The Demographic and Behavior Determinant of Credit Card Default in Indonesia

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Abstract

The purpose of this paper is to analyze the demographic and behavioral factors that significantly affect the credit card Non-Performing Loan (NPL). This study is carried out to provide managerial recommendations for controlling credit card NPL. This study uses secondary data from Indonesia's most significant private bank with 100,000 samples of cardholder data. Demographic factors and cardholder behavior that significantly influence credit card NPL can be used to improve the credit scoring system for new cardholders and as indicators for a behavior scoring system for existing cardholders. This research uses a probability stratified random sampling technique. Logistic regression uses demographic factors and cardholder behavior significantly affected credit card NPL. According to the logistic regression model, cardholder behavior was more likely to NPL than demographic characteristics. The number of credit cards showed the highest credit card NPL probability.

Keywords:

credit card, behavior, demographic, logistic regression model, non-performing loan

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INTRODUCTION

Indonesia is a developing country with the fourth largest population in the world (2,642 million in December 2018). Indonesia has a demographic bonus where the economic productive population is 68% of the total population. Indonesia will experience a demographic bonus up to 2045. Furthermore, in December 2018, household consumption was still the main pillar of national economic growth. The composition of household consumption in 2018 was 55.7% of Gross Domestic Product (GDP). Household consumption expenditure in the fourth quarter of 2018 grew 5.08% compared to 2017. Thus, the dominance of the productive age population will push household consumption even higher in the coming years. This condition strengthens Indonesia as a potential emerging market economy and a place for investment.

One of the prospective businesses in Indonesia is credit cards, as indicated by the number of credit cardholders, which is low compared to the productive age population in Indonesia (9,53% in December 2018). In addition, the number of cards and credit card transaction values from 2014-2018 experienced growth (Figure 1). In 2019 there were 25 credit card issuers, consisting of banks and non-bank financial institutions (Central Bank of Indonesia, 2019). The number of credit card issuers has increased compared to 2005 (17 issuers).

Figure 1. Number of Credit Card and Transaction Values

Credit cards make it easy for cardholders to make payments for purchases made. Cardholders do not need cash, and the credit card issuer makes payment transaction purchases first. Cardholders are obliged to pay off the issuer at the agreed time, either immediately or in installments. Credit cards also make it easy for cardholders to withdraw cash from an ATM (Automated Teller Machine). In addition, according to the Central Bank of Indonesia (BI) regulation No. 18/33/DKSP reduced the maximum limit on credit card interest rates from 2.95% to 2.25% per month since 2 December 2016. This will ease the burden on cardholders when bill payments are not made in full. Credit cards are unsecured consumer loans offered by banks (Wilson, 2007). This indicates the bank

will have a greater percentage of losses than other types of credit if a borrower defaults. Therefore, growth of credit card business must be balanced with good credit quality.

According to Central Bank of Indonesia (BI) regulation No. 14/15/PBI/2012, bank credit quality is grouped into five areas, consisting of current (L), special attention (DPK), substandard (KL), doubtful (D), and bad (M). Credit quality can be measured using a Non-Performing Loan (NPL), which is the ratio of outstanding loans that are substandard, doubtful, and bad to a total loan. Therefore, NPL can reflect credit default risk. According to the description above, it is important for banks to understand the factors that affect credit card NPL. By understanding the factors that influence the level of NPL, credit quality and bank soundness can be maintained, so that the growth of the credit card business can provide long-term benefits for banks.

Wang et al. (2011) showed that only three factors significantly influenced credit card quality (demographics, behavior, and cardholder personality). According to Agarwal et al. (2011), the factors that significantly influence credit card quality are marital status, homeownership, and urbanization. Furthermore, Bellotti and Crook (2013) showed that these three factors had a significant effect on the credit card quality of cardholders through variables of occupation, age, income, the number of credit cards, the ratio of payment to bills, transaction frequency, and credit limit. Kiarie (2015) showed that homeownership and age significantly affected credit card quality. In addition, Porto et al. (2017) showed that cardholders who live in rural areas have a greater probability of delaying payment/not full payment than cardholders who live in urban areas. Li et al. (2019) studied factors that affect the quality of credit cardholders by using demographics and cardholder behavior. The results showed that factors that significantly influenced the credit quality of cardholders were gender, age, marital status, type of transaction, transaction frequency, and nominal per transaction. One study on factors affecting credit card defaults in Indonesia has been conducted by Sayono et al. (2009) and showed variables like gender, marital status, and income increased the probability of credit card defaults.

