

The Implementation of Credit Scoring in Order to Analyze the Importance of Non Performing Loans on Peer To Peer Lending towards Credit Distribution for Micro, Small and Medium Enterprises

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Abstract

This research is motivated by an increase in the number of Micro, Small, and Medium Enterprises from year to year but it is still difficult to get access to financing in banking due to the many requirements and long process (unbankable). The existence of fintech lending companies, one of which is Peer to Peer Lending is present to answer the problem of public financial access to conventional financial institutions. This research aims to find out the influence of Non Performing Loans on Micro, Small, and Medium Enterprises Credit Distribution with the implementation of Credit Scoring as an intervening variable (Case Study on Micro, Small, and Medium Enterprise in Indonesia Period 2018-2020). The method of data collection is done by accessing data through the website of PT Amarta Mikro Fintek and the Financial Services Authority. The sample used in this study was purposive sampling with criteria that had been determined by the authors. The data obtained is then processed using Eviews 10 Software. This analysis includes statistical tests, classical assumption tests and pathway analysis tests. The results of the t-test showed that the Non Performing Loan variable had a significant negative effect on the distribution of Micro, Small, and Medium Enterprise credit. Non Performing Loan and Credit Scoring variables had not effect on the distribution of Micro, Small, and Medium Enterprise credit. Based on the track analysis test, Credit Scoring was able to mediate the influence of Non Performing Loan on Micro, Small, and Medium Enterprise credit distribution.

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INTRODUCTION

Financial Stability Board (2021), states that Financial Technology or popularly known as fintech is an innovation which combines financial services and technology as an alternative choice for the public other than conventional financial institutions. Fintech is here to answer the problem of public financial access to conventional financial institutions. Previously, in dealing with conventional financial institutions (banks) was quite complicated and took a times. So with the existence of fintech, people who do not have access to finance in banking, especially for MSMEs that do not meet bank requirements (unbankable) in applying for its loans and now can apply for credit through fintech.

One of fintech type that has just started operating in Indonesia is Peer to peer lending (P2P lending). P2P lending is a place to invest and lending the funds for community. Financial Services Authority Regulation (POJK) No. 77 of 2016 explains that P2P lending is an information technology-based lending and borrowing service. The increasing number of fintech lending in Indonesia has an impact in increasing the distribution of information technology-based loans. In Indonesia, there is an increase in lending from 22.67 trillion in 2018 to 155.90 trillion in 2020, an increase in debtor accounts from 4,359,448 accounts in 2018 to 43,561,362 accounts in 2020 and an increase in creditor accounts from 205,511 accounts In 2018 to 716,963 accounts in 2020. This indicates that there is an increase in the use of P2P lending and loans distributing during period 2018-2020. Giudici (2018) explains that there is no risk-free investment, includes investing in P2P lending. If there is a non-performing loan, it will be fully borne by the creditor (not a P2P lending company), in opposites to the banking system which will be borne by the bank itself.

Table 1 Development of Fintech Lending in Indonesia 2018-2020

Indicator	Unit	2018	2019	2020
Accumulated Loans Distribution	Rp (Trillion)	22,67	81,49	155,9
Debtor Accumulation Account	account	4.359.448	18.569.123	43.561.362
Creditor Accumulation Account	account	205.511	602.179	716.963

Source: Financial Services Authority (2021)

Through the letter of No S-5/D.05/2019 AFPI which was appointed by OJK as the official association of information technology-based lending and borrowing service providers in Indonesia. In the AFPI Code of Conduct it is stipulated that the maximum interest is 0.8 percent per day. The amount consists of interest, interbank transfer fees, verification fees, fines and others. The accumulation of all costs including fines is 100 percent of the principal value of the loan. The presence of fintech loans are expected to have a significant impact for MSME partners who lend the funds in an efforts to increase their income.

Many factors which affecting the lending, including fundamental factors and technical factors. Fundamental factors namely company external factors such as political conditions and economic conditions which includes: inflation, exchange rates, economic growth and so on. Technical factors are factors from the company's internal related to the financial performance and regulations of the company. Financial performance that is often used to analyze credit distribution is Non Performing Loan (NPL) and credit scoring.

