Probability of Default (PD) per Province to Estimate a More Granular Impairment Credit Loss for Bank ABC

Mompo Octaria Tambunan[1], Dewi Hanggraeni[2]

Fakultas Ekonomi dan Bisnis, Universitas Indonesia[1], FEB Universitas Pertamina dan FEB Universitas Indonesia[2]

{mompo.octaria@gmail.com[1], dewi.hanggraeni@ui.ac.id[2]}

Abstract. This paper aims to provide a more granular approach to the Probability of Default (PD) modeling process following the International Financial Reporting Standard (IFRS) 9 framework by calculating PWD credits per province at ABC Bank. The PD model will be formed using a transition matrix and multiple regression analysis, using historical credit data on Bank and macroeconomic factors for 2013-2020. The results showed that inter-provincial PD credit at ABC Bank resulted in more granular PWD credit than the model without provinces. The new model develops a smaller and actual impairment according to conditions in the province. Based on this analysis, the Bank can determine its expansion strategy in the future, namely channeling credit to regions with small PD.

Keywords: IFRS 9, Probability of Default, Granular, Transition Matrix, Regression Model.

1 Introduction

In Indonesia, the mandatory implementation of new financial standards that refer to IFRS 9 starting January 1, 2020, has significantly impacted the banking industry at various levels, particularly in recognizing impairment for financial assets in bank balance sheets. Indonesian Banking Statistics (IBS) record that the total impairment of conventional banks in Indonesia increased by 180% in the fourth quarter of 2020 compared to the fourth quarter of 2019 before this regulation was implemented [1].

This significant increase in impairment has a direct impact on the Bank's income statement because the impairment will be used as a deduction from profit in the financial statements. For example, ABC Bank's 2020 financial report reported a decrease in profit due to an impairment listing of almost 38% of its total operating costs.

The new standard introduced a paradigm shift in impairment based on "losses incurred" to one based on Expected Credit Loss (ECL). IFRS 9 stipulates that an estimate of credit losses must include not only information that is past due but also forward-looking. In this case, the observed

ICONIC-RS 2022, March 31-April 01, DKI Jakarta, Indonesia

DOI 10.4108/eai.31-3-2022.2320969

past default rate must be adjusted for changes in macroeconomic variables. For many entities, impairment is the most significant change (with the highest impact) [2].

IFRS 9 is a more principles-based standard; therefore, it defines broad guidelines and does not define a specific methodological approach in most cases. IFRS 9 requires that the model approach be granular and dynamic in the portfolio segmentation process. Because of this approach, the actual implementation method is the responsibility of each bank. Referring to that, until now, Banks are still looking for a model that fits their loan portfolio.

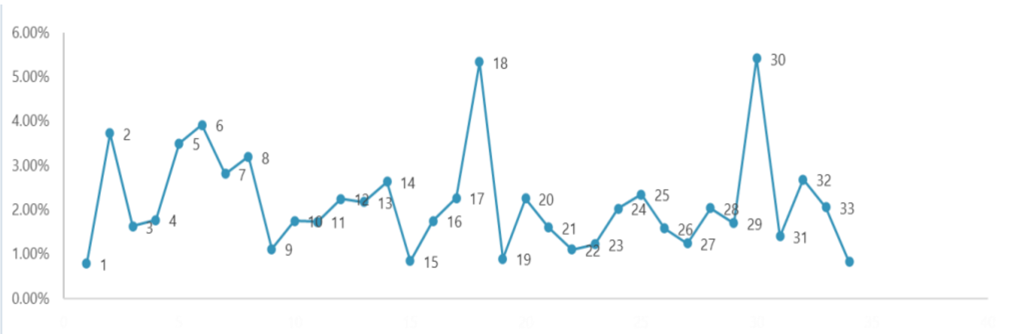
The expected credit loss (ECL) model is at the center of the new approach for the impairment accounting of financial instruments. This model comes along with the need for quantitative modeling of its input parameters, which are the probability of default (PD), the exposure at default (EAD), and the Loss Given Default (LGD). Academia and practitioners from various research areas were fast to propose various modeling approaches to comply with the principles defined by the standard setter.

