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Factors influencing Indonesian rural banks' credit disbursement

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Abstract

Distribution of microcredits has a great opportunity, considering micro-businesses in Indonesia reaches 98 percent of all types of businesses. Microlending has become the leading market share for *BPR*s to channel their funds. This research aims to identify factors that effect the increase of micro-credit disbursements. This study uses a Vector Error Correction Model (VECM) method with a type of monthly time series data from 2012 to 2018. The sample of this study is the Rural Credit Banks. The results of this study explain that the *BPR* non-performing loan (NPL) variable, both in the long term and short term, does not significantly influence the increase in micro-credit distribution. In contrast, the variable spread in the short term and long term shows a significant positive effect on increasing microcredit distribution. Forecasting for variable increases in credit distribution fluctuates with a downward trend. The NPL variable has an increasing trend, and it is projected that the next 90 months will reach 12 percent. The spread variable has a downward trend for the next 40 months which then the trend will continue to increase for the next 90 months.

Kata kunci:
Peramalan; Mikro kredit; Non-performing loans; *Selisih;* Vector Error Correction Model

Abstrak

Distribusi kredit mikro memiliki peluang besar, mengingat usaha mikro di Indonesia mencapai 98 persen dari semua jenis usaha. Pembiayaan mikro telah menjadi pangsa pasar utama bagi BPR untuk menyalurkan dana mereka. Penelitian ini bertujuan untuk mengidentifikasi faktor-faktor yang mempengaruhi peningkatan penyaluran kredit mikro. Penelitian ini menggunakan metode Vector Error Correction Model (VECM) *dengan jenis data deret waktu bulanan dari 2012 hingga 2018. Sampel penelitian ini adalah Bank Perkreditan Rakyat. Hasil penelitian ini menjelaskan bahwa variabel kredit bermasalah BPR (NPL), baik dalam jangka panjang dan jangka pendek, tidak secara signifikan mempengaruhi peningkatan distribusi kredit mikro. Sebaliknya, variabel* spread *dalam jangka pendek dan jangka panjang menunjukkan pengaruh positif yang signifikan terhadap peningkatan distribusi kredit mikro. Peramalan untuk peningkatan variabel dalam distribusi kredit berfluktuasi dengan tren menurun. Variabel NPL memiliki tren meningkat, dan diproyeksikan bahwa 90 bulan ke depan akan mencapai 12 persen. Variabel* spread *memiliki tren menurun untuk 40 bulan ke depan yang kemudian tren akan terus meningkat selama 90 bulan ke depan.*

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1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) still dominate the Indonesian business market. The MSMEs' market share in Indonesia is estimated at 99 percent and 1 percent of major corporations. The growth rate of MSMEs in 2016 and 2017 was at 2.06 percent. The most significant growth was from medium enterprises (67 percent), small businesses at 3.56 percent, and micro-businesses at 2.04 percent. The number of workers absorbed from MSME businesses is also more significant than major corporations. In terms of microenterprise, more specifically, it is estimated that more than 80 percent of the total workforce in Indonesia work in MSMEs companies. In addition to being able to absorb a large workforce and dominate Indonesia's business market share, MSMEs also contribute more than 55 percent of Indonesia's GDP. This description highlights *BPR* as the main actor in various sectors. They serve as the largest provider in business fields, play an essential role in developing local economic activities and community empowerment, create innovations and develop new markets, and contribute to the balance of payments originating from export activities and also support in reducing poverty.

