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Profitability Level Modelling of Manufacturing Companies based on Binary Logistic Regression with Random Effect on Panel Data

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Abstract

The manufacturing company is the main pillar of industrial development in a country. The development of manufacturing industry can be used as a benchmark to see national industrial development in the country. The performance of a good manufacturing company can be seen from profitability. Profitability is the ability of companies to earn profits in relation to sales, total assets capital. Profitability ratios are measured by Net Profit Margin (NPM). This ratio measures the ability of a company to generate profitability at a certain level of sales, assets, and capital stock. The greater the Net Profit Margin, the more efficient the company is in issuing the costs associated with its operations. The relationship between profitability and the factors that influence it will be studied to obtain a mathematical model. This mathematical model will show the factors that influence profitability significantly. Predictor variables which determine profitability are Leverage, Manufacturers' Size, Liquidity, and Tangibility. In conducting research on profitability, the data used is a combination of cross section and time series or panel data. This data is used because it is necessary to observe the behavior of research units at various time periods. This study used secondary data of 2008 – 2016 Annual Reports which were downloaded from 21 related manufacturers' official websites. One of the statistical analysis tools used, to observe the behavior of research units at various time periods, is ordered logistic regression analysis in panel data, which is an extension of logistic regression when it is used in panel data.

Estimation of binary logistic model parameters in panel data using maximum likelihood estimation method with Gauss-Hermitte Quadrature iteration. Based on the best model obtained, the factors that influence manufacturers' profitability, in Indonesia, are leverage and tangibility. The result of the Likelihood Ratio Test shows that the random effect panel binary logistic regression model is better model than standard binary logistic regression with a classification of accuracy of 73.54%.

Keywords: *Profitability, NPM, Binary Logistic Regression, Panel Data, Random Effect*

Introduction

Manufacturing companies are the main pillar of industrial development in a country. The development of the manufacturing industry can be used as a benchmark to the see industrial development nationally. Manufacturing itself is a branch of industry that applies machinery, equipment, labor, and a process medium. Manufacturing comes from the word manufacture which means making by hand (manually) or by machine to produce something (Heizer & Render, 2005). Manufacturing companies are also companies whose activities are to buy raw materials and then process raw materials, by issuing other costs, into finished goods ready for sale. The number of companies in the industry, as well as the current economic conditions have created a fierce competition between manufacturing companies. Competition in the manufacturing industry makes every company increasingly improve its performance so that its goals can still be achieved. In general, the main objective of the establishment of a company is to obtain optimal profit for investments that have been invested, so as to maintain the smooth running of the business in the long term. The performance of a good manufacturing company can be seen from its profitability. Profitability is the ability of a company to gain profits in relation to sales, total assets and own capital. Profitability in relation to sales uses the ratio of gross profit margin and net profit margin, while profitability in relation to investment uses two measurements namely Return on Investment (ROI) or Return On Asset (ROA) (Van Horne & Wachowicz, 2005) Every business entity will always strive to increase its profitability, because the higher the level of profitability of a business, than the more feasible the business entity.

Profitable companies will generally develop in the future. Profitability is measured by Net Profit Margin (NPM) which is a measure of profit after interest and tax (net profit) (Kasmir, 2012). Profitability can be used to determine whether the company has good prospects. A low NPM indicates that sales are too low for a certain level of costs. The NPM value is obtained from net profits divided by sales (Hanafi & Halim, 2003). This NPM is very important for operations managers because it reflects the sales pricing strategy applied by the company and its ability to control operating expenses. The greater the NPM, the more efficient the company is in managing costs related to its operations. The greater the NPM, the greater the ability of the company to achieve high profits. An increase and decrease in NPM is suspected to be influenced by various factors. These factors include leverage, size (company size), liquidity, and tangibility. Tangibility as well as fixed assets are a guarantee from the company, and will be used as collateral in a debt contract (Barros and Silveira, 2007).

