Predicting Volatility of Non-Performing Financing: Lessons from Indonesian Islamic Banking Industry

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Abstract

Islamic banking financing is carried out into three categories, namely financing based on economic sectors, financing based on contracts, and financing based on types of use. The funding is faced with risks where the customer is unable to pay the loan. This study discusses the forecasting of Islamic banking problem financing in Indonesia using monthly data from 2003 to 2019. Prediction is made using the Autoregressive Conditional Heteroscedasticity-Generalized Autoregressive Conditional Heteroscedasticity (ARCH-GARCH) method. Forecasting from the results of this study shows that non-performing financing tends to decrease in Indonesia. Islamic banking has been able to manage problem financing well. Islamic banking financing should be focused on sectors that have low risk. The results of this study are undoubtedly useful for stakeholders to make policies to improve the quality of the funding.

Keywords: problem funding, volatility, ARCH-GARCH, Islamic banking

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INTRODUCTION

Banking as an intermediary institution that connects investors with those who need capital has a strategic role in the economy of a country (Levine, 1997). The development of the banking world, especially sharia banking will surely face challenges that must be responded appropriately (Budiono, 2017). One of the challenges is that there are changes in world economic conditions that can have an impact on bank financing (Supartoyo, Juanda, Firdaus, & Effendi, 2018).

Islamic banking has gained traction in Indonesia, although the market share of Islamic banking is still small but the potential for growth continues to exist considering that Indonesia is the largest Muslim population in the world with various challenges (Rizvi, Narayan, Sakti, & Syarifuddin, 2019). One of the challenges is that financing carried out by Islamic banking will be faced with conditions where the capital borrower is no longer able to pay bills. Non-performing financing is defined as loans that are past due and cannot be repaid (Bolognesi, Stucchi, & Miani, 2019). In Islamic banking, the problematic financing indicator is reflected in the problem financing with non-performing financing (NPF) indicator.

Research related to NPL/NPF has been conducted by Li and Zhang (2019) analyzing related to credit options and risks in Hong Kong. Zhang, Cai, Dickinson, and Kutan (2016) who examined the impact of NPLs on bank behavior in China. Tsai, Lu, and Hung (2016) investigated information in newspapers influencing credit risk in the United States. Gatfaoui (2017) investigates the relationship between credit and equity markets in the United States. Chang, Fuh, and Kao (2017); Cucinelli, Battista, Marchese, and Nieri (2018); Binici and Hutchison (2018); Ashour and Hao (2019) have improved the credit risk of companies in China and Western Europe.

Bian, Lin, and Liu (2018) study credit risk with property prices in China. Dendramis, Tzavalis, and Adraktas (2018) investigated economic recession, pressures on the financial sector and political instability are factors that influence problematic financing. Zamore, Beisland, and Mersland (2019) analyze the relationship between geographical diversification and credit risk in microfinance. Niu and Hua (2019) studied the optimal contract between managers and shareholders in the credit risk model and the impact of moral hazard on corporate credit risk. Aysan and Disli (2019) examine whether there is a causal relationship between loans and problem loans in Turkey.

From the existing research, most of them discuss the effect of problem financing and none have discussed the forecasting of problem financing. Therefore, this research was conducted to fill the gap of existing research. Thus, the purpose of this study is focused on discussing forecasting problematic financing. This research has important implications for risk

managers and investors for optimal investment strategies (Troster, Tiwari, Shahbaz, & Macedo, 2019). This research is also deemed necessary because it can contribute to stakeholders to determine policy alternatives.

METHOD

The data used in this study are secondary data from non-performing loans (NPF) of 14 sharia commercial banks and 20 sharia business units monthly from January 2003 to November 2019. Sharia banking sector data is random (random) and has high volatility, causing variable that is not constant. Volatility modeling is very important for risk management (Caporale & Zekokh, 2019). Therefore, we need a model that can be used to predict problem financing with the condition that there is heteroscedasticity(McCauley, 2009).

