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FORECASTING THE INDONESIAN RURAL BANKS' PROFITABILITY: THE CASE OF DYNAMIC AND STATIC FORECASTING

Regi Muzio Ponziani
STIE Trisakti
E-mail: regi@stietrisakti.ac.id

Abstract: This research aims to forecast the profitability of Indonesian rural banks. The forecasting methods employed dynamic and static forecasting. Dynamic forecasting was represented by regression with Autoregressive Integrated Moving Average (ARIMA) errors while static forecasting was represented by Holt-Winters seasonality and Seasonal Autoregressive Integrated Moving Average (SARIMA). The regression with ARIMA errors included additional independent variables namely inflation and interest rate. The dependent variable being forecast was return on assets (ROA) of the rural banks. The data extended from January 2010 to July 2021. The data will be divided into training and test data. Training data extended from January 2010 to December 2020. The test data extended from January 2021 to July 2021. Training data were used to derive the models. The models generated then were used to yield forecasts for January until July 2021. The forecasts were later compared to the test data for accuracy. The research found that regression with ARIMA errors had the best forecast accuracy, followed by SARIMA and Holt-Winters seasonality. Therefore, the research proposed that regulators, analysts and all stakeholders of the Indonesian rural banks employ regression with ARIMA errors to predict the profitability and financial position of the rural banks.

Keywords: *Holt-Winters seasonality, Seasonal Autoregressive Integrated Moving Average, regression with ARIMA errors*

1. Introduction

Indonesian banking system adopts dual system. There are two kinds of banking system exist, conventional and Islamic banks. These bank operate differently. Conventional banks operate base on the regulations from the regulators. Islamic banking system also adheres to the regulations imposed by the Finanial Supervidory Agency (OJK) and the central bank (Bank Indonesia/BI). Furthermore, Islamic banks also observes the Islamic rulings and law in their operations. Any deviations from the shariah will be considered unlawful. Within each banking system, there lie two types of banks, commercial and rural banks. So there are commercial conventional and Islamic banks and conventional and Islamic rural banks. This research will focus on the conventional rural banks. Conventional rural banks target middle and lower segment and mostly located in the rural areas. Therefore, rural banks performance will be analyzed financially and socially. Socially, rural banks are expected to increase the welfare of surrounding community. This has been stated in the banking bills. Therefore, we can expect that rising profitability means also surging welfare in the surrounding community (Afriyeni & Fernos, 2018).

A profitable rural bank means the bank is more capable of serving the community. It has more robust capital at disposal if it can obtain net earnings. According to the regulations, rural banks cannot create secondary money and are very limited in their operational scopes. This explains why populations that cannot be served by the commercial banks depend so much on the rural banks for banking service (Simanjuntak, 2019). The following chart describes the development of loans distributed by the Indonesian rural banks.

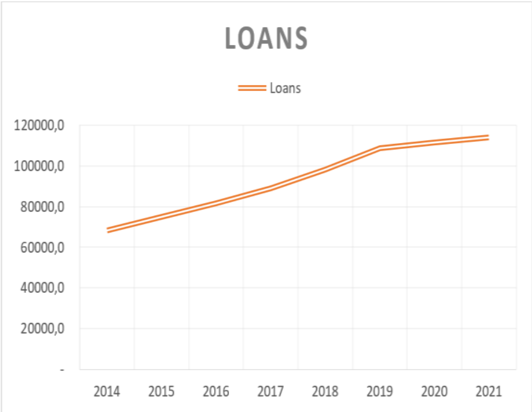

Figure 1. Loans by Rural Banks

The progress of the loan resembles that of the third-party fund. Overall, the loans distribution is always increasing. In 2014, Rp. 68 trillion was distributed. The number increased to Rp. 89 trillion in 2017, a 30.25% increase. In 2019, the total loans became Rp. 108 trillion. In July 2021, it became Rp. 113 trillion. The loan to deposit ratio always goes beyond 100%. Some of the rural banks are owned by the local government. In this case, the rural banks carry the mission to uplift the welfare of the local population and provide liquidity to the small, medium, and micro businesses according to the development program established by the local government. Loans given by the rural banks have been instrumental in empowering the financial condition of the local population (Wurarah & Mokodompit, 2020).

Rural banks have the individual and personalized approach to their customers and therefore are very much required by the community. Considering that micro, small, and medium enterprise comprise 55% of Indonesia's GDP the importance of rural banks cannot be overstated (Murningsih, Firdaus, & Purwanto, 2020).

Third-party fund also always steadily increases annually. In 2014, the total third-party fund amounted to Rp. 58 trillion. The number surged to Rp. 84 trillion in 2017, a huge 44% increase. In 2019, the rise continues to Rp. 102 trillion. The last position in July 2021 was Rp. 112 trillion. This shows that the customers still entrust rural banks with their funds. They do not hesitate to deposit their funds in the rural banks funding products. Even during pandemic, third-party fund deposited in the rural banks still undergoes increase. Although, the slope decreases a little bit, the surge keeps on perpetuating. The decrease in the slope shows that there is a slight slowdown of funding activities within the rural banks. This is normal especially because it is an extraordinary circumstances occurring. With all the social distancing and lock down, rural banks still succeed in collecting more deposits. This supports the contention that rural banks indeed have the capability to withstand crisis stemming from the pandemic (Yasin & Fisabilillah, 2021). Considering the intermediary function of the bank, all the deposited fund will be allocated back to the society. The loans will be given to individuals or small businesses that require liquidity. The figure below depicts the loan distributed by rural banks.