Table 1. Growth of Card Number, Transaction Value, and Outstanding Credit Card (2014 – 2018)

	Growth (%)					Average (%)
	2014	2015	2016	2017	2018	
Number of Card						
National	6.31	5.11	3.22	-0.93	0.18	2.78
Bank	5.09	6.39	8.55	10.49	9.50	8.00
Transaction Value						
National	14.19	9.99	0.17	5.96	5.55	7.17
Bank	17.90	9.76	6.13	13.41	14.45	12.33
Outstanding						
National	22.57	12.0	7.16	4.63	1.38	9.55
Bank	18.35	8.10	13.71	6.96	11.80	11.78

Some previous studies have been conducted to examine the factors that significantly affect the credit quality of credit cards. This study uses secondary data obtained from the biggest private bank in Indonesia with average card growth, transaction value, and outstanding credit cards above the national average (Table 1). Various diverse emerged, but several commonalities were found, such as the demography and behavior of cardholders. The difference between this study and previous studies lies in the variables, data collection, and analysis methods. This study uses a complete variable by combining demographics and cardholder behavior so that it is expected to get more comprehensive results.

Figure 2: NPL Credit Card and Total Credit Bank

The purpose of this study is to analyze the demographic and behavioral factors that significantly affect the credit card Non-Performing Loan (NPL). Furthermore, from 2014 to June 2019, the trend of credit card NPL has increased and is always higher than the NPL of total credit banks (Figure 2). This study is carried out to provide managerial recommendations for controlling credit card NPL. Our results are also expected to enrich the existing literature on credit card products.

METHODS

Analyses of demographic factors and cardholder behavior were conducted by taking a sample of the cardholder data population as of June 2019. The sampling method used probability sampling with a stratified random sampling technique. The total sample used was 100,000 cardholders spread over each island in Indonesia. Variables were grouped into two categories that describe demographic factors and cardholder behavior. Types and definitions of variables are shown in Table 2.

This research is using logistic regression to determine demographic factors, social status, and cardholder behavior that significantly influenced cardholder NPL. Logistic Regression was chosen to examine the effect of independent variables on dependent variables that consists of two or more categories (Firdaus et. al., 2011). Press and Wilson

(1978) state that the advantages of logistic regression is that it does not require the assumption of normality of the independent variable, meaning the independent variable must not have a normal distribution. Categorical independent variables tend not to be normally distributed (Halperin et al., 1971). Logistic regression can be used to analyze independent variables that are continuous, discrete, and dichotomous (Kuncoro, 2005). Firdaus et al. (2011) added that logistic regression is not required to fulfil the non-multicollinearity and the size of each group does not have to be the same.

Table 2. Type and Definition Variables

Factors	Type of Variables	Variables	Variables Definition
Demographic	Independent	<ul style="list-style-type: none"> • Age • Gender • Education • Occupation • Income • Residential Area 	Year Male; Female Under/Graduate/Post; Non-Under/Graduate/Post Self Employed; Non-Self Employed ≤ 10 million; > 10 million (Rupiah) Java; Non-Java
		<ul style="list-style-type: none"> • Marital Status • Home Ownership Status 	Married; Single/Widow/Widower Own; Not Own
Behavior	Independent	<ul style="list-style-type: none"> • Bill to Income Ratio • Bill to Credit Limit Ratio • Payment to Bill Ratio • Credit Limit to Income Ratio • Cash Advance Frequency • Number of Card • Credit Limit 	Percent Percent Percent Percent Average per Month Card < 20 Million; ≥ 20 Million (Rupiah)
		Dependent	Non-Performing Loan NPL; Non-NPL

The logistic regression model for demographic factors, social status, and cardholder behavior that affect cardholder NPL was as follows:

$$\text{Logit}(Y_i) = \alpha + \beta_1 X_{1i} + \dots + \beta_n X_{ni} + \varepsilon_i \quad (1)$$

Where:

Y = Independent Variable

X = Dependent Variable

α = Constant

β = Dependent Variable Coefficient

ε = Error

i = Cardholder

RESULT AND DISCUSSION

The estimation results of the logistic regression model consist of 12 independent variables (Table 3). An omnibus test of model coefficient shows Chi square statistics with a significance level ≤ 0.05 , meaning there is a significant influence of the independent variables simultaneously on the dependent variable. A Nagelkerke R square of 65.5%, meaning that the ability of independent variables to explain the dependent variable is 65.5%. The percentage correct classification value is 98% and above Cpro (93.84%), which shows that the model has good predictive accuracy.

