PROBABILITY OF DEFAULT, INTEREST MARGIN, AND BANK EFFICIENCY: EMPIRICAL TEST OF MERTON MODEL IN INDONESIAN BANKING

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Abstract: Measurement of bank failure risk is still a challenging research problem. This study is aimed to measure the Indonesia banks probability of bankruptcy with Model Merton which has the better predictive power and is based on a far stronger financial theoretical framework compared to the popular bankruptcy prediction model which is categorized by Sundaresan (2013) as a theoretical model such as Altman Z-score model and Ohlson 0 score more popular. The study also examine the relationship of bank efficiency and market power with its probability of default. The test results demonstrate that bank efficiency significantly affects the dynamics of bank’s default risk.

Keywords: Probability of Default; Risk; Efficiency; Bank; Merton Model

The risk of bankruptcy or default risk obtains great attention from business actors in capital markets, companies that provide accounts receivable, as well as regulators who need early warning system tools on the condition of the financial institutions under their supervision. Deposit Insurance Corporation (LPS) requires the measurement of default risk so that the rate of deposit insurance on each bank can be adjusted to the default risk of each bank. The way of measuring the default risk of a company has been a longstanding research problem and is still facing problems in the aspect of methodology and data availability up to now (Ferreira Filipe, et al., 2016; Afik, et al, 2016).

The first approach to measure the default risk of a company was started by Altman (1968). The approach used by Altman (1968) was the statistical method, namely multi-discriminant analysis. By using the data of 66 companies that split into two equally large groups between bankrupt and nonbankrupt companies during the period of 1946-1965 in the United States, Altman acquired a linear equation that could predict corporate bankruptcies with the data ofcompany’s financial ratios. The value obtained from the linear equation contains five financial ratios obtained by Altman through discriminant analysis, which is called Altman’s Z-score. High Z-score reflects low default risk. If $Z < 1.80$ then the probability of default of the company in the next 2 years is quite high. If $Z > 3$ companies can be categorized as quite safe from the threat of bankruptcy. If the Z-score is between 1.80 and 2.99, then the company is in the zone of uncertainty. Although the prediction of
Altman model has been criticized, such as Johnson (1977), it is quite popular, widely used by practitioners and taught in financial textbooks because of its simplicity and quite good predictive power.

In addition to Altman model, there are other models of bankruptcy prediction by using discriminant analysis, namely Taffler model (1982), Beaver model (1966), and Edmister model (1972). All discriminant analysis based models have the same disadvantage, which is the selected model has no logical basis and strong financial theory. Such model is obtained in a priori with ex-post data and the choice of financial ratios is performed arbitrarily, and the coefficient of each financial ratio in the resulting model depends on the data used as the modeling basis. Generalizing model to other data becomes the main problem. Taffler model (1982), Beaver model (1966), and Edmister model (1972) are different from Altman model because the data of companies in the United States used by each researcher is different. Taffler (1982) obtained a different model for companies in the UK, while Edmister (1972) found a different model for companies with small assets. Discriminant analysis based models like Altman (1968) and others have their own problems in predicting the bankruptcy of a financial institution such as a bank because the financial ratios in the model are more accurate in measuring the financial condition of the non-financial company, especially in manufacturing companies.

Another model of bankruptcy prediction is a model based on linear probability models such as Logit model, Probit model, and Normit model. Ohlson (1980) became the first person who used Logit model for predicting non-financial company. Martin (1996) used Logit model as an early warning system in the United States banking. Hadad, et al (2004) predicted bankruptcy of banks in Indonesia. Betz, et al (2014) predicted financial distress of banks in Europe with Logit model. Criticism of the use of Logit model as a prediction model of bankruptcy or bank failure is almost similar to the criticism of the discriminant analysis model; that the development of a model that does not have an intuitive basis and adequate financial theory, highly depends on ex-post data, and its generalization is questioned to other companies or to financial institutions.