Several studies have discusses profitability, namely testing the effect of variables leverage, assets mix and size of NPM using multiple linear regression and the conclusions obtained are leverage variables that have a significant effect on NPM (Rice, 2014). Furthermore, (Pratheepan, 2014) examined the effect of variable size, leverage, liquidity and tangibility using the panel regression method and concluded that the variable size, leverage, liquidity and tangibility had a significant effect on profitability. The outcomes of the two researchers, resulted in a coefficient of determination that tends to be low (ie 30%); the structure of panel data in the Rice study was not in accordance with the method used. Logistic regression is a regression method that connects between categorical response variables with predictor variables that are categorical or continuous (Hosmer Jr, Lemeshow, & Sturdivant, 2013).(Neuhaus, Kalbfleisch, & Hauck, 1991) discusses the comparison of cluster-specific approaches and population-averages for analyzing correlated binary data. Statistical method for the design of longitudinal data and clusters with binary response variables are discussed by (Berg & Neuhaus, 1992). A survey of methods for analyzing clustered binary response variable data is discussed by (Pendergast et al., 1996).The maximum marginal likelihood method for analyzing binary data with random effect and examples of its application to panel data has been discussed by (Conaway, 1990). Logistic regression models with random effects are discussed by (Li, Lingsma, Steyerberg, & Lesaffre, 2011) by comparing binary outcomes and ordinal using statistical packages. The data used in this study was taken based on observations of a number of manufacturing company units in the same time period; panel data. Panel data sets for economics possess several major advantages over conventional cross-sectional or time-series data sets. Panel data usually gives the researcher a large number of data points, increasing the degree of freedom and reducing the collinearity among explanatory variables, improving the efficiency of econometric estimates (Hsiao, 2003). Panel data econometrics is one of the most exciting fields of inquiry in econometrics today. Many interesting and important problems remain to be solved, general as well as specific to particular applications (Matyas & Sevestre, 2008). The advantage of panel data is that it can provide information about changes in the behavior of the manufacturing company units studied. Random effects are factors that are not directly observed but affect the variability of the profitability of manufacturing companies. Based on this description, researchers are interested in discussing the profitability modeling of manufacturing companies using a binary logistic regression approach with random effects on panel data. The estimation results are expected to be able to identify the factors that influence the NPM and calculate the probability of a manufacturing company in a certain period of time in a condition that is reasonably healthy or unhealthy if the factors are known.

Materials and Method

Logistic Distribution

Random variable X is said to be logistic distributed, written $X \sim Lo(a,b)$ if it has the probability density function (pdf) as follows

$$h(x) = \frac{exp\left[-(x-a)/b\right]}{b\left\{1+exp\left[-(x-a)/b\right]\right\}^2} \ ; \ -\infty < a < \infty,\ b > 0,\ -\infty < x < \infty \qquad (1)$$

From equation (1) obtained cumulative distribution function (cdf) of X is

$$H(x) = \frac{1}{1+exp\left[-(x-a)/b\right]} \qquad (2)$$

with a as the location parameter, and b is a scale parameter. The mean and variance of X is a random variable which has logistic distribution $\mu = a$ and $\sigma^2 = b^2\pi^2/3$ respectively (Balakrishnan & Nevzorov, 2004) .

Binary logistic regression model

Binary logit model is a logistic regression model with a Y response variable consisting of two categories, namely Y = {0.1} with a successful probability of the experimental results based on logistical distribution. This binary logit model is a regression model based on the concept of probability. The binary logit model is defined as follows

$$g\left(\pi_i\right) = \boldsymbol{X_i\beta} \ ; \ i = 1, 2, \ldots, n \tag{3}$$

where $g(\pi_i) = ln(\pi_i / (1-\pi_i))$ is logit link function, $\boldsymbol{X_i} = \left(1, X_{1i}, X_{2i}, \ldots, X_p\right)$ is a vector from the predictor variable of observation to i, and $\boldsymbol{\beta} = \left(\beta_0, \beta_1, \ldots, \beta_p\right)$ is a vector of parameters that corresponds to the predictor variable. From equation (1), a successful probability is obtained if the predictor variable of $\boldsymbol{X_i}$ is known, i.e.

$$\pi_i = \frac{exp\left(\boldsymbol{X_i\beta}\right)}{1 + exp\left(\boldsymbol{X_i\beta}\right)} \tag{4}$$

with $\pi_i = Pr\left(Y = 1 \mid \boldsymbol{X_i}\right)$ [9].