The independent variable that partially affects the credit card NPL can be seen from the Wald Test results with a significance level ≤ 0.05 . Based on the Wald Test results, demographic factors that significantly affect the credit card NPL consist of age, gender, education, occupation, and residential area. Cardholder behavior factors that have a significant influence on credit card NPL are Payment to Bill (RP) Ratio, Ratio of Bill to Limit Credit (RL), Cash Advance Frequency (CA), Number of Credit Cards, and Credit Card Limit. Exp (B) of each variable on the cardholder behavior factor is greater than the demographic factor. This shows that cardholder behavior factors have a higher probability of influencing credit card NPL than demographic factors.

Table 3. Logistic Regression Estimation Result

Variables	Coefficient	Wald Test		Exp (B)
		Values	Sig.	
Gender (Male)	0.383	54.837	0.000	1.466
Marital Status (Single/Widow/ Widower)	0.016	0.065	0.798	1.016
Education (Non-Undergraduate)	0.442	73.717	0.000	1.556
Occupation (Self Employed)	0.269	18.472	0.000	1.309
Residential Area (Java)	0.405	23.968	0.000	1.499
Income (≤ 10 million)	-0.098	2.525	0.112	0.907
Credit Limit (≥ 20 million)	-0.415	18.571	0.000	0.661
Age	-0.032	83.385	0.000	0.969
Number of Card	-4.879	3,471.649	0.000	0.008
Payment to Bill Ratio	-4.233	1,148.232	0.000	0.015
Cash Advance Frequency	-0.555	95.109	0.000	0.574
Bill to Credit Limit Ratio	1.122	158.076	0.000	3.071
Constant	5.656	593.204	0.000	285.951
Model Goodness Test				
<i>Omnibus Test of Model Coefficient (Chi-square Statistic = 1,7519.937; Sig. = 0.000)</i>				
<i>Nagelkerke R Square = 65.5%</i>				
<i>Percentage Correct Classification = 98%; Cpro = 93.84%</i>				

Age has a negative coefficient, meaning that young cardholders tend to have a higher probability of NPL. This condition is in line with the results from Kim (2000), Stavins (2000), Muthomi (2005), Nyamongo (2011), Bellotti and Crook (2013), Wang et al. (2014), Kiarie et al. (2015), Huang (2018), Kim et al. (2018), and Li et al. (2019). Based on Figure 3, the percentage of the number of NPL cardholders compared to the total cardholders continues to increase with the younger age group. Conversely, the percentage of non-NPL cardholders continued to decline compared to total cardholders by age category.

Figure 3. Percentage of Non-NPL and NPL Cardholders by age category

Figure 4 shows the relationship between age categories and cardholder income. The figure shows that the younger age category has a lower income than the older age category. Young cardholders have a higher probability of NPL because their cardholder income is still low, while the desire of young cardholders to try new things is very high.

Figure 4. Credit Limit and Income of Non-NPL and NPL Cardholders by Age Category

Male has a positive coefficient, so males tend to show a higher probability of NPL than females. This condition is in line with the results from Muhmin and Umar (2007), Muchiru (2008), Sayono (2009), Wang et al. (2014), Chin et al. (2017), Huang (2018), Kim et al. (2018), Li et al. (2019). Based on the sample, 60.09% of the NPL cardholders are male. Table 4 shows that the male NPL cardholders are not yet financially secure (61.29% income $\leq$ 10 million) and must provide family support (61.45% are married). The level of education of most non/under/postgraduates (54.79%) makes it difficult to pursue a career at a higher level (70.30% of cardholders with non-self-employed). Cardholders mostly live in Java (90.52%), especially in the regions of DKI Jakarta, West Java, and Banten, so they have a higher expenditure level than other regions.