Microbusinesses are seen to have the most significant number of business units from all MSMEs categories, able to employ 89 percent of the workforce and dominate a market share of 98 percent. With more than 62 million business units, MSMEs become the target market for banks to extend their credit services. Microlending in Indonesia continues to increase year by year. Shaban et al. (2014) and Anwar (2014) state that large banks in Indonesia are less interested in extending loans to small business units compared to small banks. Profitability is an essential determinant for large banks to provide loans to small businesses. This condition is an opportunity for small banks and rural credit banks (*BPR*) to distribute credit. *BPR* can be the banking solution needed by micro-business units to help with their capital requirements. Limited capital is a major issue for MSMEs businesses growth (Ariani & Utomo, 2017), especially for micro-businesses. Banks apply the principle of precautionary in order not to increase credit risk (Yuniarti, 2011). Microbusinesses face problems to apply for funding support from large banks, mainly because of several reasons. Firstly, their administrative system is still not sound enough (character issues), followed by low capital ownership (capital issues) and low collateral issues. The ability to pay (capacity to repayment) for micro-businesses are not clear enough, mainly because micro-business actors have not separated the company's financial administration from their family's financial matters (Susilo, 2010).

Initially, microbusinesses were the primary market for *BPR* to channel their funds. After the passing of Bank Indonesia Regulation 14/22/PBI/2012, commercial banks were then required to also channel funds in the form of credit or financing to MSMEs with a 20 percent minimum market share. This regulation curbs *BPR*'s movement. For commercial banks, *BPR*s may not be a threat, but they are different from *BPR*s who view commercial banks as a threat that can hamper the process of channeling microcredit. BPR's third-party funds used as a source for microcredit are limited, unlike commercial banks, which have higher third-party funds. This limitation is also one of the limitations of *BPR*s in distributing microcredit. When a big credit request comes, a mid-size *BPR* which has limited third-party fund has to ask for loan support from bigger banks. This ultimately creates a higher cost for the *BPR*, and eventually, impacts the *BPR*'s profit.

Microlending from 2013 to 2018 continues to grow. In 2018, the amount of micro-lending was 262 trillion rupiahs, which is 32 trillion rupiahs increase compared to 2017. The escalation in micro-credit distribution is higher than the change in lending from 2016 to 2017, a sum of 17 trillion rupiahs. However, these variances are still lower when compared to changes in lending in 2015-2016 of 35 trillion rupiahs. This instability in increasing lending is determined by several factors, such as the number of third party funds, loans spent, non-performing loans, spreads, and capital. Some of these factors are considered as obstructions, while, in contrast, a couple of them generated the amount of *BPR* micro-credit distribution. Microlending is part of lending carried out by banks, where lending is the main focus and activity of banks (Haryati, 2009). Exceptional lending indicates that the bank intermediary function is working fine. The inability of banks to distribute funds suggests that the intermediation function at the bank is not performing well. Therefore, research is needed to find out what factors can cause an increase in the growth rate of microcredit at the rural credit bank in Indonesia.

2. Hypotheses Development

Third-party funds (TPF) refers to funds collected from the community that comes from individuals and legal entities (Riadi, 2018). The collection of deposits is one of the critical tasks of the bank (Mukhlis, 2011). Funds collected from this community can reach 80-90 percent. A large number of deposits will increase the amount of lending (Riadi, 2018). This finding is consistent with research conducted by Mukhlis (2011) and Purba, Syaukat, & Maulana (2016). When the funds raised from the community are small, the bank will only rely on the current credit cycle. The limited number of deposits forces banks to limit the amount of lending. If the loan disbursement exceeds the amount of their current TPF, the bank is in risk of being defaulted. This risk rises if debtors are unable to repay their loans on time, and bank reserves have been allocated to credit. If creditors are withdrawing their savings, the bank will suffer a credit risk of default.

For this reason, it is necessary to reserve funds from TPF, which are used to anticipate credit risk. In order to continue being able to extend credit, one of which is microcredit, *BPR* will increase the funds it collects. The purpose of increasing deposits is to increase lending and maintain reserves as risk mitigation. *BPR*s must approach large companies to increase their deposits and, in turn, the *BPR*'s TPF. According to Anisah, Ridwan, & Amanah (2013), Prasetya, Tan, & Delis (2015), and Akhtar, Akhter, & Shahbaz (2017), increasingly large companies can help increase third-party bank funds. Large companies have substantial assets. So if the company entrusts some of its assets in the *BPR*, it will be able to increase the TPF.