In 1974, Robert Merton introduced a new approach to bankruptcy risk modeling by using option contract model. Black-Scholes option formula. The model of bankruptcy prediction with approach mentioned in Merton (1974) is called structural model. This structural model uses Modigliani-Miller assumption about the capital structure of a company that does not influence the value of a company. The value the company referred to in Merton model is the market value of the asset that reflects the prospects and the business value of the company in the future. The market value of the asset of a company changes over time, depending on external and internal situations; therefore it is assumed to move in a random walk. The next pillar in Merton model is the market value of equity and, the debt of company can be modeled as a contingent claim of the company’s assets. The debt of company can be assessed as a put option contract of company’s asset with a strike price as much as the face value of debt and the selling option is due to the due date of the debt. If the market value of the asset (Vt) is much greater than the principal of the debt to be paid on the due date (Ft), then the lender will receive all principal of the debt. If the market value of the asset is lower than the principal of the debt that should be paid on the due date, (Vt< Ft) the company is claimed to be in default condition and cannot pay the debt fully. The bond holder will only acquire as the asset value (Vt) and suffer a loss of (Ft-Vt). However, if the bondholder holds a sell option contract with the specifications explained above when in the default condition, the bond holder can still obtain the principal of the debt fully by exercising the sell option contract, which strikes price is as much as the amount of principal of the debt. Portfolio risk bond with put option can be a risk-free bond. The price of sell option contract will be more expensive if the probability of bankruptcy of the indebted company is higher. The bankruptcy probability of bank can be reflected in the probability of the exercise of sale option contract or in terms of a derivative contract, the probability of
sell option contract is included in the in-the-money contract (Anginer, et al 2014). With Merton approach, the equity value of a company can be modeled as call option while the company’s debt value can be modeled as a put option.

The estimation method of company’s market value of asset becomes the focus of attention in the implementation of Merton model because it is a variable that cannot be observed in the market (unobserved variable). The value of the stock market is approximated from the equity market value that can be known from the stock price of the company being traded in the stock exchange. The estimation method of the market value of asset of company and its volatility become one of research topics and is still developing in the implementation context of Merton model (Afik, et al., 2016).

In measuring the default risk, some researchers often use distance to default, which is the difference between the market value of asset estimated with Merton model and the amount of debt principal, which is then scaled with the standard deviation of the market value of an asset. Distance to the default of Merton model has been proven to be a better default prediction tool compared with accounting data-based models (Hovakimian et al, 2012; Bharath and Shumway, 2008). Compared with accounting data-based risk such as Z-score, distance to default based on market data has some advantages. First, distance to default can be calculated more frequently and in a shorter period to know the default estimation at a certain point of time. Audited financial statement information is available once a year and the unaudited financial statement information is available daily. Second, information on the stock market is usually forward-looking, so distance to default can reflect the market’s perception of future bank conditions.

The probability of bankruptcy is a key indicator of bank stability. The instability of banking sector can be transmitted to other sectors through various forms, namely the disruption of the payment system, the decline in the amount of credit, and frozen deposits of bank customers. Due to its serious and widespread impact on the economy as a whole, regulators generally issue regulations aimed at maintaining the stability of banking sector by regulating the level of interbank competition and the level of bank efficiency. More efficient banks are expected to be more stable and resistant to the economic and business cyclical shocks (Ferreira Filipe, et al., 2016).

Hughes and Mester (2013) show that if banks have quite great strength in the market, then the franchise value of bank will increase because the share price of banks in the stock market is increasing. Because the franchise value reflects the intangible capital that can only be maintained by the bank if the bank is still operating prudently and generates profit according to the expectation of investor, then the bank is faced with the opportunity cost that is too large to be involved in high-risk business activities. The bank becomes more cautious in delivering credit and maintaining capital adequacy according to existing banking rules and continues to improve its efficiency. The stability of banking sector is increasing when the competition between banks is limited by regulators (Beck, et al.2012). This view is often referred to as competition-fragility, banking competition makes the banking system becomes fragile instead.

The “competition-stability” view has a logic flow that is different from the “competition-fragility” view which has been described above. In the view of competition-stability, banking stability will only worsen as the level of inter-bank competition declines. Banks with large market forces will tend to set higher lending rate. Hovakimian, et al (2012) indicates that high lending rate will increase the risk of bank loan portfolio due to adverse selection in the bank lending process, in which projects financed by banks are classified as projects with poor quality. The high cost to be paid by the company will encourage low-risk borrowers to avoid banking funding and look for other sources of funding through the capital market with the much lower cost of fund. Prospective borrowers who cannot access funding except banking are generally due to their business risk and high-risk project so that they do not attract investors in the capital market to become bank customers who receive banking credit. The
bankruptcy probability of companies which receive credit from banks becomes relatively high and sensitive to economic changes and business cycles. The number of bad loans of banks tends to increase and threaten the stability of the banking system.

