Bigger, Richer, Safer? Examining the Probability of Default among Ultramicro Credit Clients in Indonesia

Arief Wibisono Lubis

Department of Management, Faculty of Economics and Business, Universitas Indonesia, Depok, Indonesia.

Corresponding author: ariefwl@ui.ac.id

Rofikoh Rokhim

Department of Management, Faculty of Economics and Business, Universitas Indonesia, Depok, Indonesia.

Nahla Nurusshafa

Department of Management, Faculty of Economics and Business, Universitas Indonesia, Depok, Indonesia.

Abstract

Credit assessment is essential in lending activities. On the one hand, errors in credit assessments can lead to financial losses in banking or financial institutions that provide credit due to the higher credit risks. This article examines the performance of clients' loan repayments in the case of YCAB Venture, one of the ultramicro credit providers in Indonesia. Using a sample of 500 clients in Jakarta, Indonesia, and employing a probit model, it is indicated that credit duration and loan cycle are the two most important loan characteristics that can predict the probability of default. Interestingly, the result shows that period of loan, years of operating business, income and family expenses has positive significant determining probability of default. On the other hand, loan size shows negative significant. The results bring several implications in further product development of ultramicro credit providers, particularly in the country.

Keywords: credit scoring, microfinance, probit, loan repayment, probability to default

Acknowledgements

We thank the management of YCAB Ventures for providing the data needed for this research.

1. Introduction

The need for credit assessments starts with a mechanism that has been applied massively to lending and borrowing activities; this mechanism prompts and ensures the need to repay loans in the future. The modern credit assessment mechanism was introduced by Durand (1941). Microfinance institutions (MFIs) use credit scoring in order to increase the productivity of their loan officers, which can lead to an increase in the number of borrowers and may make higher growth in the number of loans and, thus, expands financial inclusion and developmental opportunities (Bumacov, 2014). These are possible because credit assessment is expected to assure credit risk handling by MFIs.

Credit assessment is a significant process in lending activities (Lewis, 1992). On the one hand, errors in credit assessments can create a risk of default on the borrower and lead to financial losses for the banking or financial institutions that provide credit. On the other hand, from a more macroeconomic perspective of the argument, credit defaults may also have significant impact on overall macroeconomic conditions. As financial institutions are tightly regulated, defaults within their operations may lead to systemic risks to the economy on a macro basis.

Moreover, the existence of a rigorous and prudent credit assessment system will lead to prolonged credit assessment processes, thus creating an opportunity to push the economy down. In addition, convoluted credit assessment processes may give bad impressions to prospective debtors (Maldonado et al., 2020).

The emergence of microcredit is aimed to support disadvantaged people, thus requires special tools to minimise credit risk. Credit risk in the microfinance industry is influenced by two main factors that differentiate microcredit from mainstream banking. These factors are the lack of collateral by the borrower and the asymmetry of information between the borrower and the lender. Theoretically, both these problems can be overcome by monitoring procedures carried out by account officers and the mechanism of joint responsibility, which is more commonly referred to as group lending (Emekter et al., 2015). But in its implementation, particularly when this activity occurs massively, credit assessment systems are also needed to support microfinance operational activities (Durand, 1941).

One of the most recognised studies in probability of default is the one by Altman (1968). In this model, probability of default, or denoted as the Z-score, can be predicted by financial ratios reflecting profitability, leverage, liquidity, solvency and activity. Altman et al. (1995) then developed another model that is claimed to be useful in the context of emerging markets. The difference between this model and the previous one is in the variables used due to data limitation in emerging markets. These differences show that the probability of default models is sensitive to the contexts, types, data availability, and size of businesses. With regard to the latter, it is thus important to develop a robust credit model for ultramicro clients, or those clients that can be characterised as informal business with majority of seasonal type of business, woman, medium length of business establishment (average 5 years), and average family expense below the poverty line IDR 337,460/week (approximately USD 70, ppp-adjusted) (standard: Rp 1.9 mio/month based on Indonesia's National Development Planning Agency / Bappenas' criteria). Limited information among them makes credit analysis process more challenging, and thus a dedicated robust model is needed.