Suppose that observations are made n times and that each observation is repeated one time, so that success is obtained y_i times with the probability of success π_i and the probability of failing $(1-\pi_i)$, for $i = 1, 2, \ldots, n$ then the Y_i response variable has binomial distribution with probability density function (pdf) as follows:

$$f(y_i) = \binom{1}{y_i} \pi_i^{y_i} \left(1-\pi_i\right)^{1-y_i} ; y_i = 0,1 \tag{5}$$

Because Y_i is mutually independent, then from equation (5) the likelihood function is obtained as follows:

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{N} f(y_i) = \prod_{i=1}^{N} \pi_i^{y_i} (1-\pi_i)^{1-y_i} \quad ; y_i = 0,1 \tag{6}$$

From equation (6) the log-likelihood function is obtained as follows:

$$\ell(\boldsymbol{\beta}) = \sum_{i=1}^{N} \left[y_i \ ln(\pi_i) + (1-y_i) \ ln(1-\pi_i) \right] \tag{7}$$

The vector estimation parameter $\boldsymbol{\beta}$ in equation (7) is obtained by maximizing the function $\ell(\boldsymbol{\beta})$

Binary logit model with random effect on panel data

It is assumed that panel data $(y_{it};\boldsymbol{X}_{it})$; $i=1,2,\ldots,N$;$t=1,2,\ldots,T$ meets the binary logistic regression model with random effect expressed in the form of the variance component as follows:

$$y_{it}^{*} = \boldsymbol{X}_{it}\boldsymbol{\beta} + v_i + \epsilon_{it} \quad , \quad i = 1,2,\ldots,N \ ; \ t = 1,2,\ldots,T$$

(8)

with y_{it}^{*} variable, $\boldsymbol{X}_{it} = (X_{1it}, X_{2it}, \ldots, X_{pit})$ is the vector of predictor variables in the unit of cross section *i* and time *t*, $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_p)'$ is a vector of parameters, v_i is the random effect of the unit of the cross section i assuming an identical independent distribution $N(0, \sigma_v^2)$, and ϵ_{it} is the error of the unit cross section *i* and time *t* which is assumed to have a logistic distribution with mean 0 and variance $\pi^2/3$ and independent of v_i. Suppose y_{it} is the observed response variable from unit cross section *i* and time *t* which are categorized as follows:

$$y_{it} = \begin{cases} 0 \ , & y_{it}^{*} \leq 0 \\ 1 \ , & y_{it}^{*} > 0 \end{cases} \tag{9}$$

If $\pi_{it} = \Pr(y_{it} = 1 \mid \boldsymbol{X}_{it})$ is a successful probability that corresponds to predictor variable $\boldsymbol{X}_{it}$, then equations (8) and (9) are obtained

$$\pi_{it} = \frac{\exp\,(\boldsymbol{X}_{it}\boldsymbol{\beta} + v_i)}{1 + \exp\,(\boldsymbol{X}_{it}\boldsymbol{\beta} + v_i)} \ , \quad i = 1,2,\ldots,N \ ;t = 1,2,\ldots,T \tag{10}$$

From equation (10) is obtained

$$g(\pi_{it}) = \boldsymbol{X}_{it}\boldsymbol{\beta} + v_i \tag{11}$$

where $g(\pi_{it}) = ln\,[\pi_{it}/(1-\pi_{it})]$ is the logit link function. Furthermore, from equation (11), defined Odd is the ratio between the probability of success and the probability of failure for the second individual to *i* and time *t* as follows:

$$Odd = \frac{\pi_{it}}{1-\pi_{it}} = exp(\boldsymbol{X}_{it}\boldsymbol{\beta}) \tag{12}$$

Based on the Odd value in equation (12), then Odd Ratio (OR) for the predictor variable X_j is defined as the comparison between the Odd value for $X_j = 1$ and the Odd value for $X_j = 0$ as follows

$$OR(X_j) = \frac{Odd(X_j = 1)}{Odd(X_j = 0)} = \exp(\beta_j) \; ; \; j = 1, 2, ..., p \tag{13}$$