H_1: third-party funds have a positive and significant impact on microcredit distribution growth.

Loans distributed by banks depend on the number of applications (Pranata & Nurzanah, 2018). If credit request increase, rural and commercial banks will increase their credit disbursements. For newly established *BPR*s, they will continue to increase the amount of lending. They will try to maximize lending. In contrast to *BPR*s that are already well established, the loans they distribute are optimal. So they do not aim to continue to increase the amount of lending, but rather towards the stability of lending. Not only that, firm *BPR*s will compose the optimal composition of each type of credit owned by *BPR*s. That is percent for microcredit, consumer credit, and other allocations.

H_2: credit has a significant and positive effect on increasing microcredit distribution.

Non-performing loans (NPL) represent bad loans that occur in banks. Increasing default credits increase the risk of default. Moreover, *BPR* NPLs are still above 5 percent. Sari (2013) and Arianti, Andini, & Arifati (2016) stated that NPLs had a significant adverse effect on public bank lending. The higher the NPL, the lower the level of bank lending. Banks, both commercial banks and rural banks, take prudential attitudes when the bank NPL is high so that the chance of default risk does not happen. This condition is in line with Cucinelli (2015), that when the bank NPL is high, the bank will reduce its lending activities, therefore, have an impact on the decline in the profitability of the banking sector Gizaw, Kebede, & Selvaraj (2015). Balgova, Nies, & Plekhanov (2016) research results explain that reducing NPL has a positive impact on the economy in the medium term. Countries that have increasing amounts of new credit affect the level of their economy, which ultimately results in economic circulation. Economic circulation can help solve NPL problems. Neglected NPL will also be dangerous for the economy. Based on this explanation, it can be seen that NPLs are an early warning system for banks, and NPLs also harm the economy.

H_3: non-performing loans have a negative effect on increasing the distribution of micro-credit.

Spreads are a source of net banking income (Barus & Lu, 2013). Income derived from lending (cost of funds), which is then reduced by the costs spent to acquire funds (lending rate). High spreads benefit the bank in the shape of greater bank profits. High spread that happens at the bank becomes a loss for customers. They pay higher loan interest rates or receive smaller deposit interest. High spreads can be obtained from high loan interest rates. Interest rates from lending are determined by funding costs, loan sizes, and the level of efficiency (Cotler & Alzaman, 2013). High spreads will make *BPR* choose to increase lending, one of which is micro-lending. Puspita & Santoso (2017) revealed that the greater spread would make banks increase their SME lending.

H_4: spreads have a significant and positive effect on increasing microcredit distribution.

Capital is an important variable to research. Bank capital adequacy is one indicator of the bank's health since it can dampen shock on bank's operational activities (Osei-Assibey & Asenso, 2015; Haryanto & Widyarti, 2017). High minimum capital requirements and above-minimum capital excess will boost credit growth in the banking sector. However, an oversized capital can increase the bank's high-risk activity. This is due to the large capital is found in banks that have a high NPL. The existence of capital is able to absorb the possibility of loss and will have an impact on increasing the trust of the account and become the main determinant of the credit distribution capacity (Osei-Assibey & Asensoso, 2015). High capital shows the ability of a bank to provide funds for business development purposes (Pratiwi & Hindasah, 2014). One indicator of the capitalization is CAR (capital adequacy ratio). The bank that has higher CAR reflects healthier equity (Taswan, 2010) and the better the ability of the bank to assume the risk of any credit or productive assets at risk (Murdiyanto, 2012). Banks with greater capitalization are willing to take risks by increasing their credit distribution for business and household loans (Osei-Assibey & Asenso, 2015). CAR also positively impacted the credit distribution (Satria & Subekti, 2010; Asmara & Supardi, 2019).