This study aims to fill in the gap in the literature by developing a model that can be used to assess the probability of default of ultramicro clients in Indonesia, particularly those of YCAB Ventures. In July 2020, this MFI has 14,000 active clients across Indonesia, all of whom are women, with a maximum loan of IDR 5 million (approximately USD 357). By employing the probit technique in 500 observations, it is found that among loan characteristics, duration of credit and loan cycle are the ones that relevant in predicting default risk.

The remaining parts of this article are structured as follow. Section 2 presents some important literature on credit risks, particularly variables that have been shown to be relevant in predicting the probability of default. Section 3 focuses on the data and methodology used, while Section 4 provides the results and findings, as well as some relevant discussions. Section 5 concludes the overall article.

2. Literature Review

2.1 Credit Risk

Credit risk can be defined as the potential contractual parties who do not fulfil their obligations in accordance with agreed conditions. Credit risk is also variously referred to as the risk of default, performance risk or the risk of the other party (Brown and Moles, 2016). This can be defined as the risk of a borrower's default, which occurs when a borrower fails to pay. The condition of default is when the borrower is in a financially depressed situation (Gestel and Baesens, 2008).

The fundamental difference regarding credit risk between banks and MFIs is often associated with loan size. In addition, micro and ultramicro loans are associated with reducing the principle of collateral in credit valuation (Vogelgesang, 2003). The starting point of this review is the latest study by Lassoued (2017) which found that the methodology of group lending, and the high percentage of loans given to women, significantly reduced the credit risk of 638 microfinance institutions taken from 87 countries during the period 2005-2015. Aghion and Morduch (2000) underline that some parties can reduce deviations from low-income borrowers by using group loans, which are small routine payments, and through the provision of free non-financial services.

2.2 Credit Assessment Conceptual Framework

Credit assessment is one of the crucial processes in managerial decision making related to credit granting. This process consists of collecting data, analysing, and classifying credit elements and variables contained in credit assessments. The quality of bank loans is the key to competition, defines, and also the profitability of lending institutions. One important thing to make sure creditors do not lend to the wrong person is to use credit scoring. Hand and Jacka (1998) state that processes (conducted by financial institutions) regarding creditworthiness modelling commonly apply credit scoring models.

The practical and empirical evidence regarding credit assessment implies that the characteristics and environment of borrowers, which have an influence or contribution to the risk of default must be used in the credit scoring system (Lewis, 1992). There are no other justifications for including a specific factor as a credit scoring variable. If these factors help predict credit score, then it should be used. In addition to these inclusion/exclusion criteria, there are also restrictions with regard to the exclusion of factors that may imply discrimination, such as race and religion; these factors should not be utilised to determine credit scoring. Below are several factors that potentially can predict the risk of default.

2.2.1 Loan Period

Kočenda and Vojtek (2009) state that the amount of credit previously carried out is a characteristic that indicates the relationship between borrowers and banks. Dinh and Kleimeier (2007) and Schreiner (2004) found that defaulted borrowers had difficulty receiving new loans. In this case, the loan cycle referred to in YCAB is the amount of the loan made by the customer. YCAB also seeks to maintain relationships with its clients who have good loan repayment behaviour.

2.2.2 Loan Size

Loan size is defined as the amount of agreement between the borrower and the lender. Here we can assume that the loan size is the amount requested by the borrower. This amount reflects the planned borrower's desires, the borrower's risk tolerance level and the assessment of payment ability. According to Baesens et al. (2011), the incentive to deviate payments increases for larger amounts of credit, so the level of payment will decrease in the larger number of loans.

2.2.3 Other Loans

Other loans are indicating whether the consumer has other loan than the YCAB offered or not. This variable is basically strengthened the variable loan size. If someone has other loans, this means the amount of loan that she has to repay is bigger. Therefore, the borrower’s default risk is supposedly lower when she does not have other loans.

2.2.4 Duration of Credit

The duration of credit reflects the intention of the borrower to repay the debt, the risk-appetite of the borrower and the ability of the borrower to repay. Based on Jiméneza et al. (2006) and Calcagnini et al. (2009), the maturity of the loan represents the approach to the relationship of the length of the loan period. In YCAB, the payment period is divided into 25 instalments and 50 instalments. Each borrower registered with YCAB will repay the loan principal and interest every week.