Competition between banks in Indonesia can be categorized as nonprice competition. This can be indicated from Prime Lending Rate (SBDK) of Indonesian banking which has a wide dispersion range between banks. The standard deviation of Prime Lending Rate of Indonesian banking was recorded at 2.09% (Table 1). In comparison, the standard deviation of the Prime Lending Rate of Malaysian and Thai banking is only 0.3% (Table 2). Banks with much higher credit interest can still exist because they offer other valuable features in the perspective of their customers. The average and standard deviation of Prime Lending Rate of bank serving SME customers tend to be much higher compared to corporate and retail credit. The segmentation of banking service market in SMEs seems to be even tighter in its segment. The standard deviation of Prime Lending Rate of SME credit reaches 4.5%. The large range of Prime Lending Rate can be an indication of segmented banking market that enable banks to behave as monopolists in their segments, determine the various lending rates, as well as compete through factors other than price (interest rate).

**Research Objectives**

This study will measure the default probability of bank whose shares are listed on the Indonesia Stock Exchange by implementing Merton Model and testing the significance of the relationship between default probability, which is a measurement of bank stability, and the efficiency and market power of each bank.

**Literature Review**

The first approach to predict corporate bankruptcy is discriminant analysis method. The most popular model in this discriminant model family is Altman model. Altman model used to predict the probability of bankruptcy is:

$$Z = 1.2X_1 + 1.4X_2 + 3X_3 + 0.6X_4 + 0.99X_5 \ldots (1)$$

In which $X_1$ is Working Capital/ Total Assets, $X_2$ is Retained Earnings/Total Assets, $X_3$ is Earnings before Interest and Taxes/Total Assets, $X_4$ is Market Value of Equity/ Book Value of Debt, and $X_5 = \text{Sales}/ \text{Total Assets}$.

This Altman model is a discriminant equation which is estimated from 66 companies in the United States and is able to separate between companies that go bankrupt and those who do not.

The prediction model of Beaver (1966) also used discriminant analysis obtained from the analysis of financial statements of 23 companies that are failed to pay their debts in the United States. Unlike Altman (1968), Beaver found the ratio that can be used to predict the failure of a company, namely cash flow ratio, net income ratio, debt-asset ratio, and working capital ratio.

Taffler (1982) used the data of 32 British companies to find discriminant linear equations with four financial ratios: EBIT/ total asset of the previous year, net capital employed, net worth, quick

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**Table 1** Prime Lending Rate of Indonesian Banking

| Suku Bunga Dasar Kredit (%) | Malaysia | Thailand | Philippines |
|-----------------------------|----------|----------|-------------|
| Rata-rata                   | 3.99     | 6.75     | 5.35        |
| Median                      | 3.95     | 6.75     | 5.05        |
| Standard Deviation          | 0.35     | 0.57     | 0.75        |

Source: Financial Services Authority (OJK) of Indonesia

**Table 2** Prime Lending Rate of Malaysia, Thailand and the Philippines Banking

| Suku Bunga Dasar Kredit (%) | Kredit Korporasi | Kredit Ritel | Kredit Mikro |
|-----------------------------|------------------|--------------|--------------|
| Rata-rata                   | 10.70            | 11.65        | 14.04        |
| Median                      | 10.75            | 11.65        | 13.43        |
| Standard Deviation          | 2.09             | 1.92         | 4.53         |

Source: Bank Negara Malaysia, Bank of Thailand, and Central Bank of the Philippines
Discriminant analysis based model has different variables because the determination of any variable that can predict the default possibility is arbitrary without being based on a particular theory. Altman (1968) claims that the ratio chosen is based only on the number of people using those ratios. Financial ratios calculated from the financial statements considered by many researchers to not able to be functioning as ex-ante because the accounting report is historical or ex-post. The accounting statements also appear with quite long period of time, annually for the audited, making it impossible to measure the probability dynamic of defaults in a shorter period of time. However, Z score often can produce the right indication if it is used to measure the default in the annual period because of the amount of working capital, total retained earnings and EBIT directly gives an indication of the amount of cash that a company can earn to pay its liabilities in that year. The relationship of financial ratios used in the model and the amount of cash in the future is a tautology, which indeed will result in a good match and significance in the statistical test but it still cannot predict bankruptcy with a measurable probability.

