HISTORICAL STRESS TEST OF CREDIT RISK USING MONTECARLO SIMULATION: INDONESIA ISLAMIC BANKING

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ABSTRACT

This study was conducted to assess the vulnerability of Islamic banking credit portfolios under macroeconomic shocks and their impact on NPFs, using the linear regression analysis. From the three proposed models, namely OLS, ARIMAX and Error Correction Model (ECM), the ECM model was selected as the best. By using the Montecarlo simulation, an estimate was made of the possible future value of the NPF in Islamic banking. The study established that exchange rates, economic disparities, inflation, economic growth and interest rates showed positive and significant effects on bank credit risk whereas inflation produced negative effects. The non-performing finance (NPF) was also estimated using the Montecarlo simulation using one million trials. The results were subsequently used to conduct a stress test for the projected NPF. With 99% confidence, the maximum potential value of bad credit was 21%. The maximum NPF bad credit was attained under confidence level of 95%.

Keyword: Inflation, Economic Growth, Exchange Rate, NPF, ECM, ARIMAX

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1. INTRODUCTION

Indonesia is a country, which makes a large credit contribution of about 75% to development financing. As such, credit risk has become the dominant risk threatening domestic financial stability. This paper examines the potential impact of a macroeconomic shocks scenario on credit risk variables.

In considering the probable impact of a macroeconomic downturn and its influence in the form of a reduction scenario of a bank loan quality, a critical question needs to be addressed is the way on how to measure the impact of stressed macroeconomic variables on credit risk associated with single or portfolio loans. Ideally, shocks to macroeconomic variables are capable of predicting losses to the loan portfolio. However, there is no accepted technique for making such an estimate. Hence, the modeling made during stress test can be very diverse. As a result, stress tests translate risk models into stress test results.

According to Indra (2019) in the last two decades, Indonesia has experienced two financial crises, namely in 1998 and 2009. The 1998 financial crisis in Indonesia was triggered by external shocks through the exchange rate, which affected domestic banking stability leading to a multi-dimensional crisis. In the crisis of 2009, Indonesia was affected by the subprime mortgage in the United States, namely the failure of borrowers to pay back housing loans.

The 2007-2008 global financial crisis were a turning point for banks at a global level as it triggered the need for more rigorous stress testing related to the Internal Capital Adequacy Assessment Program (ICAAP) under the Basel Committee. Its scope was limited to supporting capital policy decisions but also covered credit risk, liquidity and the ability to comply with regulations. Weak stress testing practices will decrease bank resilience. At the bank level, it makes management unaware of what they might face at any time.

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There are many empirical studies on the impact of the developments of macroeconomic conditions on credit risk. Yet, the the research is generally focused on how economic growth, interest rates, and other macroeconomic variables that affect credit quality. Buncic and Melecky (2013), Castro (2013) and Jakubík and Reininger (2013) found that credit risk is strongly influenced by the macroeconomic environment. It is more significant when economic conditions are under recession or depression. However, the impact of macroeconomic variables on credit risk is not consistent. Further, despite its strong impact on financial institutions (Al-Jarrah, 2012; Castro, 2013), the macroeconomic environment is beyond the control of a banking system.

One of the performance indicators used to measure the stability level of Islamic banking is Non-Performing Financing (NPF). The NPF ratio measures the stability of a bank based on the quality of the productive assets owned by the bank. This high ratio can be translated into potential instability and vulnerability. Default occurs when the debtor is unable to fulfill his contractual obligations due to factors such as an economic downturn. A good example is the 1998 economic crisis where the NPF of Islamic banks in Indonesia were 65.61%. Therefore, this study aims to assess and predict the vulnerability of Islamic financing quality to changes in key macroeconomic variables. The hope is that this stress test can also be used for macro prudential supervision, especially in identifying vulnerabilities in the financial sector. Kabir et al. (2015) using accounting-based credit risk measures, confirmed that Islamic banks have higher credit risk.

From banking authority perspective, Kontan daily (2018) reported that Indonesia Financial Authority (OJK) performed a stress test on selected 20 banks. In general, all the banks had strong capital to absorb losses from capital perspectives; deteriorating economic conditions can make the CAR value fell 600 bps from 22.78% to 16.78%. For credit risk, the result showed that the NPF value rose 628 bps from 1.77% to 8.05%. However, no Islamic bank was included in the current stress test.

The aim of this paper is to examine the determinant of Non-Performing Finance (NPF) and potential of NPF when a certain macroeconomic scenario is applied in the stress test. The paper is the first contribution made using the montecarlo simulation to estimate credit risk in Indonesia. Further, the paper provides the insight into how sensitive is credit risk to economic variables when simulation method is applied.

2. LITERATURE REVIEW

There are several empirical studies that investigated the influence of macroeconomic factors on the credit risk or non-performing loans (NPF). In general, these studies underlined the importance of the Gross Domestic Product (GDP) as the determinant of credit risk. GDP is regarded the best measure of economic performance and it describes the overall economic activity. For example, if there is GDP growth, the economy will also experience growth. This growth is an increase in income and the lack of financial difficulties experienced by the community. In this way, the ability of the community and business units to pay off debts (credit) increases and the impact on non-performing loans (NPFs) decreases. On the contrary, if the economy goes into a recession, economic activity will deteriorate, resulting in decreased income, failed businesses, and difficulty in paying back loans. This causes the quality of the portfolio to deteriorate (Zeman and Jurca, 2008).

Buncic and Melecky (2013) found that credit risk is strongly influenced by macroeconomic environments, especially during the recession period. Fiordelisi and Marques-Ibanez (2013) also confirmed that an economic downturn significantly influences banking performance, and this effect is much higher than that on other industries. Kabir et al. (2020) suggested that GDP growth reduced credit risk. Wiryono and Effendi (2018) who also investigated the determinant of credit risk in Islamic banking discovered that GDP growth negatively affects credit risk or financing risk. Othman et al. (2020) who studied the credit risk of Islamic bank in Malaysia, found that economic growth (GDP) affects negatively Islamic bank credit risk.

According to Klein (2013), GDP growth is the only variable which is widely used for identifying the level of NPF. Mpofu, & Nikolaidou (2018) used the sample of Sub-Sahara banks and concluded that an increase in real GDP growth rate significantly reduced, both statistically and economically, the ratio of NPFs to total gross loans.