2.2.5 Length of Business

Length of business is years the business has been operating. The longer length of business means it has been established longer. This can be interpreted by the stable cashflow and good reputation to build in credit scoring.

2.2.6 Family Income

Jacobson and Roszbach (2003) show that, if there is a negative relationship between income and the failure rate, which means that the higher the income, the lower the risk of default. Income is an approach to find out the financial condition of the borrower and the ability to pay debts (Dinh and Kleimeire, 2007). Chien and Devaney (2001) conducted a study which stated that when a person's income level rises, a person is less likely to be hindered by debt, which indicates more ability to repay debt. People with higher income levels tend to have better attitudes towards using credit. Therefore, the higher the level of household income will indicate the low risk of default. Limsombunchai et al. (2005) state that borrowers with low income volatility have the opportunity to obtain a larger loan amount.

2.2.7 Business Revenue

Business revenue is defined as the amount of money that is generated by business' operational activities. Revenue is one approach that strengthens income variable to define credit risk default probability. According to Jacobson and Roszbach (2003), probability of credit default increases when the income decreases. Income and business revenue normally should be aligned, because business revenue is a component of income itself. A higher income indicates a higher ability of loan repayment.

2.2.8 Capital

Capital is one of the factors of credit rating determinant that is widely used in banking and financial institutions. It shows commitment and credibility to make repayment of loan. The evidence shows that, in Ghana, capital plays an important role to define credit risk of consumers (Kwasi-Peprah et al., 2017). The bigger the capital, the least credit risk consumers have.

3. Data and Research Method

3.1 Data

This study collects data from 500 clients of Yayasan Cinta Anak Bangsa (YCAB) Venture, an MFI based in Jakarta, Indonesia. These clients are divided into two groups based on events of default, i.e. 61 clients belong to the default group and 439 other customers are classified into the non-default group. Data collection in this study was carried out in the period of March 2019 - June 2019. The authors use stratified random sampling in order to collect the overall dataset.

3.2 Method

This research uses probit model in order to predict the default of repayment in our model. According to Thomas (2000), the probit model is a predictive model that is widely used for classification and forecasting. Our model consists of eight independent variables, as shown in Table 1, to build the default model of ultramicro credit institution.

Table 1. Variables for Building the Default Model

Variable	Type	Definition
Loan Period (*PERIOD*)	Numeric	Period of the credit
Loan Size (*LOANSIZE*)	Numeric	Amount of credit (in Rupiahs)
Other Loans (*OTHERLOAN*)	Dummy	1 (Yes) 0 (No)
Length of business (*BUSINESSYEARS*)	Numeric	Length of business (years)
Type of Business (*BUSINESSTYPE*)	Dummy	1 (Permanent) 0 (Seasonal)
Income (*INCOME*)	Numeric	Accumulative income in family (in week)
Total Revenue (*REVENUE*)	Numeric	Revenue in business (in week)
Capital (*CAPITAL*)	Numeric	Total of capital used (in week)
Family Expenses (*FAMILYEXPENSE*)	Numeric	Accumulative expenses of family (in week)
Default Event (PD)	Binary	1 (default event) 0 (non-default event)

$$PD\ (1|X) = \beta 0 + \beta 1 period + \beta 2 loansize + \beta 3 otherloan + \beta 4 businessyears + \beta 5 businesstype + \beta 6 income + \beta 7 revenue + \beta 8 capital + \beta 9 familyexpense + \varepsilon$$

where *PD* in the model represents the default probability as the dependent variable with statement 1 for default event and 0 for non-default event. The independent variables are *PERIOD* (loan period), *LOANSIZE* (loan size), *OTHERLOAN* (dummy of other loan), *BUSINESSYEARS* (length of business), *BUSINESSTYPE* (type of business), *INCOME* (business income), *REVENUE* (business revenue), *CAPITAL* (capital), and *FAMILYEXPENSE* (family expenditure). β0 is an intercept, where βj = (1, ..., 9) represents the coefficient of each predictor variable of its marginal value (*i* = 1, ..., 9); and ε is an error.

The default probability model could be interpreted by the probit model result, the direction or effect and significance of each independent variable on the dependent variable can be seen from sign of coefficient in the probit regression result. Nevertheless, to interpret the value of the numerical coefficient, it is necessary to look at the marginal effects obtained from the test marginal effect (*mfx*) step. In this case, the marginal effect shows the impact of changes in a variable on the probability of default of ultramicro credit customers.