This research was conducted because there is the research gap from previous researchers, who have been conducted previously and relevant to this research. The existence of this gaps are suspected because the performance of fintech lending is sensitive and fluctuating so it is necessary to conduct periodic research to get an accurate direction of performance movement. From these previous research, it can be seen that there is a correlation between Non-Performing Loans and Credit Scoring on MSME lending. Research on the effect of Non-Performing Loans (NPL) and credit scoring towards credit distribution has been done by many previous researchers. Kuncayono's research (2016); Haryanto & Widyarti (2017); Princess (2021); Kartika & Umam (2021) in their research states that NPL has a positive affect on MSME lending. The results from research by Sania & Wahyuni (2016); Desya, et al (2019) found that NPL did not have a significant impact to MSME lending. In contrast to the research of Prihartini & Dana (2018); Rosalina, et al (2019); Choudhary (2020) who found that NPL had a significant negative affect on lending.

The research relates to the importance of Non Performing Loans (NPL) on credit scoring were also has been done by so many previous researchers. Siagian's research (2020) found that NPL had no impact to the credit scoring. While Pastini & Priantara (2018) on their research state that NPL has a positive affect on Credit Scoring. Research related to the effect of credit scoring on credit distribution was carried out by Fatimah, et al (2017); Fitriyadi (2019); Bao et al. (2019); Desantis & Lars (2021) those are found that credit scoring had a positive affect on MSME lending. In opposites to the research whom conducted by Jumingan (2015); Sefriawan & Curry (2018); Sari, et al (2021) who found that credit scoring had no impact to the credit distribution

These gaps in the previous research results are related to the factors which affect credit distribution, it is necessary to conduct research that aims to analyze Non-Performing Loans in Peer to Peer Lending on lending to Micro, Small and Medium Enterprises by implementing the Credit Scoring as a mediating variable. This research was conducted on MSMEs in Indonesia during period 2018-2020. This research aims to learn about the affect of Non-Performing Loans on Peer to Peer Lending which mediated by Credit Scoring on the distribution of Micro, Small and Medium Enterprises loans. With hoped that these research will be more relevant to the conditions that will occurs in the future.

LITERATURE

According to the Financial Services Authority (OJK) (2016), fintech lending is an financial service that brings together the lenders and loan recipients to conduct its transactions through the use of technology. OJK as the supervisory agency for the financial services industry in Indonesia, which written detailed in regulations governing the profile of providers and users, namely POJK number 77/POJK.01/2016 dated 28 December 2016 concerning Information Technology-Based Lending and Borrowing Money Services and POJK number 13/POJK.02/ 2018 on Digital Financial Innovation in the Financial Services Sector.

Kasmir (2019) states that credit is an agreement between bank or a non-bank with other party to provides the money and requires the debtors party to repay the money within a certain period of time in exchange for or sharing the results. In conducting credit scoring, the criteria and aspects of the assessment remain the same. Likewise to the established measures which have become the standard for each bank's assessment. The assessment criteria should be carried out by banks to get the right customers through 5C analysis. According to Kasmir (2019), these principle of providing credit with 5C analysis can be explained as follows: Character, Capacity, Capital, Collateral, and Condition.

In assessing credit, current and future economic and political conditions also should be assessed according to their respective sectors, as well as the business prospects of the sector that they are running. The assessment of prospects business sector which later being financed should really have good prospects, so that the probability of the credit being non-performing is relatively small. To find out if a credit is feasible, it can be done by analyze the prospective debtor so that it will provide confidence to the bank. Meanwhile, the 5P credit analysis could be described as follows (Kasmir, 2019): Personality, Party, Purpose, Prospect and Payment.

According to (Subagyo 2015) relates to the causes of non-performing loans (Subagyo, 2015) in order to see its symptoms and its causes, we can classify the sources into several ways: 1) deviations from credit agreements; 2) the credit disbursement schedule is not in accordance with the credit agreement; 3) a decrease in the number of savings, deposits and debtors' wealth; 4) debtors often ask for delays in payments; 5) the occurrence of irregularities in the use of credit; 6) the debtor applies for a credit extension; 7) debtors apply for additional credit.