Castro (2013) investigated the determinant of credit risk using macroeconomic data. His study in part concluded that the credit risk increased with the growth of GDP and interest rate. Further, credit risk also increased when the real exchange rate appreciated. In addition, inflation rates showed a negative relationship with problem loans. The relationship between macroeconomic development and credit risk, for a group of five European banking systems, was confirmed in the study. The study also established that housing price, exchange rate and global finance are significantly related to credit risk.

Inflation is a proxy of monetary policy that measures a general increase in price levels. Inflation affects the performance of the banking sector in terms of money supply and price stability. Hyperinflation increases loan interest rates but hinders the ability of borrowers to pay off their loan payments on time (Klein, 2013). Thus, the inflation rate is assumed to have a positive effect on NPF. Several empirical studies have shown that periods of high inflation were followed by high NPFs in commercial banks (Ghosh, 2015; Baselga-Pascual et al., 2015). Conversely, some studies have established that inflation exerted negative effect on credit risk (Appiah & Bisiw, 2020; Morina, 2020; Chalibi & Ftiti, 2015). Inflation is the process of continuously increasing price of goods thus reducing people's purchasing power since in real terms their income level also decreases under the assumption that the level of public income is constant (Simionescu, 2020).). The inflation rate has a positive effect on NPF. Mpofu, & Nikolaidou (2018) similarly concluded that inflation rate has positive and significant impact on NPFs.

Mpofu, & Nikolaidou (2018) and Valahzaghard, et al (2012) also confirmed that all foreign exchanges had positive and significant impact on NPFs. Based on regression analysis of combined data, they concluded that there was no significant relationship between inflation rate, employment rate, unemployment rate, the dollar, the euro on credit risk in Iranian banking. Effendi & Yuniarti (2018) established that macroeconomic variables such as GDP and unemployment contributed less than 20% to credit risk. They also mentioned that GDP and unemployment rate (UNEMP) showed significant negative effect on credit risk in Islamic banking in Indonesia. Yücememis¸ and Sozer (2011) concluded that credit risk was determined mostly by exchange rate depreciation.

In Indonesia, the determination of interest rates, for both cost of funds and interest rates on loans, refers to the Bank Indonesia (BI) rate. Lin et al. (2016) examined Islamic and conventional banks in Indonesia. The empirical results showed that Islamic banks were more resilient during a crisis and only two variables (Exchange Rate and MS) were significant for credit risk. In comparison, almost all variables in conventional banks, namely economic growth, policy interest rate (SBI), inflation, exchange rate, and money supply were significant except for the Industrial Production Index. Dua and Kapur (2017), Badar et al. (2013) and Siddiqui et al. (2012) found that NPF is influenced by loan interest rates that must be paid. Further, Bofondi and Ropele (2011) also stated that the higher the cost of credit, the more difficult it becomes for debtors to pay their credit obligations.

Jakubik & Schmieder (2008) investigated the impact of output gap (GDP-Gap), the ratio of loans to GDP, and the ratio of interest paid to disposable income, on NPFs. Edge and Meisenzahl (2011) suggested that nominal GDP gap can explain the credit to output gap ratio. Further, GDP growth gap may provide policy with relevant information to manage financial system stability.

Some studies used data from developing countries. Taskinsoy (2018) conducted a macro stress testing exercise for Malaysia’s banking sector. Two scenarios were examined, the adverse and severely adverse. He concluded that Malaysia’s banking industry is resilient, well diversified, and highly interconnected. The study also found that the aggregate capital shortfall in the form of needed capital injection under adverse scenario was 1.55% of the GDP and this rose to 3.55% of GDP under severely adverse scenario. All banks however passed the test.

Kurniadi et al. (2018) conducted a stress test for Islamic banking in Indonesia that focused on the capability of the industry to absorb credit risk. In general, Islamic banking is able to absorb the loses if NPF is less than 8.5%, ceteris paribus, the loss given default (LGD) was at 40% or less.

In contrast, Kurniawati and Koesrindartoto (2003) conducted the dynamic macroprudential stress test to evaluate the resilience of the Indonesian banking sector. Two capital measures were used; regulatory capital (CAR) and Economic Capital (EW-CAR). In short, the finding was satisfactory in that there was no risk of capital insolvency although there was a decrease in economic capital adequacy. The Basel Minimum Capital requirement of 8% was satisfactorily met.

Ganbaatar and Selenge (2012) conducted credit risk stress test for individual banks in Mongolia. They applied the loan transition matrices method to estimate the migration from good to low quality loan. The result showed that non-performing loans of bigger banks are negative to GDP. Curiously, mid-sized and smaller banks have positive relationships between their non-performing loans and GDP. From the sectoral perspective, agriculture is the most risky. The stress test also unveiled the risk of failure in state banks.

3. METHODOLOGY

In this study, forecasting the level of NPF was carried out with a slightly different approach from those of previous studies. The first step was to develope a econometric model to determine credit risk in Islamic banks. In this approach, the macroeconomic variables were regressed with the value of the NPF from Islamic banking. In the estimation process, data replacement was minimized through various common manipulations such as the use of logarithms and lag transformations that produced data that met the requirements for modeling. Further, this approach increases the chance to produce a model that meets classical assumptions. However, classical assumptions and model requirements can be disregarded if the forecasting results provide the best value. In other words, modeling was used not to produce the best model but rather to achieve a low level of forecast deviation. This suggests that the econometric model is adopted for the purpose of producing forecasts that are in accordance with existing data, although there may be non-compliance with current econometric standards.

3.1. Data and Variables

From the literature review, we can discern that the effect of macroeconomic variables on credit risk can be identified. Several macroeconomic variables have direct and significant effect on credit risk, such as economic growth, inflation, exchange rates and interest rates. GDP is the indicator of the economic cycle. High GDP growth thus affects credit risk through its positive and negative effects. This paper refers to past studies by Wiryono and Effendi (2018) and Castro (2013).

Inflation has a positive or negative effect on credit risk. When inflation increases, the borrower's real income decreases even though their real interest rate may decrease. This causes a decrease in the borrower's capacity to repay debts, which thus increases the credit risk for the bank. In fact, a high inflation rate actually reflects the strengthening of purchasing power so that household cash flow exerts a positive impact on companies. This variable was adopted in Fakhrunnas et al. (2021), Kabir et al. (2020) and Othman et al. (2020).