Bank ABC currently has an ECL model calculated based on segment groups and credit products. However, considering that Bank ABC operates in Indonesia, which has scattered provinces, and the characteristics of non-performing loans are different for each region,

Bank ABC currently has an ECL model calculated only based on segment groups and credit products. However, considering Bank ABC, which operates in 33 provinces of Indonesia with different economic levels, grouping based on segment and product is not enough; it is necessary to consider regional factors to obtain granular figures according to IFRS 9.

The following table will present the distribution of Non-Performing Loan bank ABC by province.

Graph 1. ABC Bank Non-Performing Loans (%) in 33 provinces:



There is room for changes to the ABC bank's impairment model from graph 1. To obtain a more granular and dynamic impairment following IFRS9, we can convert an existing model into a new, more granular model by adding customer groupings by province.

Considering that 80% of Bank ABC's loan portfolio is financing for the micro-segment, this research will be limited to one of the Micro products at Bank ABC.

The main contributions of this article are threefold:

1. Propose an ECL calculation scheme using PD formed according to risk groups per Province.

2. This study will show the differences between the PD currently used by the Bank and estimates from the model by Province.
3. Credit risk managers can use this study to make accurate ECL calculation decisions to prevent the Bank from unstable Income Statements or the allocation of too large amounts in impairment.

2 Literature Review

2.1 Credit Risk

Basel Committee on Banking Supervision [3] defines credit risk as "the potential that a bank borrower or counterparty will fail to meet its obligations under agreed terms." It is usually associated with loans and securities that generate interest income, thus being the primary source of bank revenue.

The increase in credit risk is an assessment of changes in the possibility of default, namely by comparing the initial credit risk of a financial instrument with the credit risk at the reporting date. Suppose the increase in a credit rating is considered significant. In that case, the expected credit loss value calculation will be carried out over the remaining life of the financial instrument. The average percentage of a debtor defaulting in a certain period is called the probability of default [4].

To anticipate losses due to the debtor's failure to fulfill its obligations, the Bank determines impairment which is calculated based on the actual and current conditions of the debtor. The formation of impairment must refer to the disclosure standards set by the regulator. Currently, the reference standard refers to IFRS 9.

2.2 IFRS 9

IFRS 9 requires banks to estimate impairment for each loan and establish appropriate provisions. The new standard requires various ECL measures for loans classified into three progressively different default risk groups compared to the initial default risk when the loan is issued. Table 1 provides a summary of the structure of the IFRS 9 bucket.

Table 1. ECL calculation criteria for loans, relative to their IFRS 9 classification.

IFRS 9	Loan Type	ECL
bucket 1	performing	one-year
bucket 2	underperforming	lifetime
bucket 3	impaired	lifetime

ECL is estimated over one year for loans in bucket 1 when the obligor is generally "good credit" relative to their initial credit quality and is therefore considered a performing loan in this case. IFRS 9 bucket 2 is an underperforming loan that has experienced a significant increase in credit risk since initial recognition. Furthermore, loans with decreased value so that banks experience credit losses are classified in bucket 3.

The expected credit loss (ECL) model is at the center of the new approach for the impairment accounting of financial instruments.

2.3 Expected Credit Loss Model

The general formula for impairment estimation is as follows EY:

$$Expected\ Loss = EAD_t \ x\ PD_t \ x\ LGD_t. \qquad (1)$$

Where:

- EADt: represents the Exposure at Default at time t. This is the entity’s risk exposure at the time of default.
- PDt: represents the Probability of Default at time t.
- LGDt: represents the Loss Given Default at time t. LGD is calculated as 1 minus the expected recovery rate.

