}$$

with,

$$a = exp(-6{,}7649 + 0{,}2784CR_i + 6{,}1418GPM_i - 5{,}335SFA_i - 1{,}9689BI.Rate_i)$$

Furthermore, a simultaneous test was carried out to determine whether the predictor variables affect the rate of financial distress of manufacturing companies. Simultaneous testing was carried out using the likelihood ratio test and the $\chi 2$ value was 27.956 while the $\chi 2$ value was 7.78. Because the value of $\chi 2$ is greater than $\chi 2$, then reject H0, which means that there is at least one predictor variable that has a significant effect on the model. Furthermore, partial testing is carried out, the partial test values are shown in the following table.

Table 2. Partial Test Wald Value

Variable	Estimate	Std. Error	Z Value	Pr(>|z|)
(Intercept)	6.7649	5.2845	1.2800	0.2005
CR	0.2784	0.1290	2.1590	0.0309
GPM	6.1418	3.1744	1.9350	0.0530
SFA	-5.3350	2.7433	-1.9450	0.0518
BI.Rate	-1.9689	0.8820	-2.2320	0.0256

In Table 4.2, the four variables have a significant effect at the 90% confidence level on the occurrence of financial distress for manufacturing companies on the IDX, namely CR (Current Ratio), GPM (Gross Profit Margin), SFA (Sales to Fixed Assets) and BI rate. Based on the modeling that has been done, the parameter values for the Current Ratio and GPM variables are 0.2784 and 6.1418, respectively, these values indicate that the greater the value of the Current Ratio and Gross Profit Margin, the chances of a company experiencing financial distress will increase. at one time period. Meanwhile, the parameter value for the Sales to Fixed Assets (Fixed Asset Turnover Ratio) variable is -5.335, this value indicates that the greater the Sales to Fixed Assets value, the less chance the company will experience financial distress during a period of time. The Sales to Fixed Asset Ratio measures the company's ability to make sales of the fixed assets used. The more efficiently a company uses its fixed assets, the smaller the chance the company will experience financial distress at one time.

Bank Indonesia interest rates also have a significant influence on the chances of financial distress for manufacturing companies on the IDX in a certain period. Bank Indonesia's interest rate reflects the government's response to Indonesia's economic conditions. In the multiperiod logit model obtained, the estimated value of the BI rate parameter is -1.924, this value indicates that the greater the value of the BI rate, the chances of a manufacturing company experiencing financial distress in a certain period will decrease.

F. Hazard, Survival, and Delisting Opportunities for Manufacturing Companies Based on the Multiperiod Logit Model

The hazard opportunity is obtained by adding up the hazard rate for each company in each quarter until the last determined quarter. Meanwhile, calculating the probability of survival is obtained by using the relationship between the hazard function and the survival function which has been described in equation (2.14). Opportunities for financial distress are obtained from the remaining survival opportunities. For example, it will calculate the value of the opportunity hazard, survival and financial distress of a glass producing company with the issuer code AMFG in the last quarter or the 103rd quarter. So it must be known in advance the value of the company's hazard rate from the start of the IPO in the 23rd quarter to the end. The hazard rate is calculated using the hazard function that has been obtained from the multiperiod logit model.

$$h(t_i, x_i) = \frac{a}{1+a}$$

with,

$$a = exp(-6{,}7649 + 0{,}2784CR_i + 6{,}1418GPM_i - 5{,}335SFA_i - 1{,}9689BI.Rate_i)$$

The hazard opportunity is obtained by adding up the hazard rate in the 23rd quarter to the end so that the hazard opportunity for AMFG issuers is 0.0334. After knowing the probability of hazard, the probability of survival is known to be 0.9672 so that the probability of financial distress for AMFG issuers is only 0.0328. The full value of hazard, survival and financial distress opportunities can be seen in the attachment. Descriptive value of hazard, survival and financial distress opportunities is shown in the following table.

Table 3. Description of Hazard Opportunity Statistics, Survival and Financial Distress

Probability	Statistik					
	Mean	**Min**	**Q1**	**Median**	**Q3**	**Max**
Hazard	0,051	0,000	0,002	0,013	0,042	0,861
Survival	0,955	0,422	0,959	0,987	0,998	100,0
Financial Distrees	0,044	0,000	0,002	0,013	0,041	0,577

Based on Table 3, it is known that there are companies with a large probability hazard value of up to 85% while on the contrary, there are also companies with the smallest hazard value of 0%. Companies with smaller hazard values will be safer to invest because the chances of financial distress occurring in these companies are smaller, and vice versa. The five companies with the smallest opportunity hazard values are companies with company codes SKBM, IGAR, PBRX, PSDN and UNIC.

While the companies with the greatest opportunity hazard values are IIKP, UNIT, SIMM, PWSI and DAVO. Companies with the codes SIMM, PWSI and DAVO are companies that have experienced financial distress, so it is only natural that these three companies have a high probability hazard value. Companies that need to be considered are IIKP and UNIT, these two companies have high hazard opportunities. A company rescue step is needed so that the two companies are not in financial distress from the stock exchange.

CONCLUSSION AND SUGGESTIONS

Descriptively, surviving and financial distress companies have a prominent difference in the profitability ratio and market measure ratio. In the variable profitability ratios the different financial ratios of the two groups of companies are Book Value, Debt on Equity Ratio, Return on Assets, Operating Profit Margin and Net Profit Margin. Meanwhile, in the market measure ratio, the variables that differ between the two groups of companies are EPS, Book Value per Share and Debt Equity Ratio. Meanwhile, a relisting company has a lower profitability ratio than during financial distress, but when it improves again on the stock exchange, the company's profitability ratio increases again. Differences in the company sector do not show significant differences in survival curves. This is evidenced by the insignificant Log Rank test.

The resulting model from modeling using multiperiod logit using the backward variable selection results produces the following model.

$$h(t_i, x_i) = \frac{a}{1 + a}$$

with,

$$a = exp(-6{,}7649 + 0{,}2784CR_i + 6{,}1418GPM_i - 5{,}335SFA_i - 1{,}9689BI.Rate_i)$$

Based on the results of the simultaneous test of the multiperiod logit model, it is concluded that there is at least one predictor variable that has a significant effect on the financial distress of manufacturing companies on the IDX. From the partial test results it is known that of the five variables in the model there are four significant variables namely CR (Current Ratio), GPM (Gross Profit Margin), SFA (Sales to Fixed Assets) and BI rate. The five best companies to invest in with minimum hazard opportunity values are companies with issuer codes SKBM, IGAR, PBRX, PSDN and UNIC. Accuracy and geometric mean values are used to measure the accuracy of the model. The multiperiod logit model obtained has accuracy and geometric mean values of 0.9726 and 0.8541, respectively.

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