H_5: capital have a significant and positive effect on increasing microcredit distribution

3. Method, Data, and Analysis

Rural banks (*BPR*) is the object of this study. *BPR* is a bank that has an excellent opportunity to distribute microcredit. The type of data in this study is secondary data. This analysis applied time-series data acquired from several sources i.e., the Indonesian Banking Statistics (SPI), Financial Services, Authority reports, and Bank Indonesia MSME Credit Statistics data. The data were monthly data from 2012 to 2018. There were 84 observations collected. The independent research variables used are third party funds (*TPF*), the number of loans disbursed (*CREDIT*), non-performing loans (*NPL*), spreads (*SPREAD*) and capital (*CAPITAL*), while the dependent variable is credit growth (*CG*). In general, capital variable is projected by CAR however, due to data limitation, therefore capital varible is projected by total equity to total assets. Credit growth is growth rate of total microcredit *BPR*.

This research used Vector Auto Regression (VAR) or Vector Error Correction Model (VECM) analysis tools. The choice of using this model is from the presence or absence of cointegration. If there is no cointegration, the model used is VAR. Conversely, if the equation is built there is cointegration, the model used is VECM. Both of these models are models with all existing variables being endogenous. The model can be applied if the examined variables pass the classical assumption tests (autocorrelation and heteroscedasticity). Time series data are often disrupted by autocorrelation. The existence of a time-relationship within the equation can make the model experience misspecification, causing bias on parameters, while heteroscedasticity will cause difficulties on deductions (Ariefianto, 2012).

Prior to applying the main testing, the data had an early checking of stationarity. There are two types of data, i.e., stationary data, and non-stationary data. Stationary data means the model testing can be done with the Ordinary Least Square (OLS) procedure. A non-stationary data that is executed with OLS will potentially produce non-sensical regression (Ariefianto, 2012). The use of non-stationary time series data requires special handling because it has the potential to cause spurious regression problems. Spurious regression problems arise as a result of interference. It says there is a significant relationship between the dependent variable and the independent variable, while, in reality, there is no relationship between the two variables mentioned. The conclusions drawn are incorrect or misleading.

Data stationary testing uses the root unit test. Test results that reveal non-stationary data progressed with testing the difference form (first difference or second difference). Then the optimal lag and the stability of the VAR will also be determined. Furthermore, cointegration testing will decide which model uses VAR or VECM. The formulation of a general model that will be used if stationary data can be seen in Equation 1 or 2.

$$Y_t = \alpha_1 + \sum_{i=1}^{k} \beta_{1i} Y_{t-i} + \sum_{i=1}^{k} \gamma_{1i} X_{t-i} + \varepsilon_{1t} \quad (1)$$

$$X_t = \alpha_2 + \sum_{i=1}^{k} \beta_{2i} Y_{t-i} + \sum_{i=1}^{k} \gamma_{2i} X_{t-i} + \varepsilon_{2t} \quad (2)$$

The plus point of VAR is that it does not require model specifications, because it does not require differences in the names of exogenous and endogenous variables. Not only that, the estimation method of the VAR model can use the OLS equation for each equation separately. The advantages of VECM are also similar to VAR since VECM is the development of the VAR model. VECM has other advantages where this model can evaluate results in the short and long term (Mukhlis, 2011). The formulation of VECM general model can be seen in Equation 3 or 4.

$$\Delta Y_t = \alpha_1 + \sum_{i=1}^{k} \beta_{1i} \Delta Y_{t-i} + \sum_{i=1}^{k} \gamma_{1i} \Delta X_{t-i} + \varepsilon_{1t} \quad (3)$$

$$\Delta X_t = \alpha_2 + \sum_{i=1}^{k} \beta_{2i} \Delta Y_{t-i} + \sum_{i=1}^{k} \gamma_{2i} \Delta X_{t-i} + \varepsilon_{2t} \quad (4)$$

4. Results

Data stationary testing

Stationary test results in Table 2 show that only *CG* variables are stationary at the level stage. Stationary *NPL, SPREAD* and *CAPITA*l variables at the level of 1st difference. Whereas the variable *TPF* and stationary *LDR* at the level of 2nd difference.