Estimation of the binary logit model with random effect on panel data

Assumed random effect v_i is identical independent $N(0, \sigma_v^2)$ distribution with probability density function (pdf) as follows

$$\varnothing(v_i) = \frac{\exp(-v_i^2 / 2\sigma_v^2)}{\sigma_v \sqrt{2\pi}} \tag{14}$$

Then the conditional pdf from $y_{i1}, y_{i2}, \ldots, y_{iT}$ is

$$f(y_{i1}, \ldots, y_{iT} | \mathbf{x}_{it}, v_i) = \prod_{t=1}^{T} F(y_{it}, \mathbf{x}_{it}\boldsymbol{\beta} + v_i) \tag{15}$$

From equations (14) and (15) is obtained joint pdf from $y_{i1}, y_{i2}, \ldots, y_{iT}, v_i$ as follows

$$f(y_{i1}, \ldots, y_{iT}, v_i | \mathbf{x}_{it}) = \frac{\exp(-v_i^2 / 2\sigma_v^2)}{\sigma_v \sqrt{2\pi}} \prod_{t=1}^{T} F(y_{it}, \mathbf{x}_{it}\boldsymbol{\beta} + v_i) \tag{16}$$

From equation (16) is obtained marginal density function from $y_{i1}, y_{i2}, \ldots, y_{iT}$ as follows

$$f(y_{i1}, \ldots, y_{iT} \mid \mathbf{x}_{i1}, \ldots, \mathbf{x}_{iT}) = \int_{-\infty}^{\infty} \frac{\exp(-v_i^2 / 2\sigma_v^2)}{\sigma_v \sqrt{2\pi}} \left\{ \prod_{t=1}^{T} F(y_{it}, \mathbf{x}_{it}\boldsymbol{\beta} + v_i) \right\} dv_i \tag{17}$$

with $F(y, z) = 1/(1 + \exp(-z))$ for $y = 1$ and $F(y, z) = 1/(1 + \exp(z))$ for $y = 0$.

Based on equation (17) the marginal likelihood function on panel data l_i is obtained as follows

$$l_i = \int_{-\infty}^{\infty} \frac{\exp\left(-v_i^2 / 2\sigma_v^2\right)}{\sigma_v \sqrt{2\pi}} \left\{ \prod_{t=1}^{T} F\left(y_{it}, \mathbf{x}_{it}\boldsymbol{\beta} + v_i\right) \right\} dv_i \approx \int_{-\infty}^{\infty} g\left(y_{it}, \mathbf{x}_{it}, v_i\right) dv_i \tag{18}$$

Integral in equation (18) can be approximated by the M-point Gauss-Hermit Quadrature as follows

$$\int_{-\infty}^{\infty} e^{-x^2} h(\mathrm{x}) dx \approx \sum_{m=1}^{M} w_m^* h(a_m^*) \tag{19}$$

Equation (19) is equivalent to

$$\int_{-\infty}^{\infty} f(\mathrm{x}) dx \approx \sum_{m=1}^{M} w_m^* \exp\{(a_m^*)^2\} f(a_m^*) \tag{20}$$

with M are many quadrature, w_m^* are quadrature weight and a_m^* are quadrature absences. The log likelihood L is the sum of the logs of the panel-level likelihoods l_i. The standard approach to log-likelihood with mean-variance Gauss-Hermite Adaptive quadrature that is approached with the likelihood function panel data as follows

$$l_i \approx \sqrt{2}\hat{\sigma} \sum_{m=1}^{M} w_m^* \exp\{(a_m^*)^2\} g(y_{it}, \mathrm{x}_{it}, \sqrt{2}\hat{\sigma}_i a_m^* + \hat{\mu}_i) \tag{21}$$

with $\hat{\sigma}_i$ and $\hat{\mu}_i$ are the adaptive parameters for panel i. Therefore, using the definition of $g\left(y_{it}, \mathbf{x}_{it}, v_i\right)$, the total log likelihood is approximated by