Credit scoring is a statistical method that use to predict the likelihood that a borrower will default or become in arrears. Estimates of the probability of default or arrears are widely used for customer loans and mortgage loans (Kenton, 2021). Credit scoring is a valuable tool for improving financial inclusion; access to credit for individuals and micro, small and medium enterprises; and efficiency (World Bank, 2018). The use of credit scoring and variation scoring has increased significantly in recent years due to better access to a wider variety of data, increased in computing power, greater demand for increased the efficiency and economic growth.

Credit scoring provides an indication of creditworthiness. In general, the higher the borrower's credit score, the lower the risk of bad credit. Credit service providers may use credit scoring in risk-based pricing where the terms of the loan, including the interest rate offered to the debtors are based on the debtor's credit risk. The main advantage of credit scoring is that it is a fast, consistent and effective way for credit service providers to be able to

decide an applicant's eligibility for a loan or contractual payment scheme. It also has an impact on the relative product prices and profitability of credit service providers.

Credit ratings can apply to companies, sovereigns, and the entity's securities, as well as to asset-backed securities. Good credit ratings of the counterparts indicate a high probability of repaying full of their debts. Poor credit ratings indicate that counterparts have had difficulty in paying their debt obligations in the past and may face these challenges again in the future (Kagan, 2021). Credit ratings usually apply to companies (usually large companies) and governments, while credit scoring usually applies to individuals and to micro, small and medium enterprises (MSMEs). Credit ratings are assigned either by credit rating agencies or, internally, by credit service providers. For example, Standard & Poor's has a credit rating scale ranging from AAA (very good) to C and D (a rating below BBB- is considered as speculative rating, meaning counterparts are more likely to default on financial obligations).

Credit scoring has enormous potential to help the world economy grow and can be a valuable tool for increasing financial inclusion and efficiency. According to FSB (2017), there are potential benefits and risks for financial stability along with the implementation of technology in the coming years and as more data becomes available. More efficient information processing, such as in credit decisions can contribute to a more efficient financial system. Innovation opportunities in credit scoring includes: 1) greater financial access and inclusion; 2) process automation; 3) improved model accuracy; 4) improvement of consumer experience. Innovation risks in credit scoring include: fairness, interpretability, accountability, privacy and data security, unintended consequences. Innovation challenges in credit scoring include: Potential discrimination, consumer protection, governance models, disparities in maturity across market. Trust is a prerequisite for credit service providers in designing, developing, deploying and using credit scoring methods. With innovative methods, several challenges that requires attention, such as the potential for discrimination, protection of customers rights, governance models and maturity gaps between markets. The technology that supports innovative credit scoring methods still evolving therefore the legal and ethical framework needed to cope it and should be evolve in maturity time.

Non Performing Loan (NPL) is one of the indicators used to measure the performance of bank or non-bank financial institutions. Non Performing Loans (NPL) will affects the firm value, as it stated by Kasmir (2019) whom defined that NPL is a ratio used to measure a bank's ability to mitigate the risk of credit failure by debtors. This ratio compares total non-performing loans, such as substandard, doubtful and non-performing loans to total loans. Bank Indonesia's regulations tells that fintech lending should keep the NPL below 5 percent.

According to POJK Number 40 of 2019 concerning Asset Quality Assessment of Commercial Banks, credit is a loan agreement between a bank or non-bank with another party that requires the borrower (debtor) to repay the debt after a certain period of time plus with an interest. These following are the 5 credit collectability which has been set:

Collectibility 1 (fluent), collectibility 2 (under special attention), collectibility 3 (substandard), collectibility 4 (doubtful), and collectibility 5 (lost). If the NPL ratio of fintech lending shows a value below 5 percent, then the non-performing loans faced by fintech lending are very minimal to the total credit disbursed by fintech lending.

Non Performing Loans (NPLs) affect firm value, as stated by Kasmir (2019), that NPL is a ratio used to measure a bank's ability to mitigate the risk of credit failure by debtors. This ratio compares total non-performing loans, such as substandard, doubtful and non-performing loans to total loans. Bank Indonesia's regulations stated that the banks should be maintain the NPLs below 5 percent. The lower the NPL, the lower the credit risk borne by the company. Prihartini & Dana (2018); Rosalina, et al (2019); Choudary (2020) proves that NPL has a significant negative affect on lending.