The focus of this article is on PD modeling. The LGD and EAD values that will be used in the ECL calculation are the current bank's existing numbers.

2.4 Probability of Default Micro Credit

According to Pindyck, Rubinfeld [5], macroeconomics is a branch of economics that deals with economic aggregate variables, such as the rate and average growth of national production, unemployment, interest rates, and inflation. According to Caro [6], macroeconomic variables which can affect the performance of the Micro Finance Institution are the growth of GDP, the unemployment rate, inflation, and investment from abroad. Louzis and Vouldis [7] conducted another study related to the effect of macroeconomic variables on NPL. Their results state that a deteriorating economic development of a country could increase banking's bad credit. Similarly, when a country's economy improves, the level of bad credit decreases.

In IFRS, there are two values of PD:

1. Point-in-Time PD (PiT PD): The possibility of a debtor or group of debtors defaulting on a certain date.
2. Through-the-Cycle PD (TtC PD): The average of the moving probability of one or a group of debtors to default over a certain period.

The steps taken to calculate the estimated PD credit for the micro-segment are as follows:

1. Calculating PD PiT per Province using a transition matrix.
2. Calculate PD TtC.
3. Calculate the credit index utilizing the difference between PD PiT and TtC and transform it into scalar form.
4. Regressing CI with macroeconomics.
5. Calculate forecasted PD based on macroeconomic forecasts determined by the Bank ABC.

3 Methodology

3.1 Data

The data used in this study is secondary data consisting of internal and external data of the Bank:

1. Internal data, namely credit and NPL data for quarterly microcredit Banks historically for March 2012 to December 2020 per province.
2. External data with the same historical period, namely March 2013 to December 2020 per province, consisting of:
   - Gross Regional Domestic Product (X_1)
   - Private Consumption (X_2)
   - Unemployment Rate (X_3)
   - Public Consumption (X_4)

While the Y variable is the credit index obtained from reducing PD PiT and TtC. This deviation will show how much increase/decrease in PD micro debtors per region is affected by changes in economic factors (X_1 – X_4).

3.2 Method

3.2.1 Matrix Transition

The transition matrix is formed by classifying facilities based on credit quality at the beginning of observation and credit quality at 12 months after that based on days past due and collectability. The grouping of credit quality at the beginning of the observation was carried out into the following buckets:

— Bucket 1: credit reaches maturity date less than or equal to 0 days
— Bucket 2: credit past maturity date from 1 - 30 days
— Bucket 3: credit past maturity date of 31 - 60 days
— Bucket 4: credit past maturity date from 61 - 90 days
— Bucket 5: credit past maturity date more than 90 days

Transition matrix calculated with the following formula:

$$\text{PD PiT} = Pi,j \;=\; \frac{Nij,t}{Ni,j}\,. \tag{2}$$

PD TtC is the average of PD Pit which is formulated as follows:

$$\text{PD Ttc} = \sum_{n=1}^{n} \frac{PD\ PiT_{\ i}}{n}\,. \tag{3}$$

The deviation of PD Pit and PD Ttc is called the Credit Index. This variable will be used as the dependent variable in this study. A positive CI means that the probability of default will be greater in the long run.

$$\text{CI} = \text{PD PiT} - \text{PD TtC} \tag{4}$$

3.2.2 Multiple Regression Model

In multiple regression analysis, the dependent variable is influenced by two or more independent variables so that there is a functional relationship between the dependent variable (Y) and the independent variables (X_1, X_2, X_n). The multiple regression analysis can be formulated in the following equation:

$$CI_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i \, . \quad (5)$$

CI_i is the deviation of PD per province, which four economic (X_i) factors will estimate.