Table 4. Characteristics of Male NPL Cardholders

Male	NPL	
	Number of Cardholder	%
Age		
12-25	181	9.48
26-35	818	42.85
36-45	557	29.18
46-65	349	18.28
> 65	4	0.21
Education		
Under/Graduate/Post	863	45.21
Non Under/Graduated/Post	1,046	54.79
Occupation		
Self Employed	567	29.70
Non-Self Employed	1,342	70.30
Income (Rupiah)		
$\leq$ 10 Million	1,170	61.29
3 - 5 Million	713	60.94
> 5 - 10 Million	457	39.06
> 10 Million	739	38.71
Residential Area		
Java	1728	90.52
Non-Java	181	9.48
Marital Status		
Married	1,173	61.45
Single/Widow/Widower	736	38.55
Home Ownership Status		
Own	734	38.45
Not Own	1,175	61.55
TOTAL	1.909	

Non-under/graduate/post education has a positive coefficient. This shows that cardholders with a non-under/graduate/post level of education have a higher probability of NPL than a cardholder with a level of under/graduate/post education. This condition is in line with the results of study by Stavins (2000), Norvilitis & Maria (2002), Muhmin & Umar (2007). Based on Table 5, non-under/graduate/post education NPL cardholder are mostly non-self-employed (70.44%), married (59.92%), living in Java (92.72%), and do not yet have their own home (64.81%). The level of non-under/graduate/post education makes it difficult for cardholders with non-self-employed status to pursue a career at a higher level, give their married status, cost of living in Java, and not yet owning a home, which causes higher cardholder spending, while most of the income is between IDR 3-5 million (68.02% of income $\leq$ 10 million).

Self-employed status is a positive coefficient. This shows that self-employed individuals have a higher NPL probability than cardholders with non-self-employed status. This condition is in line with results from Muthomi (2005), Muchiru (2008), Bellotti and Crook (2013), Leow & Crook (2014), and Warnakulasuriya (2016). Living in Java has a positive coefficient value. This shows that cardholders who live in Java have a higher NPL probability than cardholders who live in other areas. This condition is in line with the results from Porto et al. (2017) and Kim et al. (2018), which state that the area of residence affects the probability of NPL.

Table 5. Characteristics of Non-Under/Graduate/Post NPL Cardholders

Non-Under/Graduate/Post	NPL	
	Number of Cardholder	%
Occupation		
- Self Employed	520	29.56
- Non-Self Employed	1,239	70.44
Income (Rupiah)		
$\leq$ 10 million	1,229	69.87
3 - 5 million	836	68.02
> 5 - 10 million	393	31.98
> 10 million	530	30.13
Residential Area		
Java	1,631	92.72
Non-Java	128	7.28
Marital Status		
Married	1,054	59.92
Single/Widow/Widower	705	40.08
Home Ownership Status		
Own	619	35.19
Not Own	1,140	64.81
TOTAL	1,759	

The payment to bill ratio (RP) is a negative coefficient, meaning low RP will increase the probability of NPL cardholders. This condition is in line with the results from Stavins (2000), Muthomi (2005), Muchiru (2008), Zhao et al. (2009), Bellotti & Crook (2013), and Warnakulasuriya (2016). Bill to credit limit ratio (RL) has a positive coefficient, meaning high RL will increase the probability of NPL cardholders. This condition is in line with the results from Kim (2000), Muthomi (2005), Muchiru (2008), Zhao et al. (2009), Nyamongo (2011), and Wang et al. (2014).

Cash Advance (CA) frequency has a negative coefficient, so low CA will increase the probability of NPL cardholders. This condition differs from Muthomi (2005), Muchiru (2008), and Zhao et al. (2009), who all showed that a high CA frequency would increase the probability of NPL. This condition can occur because of differences in cardholder behavior, regulator policies in each country, and credit card provisions in each bank. According to BI regulation No. 17/51/DKSP/2015, the maximum CA limit per day through an ATM is IDR 10 million (magnetic stripe card) and IDR 15 million (chip card). Banks apply a maximum CA limit of 40% of the credit limit with a minimum nominal limit per CA of IDR 100,000. The maximum percentage of the credit limit related to cash withdrawal transactions means that cardholders who do not pay off their credit card bills will not be able to perform CA if they have reached the maximum limit. Thus, cardholders who pay bills tend to have higher cash advance transaction frequencies than cardholders who do not pay credit card bills.

The number of credit cards has a negative coefficient, so a low number of credit cards will increase the probability of NPL cardholders. This condition is consistent with a study by Bellotti & Crook (2013). Banks tend not to approve the addition of credit cards to cardholders who make partial payments or have a history of late payments. Therefore, cardholders have a slight chance of getting more credit cards than cardholders who always make total payments.