$$L \approx \sum_{i=1}^{n} w_i \log \left[\sqrt{2}\hat{\sigma}_i \sum_{m=1}^{M} w_m^* \exp\left\{\left(a_m^*\right)^2\right\} \frac{exp\{-(\sqrt{2}\hat{\sigma}_i a_m^* + \hat{\mu}_i)^2 / 2\sigma_v^2\}}{\sqrt{2\pi\sigma_v}} \right.$$

$$\left. \prod_{t=1}^{T} F(y_{it}, \mathrm{x}_{it}\beta + \sqrt{2}\hat{\sigma}_i a_m^* + \hat{\mu}_i) \right] \tag{22}$$

where w_i is the user-specified weight for panel i; if no weights are specified, w_i = 1. The default method of adaptive Gauss–Hermite quadrature is to calculate the posterior mean and variance and use those parameters for $\hat{\mu}_i$ and $\hat{\sigma}_i$ by following the method of (Naylor & Smith, 1982), further discussed in (Harrell Jr, 2015)(Rabe-Hesketh & Skrondal, 2004). We start with $\hat{\sigma}_{i,0} = 1$ and $\hat{\mu}_{i,0} = 0$, and the posterior means and variances are updated in the *k* th iteration. That is, at the *k* th iteration of the optimization for l_i we use

$$l_{i,k} \approx \sum_{m=1}^{M} \sqrt{2}\hat{\sigma}_{i,k-1} w_m^* \exp\{(a_m^*)^2\} g\left(y_{it}, \mathrm{x}_{it}, \sqrt{2}\hat{\sigma}_{i,k-1} a_m^* + \hat{\mu}_{i,k-1}\right) \tag{23}$$

letting

$$\tau_{i,m,k-1} = \sqrt{2}\hat{\sigma}_{i,k-1} a_m^* + \hat{\mu}_{i,k-1} \tag{24}$$

$$\hat{\mu}_{i,k} = \sum_{m=1}^{M} \tau_{i,m,k-1} \frac{\sqrt{2}\hat{\sigma}_{i,k-1} w_m^* \exp\{(a_m^*)^2\} g(y_{it}, \mathbf{x}_{it}, \tau_{i,m,k-1})}{l_{i,k}} \tag{25}$$

and

$$\hat{\sigma}_{i,k} = \sum_{m=1}^{M} (\tau_{i,m,k-1})^2 \frac{\sqrt{2}\hat{\sigma}_{i,k-1} w_m^* \exp\{(a_m^*)^2\} g(y_{it}, \mathbf{x}_{it}, \tau_{i,m,k-1})}{l_{i,k}} - \left(\hat{\mu}_{i,k}\right) \tag{26}$$

and this is repeated until $\hat{\mu}_{i,k}$ and $\hat{\sigma}_{i,k}$ have converged for this iteration of the maximization algorithm.

Inference on binary logit model with random effect

According to (Harrell Jr, 2015) to examine the effect of predictor variables simultaneously on the response variable used the following hypothesis :

$H_0: \beta_1 = \beta_2 = \cdots = \beta_p = 0$

H_1: There is at least one $\beta_j \neq 0$; $j = 1,2, \dots, p$

to test this hypothesis used wald test statistic as follows :

$$W = \hat{\boldsymbol{\beta}}^T \boldsymbol{V}^{-1} \boldsymbol{\beta} \tag{27}$$

with $\boldsymbol{V}^{-1} = I(\hat{\boldsymbol{\beta}}) = -H(\hat{\boldsymbol{\beta}}) = -\dfrac{\partial^2 l}{\partial \hat{\boldsymbol{\beta}}\, \partial \hat{\boldsymbol{\beta}}^T}$.

Wald test statistic in (27) distributed Chi-square with p degree of freedom. The decision is that H_0 is rejected if $W > \chi^2_{(p,\alpha)}$.