3.2.3 Probability of Default Forecasting

After obtaining a macroeconomic model that is considered appropriate to the characteristics of each province in step 3.2.2, the modeling process will continue by forecasting the PD per province. This forecasting process will use predictive macroeconomic data entered through the multiple regression function in formula (5) to obtain the following equation:

$$Forecasted\ CI_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i \, . \quad (6)$$

3.2.4 Testing the Significance of Regression Parameters

Testing the significance of the regression parameters needs to be done so that researchers know the significance of the relationship between the independent variable and the dependent variable statistically. The following models are used to test the significance of the regression parameters, namely:

a. Simultaneous Test (F Test): This test determines whether all independent variables together influence the dependent variable. The hypothesis:

$$H_0 : \beta_1 = \beta_2 = 0$$
$$H_1 : at\ least\ one\ of\ \beta \neq 0$$

b. Partial test (t-Test): The t-test determines the effect of each independent variable and the dependent variable individually.

c. Coefficient of Determination Test (R^2): R^2 reflects how much variation of the dependent variable Y can be explained by the independent variable of X. The value of R^2 is in the range of zero and one.

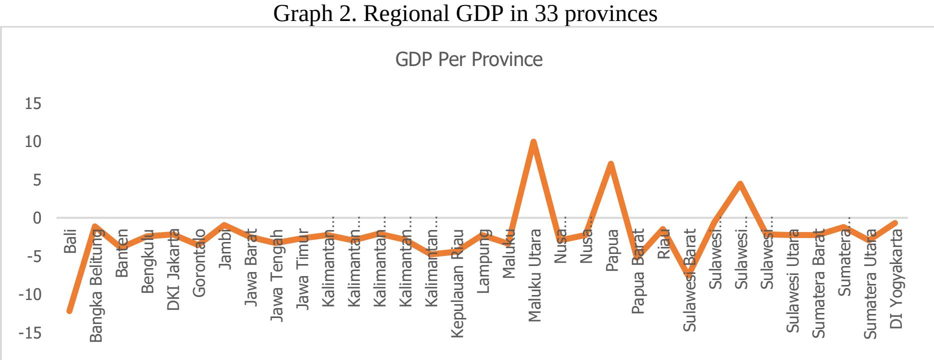
4 Result and Discussion

4.1 Descriptive Analysis

Based on the data at the end of 2020, the macroeconomic conditions per province are as follows:

1. Growth Regional Domestic Product (X_1)

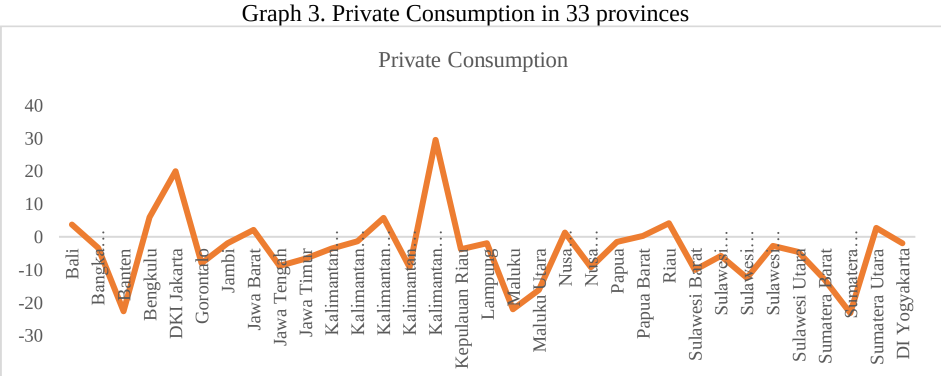
Graph 2. Regional GDP in 33 provinces



As a result of the pandemic, out of 33 provinces in Indonesia, only three provinces have positive GDP, namely Central Sulawesi, North Maluku, and Papua.