The interest rate is the price for money or a loan that affects credit risk through debt burdens. Increase in interest rates increases the debt burden, resulting in a higher level of bad credit. Poudel (2013) also proved the role of interest rate.

The exchange rate has a major influence on foreign trade and its fluctuation is one of the main sources of economic growth and economic stability. According to Zameer & Siddiqi (2010), exchange rate is a plausible variable.

The output gap refers to the gap between potential and real output. The higher the gap, the lower is the economic realization, and the higher the NPFs as in Jakubik & Schmieder (2008).

Table 1: Variables, Definition and Expected Results

No	Variable		Definition of the Variable	Expectation to NPF	Sources
1.	NPF	Y	Non Performing Finance		Banking Statistics (OJK)
Independent Variables					
2.	L.KURS	X1	Log of USD exchange rate to Rupiah (IDR)	Positive / Negative	ADB
3.	EGAP	X2	Economic Growth gap with its potential growth	Positive	ADB Authors
4.	INFL	X3	Consumer price index	Negative/Positive	Office of Statistics
5.	EGRW	X4	Monthly of GDP growth (Interpolated from quarter data)	Negative/Negative	ADB Interpolated using Eviews
6.	Interest	X5	Lending rate of commercial bank (Working capital loan)	Positive	Bank Indonesia

Data used in this study were sourced from Indonesian Banking Statistics. These were consolidated Islamic banking data, obtained from OJK, BI, and ADB. Detailed data definition and sources are shown in Table 1.

In this study, the variables used to estimate the NPF include exchange rate (L.KURS), economic growth gap (EGAP), inflation rate (INFL), economic growth (EGRW) and lending rate for working capital (Interest). We used the terms NPF and NPF intechangebly as NPF is more accepted in academic circles

3.2. Model

The estimated NPF ratio in the stress test scenario is measured using the following model or equation:

$$NPF_t = \beta_0 + \beta_1 L.LKURS_t + \beta_2\, EGAP_t + \beta_3\, INFL_t + \beta_4\, EGRWt + \beta_5\, INTEREST_t + \varepsilon_t \tag{1}$$

Estimation was carried out using Eviews 8 with three models employed: namely Ordinary Least Square (OLS), ARIMAX model and Error Correction Model (ECM). Testing for multicolonierity, heteroscedasticity and autocorrelation were simultaneously conducted in order to identify the best model. In this study, various methods were applied for this purpose. Besides using Ordinary least square (OLS) to estimate the determinant of non-performing finance (NPF), the study also applied the ARIMAX model for the purposes of forecasting whether other variables may also affect the model. According to Liu et al., (2018), the ARIMAX model is an extension of ARIMA models that use additional or exogenous variables considered to have significant influence on the data and may perform better than ARIMA.

Forecasting on the state of the economy will generally focus on using linear regression models. In its further development, OLS becomes the basis for developing an empirical model with a cointegration approach, namely the error correction model (ECM). ECM is used to examine the long-term and short-term effects of each independent variable. The model corrects short-term imbalances into long-term balance. This model provides a more accurate level of forecasting for time series data. The procedure for estimation with ECM includes stationarity test, degree of integration test, and Granger causality test.

4. STRESS TEST METHOD

Once the best model was identified and chosen, stress testing was carried out with Monte Carlo Simulation, which was more stable compared to static simulation. Historical data were used in this process, namely the average and standard deviation. Given the availability of data as well as the constraints associated with the stationary time series data, the available macroeconomic data and configuration were used as the sources.

Macroeconomic variables were used for estimation of NPFs, following past studies related to credit risk modeling, allowing for the adoption of direct effect approach. A similar approach was used by Moinescu and Codirlasu (2012) for Romania which produced acceptable results. Ruja (2014) also conducted a similar study on Romania, using relatively comparable approach and obtained sound results from a stress test.

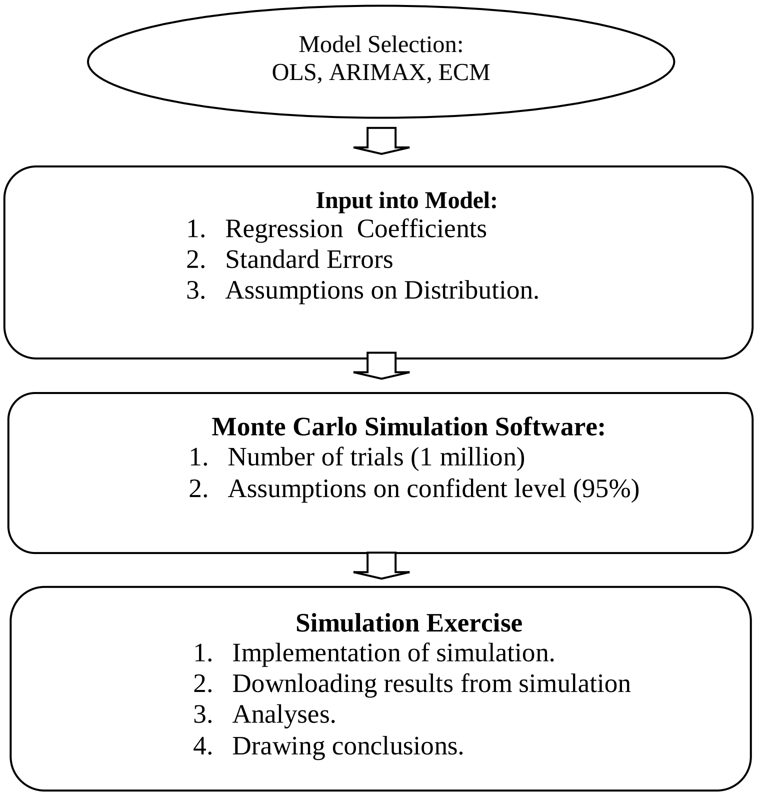
Stress test is a tool used by bank supervisors, especially those from the central bank, to assess the level of resilience and soundness of a bank when facing extreme conditions. It also serves as an instrument for bank management to provide risk information through an internal system to measure risk. The methodologies used in stress testing are as follows:

a. Sensitivity Analysis; Estimation of the impact of changes in one particular risk factor (risk driver) on the value of a bank portfolio.

b. Scenario Analysis; Evaluation on the combined effect of changes across all risk factors using simulated extreme stress scenarios. As such, scenario analysis is often used for overall stress testing (bank-wide) in the banking industry.