The use of this credit scoring method can help the lender (creditor) to determine whether a debtor's credit application can be approved. As for the customer data that needed in the credit scoring process, it is taken from each customer's loan application data, in addition to use the statistical program that contains with history of the customer's loan. The implementation of credit scoring are used in conducting business feasibility analysis as a first step in mitigating the occurrence of failure to fulfill obligations by debtors (Jumingan, 2015). So the higher the NPL, the lower the credit scoring of the MSME partners. Byanjankar & Viljanen (2020) proved that NPL has a significant negative affect on the implementation of credit scoring.

The score which determined for the distribution of MSME loans will have an impact to the number of credit facilities that are unapproved. If the credit expansion is desired, then the policy that can be taken is to lower the score, and vice versa if you want to tighten the analysis, then the score can be increased. To facilitate each of

these changes, in determining the passing grade or the limit on the acceptance of credit analysis are through the calculation of the standard deviation. The desired standard deviation used to make changes to the desired score limit (Jumingan, 2015). Credit scoring reflects the feasibility of providing credit, the higher the credit score, the higher the distribution of MSME loans. Fitriyadi (2019); Bao et al(2019) proves that credit scoring has a positive influence on MSME lending.

Non-performing loans and credit scoring provide the decision making for MSME lending. The credit scoring ratio is an internal factor that influences NPL and MSME lending. The Determination of credit scoring are made based on existing data so that it will continue to grow accurate and precise from time to time along with the increase in the number of loan recipients. Through the implementation of credit scoring, it will strengthen the influence of NPL on MSME lending. (Fatimah, et al 2017) proves that NPL mediated by credit scoring has a positive impact on MSME lending. Based on the theory and the results from previous studies, the hypothesis which made for the influence of non-performing loans that mediated by credit scoring on the MSME loans distribution can be formulated as follows:

H₁: NPL has a significant negative impact on MSME lending.

H₂: NPL has a significant negative impact on credit scoring.

H₃: Credit Scoring has a significant positive impact on MSME lending.

H₄: Non-Performing Loans which mediated by Credit Scoring have a significant positive impact on MSME lending.

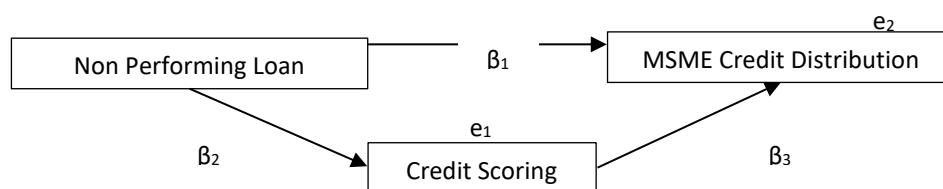
METHODS

This research are discusses about the factors which determine the distribution of Micro, Small and Medium Enterprises (MSME) financing in the context of Peer to Peer Lending (P2P) on the Amarta website. The method used in this research was a quantitative method which is called the positivistic method because it is based on the philosophy of positivism (Sugiyono, 2019) as Dependent variable. The scope period of this research was conducted for 3 (three) years, starting from 2018 to 2020.

The data was processes through Software of Eviews 10 Enterprise Edition. The first step to do is to determine the sample to be studied by purposive sampling. The sample studied is Micro, Small, and Medium Enterprises (MSMEs) that apply for financing to Amarta. The number of MSMEs using Peer to Peer Lending credit facilities (both funded or not) on the PT Amarta website is 308 MSMEs. The next step is to collect the required data related to NPL and credit scoring which obtained from the PT Amarta website.

This research is actually using intervening variables, which theoretically have an indirect influence on the correlation between independent variables and the dependent variable and cannot be observed and measured (Sugiyono, 2019). The way to examine the intervening variable regression are through path analysis. Path analysis is an extension of multiple linear regression analysis or uses regression analysis to measure causal relations between variables (casual models) that have been previously determined based on theory (Ghozali 2018).

According to Riduan & Sunarto (2015), the path analysis model can be used to analyze the pattern of correlations between variables with the aim in finding out the direct or indirect effect of the independent variable (independent) to the dependent variable (dependent). Decision making in the Path Analysis test can be seen from direct and indirect effects. If the indirect effect has a direct effect, then the variable is a mediating variable.