The claim of Altman (1968) that the financial ratios he used in Z score model experienced three to two year deterioration before the bankruptcy occurred was tautology construct. The evidence which was shown by Altman is only a description of a condition, not a proof of a prediction. All the ratios which were used by Altman have proven to be much worse for companies that have gone bankrupt, but the ratio has no prediction power. There is a problem of inference from ratio to the probability of bankruptcy. The assumption used by Altman in estimating his model has a difficult assumption that is mutually independent between those ratios. This assumption is very important in multivariate discriminant analysis. If those ratios are strongly correlated each other, the use of all these ratios becomes redundant and leads to instability in the coefficients in the discriminant function when used in different samples and will result in a large standard error in those coefficients, so that the significance becomes doubtful. Differences in the characteristics of the industry, a number of the company’s assets, and the length of the company’s operations are believed to also affect the company’s financial ratios so that the model of bankruptcy risk by using financial ratios cannot be general.

Another default risk model is Linear Probability Model. Ohlson O-Score is a linear model of 9 risk factors that are estimated with Logistics model. Betz et al (2014) stated that this Logit model produces a more definitive and measurable bankruptcy probability than a discriminant analysis based model. However, the use of financial ratios in Linear Probability model still generates the same criticism faced by the discriminant model, which is the theoretical basis underlying the formation of the model.

Merton model has the advantage from the theoretical framework, which is stronger than any other default prediction model. However, the implementation of Merton Model empirically has a major obstacle, which is how the estimation method of the market value of the company’s assets, and its volatility is unobservable. Afik et al (2016) shows the current methods used by researchers in using Merton model empirically. Merton model is widely implemented in predicting the risk of deposit insurance in some countries in determining risk-based tariff (Sundaresan, 2013).

### Research Method

#### Data

The period of data used was between January 2010 and December 2014. This period was chosen to avoid the influence of global economic crisis in 2008. The data of stock market data were obtained from Thomson Reuters Datastream, while the data
of monthly bank financial statements were obtained from DPI (Indonesian Banking Directory) of Bank Indonesia.

The criteria applied in determining the sample of this research are:
1. Public banks in Indonesia that have financial reports during 2010-2014.
2. Banks that have performed IPO, at the latest by 2008.
3. Banks have never been delisted from Indonesia Stock Exchange during the period of 2008-2014.
4. Banks whose shares are actively traded in the period of 2008-2014.
5. Shares of those banks are traded without suspension sanction

Referring to the criteria above, the number of samples collected from commercial banks listed in Indonesia Stock Exchange and that can be observed in this study is 24 banks.

Calculation of Default Probability
This study used a contingent claim framework of Merton (1974) to measure the default risk of a bank. Merton model positions the bank’s equity value as a call option of the bank’s assets. The probability of default occurrence is measured by using distance to default, which is the difference between the company’s value of assets and the face value of its debt.

As pointed out by Merton (1974), the equity market value of bank can be modeled as call option of bank’s assets:

\[ V_E = V_A e^{-d}N(d_1) - X e^{rT}N(d_2) + (1 - e^{-d})V_A \]

\[ d_1 = \frac{\log(\frac{V_A}{X}) + (r - d + \frac{S_A^2}{2})T}{S_A \sqrt{T}} \]

\[ d_2 = d_1 - S_A \sqrt{T} \]

Equation (3) \( V_A \) is Black-Scholes-Merton Option formula for a call option, \( V_E \) is the market value of bank assets, and is the market value of bank equity. \( X \) is the Face Value of bank debts which has a due date at time \( T \) and interpolated linearly for each daily point in a period by using the average at the beginning of the year and at the end of the year. This method needs to be done in order to obtain a smooth asset value process and avoid jumps on implied probability default generated. \( r \) is the monthly-risk-free-interest-rate, and \( d \) is the percentage of dividend against \( V_E \). \( S_A \) is the volatility of bank asset value because it is not observable to be approached by the following equation (Anginer et al., 2014):

\[ S_E = \frac{V_A e^{-d}N(d_1)S_A}{V_E} \]