Classic assumption testing

Before conducting further testing, firstly, the model will run for the classical assumption test, especially on autocorrelation and heteroscedasticity. When all variables are listed in the model and tested for autocorrelation and heteroscedasticity, the model did not pass the two classical assumption tests. Consequently, the variables were lessened, and classi-

Table 2. Root *BPR* test result

Variables	Level		1st Difference		2nd Difference	
	ADF Value	P value	ADF Value	P value	ADF Value	P value
CG	-10.482	0.000	-10.387	0.000	-10.652	0.000
TPF	5.535	1.000	-0.025	0.671	-8.169	0.000
CREDIT	4.808	1.000	-0.109	0.643	-10.211	0.000
NPL	1.564	0.970	-10.437	0.000	-6.160	0.000
SPREAD	-1.066	0.257	-10.421	0.000	-8.608	0.000
CAPITAL	0.246	0.755	-11.330	0.000	-11.539	0.000

Table 4. Portmanteau autocorrelation output

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	1.793646	NA*	1.817561	NA*	NA*
2	4.592922	NA*	4.692493	NA*	NA*
3	7.256281	NA*	7.465306	NA*	NA*
4	7.707626	NA*	7.941725	NA*	NA*
5	11.14054	NA*	11.61639	NA*	NA*
6	18.23890	NA*	19.32318	NA*	NA*
7	22.90945	0.0861	24.46756	0.0576	15
8	26.98948	0.3049	29.02759	0.2191	24
9	36.30163	0.3174	39.59062	0.1994	33
10	38.73037	0.6153	42.38736	0.4543	42

cal assumptions were re-tested until it came out with variables that pass the classic assumptions requirement. Finally, only the credit of growth variable, the *NPL* variable, and the *SPREAD* variable that passed the classic assumptions test. The *TPF* variable, the *CREDIT* variable and the capital variable were eventually excluded from the model because the three models did not meet the classical assumption test.

The autocorrelation test used the Portmanteau Autocorrelation Test. If the p-value of the Q-statistic is higher than 0.05, the result is no autocorrelation in the rest of the model. The results in Table 4 show that the p-value of the Q-Stat is more than 0.05, which indicates no autocorrelation in the rest of the model.

Heteroscedasticity testing is performed to determine the variance of the rest of the model, whether the variance of the residuals is homogeneous or still heterogeneous. Table 5 explains that the p-value of the test as a whole (joint) is higher than 0.05 by 0.9414, which suggests a homogeneous variance range.

Table 5. Output heteroscedasticity test

Chi-sq	df	Prob.
195.5457	228	0.9414

Optimal lag testing

The next step after stationary testing is optimal lag testing. This optimal lag testing uses information from Likelihood Ratio (*LR*), Final Prediction Error (*FPE*), Akaikke Information Criterion (*AIC*), Schwarz Criterion (*SC*), and Hannan-Quinn Criterion (*HQ*). One determination is to see the most asterisks in the lag. The most asterisks (*) based on Table 6 are on lag 6. Thus, it can be decided that the optimal lag is 6.

Table 6. Optimal lag testing

Lag	*LogL*	*LR*	*FPE*	*AIC*	*SC*	*HQ*
1	121.6961	NA	1.07e-05	-2.927172	-2.653221*	-2.817594*
2	126.9674	9.721108	1.19e-05	-2.830323	-2.282420	-2.611166
3	143.6945	2..54396	9.72e-06	-3.031026	-2.209173	-2.702292
4	153.0522	15.798700	9.67e-06	-3.040317	-1.944512	-2.602005
5	158.0374	8.028055	1.08e-05	-2.936036	-1.566279	-2.388145
6	172.6970	22.46542*	9.44e-06*	-3.083039*	-1.439332	-2.425571

VAR stability testing

Table 7 presents the results of testing the roots of characteristic polynomial modulus values produced are less than 1. The VAR model is said to be stable if the root of characteristic polynomial modulus value is less than 1. If there are still more than one, then it suggested reducing the lag used.