Source: Researcher (2022)

Figure 1 Path Analysis Model (Path Analysis)

The diagram above provides an explicit explanation relates to the causal relationship or the effect between variables based on the theory. Arrows are indicates the correlation between variables. Each p value represents the path and the path coefficient. Figure 1 is a path model of the relationship between variables. In theory, NPL has a

direct influence on MSME lending (β_1). However, NPL has an indirect influence on credit scoring (β_2) and then credit scoring has a direct influence on MSME lending (β_3).

The value of e_1 in credit scoring shows the amount of variance in the credit scoring variable that is not explained by MSME lending. The value of $e_1 = \sqrt{1 - R^2}$. While e_2 in MSME lending shows the amount of variance in MSME lending variables which is not explained by credit scoring and MSME lending. The value of $e_2 = \sqrt{1 - R^2}$. The path coefficient is a standardized regression coefficient. The path coefficient are calculated by making two structural equations, namely the regression equation which shows the hypothesized effect. In this case there are two equations that could written as follows:

$$\text{Credit Scoring} = \beta_0 + \beta_1 \text{ Non Performing Loan} + e_1 \dots \dots \dots (1)$$

$$\text{MSME Credit Distribution} = \beta_0 + \beta_2 \text{ Non Performing Loan} + \beta_3 \text{ Credit Scoring} + e_2 \dots \dots \dots (2)$$

Information:

β_1 : Coefficient of Non-Performing Loan with MSME Credit Distribution

β_2 : Coefficient of Non-Performing Loan with Credit Scoring

β_3 : Coefficient of Credit Scoring Path with MSME Credit Distribution

e_1 : Residual on Credit Scoring

e_2 : Residual for MSME Credit Distribution

RESULTS AND DISCUSSION

Descriptive statistical analysis is statistics that used in analyzing data by describing or explaining the data that has been collected. According to Sugiyono (2019) this analysis has purpose to provide an overview or describe the data in the variables seen from the average (mean), minimum, maximum and standard deviation values. Descriptive statistics are the statistics used to describe the data into clearer and easier-to-understand information that provides an research overview in the form of correlation of independent variables proxied by NPL and credit scoring.

Table 2 Descriptive Statistics

Variable / Parameters	NPL	Credit Scoring	MSME Credit Distribution
N	36	36	36
Minimum	0,006	0,112	0,024
Maksimum	1,28	0,17	0,179
Mean	0,119	0,132	0,083
Std. Deviation	0,261	0,014	0,034

Source: Data Processed Eviews 10 (2022)

Table 2 shows that N or the amount of data for each valid variable is 36, from 36 sample data on credit distribution, the minimum value is 0.024, the maximum value is 0.179 during period 2018-2020, the mean value is 0.083 and the standard deviation value is 0.034 which means the mean value is greater than the standard value so that the deviation of the data which occurs is low then the distribution of the values is evenly distributed. Non-Performing Loans from 36 samples are known that the minimum value is 0.006, the maximum value is 1.280, the mean value for the 2018-2020 period is 0.119 and the standard deviation value is 0.261, meaning that the average NPL value for the 2018-2020 is smaller than the standard value. So that the deviation of the data that occurs is low, the distribution of the values is evenly distributed. Credit Scoring from 36 samples is known that the minimum value is 0.112, the maximum value is 0.170, the mean value during period 2018-2020 is 0.132 and the standard deviation value is 0.014, meaning that the mean value for 2018-2020 is greater than the standard deviation value therefore there will not be a mistake so the distribution of the values is well distributed.

The Goodness of Fit test (F-test) was conducted to identify the influence of the independent variable in explaining the alteration of the dependent variable. The F-test was conducted to equating the p-value with a critical value or 5 percent significance. If the p-value > 0.05, it means that the model formed from all independent variables is not feasible to explain the dependent variable. If the p-value < 0.05, it means that the model formed

from all independent variables is feasible to explain the dependent variable. The coefficient of determination used to measure how far the model's ability to describe the variation of the independent variables. The small value of R^2 means that the ability of independent variables in explaining the variation of the dependent variable which is very limited. The value of R^2 that is close to one means that the independent variables provide almost all the information needed to predict the variation of the dependent variable. In this research it using multiple linear regression, each independent variable partially and jointly affects the dependent variable which is expressed by R^2 to define the level of determination test or how much influence that the NPL variable and credit scoring have on the MSME lending variable.