The stress test process was widely used in previous studies such as Wang et al. (2020), Vazquez et al. (2012), Ghosh (2015), Abdolshah & Moshiri (2017) and Skoglund, & Chen (2016). The process is as follows:

Figure 1: Steps of Stress Testing



Sources: Adapted from Taskinsoy (2018) and Buncic and Melecky (2012)

The econometric and simulation models used in this study estimate a direct and linear relationship between macroeconomic variables and credit risk measured using NPF. This approach involves a model that is intuitive and easy to implement. However, it carries a fundamental weakness related to its assumption of linear relationships. It lacks capabilities to estimate unexpected losses. In theory, this stress test model should only produce expected estimates, but not unexpected ones. However, unexpected values may occur beyond the 99% confidence level.

5. RESULTS AND DISCUSSION

Data for this study were obtained from various sources such as Financial Service Authority (OJK), Bank Indonesia, Statistics Office and Asian Development Bank (ADB). The data were monthly and covered the 2010-2019 period. Data after 2019 were excluded from the analysis since the advent of the Covid-19 epidemic affected data structure and overall economic environment.

Table 2 describes the data and shows the average values as well as the maximum and minimum values of the relevant parameters. The average value of NPF is 3.92, a minimum value of 2.23 and a maximum of 6.61. The exchange rates, in logarithm form, were calculated in order to achieve a balance of values with other variables. The average is 9,377 with a maximum of 9,663 and a minimum of 9,051. The Economic gap has an average of 1.09 with a maximum value of 16,709 and a minimum of -35,785. The average inflation rate is 4.5 with a maximum of 8,363 and a minimum of 1,323. The average economic growth is 4,654 with a maximum of 5,488 and a minimum of 5,325. Finally, the average interest rate is 11,822 with a maximum of 13,750 and a minimum of 10,000.

Table 2: Data Description

Variables	NPF	LKURS	ECGAP	INFLATION	EGRW	Interest
Mean	3.921603	9.376776	1.093343	4.543602	4.653594	11.82279
Median	3.824108	9.479488	2.765845	4.047500	5.049500	11.86000
Maximum	6.168241	9.663452	16.70864	8.363000	5.588000	13.75000
Minimum	2.230934	9.051228	-35.78614	1.323000	-5.325000	10.03000
Std. Dev.	1.007888	0.189676	10.18223	1.725002	1.885379	0.920423
Observations	128	128	128	128	128	128

Table 3 presents results of the correlation analysis. In general, the correlation between variables is relatively acceptable, which is below 70%. The lowest correlation between the independent and dependent variables is 40% in the credit interest rate. The highest correlation occurs between inflation and credit interest rates at 60%, as embedded. This relationship is very close and reasonable considering that high inflation is always compensated by high interest rates to maintain real returns for depositors. In general, the risk of multicollinearity is limited.

Table 3: Correlations

Variable	NPF	LKURS	ECGAP	INFLATION	EGRW	Interest
NPF	1,000	0,410	0,156	0,123	0,344	0,393
LKURS	0,410	1,000	-0,064	-0,360	-0,263	-0,546
ECGAP	0,156	-0,064	1,000	0,157	0,292	0,142
INFLATION	0,123	-0,360	0,157	1,000	0,303	0,607
EGRW	0,344	-0,263	0,292	0,303	1,000	0,419
Interest	0,393	-0,546	0,142	0,607	0,419	1,000

The estimation results of the credit risk model were calculated using three methods, namely OLS, ARIMAX and ECM. For adjusted R-squared, the highest result was through using ECM, which was 0.88 and the lowest was through the OLS model at 0.79. This suggests that the ECM is able to give a better explanation. From the ANOVA a significant F-test was obtained for the methods employed in this paper. For the Heteroscedasticity test, only the ECM model qualified. likewise, for serial correlation. For multicollinearity based on VIF, all qualified as variables in the regression because, none of them are above 10. Based on the residual, the ECM is unfortunately not normal. However, it is considered reasonable since the error term has been used in the estimation and it is freely scattered (See Table 4).

In Modelling the ECM model, the first step is to test the stationarity of the data. Using Phlips-Perron unit root test, all variables are stationary at the first difference. The second step is cointegration test to evaluate the long-term relationship using Johnsen method. Assuming linear deterministic trend, the result for the trace test is 77.12 higher than the critical value 69.82. For maximum eigenvalue, the result is 77.12 which exceeds the critical value 69.82. Both are significant at 1%. The third is to evaluate whether the residual for long-term model is stationary. Using Philips-Peron unit root test the result was shown significant at 1% since the adjusted t-test -3.754505 was smaller than the critical value of -3.482879.

Table 4: Regression Results

Variable	Model					
	OLS		ARIMAX		ECM	
	Coeff	VIF	Coeff	VIF	Coeff	VIF
C	-53,951	NA	-46,407***	NA	-53,531	NA
LKURS	4,840***	1,332	4,315***	2.605	4,814***	1,318
ECGAP	0,018**	1,557	0,001	1.426	0,018**	1,556
INFLATION	-0,099***	1,423	-0,039	1.124	-0,096***	1,474
EGRW	0,402***	1,988	0,016	1.625	0,356***	1,971
Interest	0,930***	2,079	0,0844***	3.274	0,933***	2,089

RESID-1					-0,666***	1,004
AR(-1)			0.629***	2.412		
SIGMSQ			-0.012	2.030		
	Goodness of Fits					
Adj-Rquared	0.795		0.82		0.88	
F-test	91.982	Significant 1%	85.842	Significant 1%	149	Significant 1%
Breusch-Pagan-Godfrey- Hetero	16.491	Significant 1%	3.0107	Significant 2%	4.227	Significant 64%
Breusch-Godfrey-Serial Correlation	52.136	Significant 1%	NA		1.399	Significant 48%
Residual	Normal		Not Normal		Not Normal	
Llikelihood	-66.323		-77.246		-31.295	

Sources: Eviews's Output

The exchange rate variable (LKURS) indicates the exchange rate risk. This variable is important in the modern open economy where international relation is widespread. This data is also important in assessing exchange rate stability. Changes in exchange rates have an impact on investors and the business sector. For debtor exporters, an increase in the value of the dollar or its depreciation is beneficial because with the same dollar one can get a larger rupiah. Meanwhile, most debtors will feel that depreciation will have an impact on increasing costs and other operating expenses so that their willingness to pay installments will decrease. In this context, the empirical results show that LKURS has a positive and significant impact in all models. This underlines the fact that the depreciation of the rupiah had a negative impact on credit quality. This finding is supported by Dua and Kapur (2017) and Nikolaidou (2018).