3.3 Error Specification Model

In order to detect specification error of the model, we run linktest as shown in Table 2. The importance of knowing the specification error is about the assumption used in logistic regression. We assume that logit function is a correct function to use. In that condition, the logit model outcome variable and the independent variables is not linear. The misspecification result usually means that our model has included all the relevant variables and not included any variables that should not be in the model. The model is properly specified, and one should not be able to find any additional predictors that are statistically significant except by chance. This usually means that either we have omitted relevant variable(s) or our link function is not correctly specified.

Table 2. Link Test Model Probit

Default	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_hat	1.0726	0.2996	3.58	0.000	0.48531	1.6598
_hatsq	0.0389	0.1412	0.28	0.783	-0.2379	0.3158
_cons	0.0203	0.1838	0.11	0.912	-0.3400	0.3806

Based on Table 2, for testing specification error of model, which is the result of the linktest test, the results of hatsq are not significant. This means that the model is able to describe the exact specifications (Pregibon, 1980).

4. Results and Discussions

4.1 Descriptive Statistics

Table 3. Descriptive Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
PD	500	0.1223	0.3276	0	1
PERIOD	500	6.6824	6.2778	1	25
LOANSIZE	500	2,502,000	1,209,099	1,000,000	5,000,000
OTHERLOAN	500	0.05	0.2182	0	1
BUSINESSYEARS	500	5.208	4.495	0	40
BUSINESSTYPE	500	0.122	0.3276	0	1
INCOME	500	1,518,015	731,581.10	190,000	6,000,000
REVENUE	500	1,295,410	998,361.20	100,000	1.26E+07
CAPITAL	500	764,990.10	669,375.10	30,000	7,000,000
FAMILYEXPENSE	500	337,460	181,719.80	20,000	3,000,000

PERIOD (loan period), *LOANSIZE* (loan size), *OTHERLOAN* (dummy of other loan), *BUSINESSYEARS* (length of business), *BUSINESSTYPE* (type of business), *INCOME* (business income), *REVENUE* (business revenue), *CAPITAL* (capital), and *FAMILYEXPENSE* (family expenditure)

Table 3 shows the descriptive statistics of all variables used in this study, each consists of 500 observations. The dependent variable used is probability of default (*PD*) that has a value of 0 representing a non-default event and a value of 1 representing a default event. The second variable of this research is *PERIOD* (period of the loan), with values varied between 1 and 25. The standard deviation of this data is 6.27 with the mean of 6.68.

LOANSIZE (loan size) of this research ranges from IDR1,000,000 to IDR5,000,000 (USD 71 – USD 357). *OTHERLOAN* (other loan) is the dummy variable where 1 reflects having loan other than the one from YCAB and 0 for not having another loan. *BUSINESSYEARS* (business years) represents the length of business in years ranges between 0 to 40 years. *BUSINESSTYPE* (type of business) represents a dummy variable where 1 stands for permanent type of business and 0 for seasonal type of business. Around 12% of the businesses can be classified as permanent business.

The next variables are classified into financial variables that consist of *INCOME* (income of the family), *REVENUE* (revenue of business), *CAPITAL* (capital of the business), and *FAMILYEXPENSE* (total family expenses). The values of *INCOME* vary between IDR190,000 (USD 14) per week to IDR6,000,000 (USD 429) per week with the standard deviation IDR731,581 (USD 52); *REVENUE* ranges between IDR100,000 (USD 7) and IDR12,600,000 (USD 900) with a standard deviation of IDR998,361.2 (USD 71); *CAPITAL* ranges from IDR30,000 (USD 2) to IDR7,000,000 (USD 500); and *FAMILYEXPENSE* has a value from IDR20,000 (around USD 1) to IDR3,000,000 (USD 214).

4.2. Probit Estimation Test Results

Before performing the regression analyses, we first conduct a multicollinearity test among the independent variables. As shown in Table 4, the Variance Inflation Factors (VIFs) indicate that no multicollinearity is detected.