Table 3 shows the parameter significance test using the F test which states F-statistic = 6.285962 with a probability value of 0.004864 and shows < 0.05 , so that the ability of the independent variables is feasible to explain the dependent variable. The amount of the contribution of non-performing loans and credit scoring can be identified through the coefficient of determination (adj R-squared) which is 0.231983 or 23 percent. These results show that the diversity can be explained through the NPL independent variable and credit scoring is only 23 percent, while the remaining 77 percent are explained by other variables that are not in this research. From the R-squared value of 0.275870, it can be seen that the correlation between the independent variable and the dependent variable has a weak correlation pattern because the value is only 0.275870, far from the value of 1.

Table 3 Model Feasibility Test Results

F-statistic	6.285.962
Prob (F-statistic)	0.004864
R-Squared	0.275870
Adj R-Squared	0.231983

Source: Data Processed Eviews 10 (2022)

The next stage is regression analysis which used to measure how strong the correlation between two or more variables and shows the direction of the correlation between the dependent variable and the independent variable. This analysis is needed to find out the regression coefficients and their significance so they can be used to answer the existing hypothesis.

Table 4 Multiple Linear Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0,074132	0,048606	1,525156	0,1367
NPL	-0,066216	0,019611	-3,376457	0,0019
Credit Scoring	0,129197	0,361846	0,357049	0,7233
R-squared	: 0,275870		F-Statistic	: 6,429171
Adjusted R-Squared	: 0,231983		Prob. F-statistic	: 0,000044

Source: Data Processed Eviews 10 (2022)

Based on the result of multiple linear regression analysis in Table 4, the following equation can be formed as follows:

$$\text{General Model: PK} = 0,074 - 0,066 \text{ NPL} + 0,129 \text{ CS} + e \quad \dots\dots\dots (3)$$

Information:

PK: MSME Credit Distribution

NPL: Non Performing Loan

CS: Credit Scoring

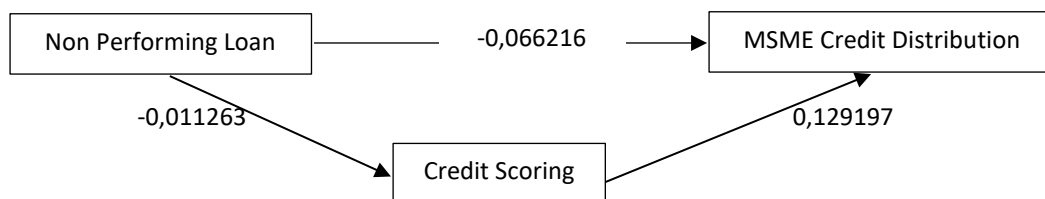
e : Std. error

The Equation (3) of multiple linear regression known that the constant value of 0.074 means that if the independent variables of non-performing loans and credit scoring are considered constant, it can be predicted that loan distribution is 0.074 units. The non-performing loan variable in the multiple linear regression model above

has coefficient value of -0.066, which means that if the value of the non-performing loan variable increases by 1 and the others are constant, it can be predicted that the value of the MSME lending variable will decrease by 0.066. The credit scoring variable in the multiple linear regression model above has the coefficient value of 0.129, meaning that if the value of the firm size variable increases by 1 person and the others are constant, it can be predicted that the value of the MSME lending variable will increase by 0.129.

Table 4 shows the research results for the t-test stating that the effect of Non-Performing Loans (NPL) on MSME lending states that the regression coefficient is -0.066 and the t-count value is -3.376457 with a probability value of 0.0019. The test results show that the coefficient is negative and the probability value is < 0.05 . So there is a significant negative that affect partially on non-performing loan (NPL) towards the distribution of MSME loans. The influence of non-performing loans (NPL) on credit scoring states that the regression coefficient is 0.066 and the t-count value is 3.376457 with a probability value of 0.7233. The test results show that the coefficient is negative and the probability value of $\text{NPL} < \text{credit scoring}$. Meaning that NPL has a partially significant negative impact on credit scoring. The influence of credit scoring on MSME lending produces a regression coefficient of 0.129 and a t-count value of 0.357409 with a probability value of 0.7233. The test results shows that the coefficient is positive and the probability value is > 0.05 , which means that the credit scoring did not affect the MSME lending.