The first step taken in this study is the identification of a model. The identification of this model is intended to find out what model will be used in research. So that data can be modeled with Autoregressive Moving Average (ARMA) or Autoregressive Integrated Moving Average (ARIMA), the thing that needs to be considered is that data must be stationary. If the stationary data is at a level, it can be modeled with ARMA. However, if the stationary data is at a difference, it can be modeled with ARIMA.

After getting data that has been stationary, then plots are made in the form of Autocorrelation (AC) and Partial Correlation (PAC) that are used to determine the order of the alleged model. Furthermore, after obtaining the alleged model, significance testing, residual testing and normality testing are carried out. Whereas in selecting the best model, it is chosen based on the value of the smallest Akaike Info Criterion (AIC) and the largest log likelihood.

The next step is to test heteroscedasticity in the residual model. If there is an element of heteroscedasticity, modeling is done using Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH). The equations that can be formed are as follows:

$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + e_t$; Model *autoregressive* orde p (AR (p)) …...................1

$Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}$; Model *moving average* orde q (MA (q)) ……....................2

$Y_t = \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_p e_{t-q}$; Model ARMA (p,q)...............…………..3

$a_p(B)(1 - B)^d X_t = b_0 + b_q(B)$; Model ARIMA orde (p,d,q)................…………………………4

$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2$; Model ARCH orde (p).................……………………………..5

$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + \text{þ}_1 \sigma_{t-1}^2 + \cdots + \text{þ}_q \sigma_{t-q}^2$; Model GARCH orde (p, q)…..................6

where

$\emptyset_1, \emptyset_2, \ldots, \emptyset_p$	: autoregressive parameter
e_t	: error at t-time
$\theta_1, \theta_2, \ldots, \theta_q$	: moving average parameter
e_{t-q}	: error at time t-q
$a_p B = 1 - a_1 B - \cdots - a_p B_p$	: AR operator
$b_q B = 1 - b_1 B - \cdots - b_q B^q$	: MA operator

RESULTS AND DISCUSSION

NPF of Islamic banking is one of the indicators of bank health regarding non-performing financing consisting of substandard, doubtful, and loss. NPF values have fluctuating movements throughout the year of observation with high volatility. This high volatility is indicated by the phase where it has high fluctuations then followed by low and high fluctuations. However, based on observations it can be shown that the high volatility of the movement of the NPF value of Islamic banking has a downward trend. This shows that Islamic banking has been able to manage problem financing well.

Based on Figure 1, the average NPF value throughout the observation was 3.9 percent, with the highest value of 6.6 percent and the lowest value of 2.2 percent. Data distribution in general is normally distributed. This condition can be seen in the Jarque-Bera probability value which is above 5 percent while the symmetrical distribution indicated by the variable generally has a long tail on the right side (positive skewness). The kurtosis that appears, it turns out that the height measure of the data distribution is generally (leptokurtic). Then the results from standard deviations indicate the distribution of data in the sample by how close the individual data points are to an average of 0.96 percent.
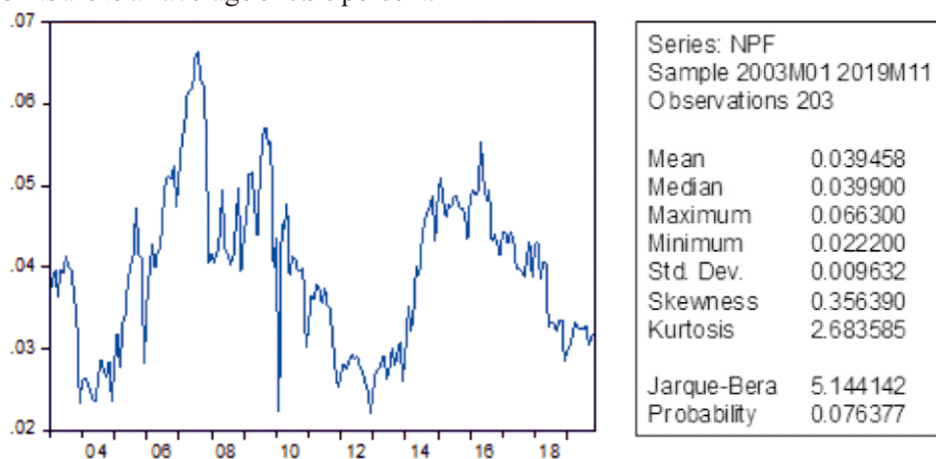