The output gap (ECGAP) is a measure that indicates the deviation of real GDP from its potential. In this context, the gap output is between negative and positive values. In theory it is a variation that actually drives inflation and deflation in the economy. Using the basic principles of the modern economy where the output gap has an impact on various aspects (Orphanides & Van Norden, 2005), we ensure that there is a good relationship between the output gap and credit risk in banks. In general, there are differing views on how to measure the ECGAP. In this study, we use a very simple approach, namely that the output gap is the difference between economic prediction and its actual outcome. The result shows that an increase in output gap enhances the NPF. This finding is consistent with those by Jakubik & Schmieder (2008).

In the theoretical aspect, inflation (INFLATION) has an uncertain influence. Generally, it exerts an adverse impact thereby increasing default. The real value of money will decrease thus reducing people's purchasing power. On the contrary, the impact of inflation is a decrease in the value of debt. The impact on credit quality in Indonesia is interesting to study because of its great significance alongside declining inflation and credit interest rates.

In this study, inflation has a significant negative effect on credit quality, which means that high inflation reduces NPF. This actually indicates that inflation in Indonesia shows more of an output gap so that high inflation reflects unaccommodated demand and thus subsequent rise in prices. This is different from Casto (2013) who concluded that inflation has a positive effect on credit risk. When inflation increases, despite a decrease in the borrower's real interest rate, real income decreases, which causes a reduction in the borrower's capacity to repay debts. This in turn increases the credit risk for the bank. In Indonesia, high inflation shows increased purchasing power, which augments company cash flow. Inflation is negative and significant at 1% except in all models. This study is in accordance with Lin, et al (2016) and their assumption that debtors earn income due to rise in commodity prices, thus exerting negative impact on credit risk. This also supports the assumption that inflation is more on excess demand, such as logistic problem, than on monetary aspect. This study is consistent with those of Mustafa (2019), Wiryono and Effendy (2018), Othman et al. (2020) and Dua & Kapur (2017), in that higher inflation rate reduces credit risk in the MENA banking market. It however contradicts those of Kabir et al. (2020), Klein (2013) Mpofu and Nikolaidu (2018).

The economic growth (EGRW) plays a very fundamental role in explaining changing behavior of credit or credit risks in banks. However, the researcher also recognizes that high economic growth has consequences that can be either positive or negative towards credit risk. When economic growth is good, that is, when the economy is booming, banks tend to provide credit carelessly (procyclicality). This may affect a future increase in credit risk (NPF). On the contrary, declining economic growth will result in poor economic development, which causes the economy to experience contraction (anticyclical). Debtors' ability to pay also reduced. Therefore, the variable of economic growth, which has a positive impact, can be negative. The result suggests that economic growth is positive and significant at 1%. This is consistent with earlier findings, such as Buncic and Melecky (2013) and Castro (2013). The finding however contradicts those reported previously by Wijoyo and Effendy (2018), Othman et al (2020) Dua and Kapur (2017). According to Huizinga and Laeven (2019), the positive impact of economic growth on NPF is known as procyclicality, a trend during the economic cycle (booming time) which inhibits excessive risk taking and as consequence incurring the loan loss provision.

When economic growth decreases, it also triggers a decline in the ability of households or companies to earn income, which may thus ultimately influence negatively the cash flow of the company. This situation causes greater increase in the debt burden. The significant effect of economic growth on credit risk is also supported in this study. It should however be noted that the relationship between credit quality and economic growth may also be a two-way relationship. Credit growth may be excessively high and becomes problematic itself causing it to decline eventually. Interest rates are the price of funds that affect credit risk through debt burdens. It may be necessary to increase the rate thus intensifying the debt burden, which may in turn contribute to a higher level of bad credits. According to Poudel (2013), interest rates have a positive and significant effect on credit risk in Islamic banks. Others including Kabir et al. (2020), Buncic and Melecky (2013), Siddiqui et al. (2012) and Jakubik & Schmieder (2008) share this view.

Taking into account the estimation results of the NPF model above, the ECM model was chosen to carry out the simulation with the Oracle Monte Carlo Software. The decision was based on the number of significant variables, the value of R-Squared and the fulfillment of the heterogeneity. ECM model is also verified free from the serial correlation problem.

6. STRESS TEST RESULT

The NPF is estimated through using the set methodology and historical macroeconomic data and based on the above-mentioned assumptions. The Monte Carlo simulation adopted in this study replicated 1,000,000 times the estimation. This is necessary to ensure that the standard error Monte Carlo (MCSE) can be reduced to zero. This statistical technique serves to show the accuracy of the forecast in the study. It is assumed that the data used follows the normal curve so that it can be referred to as the covariance variant approximation. Estimation of NPFs from the Monte Carlo simulation is expected to produce rational and plausible data for use by the management and authorities.

The stress test is designed at the beginning to assess whether a bank has enough capital to survive an adverse economy. The test measures the ability of a banking institution to maintain NPF at less than 5% for its survival under conditions of historical economic scenarios. The testing provides incentive for banks to implement robust credit risk mitigation. Banks and financial institutions will simultaneously be made aware of the potential for risk analysis to guide sound business policy input. The focus of stress test has now shifted to performance and efficiency management strategies. Stress testing is therefore no longer seen as merely a regulatory exercise but as a strategic and profitable function.