The multiple regression analysis test for the influence of Non Performing Loans towards MSME lending, the NPL coefficient value is -0.066216 with a significance of 0.0019 which means < 0.05 so that the NPL has impact to MSME lending. The coefficient value of -0.066216 is the path value of $P_1 (\beta_1)$. In path $P_2 (\beta_2)$, the coefficient value of the influence of Non Performing Loan on credit scoring is -0.011263 with a significance of $0.2239 > 0.05$ so the Non Performing Loan did not affect the Credit Scoring. The coefficient value of the influence of Credit Scoring towards MSME lending on the P_3 line (β_3) is 0.129197 with a significance of $0.7233 > 0.05$ so that the Credit Scoring did not affect the MSME lending. The complete path analysis results in this study are described in detail in Figure 2.



Source: Researcher (2022)

Figure 2 Path Analysis Results

The results from the individual parameter significance test (t statistical test) in Table 4, obtained a tcount value of -0.066216 and a significance value for Non Performing Loans of 0.0019, which means < 0.05 below the significance level. These results indicate that the first hypothesis (H_1) is accepted, which means that NPL has a significant negative effect on MSME lending. Testing the effect of NPL on credit scoring obtained a tcount of -0.011263 and a significance value for Non-Performing Loans of 0.2239, which means > 0.05 above the significance level. These results indicate that the second hypothesis (H_2) is rejected, which means that NPL has no effect on credit scoring. The results of the individual parameter significance test (t statistical test) on the effect of credit scoring on MSME lending obtained a t-value of 0.129197 and a significance value for Non-Performing Loans of 0.7233, which means > 0.05 above the significance level. These results indicate that the third hypothesis (H_3) is rejected, which means that Credit Scoring has no effect on MSME lending.

Indirect influence is a situation where the independent variable influences the dependent variable through other variables which are commonly called intervening variables. In the first regression equation, the NPL coefficient value is -0.011263 with a significance of 0.2239 and in the second regression equation the Credit Scoring coefficient value is 0.129197 with a significance of 0.7233. The coefficient values of -0.011263 and 0.129197 are the values of the P_2 and P_3 paths so that the indirect effect of NPL on MSME Credit Distribution through Credit Scoring is $-0.011263 \times 0.129197 = -0.001455$. Thus, it can be stated that indirectly, NPL has a negative effect on Credit Scoring and Credit Scoring has a positive effect on MSME Credit Distribution.

Based on the test results in the first and second equations, the total influence of NPL on MSME lending and NPL on MSME lending through Credit Scoring is $p1 + (p2 \times p3) = -0.066216 + -0.001455 = -0.067671$. This result states that the total effect of NPL on MSME lending through the Credit Scoring is -0.067671. Because the direct influence of the NPL variable on MSME lending is -0.066216 which is smaller than -0.067603 so that in increasing MSME lending, the indirect route is chosen, namely through Credit Scoring. These results indicate that the fourth hypothesis (H_4) is accepted, which means that Credit Scoring is capable to mediate the influence of NPL on MSME lending.

Non-Performing Loans have a significant negative impact on the MSME lending. NPL is used to measure a bank's ability to mitigate the risk of credit failure by debtors. According to Bank Indonesia regulations, fintech lending must keep the NPL below 5 percent. Meanwhile, the NPL at PT Amarta Mikro Fintek has a minimum score of 0.006 percent to a maximum of 1.28 percent with an average of 0.12 percent. This proven that PT Amarta Mikro Fintek can keep bad loans below 5 percent. So the potential profits to be obtained by the company will be even greater because the company will save the money that will be needed to form a reserve for loss of non-performing loans and the distribution of MSME loans will also increase. This research is supported by the research which conducted by Prihartini & Dana (2018); Rosalina, et al (2019); Choudary (2020); Byanjankar & Viljanen (2020) whom define that NPL has a significant negative impact on MSME lending, which means that the higher the NPL, the lower the MSME lending. Furthermore, the results from this research is opposites from the results of research whom conducted by Haryanto & Widyarti (2017) which states that NPL has a significant positive impact on MSME lending.