Figure 1. NPF Movements and Sharia Banking Descriptive Statistics

The downward trend in non-performing financing in Islamic banking shows an improvement in the performance of Islamic banking in managing to finance disbursed to debtors. The decline in this trend is inseparable from the role of regulators in issuing policies that support economic growth so that financing disbursed always increases and non-performing financing decreases. Islamic banking also avoids channeling financing to sectors that have high risk industries with high risks and are not in accordance with existing regulations in Islamic banking. This was done to create a sustainable financing climate.

Based on the results of the stationary data testing using the Augmented Dickey-Fuller (ADF) test, the NPF shows that the data is not stationary at the level (prob * 0.136> 0.05), but the data has been stationary at the difference (prob * 0,000 <0.05). As for using images there is a plot between observations with the time when the data level is not stationary and when the difference data is stationary by having a constant average and variance (Figure 2).
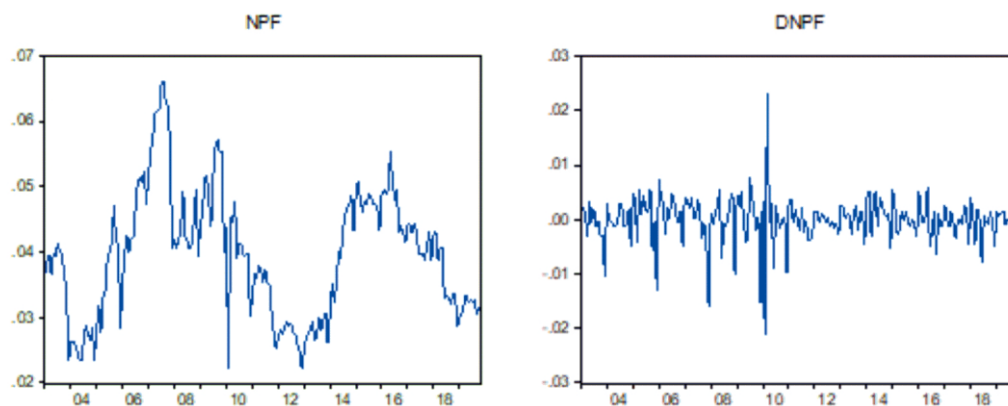

Figure 2. Data Stationarity Test Results at Level (a) and Difference (b)

Using data difference, then test the pattern of individual AC and PAC coefficients. From the test results, the ARIMA model can be determined by observing the AC and PAC patterns. The results of observing the pattern, showed that both the values of AC and PAC spikes were significant (AC and PAC> -0.138 and +0.138 <AC and PAC) contained in lag 1, lag 12 and lag 24 (Table 1).

Table 1. NPF Correlogram Difference Output

Lag	AC	PAC	Q-Stat	Prob	Lag	AC	PAC	Q-Stat	Prob
1	-0.249	-0.249	12.669	0.000	19	-0.142	-0.069	93.332	0.000
2	0.114	0.056	15.341	0.000	20	-0.008	-0.077	93.348	0.000
3	-0.141	-0.107	19.449	0.000	21	-0.042	-0.059	93.755	0.000
4	0.026	-0.040	19.588	0.001	22	-0.009	-0.027	93.774	0.000
5	-0.150	-0.147	24.292	0.000	23	-0.043	0.028	94.209	0.000