\[ S_A \] is the standard deviation of daily bank stock during the previous year. \( T \) equals 1 year. \( r \) is the yield of Government Securities of the Republic of Indonesia which matures in one year. From X With two variables can be calculated from the data of stock market, namely \( V_E \) and \( S_A \), and \( X \) obtained from bank financial statements, we can solve the problem of estimation on \( V_A \) and \( S_A \) which are unobservable by using the method of Newton for equation (3) and (4) simultaneously. Initial values included in Newton iteration process: \( V_A = V_k + X \) and \( S_A = S_k V_k / (V_k + X) \). The iteration process is done by using Solver optimization program in Microsoft Excel. This interpolation method is carried out to make the changing process of the market value of assets of the company run smoother and to avoid any jump of default probability at the end of the year (Anginer et al., 2014). In the calculation of asset volatility (\( S_A \)), winsorized is done for \( S_E \) and \( V_E / (V_k + X) \) and at the percentile level of 5% and 95% with the aim of reducing the effect of the outlier.

Once we have successfully estimated the market value of bank’s asset and its volatility and assumed the amount of \( m \), which is equity premium by 6% as used by Anginer et al. (2014), then we can calculate the size of Merton’s distance-to-default as follows:

\[ dd = \frac{\log(\frac{V_A}{X}) + (m - d + \frac{S_A^2}{2})}{S_A \sqrt{T}} \]
The default probability of bank is the normal transformation from the distance to default, namely \( PD = F(-dd) \), in which \( F \) is the cumulative distribution function of a standard normal distribution. The distance-to-default calculation for each bank is conducted monthly throughout the period of study.

The efficiency level of each a bank is measured by using BOPO ratio (Operating Expenses divided by Operating Income) obtained from the monthly report of bank to the regulator.

Empirical test of the relationship between probability of bankruptcy and efficiency, and added with LDR Bank as the control variable showing the aggressiveness of bank in delivering credit is done through the following model:

\[
\text{Probability of Default}_t = c + \beta \text{BOPO}_t + \gamma \text{LDR}_t + \epsilon_t \quad \text{............(7)}
\]

**Results and Discussion**

In Table 3, we can see the descriptive statistics of data of distance-to-default values of all banks observed monthly from January 2010 to December 2014. Distance to defaults indicates the difference between the market value of an asset and the value of debt principal scaled by the standard deviation of the market value of an asset of the bank. After obtaining the value of Merton’s distance-to-default, it can be calculated the probability of the occurrence of default of each bank monthly basis in the period of observation. The calculation results of the probability of default can be seen in Table 4. The large standard deviation of probability of default in all banks from 2010 to 2014 indicates that Indonesian banks are experiencing a very high turbulence where business cycles and economic conditions lead to fluctuating bankruptcy risks of banks with very large deviation, although on average and median,

| Name of Bank    | Mean   | Median  | Maximum  | Minimum  | Std. Dev. |
|-----------------|--------|---------|----------|----------|-----------|
| Mandiri         | -0.2655| -0.78127| 1.05257  | -1.90994 | 1.00453   |
| BRI             | -1.97662| -0.83494| 0.18288  | -30.304  | 3.97842   |
| BCA             | 0.18761| 0.14216 | 1.06519  | -1.26701 | 1.01809   |
| BNI             | -0.59922| 0.04803| 1.35721  | -7.0196  | 2.0259    |
| CIMB Niaga      | -0.20849| -0.06602| 1.06178  | -4.57107 | 1.33889   |
| Danamon         | 0.11768| 0.22401 | 1.10353  | -1.40621 | 0.8643    |
| Permata         | -0.8319| -0.38788| 1.77467  | -10.2526 | 2.00762   |
| Pan             | -0.04508| 0.13633 | 1.9154   | -3.78859 | 1.05148   |
| Maybank         | 0.15439| 0.33714 | 2.53253  | -5.2337  | 1.34103   |
| OCBC NISP       | -0.12065| 0.06235| 1.63702  | -3.38739 | 1.06391   |
| Bukopin         | -7.27824| -1.45716| 3.78307  | -2.73769 | 2.99475   |
| BTPN            | 0.83703| 0.76429 | 2.20834  | -0.95299 | 0.66313   |
| Mega            | -3.22387| 0.26498| 2.67928  | -22.1366 | 2.66688   |
| Mayapada        | 0.03009| 0.29093 | 2.02577  | -10.4157 | 3.64849   |
| Artha Graha     | -3.48065| -2.05645| 2.59464  | -20.2026 | 3.86885   |
| Victoria        | -3.03195| -1.68596| 1.64831  | -16.2737 | 3.68968   |
| QNB             | 1.20061| 0.57844 | 4.65111  | -0.92105 | 1.47912   |
| Woori Saudara   | 0.18493| 0.3203  | 1.02123  | -2.57728 | 0.56714   |
| Windu Kentjana  | -0.54411| -0.22933| 2.31324  | -7.99442 | 1.35901   |
### Table 4 Calculation Result of Merton’s Probability of Default Monthly in the period of 2010-2014