Table 7. Roots of characteristic polynomial testing results

Root	Modulus
-0.456960 - 0.771684i	0.896833
-0.456960 + 0.771684i	0.896833
0.425375 + 0.761376i	0.872145
0.425375 - 0.761376i	0.872145
-0.746501 - 0.342745i	0.821424
-0.746501 + 0.342745i	0.821424

Cointegration testing

The decision to use either VAR or VECM model is based on the results of its cointegration test. If there is cointegration in the model, the model uses VECM. Whereas if there is no cointegration, the model applies VAR. Cointegration testing is used to determine its long-term relationship. The requirement for cointegration testing is that variables or data must be stationary at the same level. Cointegration testing uses the Johansen's Trace Statistics test with the optimum lag length 6.

A cointegration test is used to find out the number of cointegration equations contained in the system. Based on the results in Table 8, the Trace Statistics and Max-Eigen values have a higher than the critical value, which means that the system has a cointegration equation. Table 8 also shows that there are three equations in a system that have a long-term relationship. Because there is cointegration, the model to be used is VECM.

Vector Error Correction estimation results

The VECM results in Table 9 explain that the *SPREAD* variable has a significant positive effect on *CG* in the long run, which 1 percent increase in *SPREAD* will increase *CG* by 0.0737 percent. This figure implies that in the long run, *BPR*s with greater SPREAD will increase their lending. In contrast, *NPL* has no significant effect on *CG* in the long run. This situation is because *BPR* does not depend on the amount of *NPL*. In the long term, *BPR* will be more directed to high-risk, high return. *BPR* will seek turnover even though the probability of risk will increase.

In the short term, 1 percent increase in *CG* in the previous 1 to 6 months will reduce this month's *CG* because the previous month's *CG* is negatively related to the current month's *CG*. Last month's NPL had no impact on *CG*. *BPR* sees that to get a substantial return, there will also be a considerable risk. Even if the short-term *NPL* continues to increase, they hope that later, they will get a high return. Changes to *SPREAD* in 1 to 2 months ago did not affect changes in *CG*, which 1 percent increase in *SPREAD* in 3 to 5 months will have an impact on the increase in *CG* this month.

Forecasting analysis

The *CG* variable is volatile for the next 30 months with a downward trend. Microlending for the next 90 months continues to increase, but the increase tends to decrease. The difference in the amount of micro-credit distribution compared to the difference in the previous month was even lower. Banks prefer to finance businesses that are more stable and have high return opportunities. Unlike the *NPL* variable. *NPL* conditions fluctuate until the 20th month. If the *CG* variable experiences a downward trend, the *NPL* variable continues to increase for the next 90 months. An increase in the *NPL* variable could reach 12 percent, which threatens *BPR* to be more careful in lending. Variable spread for the

Table 8. Cointegrations testing trace and maximum Eigenvalue

Hypothesized No. of CE(s)	Eigenvalue	Statistic	Critical Value 0.05	Prob.**
Trace				
None *	0.325036	65.16597	29.79707	0.0000
At most 1 *	0.287180	35.29063	15.49471	0.0000
At most 2 *	0.118230	9.562584	3.841466	0.0020
Maximum Eigenvalue				
None *	0.325036	29.87533	21.13162	0.0023
At most 1 *	0.287180	25.72805	14.26460	0.0005
At most 2 *	0.118230	9.562584	3.841466	0.0020

* denotes rejection of the hypothesis at 0.05 level
** MacKinnon-Haug-Michelis (1999) p-values