6	0.232	0.168	35.598	0.000	24	0.387	0.280	128.86	0.000
7	-0.132	-0.037	39.280	0.000	25	-0.094	0.084	130.91	0.000
8	-0.002	-0.102	39.281	0.000	26	0.078	0.068	132.33	0.000
9	-0.009	0.017	39.296	0.000	27	-0.056	0.043	133.06	0.000
10	-0.006	-0.019	39.303	0.000	28	-0.076	-0.054	134.44	0.000
11	-0.126	-0.121	42.738	0.000	29	-0.150	-0.108	139.82	0.000
12	0.347	0.283	68.847	0.000	30	0.170	-0.056	146.75	0.000
13	-0.121	0.032	72.040	0.000	31	-0.158	-0.108	152.77	0.000
14	0.001	-0.087	72.040	0.000	32	-0.006	-0.109	152.78	0.000
15	-0.075	-0.048	73.294	0.000	33	0.028	0.008	152.96	0.000
16	-0.064	-0.096	74.208	0.000	34	-0.075	-0.068	154.33	0.000
17	-0.115	-0.081	77.170	0.000	35	-0.102	-0.147	156.91	0.000
18	0.228	0.089	88.766	0.000	36	0.258	0.015	173.44	0.000

From the correlogram results that have been obtained, then an alternative ARIMA model will be conducted based on significant spikes. From the alternative ARIMA models tested aim to choose the best model where the difference lies in the error variant. The alternative ARIMA models are as follows:

$D(NPF) = c + AR(1) + AR(12) + AR(24)$

$D(NPF) = c + MA(1) + MA(12) + MA(24)$

$D(NPF) = c + AR(1) + AR(12) + AR(24) + MA(3) + MA(12) + MA(24)$

The selection of the best ARIMA models includes the ARCH model, the GARCH model, the ARCH in Mean (ARCH-M) model, the ARCH Threshold model (TARCH), and the Expansion GARCH (EGARCH) model. Based on the results of the processing that has been done, it can be concluded that the best model is the TARCH model based on the largest log likelihood value and the smallest AIC (Table 2).

Furthermore, after getting the best model, ARCH-LM will be tested for the best model. Based on the results of the processing that has been done, it can be seen that the value of Prob. Chi-Square (1) is 0.5074, where the value is greater than the value of 0.05 so it can be concluded that the estimated TARCH model is free from the ARCH effect (Table 3).

Table 2. Summary of Indicators for Selecting the Best Model

Model	Significance Parameters (α = 5%)						Log Likelihood	AIC
	AR(1)	AR(12)	AR(24)	MA(1)	MA(12)	MA(24)		
ARCH(1)	v	x	v	x	x	v	772.36	-8.58
GARCH(1,1)	x	v	v	v	v	v	795.31	-8.82
ARCH -M	v	x	v	x	v	v	775.46	-8.6
TARCH	x	x	v	v	x	v	796.64	-8.83
EGARCH	v	x	v	v	x	v	787.71	-8.73

Table 3. ARCH Effect Testing Results for the TARCH Model

Heteroscedasticity Test: ARCH			
F-statistic	0.435639	Prob. F(1,175)	0.5101
Obs*R-squared	0.439523	Prob. Chi-Square(1)	0.5074

After testing, the ARCH-LM can then be forecasted. Forecasting results obtained from the value of Root Mean Square Error (RMSEA), Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE) which is useful to find out how much error from forecasting is done. The value of each indicator can be known the average square root of forecasting error obtained by 0.009 (RMSE), the average absolute error obtained by 0.008 (MAE) and the average absolute percentage of error obtained by 22.13 (MAPE). From the indicator MAPE values generally obtain a small value so that the forecast results can be concluded close to the actual value (Figure 3).