The model and data input implemented in stress tests are presented in detail in Table 5. There are six columns comprising the variables, regression results and the historical data column. Next are the columns for results and distribution summaries. The variables are those used in estimation and historical data. Since ECM is used, there is only one residual entry. The residual value can actually be ignored since the historical data value is very small. However, it is retained for reason of consistency. The results are given in the column for the predicted NPF. As mentioned earlier, all data are assumed to be normally distributed.

Table 5: Simulation inputs and assumptions

Variables	Regression Coefficient	Historical Data	Result	Assumption on Distribution
C	-54		-53,53	
LKURS(-3)	4,814	9,673	45,120	Normal Distribution
ECGAP(-3)	0,018	1,678	0,030	
INFLASI(-3)	-0,956	3,593	-4,390	
EGRW(-3)	0,356	3,811	1,713	
SKBUNGA	0,933	9,823	11,036	
RESID01(-1)	0,666	0,0001	6,7E-05	
Simulation Result (NPF)			-0,02096	

Please note that it is of extreme importance that the historical data are assumed to have normal distribution. This assumption serves to avoid extreme values in the result since the cumulative estimation will follow this distribution. The result is furthermore beneficial for the management since future impact becomes predictable when it is calibrated with the expected change in economic variables. For example, if the interest rate on loan change by 50% from its historical position, in this case 9.8% to 14.0% annually, the expected NPF will be 7.1% from previously 3.5%. The predicted value depends on regression coefficient and the level of confidence.

Table 6: Simulation Results

Run preferences:		Result		
Number of trials run	1.000.000		Percentiles:	Forecast values

Extreme speed		Base Case -0,03	0%	-47.994,01
Monte Carlo		Mean 5,13	10%	-11.712,11
Random seed		Median 6,51	20%	-7.654,15
Precision control on		Coeff. of Variability 1.795,20	30%	-4.761,06
Confidence level	95,00%	Range Width 92.280,16	40%	-2.290,33
		Mean Std. Error 9,20	50%	0,649
			60%	2.309,39
Total running time (sec)	31,11		70%	4.769,52
Trials/second (average)	32.142		80%	7.667,10
Random numbers per sec	257.137		90%	11.708,08
			100%	44.286,15

It is shown in Table 6 that the total number of trials or exercise was 1 million times and this produces a range of NPF between -47 to 44%. At the 99% certainty level, the range is between -11.8 to 11.7%. The base case is 3% (historical). The total exercise required 31.1 seconds to complete using the Desktop Computer with Intel i-5 RAM 4 Giga. For each second 32.1 trials are conducted. Altogether, there were eight assumptions applied in the simulation but with only one forecast for the NPF.

Table 7: Comparison of the predicted NPF

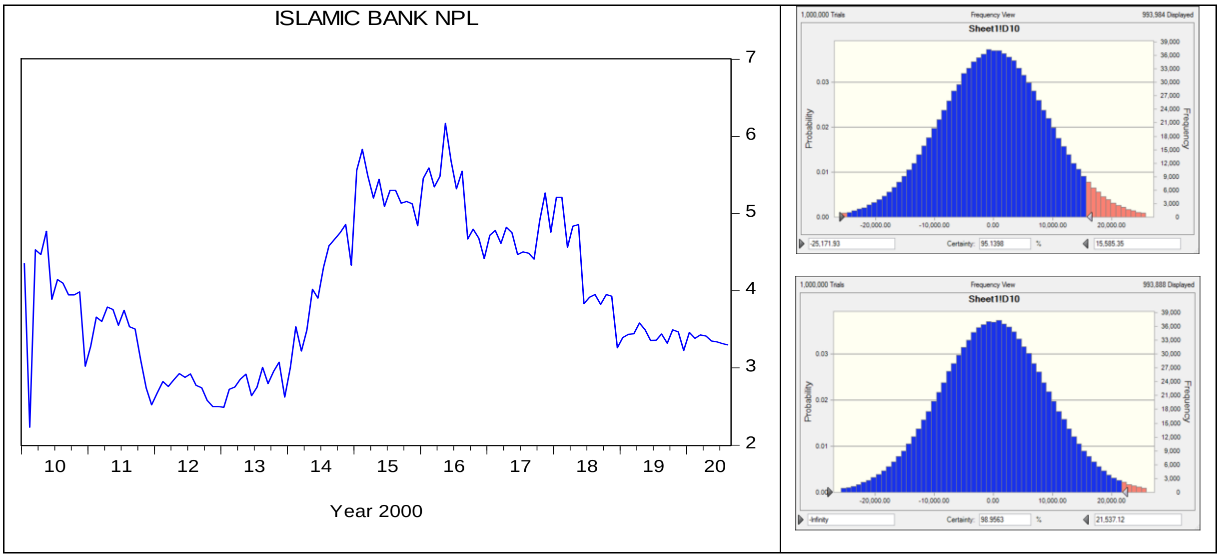
Number	Confidence level	Scenario (in Percentage)		
		Low (+/- 1 SD)	Medium (+/- 2 SD)	Maximum (+/- 3 SD)
1	95%	10	11	16
2	99%	13	15	21
3	100%	21	27	44

Note: SD is Standard Deviation

Table 7 presents a comparison between the various scenarios that were applied in the stress test. It was not based on macroeconomic assumptions but rather on the standard deviation cap or limitation. Low prediction occurs when data were confined within +/- 1 standard deviation. Medium prediction, when data were allowed within +/- 2 standard deviations. For Maximum prediction, data are allowed to vary within 3 times its standard deviation. Three levels of confidence were set for 95%, 99% and 100%. For the Low prediction scenario: the value of NPF with 95% confidence level was a maximum of 10%; for 99% confidence level it was 13%; and for 100% of confidence it was 21%. For Medium scenario NPF was 11% (95% confidence), 15% (99% confidence) and 27% (100% confidence). Likewise, for the Maximum scenario, NPF was 16% (95% confidence), 21% (99% confidence) and 44% (100% confidence). In the stress test, the scenario for Maximum was the standard.

Based on the positive percentile, the minimum value is 0.65% and the median within 6.5%. We can conclude that the maximum possible NPF for Islamic banking is 44%. At 99% certainty, the NPF will be maximum at 21%. This result is relatively unacceptable since historically, there is no precedence for such value in Islamic banking. With 95% confidence level, the possible NPF value is 15.6%. The fluctuation in NPF shown in Figure 2, suggests that the simulation reflects the real risky condition of credit in Islamic banking. In 2015, the NPF was 6.2% which is far below the stress test. This finding provides evidence that the selected model (ECM Model) performs excessively in making prediction. However, given the OJK press release that there is IDR 1000 trillion loan in the restructured position, this prediction is not baseless even though the residual normality is not achieved (Figure 2).