The results from this research indicates that Non-Performing Loans have no influence on Credit Scoring. PT Amarta Mikro Fintek uses a credit scoring system to assess the ability and willingness to pay business partners. Different from the credit score in banking which emphasizes the payment history (credit history) with BI Checking, Amarta develops its own credit score by conducting risk analysis through psychological and personality method. Amarta assess on how the probability of bad credit correlates with a person's personality such as attitude, good intentions and self-confidence of the funds recipient. This is necessary to be done because Amarta's business partners are from rural people who do not have access to banking (unbanked people). Through a credit scoring system based on computational statistics, PT Amarta wants to provide an easy access to funding that is light and without collateral. The determination of credit scoring through psychological and personality method is a very dynamic assessment. The assessment will be more accurate and precise if the number of loan recipients at PT Amarta Mikro Fintek increases. So that means the high or low NPL will have no impact on the credit scoring at PT Amarta Mikro Fintek. This research results are supported by Siagian (2020) which States that NPL has no affect on credit scoring, meaning that high and low NPL will not affect credit scoring. Furthermore, these results are differs to the research that conducted by Pastini & Prianthara 2018) whom define that the NPL has a significant positive affect on credit scoring.

Credit Scoring has no affect on MSME lending. The number on each credit scoring represents the ability to repay the installments of each loan recipient. The credit scoring function not only helps the PT Amarta Mikro Fintek to reveal whether the loan is approved or not, but also determines the amount of loans to be obtained, the tenor that provide and also the amount of interest on the loan. If it turns out that the credit scoring result is small, then the debtor may still get loan but with a higher interest rate. Therefore, it says that credit scoring will not affect the distribution of MSME loans. This research results are in line with Sefriawan & Curry research (2018); Jumingan (2015) and those who stated that credit scoring had no impact on MSME lending. But this result is different from the research result from Bao et al. (2019) which states that credit scoring has a significant negative affect on MSME lending.

Non-Performing Loans which mediated by credit scoring have a significant positive affect on MSME lending. PT Amarta Mikro Fintek applies this credit scoring by developing an analysis of the ability to pay of prospective loan recipients through psychometric tests modeled with a machine learning method so that from this behavioral analysis a feasibility mapping can be made which is useful in generating an accurate credit score. This credit score is also dynamic, whereas every time there is a change in the indicator of the loan recipient, the credit score itself will be updated automatically. Therefore the credit scoring could be able to influence the NPL in reducing the risk of default and increasing MSME lending. This means that the existence of credit scoring or credit assessment from the debtors will affect the NPLs in increasing MSME lending. This research results are

supported by the results from research of (Fatimah, et al 2017) that declared the NPL which mediated by credit scoring will have a positive affect on MSME lending.

CONCLUSION

Non-Performing Loans in P2P Lending have a significant negative affect on MSME lending decisions. This means that the higher the NPL in P2P Lending will reduce the distribution of MSME loans and conversely, the lower the NPL will increase the distribution of MSME loans. Furthermore, Non-Performing Loans will have no effect on Credit Scoring. This could be means that the high and low NPL did not affect the Credit Scoring or the high and low NPL did not affect the determination of credit distribution to the public. Credit Scoring has no impact on MSME lending decisions. Meaning that the size of Credit Scoring will not affect the decisions in the distribution of MSME loans. Overall, the impact of the Non-Performing Loan variable towards MSME Credit Distribution through Credit Scoring is -0.067671. Because the direct influence of the NPL variable on MSME Loan Distribution is -0.066216 which is smaller than -0.067671, in increasing MSME lending, an indirect route is chosen, namely through Credit Scoring (Credit Scoring is capable to mediate the correlation between NPL and MSME Credit Distribution).

P2P Lending companies should consider more on the quality of funding for MSME lending because the high quality of funding can affect the high integrity of financial statements as a benchmark for company performance. P2P Lending companies must be able to reduce the percentage of bad loans and defaults. So as to attract the investors as funders in the company. With a good track record of payments, the investor confidence will also increase. To increase the public trust in P2P Lending companies, these companies should be able to make innovative credit scoring assessments which drawn to the internal and external factors of the company.

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