Figure 5. RP and RL of Non-NPL and NPL Cardholder based on Limit Credit Categories

Credit card limit has a negative coefficient, so cardholders with a credit card limit greater than IDR 20 million have a higher NPL probability than cardholders with a lower limit. This result is supported by previous work from Muchiru (2008), Bellotti and

Crook (2013), and Gui (2019). Banks tend not to approve the addition of a credit limit to cardholders with a low payment to bill (RP) ratio and a high bill to credit limit (RL) ratio. Figure 5 shows that both Non-NPL and NPL cardholders with credit limits less than IDR 20 million have low RP and high RL compared to credit limits over IDR 20 million.

Based on the study result above, there are managerial implications that can be used by banks when making decisions. Banks can use demographic characteristics to increase credit card NPL probabilities to improve current credit card feasibility analysis indicators. In addition, banks need to consider using cardholder behavior indicators in credit scoring. This indicator is necessary because cardholder behavior factors have a higher probability of influencing credit card NPL than demographic factors. The behavior can be identified by several questions added to the credit card application form. Banks can validate the answers of prospective cardholders by confirming with other banks (bank checking) where the prospective cardholder has an existing or prior credit card.

Banks can also control NPL by selecting credit cards to customers (depositors) who do not have credit cards. The criteria for selecting potential customers can use demographic characteristics that significantly affect the credit card NPL based on the results of this study. Specifically, banks can use indicators that increase the probability for non-NPL cardholders. Banks can use SMS, email, or push notifications on Internet banking sites and mobile banking apps to inform selected customers. Interested customers can immediately confirm without filling out a credit card application form because the bank already has the customer's data. This condition will improve customer experiences and satisfaction with the bank. In addition, this mechanism will provide efficiencies (reduce bank operational costs) such as telemarketing fees, telephone costs, and printing costs for credit card application forms.

Behavior scoring reflects each cardholder's risk level based on indicators of demographic characteristics and behavior used. Bank can use demographic characteristics and cardholder behavior that significantly influences the credit card NPL as an indicator of behavior scoring for cardholders. Behavior scoring can be used as an early warning indicator of NPL opportunities from each cardholder so that banks can anticipate activity before the unpaid bills increase. Anticipatory actions that can be taken include reducing the use of credit card limits below 100%. In addition, banks can also offer installment features to cardholders with low behavior scoring (risk of default) to ease the payment process and maintain good credit cardholder quality.

Furthermore, banks can use behavior scoring to increase credit card portfolios and customer engagement by automatically increasing credit limits for cardholders with high (good) scoring. Behavior scoring can also be used as a reference to approve requests for temporary or permanent credit limit increases and credit card additions. This scoring will speed up the decision on the cardholder's request. In the current era of digitalization, banks can maximize behavior scoring to make decisions on requests for temporary or permanent credit limit increases and the addition of credit cards through mobile banking or internet banking. This action can speed up the process and reduce labor and other operational costs compared to the current credit card processing methods.

Banks can control credit card NPL through credit card promotions offered to cardholders. Currently, a bank's promotion program is based on the type of credit card and the need of the cardholder to increase the volume of the credit card transaction. Identification of needs can analyze previous cardholder transactions (event-based marketing). However, this promotion process does not consider the demographic characteristics and behavior of cardholders who have a probability of NPL. Therefore, a bank can use both factors when choosing the correct cardholder as a credit card promotion target. Thus, business targets can be achieved, and credit card NPL can also be controlled.

CONCLUSION

According to the logistic regression model, young cardholders, male, non-under/graduate/post-education, self-employed, and living in Java all increase probability of cardholder NPL. Cardholder behavior provides a higher likelihood of NPL than demographic characteristics. Cardholder behaviors that increase the likelihood of NPL are a low payment to bill (RP) ratio, high bill to credit limit (RL) ratio, low frequency of cash advance, low number of credit cards, and credit card limits < IDR 20 million. The number of credit cards shows the highest NPL probability.

Based on the results of this study, there are managerial implications that banks can use when making decisions. Demographic characteristics and cardholder behavior that significantly influence credit card NPL can improve the feasibility analysis tools for new cardholders (credit scoring system) and as indicators of behavior scoring systems for existing cardholders. Banks can maximize behavior-scoring systems to automatically increase credit limits for selected cardholders and provide automatic approval of requests to increase credit limits temporarily or permanently. Banks can also control NPL by offering credit cards selectively to existing customers who do not have credit cards and offering selective promotion programs based on demographic characteristics and behavior that significantly affect credit card NPL based on the results of this study. The consumer can add Credit cards through mobile banking and Internet banking.

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