2. Private Consumption (X_2)

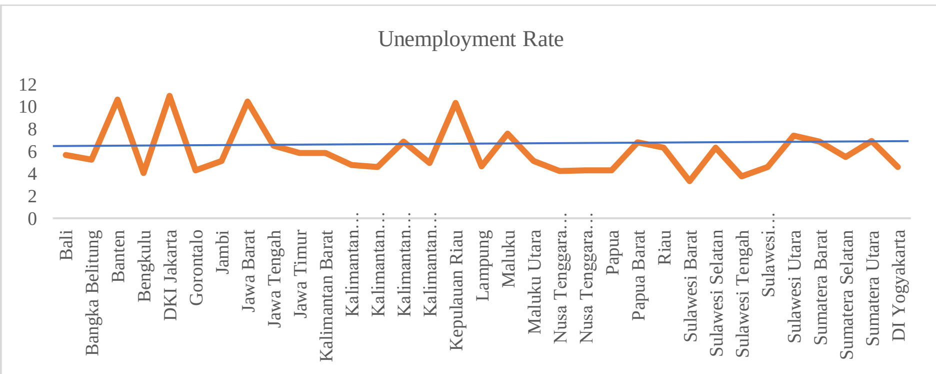
Graph 3. Private Consumption in 33 provinces



Government consumption increased significantly in 7 provinces, namely North Sumatra, Riau, Bengkulu, Jakarta, Bali, South Kalimantan, and North Kalimantan.

3. Unemployment Rate (X_3)

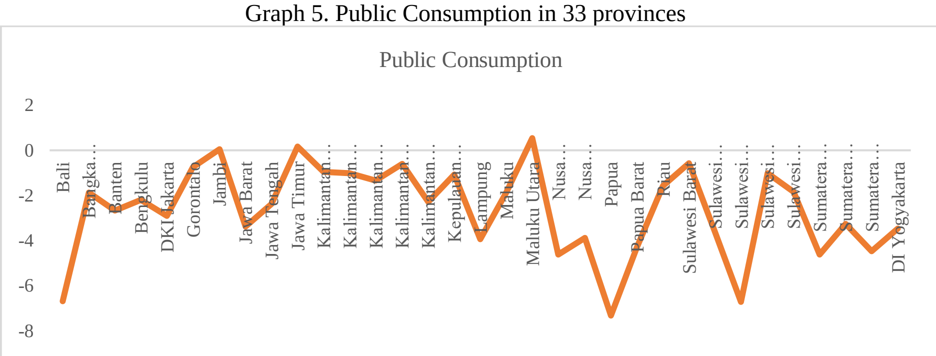
Graph 4. Unemployment Rate in 33 provinces:



The pandemic conditions have resulted in many businesses having to make layoffs. Of the 33 provinces, 13 provinces in 2020 carried out discharges above the national average, namely: North Sumatra, West Sumatra, Riau, Riau Islands, DKI Jakarta, West Java, Central Java, Banten, East Kalimantan, North Sulawesi, Sulawesi South, Maluku, and Papua.

4. Public Consumption (X_4)

Graph 5. Public Consumption in 33 provinces



Inversely proportional to private consumption, almost all provinces experienced a decline in public consumption and tended to have a negative value, as shown in graph 5.

The analysis above describes the condition of macroeconomic variables per province. Each province has different characteristics in terms of economic growth.

4.2 Regression Model

However, to determine its effect on increasing the probability of credit default in each province, a regression analysis was carried out, which modeled the CI with the four economic factors above, and the results are as follows:

Table 3. Result of Regression on the Effect of Macroeconomic Variables on CI per Province

No	Province	Model	Coefficients	P-value	R-Square
1	Sumatera Utara	Intercept	- 0.9704	0.0104	57.43%
		X_3	0.1375	0.0219	
		X_4	0.0968	0.0199	
2	Riau	Intercept	- 0.7468	0.0157	30.36%
		X_3	0.0991	0.0487	
3	Jambi	Intercept	- 1.3404	0.0098	55.75%
		X_4	0.2039	0.0002	
4	Bangka Belitung	Intercept	- 0.4721	0.0057	38.77%
		X_2	- 0.0138	0.0260	
5	Kepulauan Riau	Intercept	- 0.4662	0.1069	33.92%
		X_1	- 0.0493	0.0300	
6	Jakarta	Intercept	- 0.1422	0.3131	66.90%