If the result of the parameter test are simultaneously significant, then further test the parameters individually to see the effect of each predictor variable on the response variable in a binary logistic regression model with random effect. The hypothesis used to test the individual parameters is:

$$H_0: \beta_j = 0; \quad H_1: \beta_j \neq 0$$

To test the hypothesis using standard normal test statistic as follows:

$$Z_j = \frac{\hat{\beta}_j}{S(\hat{\beta}_j)} \tag{28}$$

$s(\hat{\beta}_j)$ is the standard deviation of the $\hat{\beta}_j$ estimator. The Z_j test statistic in equation (28) has a standard normal distribution. A critical area to test the hypothesis with a significance level of α is to reject H_0 if $|Z_j| > Z_{\alpha/2}$ (Greene, 2003).

Results and discussion

The data sources used in this study are secondary data obtained from the Annual Financial Report 2008 - 2016 regarding financial data of manufacturing companies. This data is downloaded from the official sites of manufacturing companies that are the object of research. The population in this study was 144 manufacturing companies listed on the Indonesia Stock Exchange (ISE) with a sample of 21 manufacturing companies. The response variable used in this study is the level of profitability of manufacturing companies that are categorized into two categories, namely healthy (Y = 1) and healthy enough (Y = 0). The predictor variables include leverage (X_1), size (X_2), liquidity (X_3), and tangibility (X_4).

Modelling the level of profitability of manufacturing companies

The results of modeling the level of profitability of manufacturing companies using the binary logistic regression approach with random effect on panel data obtained by the logit function as follows:

$$g(\pi_{it}) = -3.24224 - 3.47072X_{1it} + 0.18589X_{2it} - 0.06019X_{3it} - 3.62369X_{4it} \; ;$$

$$i = 1,2,\ldots,21 \; ; \; t = 1,2,\ldots,9$$

Simultaneous parameter test results using a significance level $\alpha = 5\%$ obtained a value of χ^2 of 16.21 and p-value of 0.0028. This means that the null hypothesis is rejected and it is concluded that the variables of leverage, size, liquidity, and tangibility simultaneously significant effect the level of profitability of manufacturing companies. After determining that the results of the parameter test are simultaneously significant, the next step is to test the parameters individually to see which variables are thought to influence the level of profitability of the manufacturing company. The results of individual parameter tests, with a level of significance $\alpha = 5\%$ in complete, are presented in table 1.

Based on Table 1, it can be concluded that by using a level of significance $\alpha = 5\%$, leverage and tangibility predictor variables have a significant effect on the level of profitability of manufacturing companies with p-values of 0.025 and 0.009 respectively. Then, the size and liquidity predictor variables has no significant effect on the health level of manufacturing companies with p-values of 0.15 and 0.604 respectively. The OR value for each predictor variable is presented in Table 2.

The hypothesis used to test the suitability of a binary logistic regression model with random effect on panel data is:

H_0 : Binary logistic regression model with random effect on panel data do not match

H_1 : Binary logistic regression model with random effect on panel data data accordingly.

The test result using a level of significance $\alpha = 5\%$ obtained a p-value of 0.021. The decision is that H_0 is rejected because of the p-value < α and the conclusion is a binary logistic regression model with random effect on panel data accordingly. Furthermore, calculating the classification accuracy of a binary logistic regression model with random effect on panel data based on the value of the Apparent Error Rate (APPER). The result of the model classification are presented in table 3.

Based on Table 3, the APPER value is 26.46%, so the accuracy value of the classification is 1 - 26.46% = 73.54%.

Interpretation of the model level of profitability of manufacturing companies

The leverage variable has a negative effect on the level of profitability of manufacturing companies. Leverage is used to measure how many assets a company has with regards to debt or capital. This ratio can determine the company's position and its fixed obligations to other parties and balance the value of fixed assets with existing capital. The greater the ratio, the greater the cost that must be borne by the company to fulfill its obligations, this can reduce the profitability of the company.

Size variable has a positive effect on the level of profitability of manufacturing companies because there is a positive correlation between company size and company profitability. The larger the size of the company assets owned, the larger the access to funding sources from various sources; getting loans from creditors will be easier because large companies have greater profitability (Halim, 2004).