| Name of Bank       | Mean     | Median   | Maximum  | Minimum  | Std. Dev. |
|--------------------|----------|----------|----------|----------|-----------|
| Mandiri            | 0.395312 | 0.217322 | 0.853731 | 0.02807  | 0.842438  |
| BRI                | 0.024042 | 0.201876 | 0.572554 | 5.1E-202 | 0.999965  |
| BCA                | 0.574409 | 0.556523 | 0.856605 | 0.102576 | 0.845682  |
| BNI                | 0.274513 | 0.519154 | 0.912643 | 1.11E-12 | 0.978612  |
| CIMB Niaga         | 0.417423 | 0.473681 | 0.855832 | 2.43E-06 | 0.909697  |
| Danamon            | 0.546839 | 0.588625 | 0.865101 | 0.079831 | 0.806288  |
| Permata            | 0.202733 | 0.349052 | 0.962024 | 5.76E-25 | 0.977658  |
| Pan                | 0.482022 | 0.55422  | 0.972279 | 7.58E-05 | 0.853481  |
| Maybank            | 0.561349 | 0.631994 | 0.994338 | 8.31E-08 | 0.910045  |
| OCBC NISP          | 0.451984 | 0.524858 | 0.949187 | 0.00353  | 0.856315  |
| Bukopin            | 1.69E-13 | 0.072536 | 0.999923 | 0.003094 | 0.998627  |
| BTPN               | 0.798712 | 0.777653 | 0.98639  | 0.170298 | 0.746376  |
| Mega               | 0.000632 | 0.604488 | 0.996311 | 7E-109   | 0.996172  |
| Mayapada           | 0.512002 | 0.614448 | 0.978606 | 1.05E-25 | 0.999868  |
| ArthaGraha         | 0.00025  | 0.01987  | 0.995265 | 1.68E-89 | 0.999945  |
| Victoria           | 0.001215 | 0.045902 | 0.950355 | 7.58E-60 | 0.999887  |
| QNB                | 0.885049 | 0.718516 | 0.999998 | 0.178512 | 0.930446  |
| Woori Saudara      | 0.573358 | 0.62563  | 0.846427 | 0.004979 | 0.71469   |
| WinduKentjana      | 0.293183 | 0.409306 | 0.989645 | 6.51E-16 | 0.912928  |
| MNC Internasional  | 0.673367 | 0.223771 | 0.999954 | 5.94E-21 | 0.999582  |
| Capital Indonesia  | 0.255455 | 0.311084 | 0.999047 | 1.27E-09 | 0.9512    |
| Pundi Indonesia    | 0.357567 | 0.483931 | 0.952931 | 7.22E-09 | 0.907255  |
| BRI Agroniaga      | 0.473438 | 0.529527 | 0.988469 | 0.000439 | 0.803755  |
| BumiArta           | 0.003082 | 0.085645 | 0.963568 | 1.48E-45 | 0.999487  |

Source: Process by the author (2016)
Probability of default of each bank can be said to be in a position that is still quite manageable. Table 5 shows the results of significance test of the relationship between probability of default of each bank and the efficiency and profitability of bank measured by BOPO and Net Interest Margin (NIM). All variables are proven to be significant at the error rate of 5% and 1% with the positive coefficient sign, which means that the more inefficient (high BOPO) a bank, the probability of default tends to be high. NIM also has the positive and significant relationship with the probability of default so that it can be concluded that if a bank has a great market power that can set aggressive pricing with high NIM, it will encourage the bank to become less disciplined in distributing credits that cause the probability of default tend to increase. The positive relationship between NIM and probability of default can also be caused by the adverse selection experienced by bank because the credit interest is too high, which makes the companies that apply for credit and obtain credit from bank are those who are at high risk, while companies with lower risk profile choose sources of financing other than banks. LDR also has positive and significant relationship with the probability of default, which indicates that the carrying capacity of deposit no the amount of credit distributed also influences the size of bankruptcy risk of the bank.