No	Province	Model	Coefficients	P-value	R-Square
		X_1	0.1125	0.0040	
7	Jawa Barat	Intercept	- 0.8329	0.0427	45.58%
		X_4	0.0742	0.0210	
8	Yogyakarta	Intercept	0.2255	0.2718	16.79%
		X_1	- 0.0389	0.0304	
9	Jawa Timur	Intercept	- 0.6884	0.0056	44.94%
		X_3	0.1262	0.0175	
10	Bali	Intercept	0.8323	0.0000	50.07%
		X_1	- 0.0669	0.0013	
		X_3	- 0.2944	0.0001	
11	Nusa Tenggara Barat	Intercept	0.3769	0.0235	45.39%
		X_4	- 0.0459	0.0018	
12	Kalimantan Tengah	Intercept	- 0.4280	0.0175	29.27%
		X_3	0.0855	0.0333	
		X_4	0.0664	0.0191	
13	Kalimantan Selatan	Intercept	- 0.5500	0.0135	53.48%
		X_4	0.1227	0.0013	
14	Sulawesi Utara	Intercept	- 0.5544	0.0307	36.19%
		X_1	0.1040	0.0031	
		X_4	- 0.0694	0.0212	
15	Sulawesi Tengah	Intercept	- 0.2499	0.2350	41.07%
		X_4	0.0226	0.0026	
16	Gorontalo	Intercept	- 0.3952	0.0187	51.86%
		X_1	- 0.0347	0.0428	
		X_4	0.0817	0.0002	
17	Maluku Utara	Intercept	- 0.5891	0.0072	49.11%
		X_4	0.0489	0.0122	
18	Papua Barat	Intercept	- 0.2879	0.1825	41.92%
		X_4	0.0530	0.0005	
19	Papua	Intercept	- 1.0005	0.0141	32.51%
		X_3	0.2602	0.0199	
		X_4	0.0413	0.0022	

Of the 33 provinces, only 19 provinces were able to significantly (p-value < 0.05) estimate the CI value based on four macroeconomic factors (X_1–X_4) with R^2 in the range of 16% - 67%. Thus, the other 14 provinces will use the existing formula for the Bank's approach, namely the national model.

4.3 Forecasted Credit Index

To determine the CI forecast in the 19 provinces, the Bank's macroeconomic estimates (table 4) are entered into the regression model in table 3, so that the forecasted PD results are in table 5.

Table 4. Forecasted Macroeconomic in 2021.

Forecasted Macroeconomic given by Bank ABC			
X_1	X_2	X_3	X_4
3.37%	3.47%	6.49%	4.50%

Table 5. Forecasted PD in 19 Provinces in 2021.

No	Province	Bucket				
		1	2	3	4	5
1	Sumatera Utara	2.11%*	13.06%	19.15%	21.80%	100%
2	Riau	1.65%	13.02%	18.32%	21.63%	100%
3	Jambi	1.84%*	13.63%	18.65%	21.48%	100%
4	Bangka Belitung	2.17%*	11.57%	17.09%	19.57%	100%
5	Kepulauan Riau	1.43%	12.39%	16.55%	20.26%	100%
6	Jakarta	1.71%	9.10%	13.17%	15.20%	100%
7	Jawa Barat	2.11%*	14.35%	16.45%	18.63%	100%
8	Yogyakarta	1.15%	7.34%	13.36%	16.74%	100%
9	Jawa Timur	1.27%	9.32%	12.82%	14.34%	100%
10	Bali	0.50%	5.75%	8.77%	11.29%	100%
11	Nusa Tenggara Barat	2.72%*	15.06%*	19.54%	23.06%	100%
12	Kalimantan Tengah	1.89%*	11.76%	16.05%	18.19%	100%
13	Kalimantan Selatan	1.77%*	11.96%	16.78%	18.87%	100%
14	Sulawesi Utara	4.14%*	14.86%	19.05%	20.60%	100%
15	Sulawesi Tengah	2.90%*	12.49%	15.62%	17.18%	100%