This study predicts the movement of NPF of Islamic banking over the next 22 months. From the results of forecasting that have been done, it can be seen that the tendency of NPF has decreased every month with an average decrease of 6.92 percent. Forecasting is done in early 2020, which has increased from the actual data that has been obtained. November 2019 initially NPF value of 3.18 percent to 4.09 percent in January 2020. Then in the following month NPF of Islamic banking decreased with until the end of forecasting, namely December 2021. Forecasting the movement of the NPF which tends to fall will have an impact on the increase of financing carried out by Islamic banking, especially to sectors that have low risk (Chen & Lin, 2016). The characteristics of companies which include size, sector and legal status are common obstacles faced by banks in providing financing (Mertzanis, 2016).
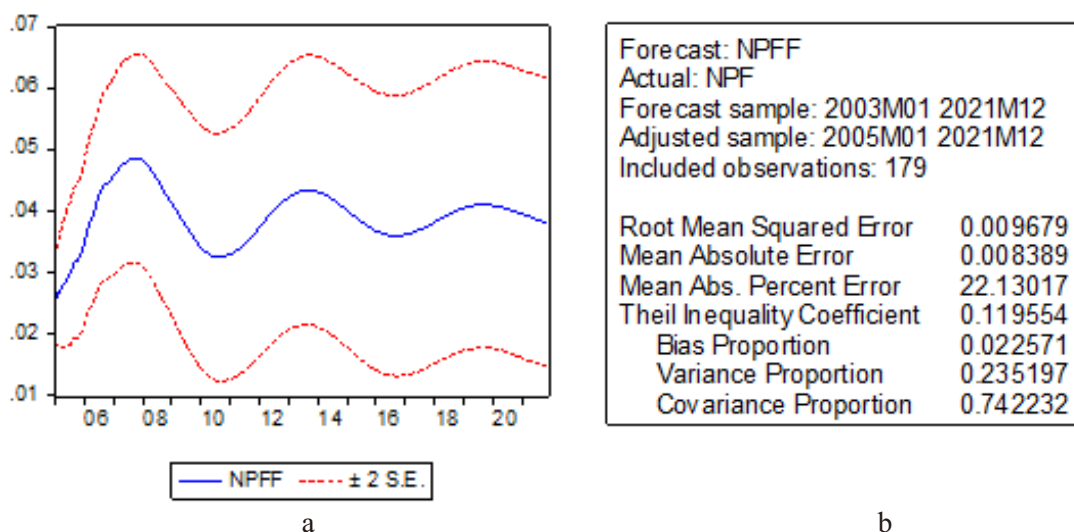
Forecast: NPFF	
Actual: NPF	
Forecast sample: 2003M01 2021M12	
Adjusted sample: 2005M01 2021M12	
Included observations: 179	
Root Mean Squared Error	0.009679
Mean Absolute Error	0.008389
Mean Abs. Percent Error	22.13017
Theil Inequality Coefficient	0.119554
Bias Proportion	0.022571
Variance Proportion	0.235197
Covariance Proportion	0.742232

a   b

Figure 3. Dynamic Forecast

NPF forecasting of sharia banking, which tends to decline is inseparable from the efforts of sharia banks to implement rescheduling, restructuring, and reconditioning programs (Ashraf, Zheng, Jiang, & Qian, 2020). On the other hand, Islamic banking has also made intensive underwriting and monitoring processes for financing customers and has been more careful in expanding financing (Hassan, Khan, & Paltrinieri, 2019). One of the efforts is by entering into financing with segments, sectors, and customers with a low level of risk (Trabelsi & Naifar, 2017). The results of this study indicate that the NPF value has decreased following the sharia banking statistics report (2019). Most of the financing uses the Musharaka and Mudharabah contracts where the contract is at low risk with the profit-sharing scheme.
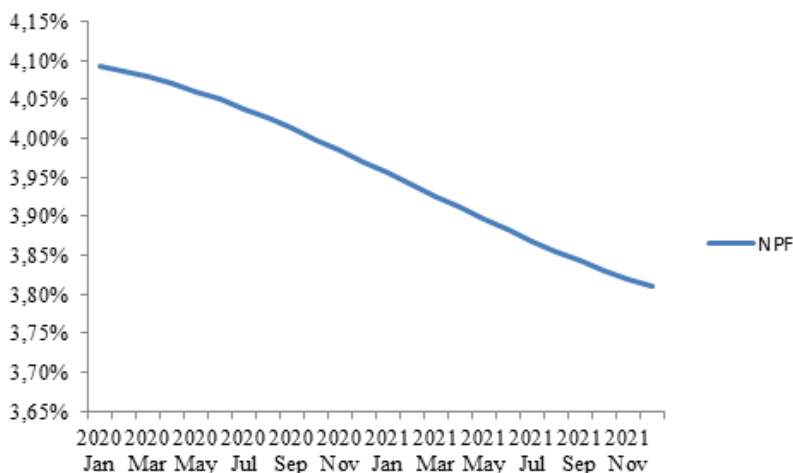