Table 4. Multicollinearity Test

	VIF	1/VIF
CAPITAL	4.60	0.2173
REVENUE	4.55	0.2197
PERIOD	1.68	0.5970
LOANSIZE	1.66	0.6029
BUSINESSYEARS	1.11	0.9006
INCOME	1.04	0.9621
BUSINESSTYPE	1.03	0.9664
FAMILYEXPENSE	1.03	0.9730
OTHERLOAN	1.01	0.9868
Mean	1.97	

Table 5. Probit Estimation

Variables	VCE (oim)	Mfx
PERIOD	0.0356**	0.0055**
	(0.0169)	0.0026
LOANSIZE	-5.42e-07***	-8.37e-08***
	(0.0000)	0.0000
OTHERLOAN	-0.4520	-0.0524065
	(0.5060)	0.0413
BUSINESSYEARS	0.0765***	0.01183***
	(0.0153)	0.0025
BUSINESSTYPE	0.0801	0.0129
	(0.2330)	0.0389
INCOME	2.81e-07***	4.35e-08***
	(0.0000)	0.0000
REVENUE	-1.02e-07	-1.58e-08
	(0.0000)	0.0000
CAPITAL	8.80e-08	1.36e-08
	(0.0000)	0.0000
FAMILYEXPENSE	6.71e-07*	1.04e-07*
	(0.0000)	0.0000
Constant	-1.232***	
	(0.2750)	

Number of observations	507	
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

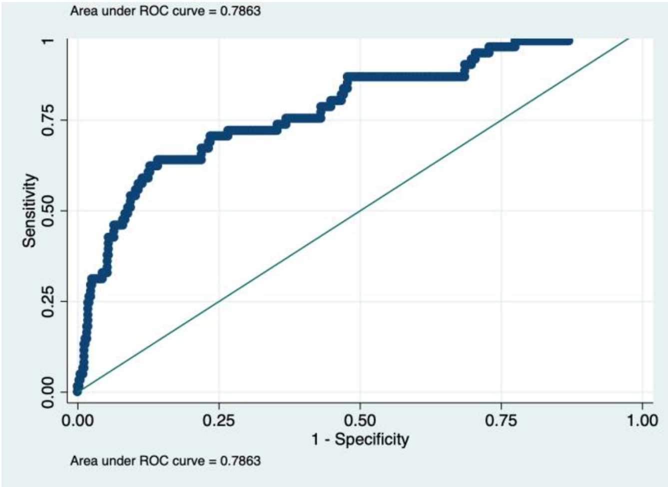
Table 5 shows how the independent variables influence the dependent variable. Based on the global test or what can be seen from the value of Prob> chi2, it can be shown that the statistical tests performed are significant with a value of 0.000. The effect of *PERIOD* on *PD* default of clients is positive significant at 5%. This means that period of loan affects the likelihood of a customer to default on their loan repayments for the ultramicro credit clients. Based on marginal effect (*mfx*) result, the increase of one period makes the probability of default increase by 0.5%

On the other hand, *LOANSIZE* has a negative effect on default probability at 1%. It means that an increase in *LOANSIZE* will decrease the likelihood of default probability. By marginal effect (*mfx*), we could say that if loan size increase by IDR1 then the probability of default will decrease by 0.000008%.

BUSINESSYEARS represent years of business that the customer has already operated. The result shows that *BUSINESSYEARS* has a positive effect at 1% level. It means that the longer the business has been operating, the higher the probability of default. An increase of one year business year leads to an increase of probability of default by 1.2%. The study shows that *INCOME* has positive significant influence on the probability of default. The last variable that has an influence on probability of default is *FAMILYEXPENSE*, which is significant at 10%. When *FAMILYEXPENSE* increases by IDR1, there is an increase in probability of default by 0.00000014%

The other four variables do not have any significant influence to determine *PD* of the ultramicro credit clients. There is no statistical evidence that *OTHERLOAN* might affect the *PD* of ultramicro credit clients. *BUSINESSTYPE* also does not have any significant statistical influence to predict *PD*. Both *REVENUE* and *CAPITAL* also do not significantly affect *PD* of ultramicro credit clients.