Liquidity variable have a negative effect on the level of profitability of manufacturing companies. Liquidity is an indicator of the company's ability to pay all short-term financial obligations at maturity using available current assets. Liquidity is not only concerned with the overall state of corporate finance, but also relates to the ability to convert certain current assets into cash. Company liquidity is inversely proportional to profitability (Van Horne & Wachowicz, 2005). Liquidity can be seen from the current ratio, the greater the current ratio, the greater the company's ability to meet short-term obligations. This shows that the company has large fund as well as the stock of current assets. Possessing Large fund has two very different consequences, namely the company's liquidity is bigger but the company loses the opportunity to get additional profits. This is because the funds, that would otherwise be used for investment, are reserved to meet liquidity.

The Tangibility variable also has a negative effect on the level of profitability of manufacturing companies. Tangibility is a company's fixed assets. Companies whose assets are sufficient to be used as collateral for loans tend to use debt quite a lot (Brigham & Houston, 2001). The greater the proportion of assets owned by a company, the more companies will be encourage get larger loans; the level of debt (leverage) will increase. This shows that the greater the tangibility, the greater the chance for the company to take a loan that will increase the company's debt.

Size and liquidity variables have no significant effect on the level of profitability of manufacturing companies. This result is in line with research conducted by (Rice, 2014) and (Pratheepan, 2014) showing that the variable is not significant because the ability of a company to earn profits is not always seen from how big the company is, but depends on the level of creativity of the business. If the company is a capital-intensive company, then naturally it will have a larger number of assets, but not necessarily more business experience compared to labor-intensive companies.

Based on Table 3, the OR value for the leverage variable is 0.0311, this means that if leverage rises by 1%, then the ratio of the probability that a manufacturing company is in healthy condition, compared to healthy enough, is down by 96.89%. The OR value for tangibility variable is 0.0267, this means that if tangibility rises 1%, then the ratio of the probability of a manufacturing company in healthy condition, compared to healthy enough, is down by 97.33%.

Conclusion

The result of modelling the level of profitability of manufacturing companies, has obtained the logit function:

$$g(\pi_{it}) = -3.24224 - 3.47072X_{1it} + 0.18589X_{2it} - 0.06019X_{3it} - 3.62369X_{4it} \ ;$$

$$i = 1,2,\ldots,21 \ ; \ t = 1,2,\ldots,9$$

For level of significance $\alpha = 5\%$ leverage, size, liquidity, and tangibility predictor variables simultaneously have a significant effect on the level of profitability of manufacturing companies. The result of individual parameter testing show that the leverage and tangibility variables significantly influence the level of profitability of manufacturing companies. The model suitability test results show that the binary logistic regression model, with random effect on panel data, is in accordance with the p-value of 0.021. The result of modelling the level of profitability of manufacturing companies using a binary logistic regression with random effect on panel data obtained the value of classification accuracy of 73.54%. The leverage, liquidity, and tangibility variables negatively affect the level of profitability of manufacturing companies, while the size variable has a positive effect on the level of profitability of manufacturing companies. The OR value for the leverage variable is 0.0311, this means that if leverage rises 1%, then the ratio of the probability of a manufacturing company in healthy condition, compared to healthy enough, is down by 96.89%. The OR value for tangibility variable is 0.0267, this means that if tangibility rises 1%, then the ratio of the probability of a manufacturing company in healthy condition compared to healthy enough is down by 97.33%.

Table 1. Individual parameter test results

Variable	Coefficient	Standard Error	Zhit	P-value
Leverage	-3.47072	1.54338	-2.25	0.025
Size	0.18589	0.12904	1.44	0.150
Likuiditas	-0.06019	0.11599	-0.52	0.604
Tangibility	-3.62369	1.38602	-2.61	0.009
Constant	-3.24224	4.02285	-0.81	0.420

Table 2. OR values for each predictor variable

Variable	OR
Leverage	0.0311
Size	1.2043
Likuiditas	0.9416
Tangibility	0.0267

Table 3. Result of classification of binary logistic regression model with random effect on panel data

	Prediksi	
	$\hat{Y} = 0$	$\hat{Y} = 1$

Pengamatan	$Y = 0$	97	20
	$Y = 1$	30	42

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