Figure 4. NPF Value Forecasting of Islamic Banking

Islamic banking also needs to improve the capability of human resources to strengthen the analysis, risk mitigation, and management relationships (Azmat, Skully, & Brown, 2014). So that Islamic banking as an intermediary institution needs to carry out its functions effectively and efficiently (Rahman, Sulaiman, & Said, 2018). This can be done by paying close attention to the conditions of the prospective financing customers so that there are no problematic financing in the future (Rahman, Zheng, Ashraf, & Rahman, 2018). In addition, an effective monetary policy in considering the nature of Islamic banking is very much needed to manage the supply of credit in the economy (Rashid, Hassan, & Shah, 2020). The quality of financing and the capital ratio have an important role in financing risk (Misman, Bhatti, Lou, Samsudin, & Rahman, 2015).

Table 4. Actual Value and Forecasting Value

Year	Month	Actual	Year	Month	Forecasting	Year	Month	Forecasting
	Jan	2.99%	2019	Dec	4.10%	2020	Nov	3.98%
	Feb	3.05%		Jan	4.09%		Dec	3.97%
	Mar	3.18%		Feb	4.09%		Jan	3.96%
	Apr	3.34%		Mar	4.08%		Feb	3.94%
	May	3.25%		Apr	4.07%		Mar	3.93%
2019	Jun	3.26%	2020	May	4.06%		Apr	3.91%
	Jul	3.24%		Jun	4.05%	2021	May	3.90%
	Aug	3.28%		Jul	4.04%		Jun	3.88%
	Sep	3.05%		Aug	4.03%		Jul	3.87%
	Oct	3.15%		Sep	4.01%		Aug	3.86%
	Nov	3.18%		Oct	4.00%		Sep	3.84%

The results of this study are also in line with research conducted by Kabir, Worthington, and Gupta (2015); Louhichi and Boujelbene (2016); Safiullah and Shamsuddin (2019) which shows that Islamic banking has significantly lower credit risk. The overall development of Islamic banking has no impact on credit constraints and has a positive impact on access to credit (Léon & Weill, 2018). Financing quality with good financing potential is an attractive opportunity by utilizing diversification which is a very attractive opportunity for investors to invest (Bhuiyan, Rahman, Saiti, & Ghani, 2019). Islamic banking needs to make the composition of the financing portfolio so that it can obtain the desired returns according to market risk (Narayan, Phan, Narayan, & Bannigidadmath, 2017).

CONCLUSION

The results of the study indicate that there are NPF values, there is an element of heteroscedasticity, which means that the residual variant of the data is not constant so that it is processed using the TARCH model to get a picture of the movement of NPF values in the coming months. The tendency of forecasting done using the TARCH model decreases. This is inseparable from the current ability of Islamic banking to manage financing risks by avoiding high risk sectors.

Overall, several policy implications that can be formulated include increasing the intensity of outreach related to the development and promotion of superior loan products to attract debtors, improve the quality of human resources, provide competitive interest rates and returns along with other facilities that can be obtained by borrowers, and service improvement and providing easy access to loan applications.

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