Table 5  Results of Significance Test of the Relationship between the Probability of Default of Bank and the Efficiency and Margin of Interest

| Variable  | Coefficient (t statistics) |
|-----------|----------------------------|
| Constant  | 0.18*** (7.58)             |
| BOPO      | 0.57** (3.98)              |
| NIM       | 0.27** (5.99)              |
| LDR       | 0.15** (1.35)              |
| R Squared | 0.73                       |
| Wald chi2 | 90.52                      |
| Prob>chi2 | 0.000                      |

***significant in alpha of 1%, ** significant in alpha of 5%

Conclusions

The banking risk of Indonesia which is measured by Merton’s probability of default model shows very high dynamics in the period of 2010 to 2014. The business cycle and the economy that experienced high turbulence during that period affected great deviation of default risk. The bankruptcy risk of a bank is strongly influenced by the level of efficiency and strength of the bank in the market. The results of this test support the competition-stability view, that the improvement in the competition will improve the efficiency and reduce the market forces of the bank, so that NIM becomes lower, while better efficiency and lower NIM can suppress the probability of default of the average bank, which indicates better banking stability.

Suggestions

Based on the results of this research, the government and banking regulators are expected to provide additional information for the government in formulating domestic banking policy related to banking competition climate that can affect systemic default risk. The stability of banking competition climate is expected to be in line with financial system stability.

For academics, this research is expected to be a reference for further researches related to banking competition and systemic risk. In addition, it is expected that the use of Merton’s distance-to-default method that requires the volatility of the market value of bank equity is improved, so that it can capture the level of systemic risk more accurately. The further research is expected to add variables related to banking regulation and institution in Indonesia.

REFERENCES

Afik, Z., Arad, O., &Galil, K. 2016. Using Merton model for default prediction: An empirical assessment of selected alternatives, Journal of Empirical Finance 35, 43–67
Altman, E. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. Journal of Finance, 189–209.
Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk? Journal of Financial Intermediation, 1-26.

Beaver, W. H. 1966. Market prices, financial ratios, and the prediction of failure. Journal of Accounting Research, 6(2), 179-182.

Beck, T., Jonghe, O. D., & Schepens, G. 2012. Bank competition and stability: Cross-country heterogeneity. Journal of Financial Intermediation, 218-244.

Betz, O., Peltonen, A, & Sarlin, B. 2014. Predicting Distress in European Banks, Journal of Banking & Finance 45, 225-241

Bharat, S. & Shumway, T. 2008. Forecasting Default with the Merton Distance to Default Model, Review of Financial Studies, 21 (3): 1339-1369.

Edmister, R. 1972. An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction, The Journal of Financial and Quantitative Analysis, Vol. 7, No. 2, 1477-1493

Ferreira Filipe, S., et al. 2016. Pricing default risk: The good, the bad, and the anomaly. Journal of Financial Stability, http://dx.doi.org/10.1016/j.jfs.2016.07.001

Hadad, M., Santoso, W., & Sarwedi, B. 2004. Model Prediksi Kepailitan Bank Umum di Indonesia, Bank Indonesia Research Paper, Direktorat Penelitian dan Peraturan Perbankan Bank Indonesia

Hovakimian, A., Kayhan, A., & Titman, S. 2012. Are corporate default probabilities consistent with the static tradeoff theory? Review of Financial Studies, 2012, vol 25, No. 2, 315-340.

Hughes, J. & Mester, L. 2013. Who Said Large Banks Don’t Experience Scale Economies? Evidence From a Risk-Return-Driven Cost Function, Journal of Financial Intermediation 22, 559-585.

Martin, D. 1996. Early Warning of Bank Failure: A Logit Regression Approach, Journal of Banking and Finance, 249-276

Merton, R. 1974. On the pricing of corporate debt: the risk structure of interest rate. Journal of Finance, 449-470.

Ohlson, J. A. 1980. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research, New York: 18(1), 109–131.

Taffler, R. J. 1982. Forecasting Company Failure in the UK Using Discriminant Analysis and Financial Ratio Data, Journal of the Royal Statistical Society, Series A, Vol. 145, No. 3, 342-358

Sundaresan, S., 2013. A Review of Merton’s Model of the Firms’ Capital Structure with its Wide Applications. Annual Review of Financial Economics, 5, 21–41.