Figure 1. Area Under Curve (AUC)



To further examine the model's performance, we investigate the Area Under Curve (AUC) value. Figure 1 shows that AUC has a value of 0.7863, which means that the model in this study is sufficient to describe the determinants that can predict the probability of default on ultramicro credit clients (Yang et al., 2017). Based on Table 6, the category of area under curve is good, meaning that this model can reflect *PD*.

Table 7. Hosmer & Lemeshow Test

N	N group	Chi-square	Prob.
500	10	528.51	0.1053

Based on the Hosmer and Lemeshow test, which is one form of measurement of goodness-of-fit, the high p-value shows that, in other words, the condition does not significantly indicate that there is no difference between the observed and predicted frequencies. This test is widely used to assess the feasibility of the regression model and the goodness of fit of the model. A good model can be indicated by a chi-square value which is not significant (Hair et al., 1998). By conducting these tests, it can be concluded that the model was able to predict the value of its observations or it can be said that this model can describe both populations, namely actual data and predictive data, whilst having no difference in frequency.

4.3. Discussion and Managerial Implications

There are some important implications of the results above. Previous studies suggest that increasing the loan size and interest rates can increase the likelihood of default on borrowers (see for example: Stiglitz and Weiss 1981). This is also in line with the opinion of Abafita (2003), who found that payment failure can increase when the loan size increases. However, the regression result strongly disagrees with this hypothesis. It stipulates that the higher size of the loan to clients is associated with the repayment rate. This situation appears to be most unlikely because the amount to be repaid was relatively larger, and if the loan was from development-oriented institutions with subsidised interest rate and little chance of repeat loans, the pressure or inclination of such clients would be to delay repayment. It would be recalled that only 27.8% of respondents had benefited from repeat loans; therefore, this reinforces this argument. However, a plausible argument in favour of the result is that higher loans make larger investments possible with potentially higher absolute returns. These findings are evident as an increased amount of the size of a customer's loan may allow the time of payment to be longer and may lead to higher loan interest rates. The loan size ranging between IDR1,000,000 to IDR5,000,000 (USD 71 – USD 357) makes a significant effect to determine default probability.

On the other hand, a longer repayment period also gives the borrower space to feel that the dependents have not been completed, so this can lead to a default. Roslan and Abd Karim (2009) find that borrowers who have a longer repayment period are more likely to default. This is in contrast to the findings by Field and Pande (2008), who examined the relationship between payment frequency and payment performance in field trials. They randomised clients with weekly or monthly payment schedules and found no statistically significant relationship between the frequency of repayments and loan repayment performance.

Contrary to the expectation, a longer business operation, higher income and higher expenditure are associated with a higher probability of default. One possible explanation for these findings is poor financial management ability, which can be due to low financial literacy and attitudes related to financial behaviour. Financial literacy is defined by Atkinson and Messy (2012) as "*a combination of awareness, knowledge, skill, attitude and behaviour necessary to make sound financial decisions and ultimately achieve individual financial wellbeing*". Based on this definition, OECD (2016) shows that the overall level of financial literacy among Indonesians equals the average among the 30 countries participating in the survey. In addition, a previous study by Gathergood (2012) shows that lack of self-control, as well as low financial literacy, can lead to over indebtedness. These, of course, need further investigations in the case of YCAB Ventures' clients. However, the management can consider providing a financial education programme to increase clients' financial literacy. There is a need for a comprehensive strategy to address this issue, as one-time financial literacy program often only has a limited impact in improving one's financial behaviour (Bertrand, Mullainathan and Shafir, 2006).

5. Conclusion

This study aims to examine the performance of clients' loan repayments in the case of YCAB Venture, one of the ultramicro credit providers in Indonesia. Using a sample of 500 clients in Jakarta, Indonesia, and employing a probit model, the results of this study indicate that the period or tenor of loan, loan size, years of operating in business, income and family expense play a significant role in determining the probability of default. The other four variables, such as other loan, business type, revenue, and capital, have no significant influence in this study. In addition, the result shows that period, years of operating business, income and family expenses have positive and significant impacts in determining the probability of default. This means that the increased values of those three variables will increase probability of default in ultra-micro credit. Meanwhile, loan size shows differently. It has a negative result, which means that a bigger loan size will decrease probability of default. This might be due to staging that applies in the microfinance mechanism in Indonesia: clients who showed positive records of repayment will have the opportunity to access bigger loan size.