Figure 2: NPF: Historic and Simulation



In mitigating the Covid-19 pandemic, there is anomaly in the NPF since it decreasess in all bank categories. This is a result of the Financial Services Authority (OJK) regulation number 11/POJK.03/2020 concerning the national economic stimulus applied as a countercyclical policy in response to the impact of the 2019 coronavirus pandemic. This suggests that those debtors affected by the spread of COVID-19 and having trouble in fulfilling obligations to the bank, need to be granted installment relief for up to a prescribed period and they should not be treated as credit defaulters (NPF). The result may indicate that there is a possibility that NPF can reach around 20% level without the regulatory treatment.

The result suggests that bank management currently faces a very complex condition for decision-making where the quantity, quality and speed of information are the main keys. Unfortunately, the ideal setting is very difficult to fulfill for quality decision, especially in risk management. Importantly too, there is a tendency for the board of management not to fully trust the authorities in their effort to contain the Covid-19 pandemic. The authorities were perceived to prioritize their own interests more and often to the disadvantage of business interests. The challenge is in the manner of using the stress testing to assist the management process and not as a negative exercise. Stress testing is undoubtedly an interesting issue for academia to investigate since corporate experience proved to be a good teacher. A good management when appropriately applied should increase market share and also enhance corporate reputation, and most importantly build better relationships between customers and the business circles.

7. CONCLUSION

Indonesia is a country with very high level of dependence in bank financing. Based on credit statistics, the contribution of bank credit to total financing is around 75%. This large figure indicates that credit risk will be a major source of instability in the financial system. Given the fluctuating macroeconomic development in Indonesia and the impact of the Covid-19 pandemic, it is highly crucial to assess bank credit risk, especially in the Islamic banking.

This study adopts an approach using stress analysis to the situation in Indonesia using a past scenario of macroeconomic, during the pandemic, which affect the financing quality of Islamic banks. There are two types of banks, namely the conventional banks and Islamic banks. Historically, the Islamic banks have a higher level of credit risk and accordingly the impact of macroeconomic changes on credit quality, like the introduction of the Shariah, will be more significant. In addition, Indonesia has experienced two major financial crises over the last 20 years, namely the Asian financial crisis in 1998 and the Global financial crisis in 2009.

This study used a linear regression approach, which elucidates the macroeconomic influence on credit quality in Islamic banking. There were three models of credit risk determinants to choose from, namely a model using the Ordinary Least Square (OLS), another for the ARIMAX and third for the error correction model (ECM). The best model was accordingly identified. The results concluded that the credit risk of Islamic banking is very high given the changing conditions of the existing macro economy. With a confidence level of 99%, the NPF can reach 21% and with a confidence level of 95%, it may exceed 15%. Such risk level is considerably high, but it is still possible since the current amount of credit restructuring has reached IDR 1,000 Trillion. Assuming a total loan of IDR 4,800 Trillions, the risk may reach the 20% level. To understand more comprehensively the impact of macroeconomic variables on credit risk, future research should elucidate the outcomes from various scenarios.

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BIBLIOGRAPHIES

Abdolshah, F., & Moshiri, S. (2017). Stress testing for default probabilities in banking industry; an application of credit portfolio approach. *Journal of Economic Research*, 52(4), 935-962.

I. M. (2012). Evaluating the riskiness of the banking sector of Jordan. *European Journal of Economics, Finance and Administrative Sciences*, 48(48), 86-95.

Appiah, T., & Bisiw, F. (2020). Determinants of credit risk in the banking sector of ghana: a panel co-integration approach. *European Journal of Business and Management Research*, *5*(4), 1-8.

Badar, M., Javid, A. Y., & Zulfiquar, S. (2013). Impact of macroeconomic forces on nonperforming loans: An empirical study of commercial banks in Pakistan. *Wseas Transactions on Business and Economics*, 10(1), 40-48.

Baselga-Pascual, L., Trujillo-Ponce, A., & Cardone-Riportella, C. (2015). Factors influencing bank risk in Europe: Evidence from the financial crisis. *The North American Journal of Economics and Finance*, 34, 138-166.

Bofondi, M., & Ropele, T. (2011). *Macroeconomic Determinants Of Bad Loans: Evidence From Italian Banks*. (Bank Of Italy Occasional Paper No 89*)*, Banca D'Italia Eurosistema.

Buncic, D., & Melecky, M. (2013). Macroprudential stress testing of credit risk: a practical approach for policy makers. *Journal of Financial Stability*, *9*(3), 347-370.

Castro, V. (2013). Macroeconomic Determinants of the Credit Risk in the Banking System: The Case of the GIPSI. *Economic Modelling*. 31, 672–683.

Chaibi, H., & Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. *Research In International Business And Finance*, *33*, 1-16.

Dua, P., & Kapur, H. (2017). Macro stress testing of Indian Bank groups. *Margin: The Journal of Applied Economic Research*, *11*(4), 375-403..

Effendi, K. A., & Yuniarti, R. D. (2018). Credit risk and macroeconomics of Islamic Banking in Indonesia. Journal of Accounting, Finance and Auditing Studies, 4(2), 1-13.

Edge, R. M., & Meisenzahl, R. (2011). The unreliability of credit-to-GDP ratio gaps in real-time: Implications for countercyclical capital buffers. *International Journal of Central Banking*, *7*(4), 261-298.

Fakhrunnas, F., Tumewang, Y. K., & Anto, M. H. (2021). The Impact of Inflation on Islamic Banks' Home Financing Risk: Before and During the COVID-19 Outbreak. *Banks and Bank Systems*, *16*(2), 78-90.

Fiordelisi, F. and Marques-Ibanez, D. (2013). Is bank default risk systematic?. *Journal of Banking & Finance*, 37(6), 2000-2010.

Ganbaatar, T. A., & Selenge, O. E. (2012). Bank Specific Credit Stress Testing: A Case of Mongolia. *Procedia Economics and Finance*, *1*, 148-157.

Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of financial stability*, *20*, 93-104.

Huizinga, H., & Laeven, L. (2019). The procyclicality of banking: Evidence from the euro area. *IMF Economic Review*, *67*(3), 496-527.

Indra, I. (2019). Macro Stress Test Model Risiko Kredit: Studi Empiris Perbankan Konvensional dan Syariah di Indonesia [A Macro Stress Test Model of Credit Risk: An Empirical Studies of Conventional and Islamic Banking in Indonesia]. *Jurnal Ekonomi & Kebijakan Publik*, *9*(2), 113-130.

Jakubík, P., & Schmieder, C. (2008). *Stress Testing Credit Risk: Is the Czech Republic Different from Germany*?. (Working Paper No.9), Czech National Bank

Kabir, M. N., Worthington, A., & Gupta, R. (2015). Comparative credit risk in Islamic and conventional bank. *Pacific-Basin Finance Journal*, *34*, 327-353.

Kabir, M. N., Dulal Miah, M. & Huda, R. N. (2022). Determinants of credit risk: a comparative analysis between islamic and conventional banks in bangladesh. *The Singapore Economic Review*, 67(1), 349-379.

Hidayat, K (2018, May 16) Inilah skenario stress test perbankan (the banking stress test scenario), Kontan Daily, https://keuangan.kontan.co.id/news/inilah-skenario-stress-test-perbankan

Klein, N. (2013), *Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance*, IMF Working Papers 13/72, International Monetary Fund.

Kurniadi, D., Mongid, A., & Hidayat, S. E. (2018). A simple stress test on Indonesian islamic banking industry. *Jurnal Keuangan dan Perbankan*, *22*(1), 148-161

Kurniawati, S., & Koesrindartoto, D. P. (2003). Macroprudential stress-testing the indonesian banking system using the credit risk model. *Bulletin of Monetary Economics and Banking*, 23(1), 121-138.

Lin, H. Y., Farhani, N. H., & Koo, M. (2016). The impact of macroeconomic factors on credit risk in conventional banks and islamic banks: evidence from indonesia. *International Journal of Financial Research*, *7*(4), 105-116.

Liu, T., Lau, A. K. H., Sandbrink, K., & Fung, J. C. H. (2018). Time series forecasting of air quality based on regional numerical modeling in Hong Kong. *Journal of Geophysical Research: Atmospheres*, 123(3), 4175– 4196.

Moinescu, B. and Codirlasu, A. (2012). Assessing the sectoral dynamics of non-performing loans: signs from financial and real economy. *Theoretical and Applied Economics* , 2(567), 69-80.

Morina, D. (2020). Determinants of credit risk in commercial banks of Kosovo. *International Journal of Economics and Business Administration*, 8(2), 179-190.

Mpofu, T. R., & Nikolaidou, E. (2018). Determinants of credit risk in the banking system in Sub-Saharan Africa. *Review Of Development Finance*, *8*(2), 141-153.

Mustafa, O. A. (2019). Assessment of the financial performance of Islamic commercial banks in Sudan under credit risk and inflation pressures (1995-2017). *Journal of Islamic Banking and Finance*, *7*(1), 14-26.

Orphanides, A., & Van Norden, S. (2005). The reliability of inflation forecasts based on output gap estimates in real time. *Journal of Money, Credit and Banking*, 37(3), 583-601.

Othman, K., Laidin, J. B., & Ismail, N. A. (2020). Determinants of islamic bank credit risk in asean countries. *Journal of Emerging Economies and Islamic Research*, 8(3), 1-16.

Poudel, R. P. S. (2013). Macroeconomic determinants of credit risk in Nepalese banking industry. In *Proceedings of 21st International Business Research Conference*, 21, (10-11).

Ruja, C. (2014). *Macro Stress-Testing Credit Risk in Romanian Banking System*. MPRA Paper id 58244

Siddiqui, S., Malik, S. K., & Shah, S. Z. (2012). Impact of interest rate volatility on non-performing loans in Pakistan. *International Research Journal of Finance and Economics*, *84*, 66-70.

Simionescu, M. (2020). Bayesian combined forecasts and Monte Carlo simulations to improve inflation rate predictions in Romania. *Research Papers in Economics and Finance*, 4(1), 7-20.

Skoglund, J., & Chen, W. (2016). The application of credit risk models to macroeconomic scenario analysis and stress testing. *Journal of Credit Risk*, 12(2), 1-45.

Taskinsoy, J. (2018). A macro stress testing framework for assessing financial stability: Evidence from Malaysia. *Journal of Accounting, Finance and Auditing Studies*, 4(3), 284-334.

Valahzaghard, M., Kashefi, M., Alikhani, A., & Hosseini, S. (2012). The effect of macroeconomic factors on credit risk in the banking system of Iran. *Management Science Letters*, *2*(5), 1747-1754.

Yücememis¸ B, & Sozer, I (2011) Non Performing Loans In Banks: A Model Implementation Intended For Predictions Of Non Performing Loans In Turkish Banking Sector¸ *Finansal Araştırmalar ve Çalışmalar Dergisi*, *3*(5), 43-56.

Zeman, J., & Jurca, P. (2008). Macro stress testing of the Slovak banking sector., (*National Bank of Slovakia working paper No. 1)*. National Bank of Slovakia

Wiryono, S. K., & Effendi, K. A. (2018). Islamic bank credit risk: macroeconomic and bank specific factors. Othman, K., Laidin, J., & Ismail, N. (2020). Determinants of Islamic bank credit risk in ASEAN countries. *Journal Of Emerging Economies And Islamic Research*, 8(3), 1-16.

Zameer, S. and M. W. Siddiqi .(2010). The impact of Export, FDI and External Debt on Exchange Rate Volatility in Pakistan. *International Journal of Contemporary Research in Business*, 2(7): 337-354.

Vazquez, F., Tabak, B. M., & Souto, M. (2012). A macro stress test model of credit risk for the Brazilian banking sector. *Journal of Financial Stability*, *8*(2), 69-83.

Wang, Z., Crook, J., & Andreeva, G. (2020). Reducing estimation risk using a Bayesian posterior distribution approach: Application to stress testing mortgage loan default. *European Journal of Operational Research*, *287*(2), 725-738.