Table 9. VECM estimates for short and long term

Variables	Coefficients	T statistics
	Long term	
D(NPL(-1))	-0.055302	-1.90908
D(SPREAD(-1))	0.073751	4.46703*
C	0.005407	-
	Short Term	
CointEq1	-0.554959	-1.82864
D(CG(-1),2)	-0.717346	-2.48220*
D(CG(-2),2)	-0.890953	-3.00558*
D(CG(-3),2)	-0.967622	-3.55436*
D(CG(-4),2)	-0.722856	-3.06703*
D(CG(-5),2)	-0.384837	-2.31953*
D(CG(-6),2)	-0.210734	-2.86130*
D(NPL(-1),2)	-0.007566	-0.44781
D(NPL(-2),2)	-0.000833	-0.04794
D(NPL(-3),2)	-0.004953	-0.28482
D(NPL(-4),2)	-0.004953	0.33610
D(NPL(-5),2)	-0.002616	-0.17808
D(NPL(-6),2)	-0.000273	-0.02671
D(SPREAD(-1),2)	0.036591	1.82964
D(SPREAD(-2),2)	0.033119	1.88204
D(SPREAD(-3),2)	0.031656	2.12927*
D(SPREAD(-4),2)	0.026804	2.26411*
D(SPREAD(-5),2)	0.017772	2.01860*
D(SPREAD(-6),2)	0.008740	1.54507
C	0.000956	0.41125

* significant at level 5 percent

next 40 months experienced a fluctuating trend. In the next 40 to 50 months, the spread rate of *BPR* tends to be stable. After the next 50 months, the variable spread of *BPR* continues to increase until the next 90 months.

5. Discussion

Based on the data processing results, in the short term, the increase in last month's lending will affect the increase in this month's lending. Table 9 explains that the growth in the distribution of microcredit last month has an impact on the decline in growth in the distribution of microcredit this month. A negative relationship happened between the growth in the distribution of microcredit in the previous month and the growth in the distribution of current microcredit. The distribution of microcredit does not always increase every month. Micro-credit distribution amount decrease is caused by the demand for micro-credit, which changes at any time, depending on the needs of micro-venture capital. Based on the type of application, *BPR* lending is divided into three types of loans, i.e., working capital loans, investment loans, and consumer loans. The proportion of lending for consumers still dominates lending. Each year the proportion of lending for consumption is about 48 percent. This proportion is still higher than the proportion of working capital loans at 45 percent, and investment loans at 7 percent. The high lending allocation for consumption makes working capital and investment loans consequently low, which also affects low micro-credit disbursement. Returns received by *BPR*s from the consumption loan payment are lower when compared to returns on micro-credit payments. Microcredit does have a high chance of a return, but the risk is also high (high-risk, high return).

NPLs in the short and long term does not affect micro-credit distribution. The results of this study are in line with the results of his research Satria & Subekti (2010), Destiana (2016), and Riadi (2018). If the *BPR* wants to increase its return, it will face a high credit risk. *BPR*s would mitigate the risk and cause Non-Performing Loan to be less impactful to micro-credit disbursement. Some studies explain that NPL cuts lending (Sari, 2013; Arianti et al., 2016). Both show that Non-Performing Loan troubles credit disbursement as *BPR*s apply prudence principles to minimize bad loans. If the existing bad loans at the *BPR* can still be tolerated, the *BPR* will continue to issue credit.

In the short and long term, the influence of the previous month's variable spread will have a positive impact on micro-lending. The research re-