It should be noted that the model used to describe the incidence of default in this study, based on the ROC curve, showed an acceptable or medium result. This means that the model can be accepted as able to describe incidences of default; however, it still cannot predict the probability of default optimally. This is due to the limitation of data that can be processed to indicate the occurrence of default. In accordance with Lewis (1992), all variables that can help predict clients' failure to pay should be included in the credit scoring model. In terms of implementation, it is hoped that this research can provide inputs to ultramicro credit players to regulate the composition of the right group by diversifying the risk of default within each group.

References

Abafita, J. (2003). *Microfinance and loan repayment performance: A case study of the Oromia Credit and Savings Share Company (OCSSCO) in Kuyu'* (Unpublished MSc thesis). Addis Ababa University, Addis Ababa.

Abid, L., Masmoudi, A., & Zouari-Ghorbel, S. (2016). The consumer loan's payment default predictive model: an application of the logistic regression and the discriminant analysis in a Tunisian commercial bank. *Journal of the Knowledge Economy*, *9*(3), 948–962.

Adanu, K., & Boateng, E. (2015). Predicting loan repayment default among second tier borrowers in Ghana. *International Journal of Entrepreneurship and Small Business*, *24*(3), 417-432.

Aghion, D. A., & Morduch, J. (2000). Microfinance beyond group lending. *Economics of Transition and Institutional Change*, *8*(2), 401-420.

Altman, E.I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4), 189–209.

Altman, E., Hartzell, J., & Peck, M. (1995). *Emerging Markets Corporate Bonds: A Scoring System*. New York: Salomon Brothers Inc.

Atkinson, A., & Messy, F-A. (2012). *Measuring financial literacy: Results of the OECD INFE Pilot Study* (OECD Working Papers on Finance, Insurance and Private Pensions, No. 15). Paris: OECD Publishing.

Baesens, B., Verbeke, W., Sercu, P., & Gool, J.V. (2011). Credit scoring for microfinance: Is it worth it? *International Journal of Finance nd Economics, 7*(2), 103–23.

Bertrand, M., Mullainathan, S., & Shafir, E. (2006). Behavioral economics and marketing in aid of decision making among the poor. *Journal of Public Policy & Marketing*, *25*(1), 8–23.

Brown, K., & Moles, P. (2016). *Credit Risk Management (4^{th} ed.)*. Edinburgh: Edinburgh Business School.

Bumacov, V., Ashta, A., & Singh, P. (2014). The use of credit scoring in microfinance institutions and their outreach. *Strategic Change*, 23(7-8), 401-413.

Calcagnini, G., Farabullini, F., & Giombini, G. (2009). Loans, Interest Rates and Guarantees: Is There a Link? (ECB Working Paper). Frankfurt: European Central Bank.

Chien, Y., & Devaney, S.A. (2001). The effects of credit attitude and socioeconomic factors on credit card and installment debt. *The Journal of Consumer Affairs*, *35*(1), 162-79.

Durand, D. (1941). *Risk Elements in Consumer Instalment Financing*. New York: National Bureau of Economics Research.

Dinh, T.H.T., & Kleimeier, S. (2007). A credit scoring model for Vietnam's retail banking market. *International Review of Financial Analysis*, *16*(5), 471–95.

Dunn, L.F., Kim, T. (1999). An Empirical Investigation of Credit Card Default' (Ohio State University working paper). Columbus: Ohio State University.

Emekter, R., Tu, Y., Jirasakuldech, B., & Lu, M. (2015). Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) Lending. *Applied Economics, 47*(1), 54–70.

Field, E., & Pande, R. (2008). Repayment frequency and default in microfinance: Evidence from India. *Journal of the European Economic Association*, *6*(2-3), 501-509.

Gan, C., Li, Z., Wang, W., & Kao, B. (2012). Credit scoring in mortgage lending: Evidence from China. *International Journal of Housing Markets and Analysis, 5*(4), 334–350.

Gathergood, J. (2012). Self-control, financial literacy and consumer over-indebtedness. *Journal of Economic Psychology*, *33*(3), 590–602.

Gestel, T.V., & Baesens, B. (2008). *Credit Risk Management Basic Concepts: Financial Risk Components, Rating Analysis, Models, Economic and Regulatory Capital*. Oxford: Oxford University Press.