16	Gorontalo	3.20%*	15.97%*	19.07%	21.98%	100%
17	Maluku Utara	3.53%*	16.04%*	20.81%	23.76%	100%
18	Papua Barat	1.91%*	12.65%	17.22%	20.24%	100%
19	Papua	1.47%	7.55%	12.18%	13.65%	100%
Bank ABC Model (one fit to all)		1.73%	14.98%	27.31%	35.72%	100%

When compared with the current Bank's existing model, there are 12 Provinces have higher PD in bucket 1, and there is 3 Provinces have bigger PD in bucket 2. From table 5, the value in the existing model tends to be higher than the PD figure if estimated per province.

4.4 Impairment Credit Loss

By using the same EAD and LGD models as the existing Bank model, the value of the impairment loss generated by the Province model is smaller than the impairment loss currently recorded by the bank. The existing model is 4.5 trillion, while the model per province generates 4.3 trillion.

5. Conclusion

Based on the research above, it is found that from 33 provinces with the distribution of ABC Bank, only 19 can be estimated using macroeconomic GDP, unemployment rate, private consumption, and public consumption. From the 19 existing models, the PD values formed can be seen to be more granular and smaller than the existing PD models. This also causes the value of impairment loss formed by Bank ABC to be smaller if using the PD model per Province.

In this study, there are still some shortcomings that can be improved in subsequent studies, such as the addition of macroeconomic variables that can be used as independent variables.

Through this research, ABC Bank can compare the PD value currently used by the Bank and the estimated PD model by province. PD per province is expected to provide a more comprehensive picture of credit risk to banks and can be used to measure bank credit quality in each province. The PD value per province can also provide additional information to ABC Bank, which province has the smallest PD. It will become a target for ABC Bank's expansion (Riau, Kepulauan Riau, Jakarta, Yogyakarta, Jawa Timur, Bali and Papua) or ABC Bank must be more careful in lending in the provinces with the largest PD (Sulawesi Utara).

References

[1] Otoritas Jasa Keuangan. Indonesian Banking Statistics [Internet]. Otoritas Jasa Keuangan; 2022. Available from: https://www.ojk.go.id/id/kanal/perbankan/data-dan-statistik/statistik-perbankan-indonesia/Pages/Statistik-Perbankan-Indonesia---Desember-2021.aspx

[2] Guégan L, Rebreanu, M. IFRS 9 Expected Credit Loss Making sense of the transition impact. United Kingdom: EY; 2018. Available from: https://www.ey.com/Publication/vwLUAssets/ey-ifrs-9-expected-credit-loss//$File/ey-ifrs-9-expected-credit-loss.pdf.

[3] Basel I. International convergence of capitalmeasurement and capital standards. Basel Committee on Banking Supervision; 2006.

[4] McNeil AJ, Frey R, Embrechts P. Quantitative risk management: Concepts, techniques and tools. Vol. 3. New Jersey: Princeton University Press; 2005

[5] Pindyck RS, Rubinfeld DL, Mehta PL. Microeconomics. 7th Edition. London: Pearson Education; 2009.

[6] Caro EJ. Effects of Macroeconomic Factors inthe Performance of Micro Finance Institutions inEcuador. International Journal of Economics and Financial Issues. 2017;7(5):547.

[7] Louzis DP, Vouldis AT, Metaxas VL. Macroeconomic and bank-specific determinantsof non-performing loans in Greece: A comparativestudy of mortgage, business and consumer loanportfolios. Journal of Banking & Finance. 2012;36(4):1012-1027.