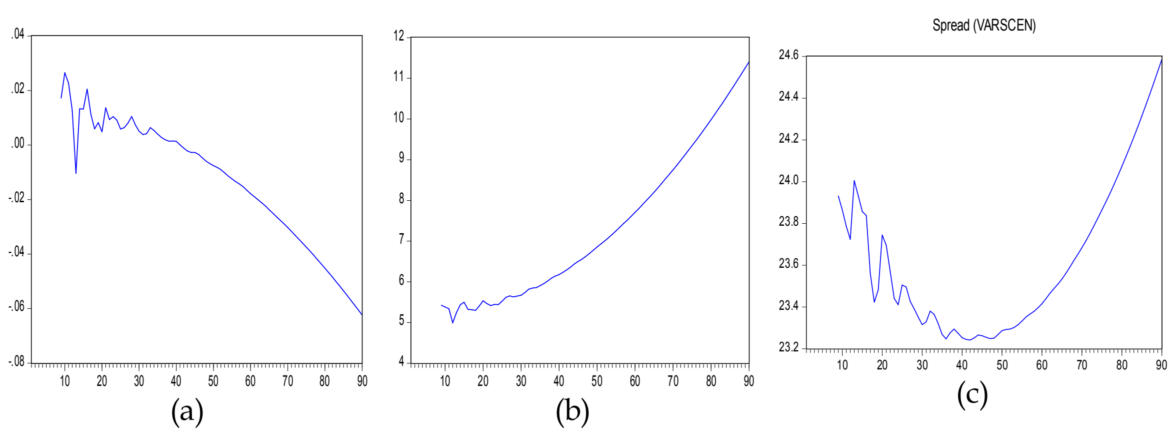

Figure 2. Forecasting variable *CG* (a), variable *NPL* (b), variable *SPREAD* (c)

sults are supported by Puspita & Santoso (2017). Higher spreads drive *BPR* to increase its micro-lending capacity. It is expected that the more extensive spread, supported by the more excellent distribution of micro-credit, will also increase *BPR*'s income. This increase in *BPR* revenue supports the higher profits for *BPR*.

The high spread can inhibit the demand for credit amount and affect the amount of credit channeled. Higher ranges are due to the higher rate of credit interest. The bank's ability to increase spreads positively impacts the bank's profitability and encourages banks to improve their credit distribution (Ivanovic, 2016). The high Market power indicates that the bank can establish interest rates, especially the higher the interest rates of lending (Moore & Craigwell, 2010). Almeida (2015) states that the Herfindahl-Hirchman Index (HHI) as a proxy of the power market has a significant positive impact on the spread. The market structure is a critical element for determining spreads in banking with the consideration that a more concentrated environment can reflect higher market strength. The more focused banking system provides support for banks to get higher spreads. Boyd & De Nicolo (2005) explains that the higher the power market in a credit market is able to create more significant risks. This is because higher interest rates can make borrowers more challenging to pay for credits and can increase the moral hazard of borrowers to use those credit funds on more risky projects. Not only that, the high level of interest rates can generate an adverse selection at the credit distribution process. Borrowers who propose to credit only those who are of high risk while borrowers with a lower risk of choosing to avoid financing from the bank by looking for another funding source (Wibowo, 2016).

High spreads are derived from high credit interest rates or the limitation of third Party Deposits (TPF) interest rate. High TPF interest rate will reduce the spreads gained by *BPR*. The Financial Services Authority (*OJK*) is responsible for improving the supervision of gathering funds. *OJK* then conducts discussions with several banks to determine the maximum interest rate of third party funds. Based on the discussion result, the maximum TPF Interest rate is then determined and adjusted to the interest rate of the loan *LPS* (Indonesia Deposit Insurance Corporation). *LPS* itself is to give a guarantee against third party deposits in banking. Therefore, the expectation of the TPF interest rate refers to the interest rate of *LPS* deposits.

2. Conclusion

Microlending continues to increase every month, although the growth in the long-run tends to decrease. The current increase in micro-credit distribution is undoubtedly influenced by an increase in lending last month despite a negative relationship. The NPL variable does not affect increasing short-term or long-term micro-credit distribution. Conversely, the variable spread has a significant positive effect on increasing micro-credit distribution in the short and long term. In the long run, the growth of micro-credit distribution continues to decline. The NPL variable in the next 90 months is predicted to increase by up to 12 percent while the spread variable for the next 45 months will continue to decline and then increase to the 90th month.

The limitation of this study is that this period is very short, from 2012 to 2018 only. If the data uses a broader timeframe, the resulting estimates may be better. Loan testing for small and medium business units is also needed, so that it can predict factors in increasing lending to MSME businesses. This paper discovers what factors can influence an increase in the distribution of *BPR* microcredit. Based on these factors, *BPR*s can produce strategies to increase spreads and reduce NPLs. Furthermore, this research can be referred to the government and related parties to control *BPR* deposit interest rates lower than the Deposit Insurance Corporation (*LPS*). The government can set optimal deposit and credit rates for rural banks.

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