Hair, J.F.J., Anderson, R.E., Tatham, R.L., & Black, W.C. (1998). *Multivariate Data Analysis, 5th Ed.* Upper Saddle River, New Jersey: Prentice Hall.

Hand, D.J., & Jacka, S.D. (1998). *Statistics in Finance*. London: Arnold.

Jacobson, T., & Roszbach, K. (2003). Bank lending policy, credit scoring and value-at-risk. Journal of Banking & Finance, *27*(4), 615–633.

Jime´neza, G., Salasa, V., & Saurina, J. (2006). Determinants of collateral. *Journal of Financial Economics*, *81*(2), 255-81.

Kocˇenda, E., & Vojtek, M. (2009). *Default predictors and credit scoring models for retail banking*

(CESIFO working paper). Prague: CESIFO.

Kwasi-Peprah, W., Agyei, A., & Oteng, E. (2017). Ranking the 5C's of credit analysis: Evidence from Ghana banking industry. *International Journal of Innovative Research and Advanced Studies, 4*(9), 78-80.

Lassoued, N. (2017). What drives credit risk of microfinance institutions? International evidence. *International Journal of Managerial Finance*, *13*(5), 541–559.

Lewis, E.M. (1992). *An Introduction to Credit Scoring, 2nd Ed.* San Raphael, CA: Fair, Isaac and Co.

Limsombunchai, V., Gan, C., & Lee, M.S. (2005). An analysis of credit scoring for agricultural lands in Thailand. *American Journal of Applied Sciences*, *2*(8), 1198-205.

Maldonado, S., Peters, G., & Weber, R. (2020). Credit scoring using three-way decisions with probabilistic rough sets. *Information Sciences*, 507, 700-714.

Mokhtar, S.H., Nartea, G. & Gan, C. (2012). Determinants of microcredit loans repayment problem among microfinance borrowers in Malaysia. *International Journal of Business and Social Research*, *2*(7), 33-45.

OECD (2016). *OECD/INFE International Survey of Adult Financial Literacy Competencies*. Paris: OECD Publishing.

Ojo, O., & Ighalo, J.I. (2008). Factors affecting borrowers' choice of housing loan package in Southwestern Nigeria. *Housing Finance International*, *23*(2), 38-43.

Onyeagocha, S.U.O., Chidebelu, S.A.N.D., & Okorji, E.C. (2012). Determinants of repayment of loan beneficiaries of microfinance institutions in Southeast States of Nigeria. *International Journal of Agricultural Management and Development*, *2*(3), 167-175.

Pregibon, D. (1980). Goodness of link tests for generalized linear models. *Applied Statistics*, *29*(1), 15-24.

Quercia, R.G., & Stegman, M.A. (1992). Residential mortgage default: A review of the literature. *Journal of Housing Research*, *3*(2), 341-79.

Roslan, A.H., & Karim, M.Z.A. (2009). Determinants of microcredit repayment in Malaysia: The case of Agrobank. *Humanity & Social Science Journal*, *4*, 45-52.

Schreiner, M. (2000). Credit scoring for microfinance: Can it work? *Journal of Microfinance*, *2*(2), 105–118.

Schreiner, M. (2004). Scoring arrears at a microlender in Bolivia. *Journal of Microfinance*, *6*(20), 65–88.

Stiglitz, J.E., & Weiss, A. (1981). Credit rationing in markets with imperfect competition. *American Economic Review*, *71*(3), 393-410.

Thomas, L.C., Edelman, D.B., & Crook, L.N. (2002). *Credit Scoring and Its Applications*. Philadelphia, PA: Society for Industrial and Applied Mathematics.

Vogelgesang, U. (2003). Microfinance in times of crisis: The effects of competition, rising indebtness, and economic crisis on repayment behavior. *World Development*, *31*(12), 2085–2114.

Wachira, A.K. (2017). Effects of credit risk management practices on loan performance of commercial banks in Nyeri County, Kenya. *European Journal of Economic and Financial Research*, *2*(2), 1-12.

Wang, W. (2010). The Probability of Chinese Mortgage Loan Default and Credit Scoring (Lincoln University working paper). Lincoln, New Zealand: Lincoln University.