The purpose of this research is to predict the profitability of rural banks in Indonesia. Forecasting profitability of banks is very rare in literature. Most research focus on the determinants of rural banks' profitability (Sofyan, 2019, Wasiaturrahma, Sukmana, Ajija, Salama, & Hudaifah, 2020; Candy, 2021; Widia & Prananta, 2021), one research deals with forecasting for companies whether trading or manufacturing companies (Tian, Yim, & Newton, 2020). Hence no research conducted on forecasting the profitability of rural banks.

Literature regarding rural banks' profitability hovers around determinants of profitability. Sofyan (2019) examined the rural banks data from 2010 to 2016 to investigate determinants of the rural banks profitability. The variables posited to affect profitability are CAR, LDR, OCOI (Operating cost/operating income), and NPL ratios. He found that three variables affect profitability namely CAR, LDR, and OCOI. CAR and LDR affect profitability positively. The higher the CAR, the stronger the rural banks. CAR depicts the capital of the banks. Stronger banks are associated with higher capital. Capital will be used to absorb loss occurring from the operating activities. LDR also affects profitability positively. Higher LDR means more opportunity to reap profits from loans distributed. Lastly, OCOI renders negative influence to the profitability. The higher the operating costs, the more depleted the profits of the rural banks. Therefore, to increase efficiency rural banks should focus on reducing the operating costs.

Amanah (2020) observed that the profitability trend of rural banks started to decrease. Therefore, she used error correction model to find out what variables affect profitability in the long-run and short-run. She found that money supply and general reserve influenced profitability in the long-run. Nonperforming loan (NPL) affected profitability in the long- and short-run. This research proved the significance of risk management in the rural banks. NPL can be mitigated by good risk management practice (Sudarsono, Afriadi, & Suciningtias, 2021). Loan must be distributed to the truly productive sector in the economy. So that economy will develop and welfare can be increased. Therefore, it is crucial for regulator to increase the personnel competence in risk management practice.

Ashari & Nugrahanti (2020) examined whether rural banks were prepared to face disruption era or not. They distributed questionnaires to 97 rural banks located in diverse geographical location. They found that in general the readiness of rural banks to face disruption era was just adequate. This adequate level is below the good level expected from rural banks that were about to face disruption. Rural banks with the most readiness to face disruption was rural banks belong to BUKU 3 category. The banks comparatively have higher capital and mostly located in the urban or sub-urban areas. The least ready rural banks were banks that belong to BUKU 1 category. These banks have the least capital and mostly are located in rural areas. These banks should begin taking steps to learn and adopt the technological progress, especially when the progress becomes more rapid as times pass. Success in adopting with technological progress will allow the rural banks to stay in competition and even progresses among the face of competitors, especially for competitors who are late in adopting technology.

Wasiaturrahma, Sukmana, Ajija, Salama, & Hudaifah (2020) took the rural banks data from 2013 to 2017 to examine their technical efficiency. Both types of rural banks, conventional and Islamic, were examined. The result showed that both types of rural banks were still very inefficient especially when looked at the intermediation terms. However, in terms of production, the banks were indeed efficient. Further, the research tried to determine factors affecting profitability. It was found that location and capital determined the efficiency. Urban rural banks were more inclined to be more efficient than rural banks located in the rural areas. In addition, the stronger the capital a rural bank has, the more efficient it becomes in terms of intermediation and production function.

Widarjono & Anto (2020) conducted static and dynamic panel data regression against rural banks in Yogyakarta and Central Java province. The objective of the research is to invetigate whether market structure influence Islamic banks' profitability. They found that imperfect competition market applies for rural banks. There was a high barrier to entry impeding the new establishment of rural banks. Hence the prift of rural banks become permanent due to the almost nonexistence of new competitors. Additionally, market share also influenced profitability. However, market concentration had no influence on profitability. Other independent variables also influenced profitability. Specifically, efficiency and nonperforming financing affected profitability. High efficiency and low nonperforming financing will drastically boost profits. Therefore it is mandatory for rural banks to have high eficiency to increase performance drastically. This research is also supported by Wardhani & Ismunawan (2021) that found efficiency mattered so much to the rural banks.

Candy (2021) conducted a survey research to examine whether internal audit department can serve function to add to rural banks' financial and nonfinancial performance. Nonfinancial performance included quality, delivery of service, personnel development, and productivity. The research focused on rural banks located in Riau island province. Around 63 questionnaires were distributed to the rural banks. She found that internal audit function affects profitability significantly. Also, nonfinancial performance was heavily influenced by the existence of internal auditors to validate and confirm.

Widia & Prananta (2021) compared the performance of rural banks differentiated by the ownership. Rural banks can be owned by the government or by private owner. The research focused on rural banks located in Central Java province beginning in the year 2016 to 2019. Overall, the difference in profitability is not statistically significant under the government or individual owner. The same case happened to the variable NPL and CAR. Government-owned and private-owned rural banks apparently do not differ in terms of NPL and CAR. However, statistically different significance occurs to quality of earnings and LDR. Government-owned rural banks usually have special assignments delegated by the government to support the government's programs. They are required to disburse loans to certain community although it is not certain that the quality of the loans is good. The rural banks are also required to provide loans to certain government's projects to develop certain region or area although the payback takes longer than expected. These are some of the causes to the difference between government-owned and private-owned rural banks. In terms of profitability forecasting, only one research focus on the appropriate methodology.

Tian, Yim, & Newton (2020) compared quantile regression to least square regression to find which method performs better. They found that quantile regression perform better in terms of econometrics. However, the sample was not rural banks. This research attempts to forecast rural banks' profitability. Profitability forecasting for banking industry is still rare, not to mention the forecasting of rural banks' profitability.The introduction includes the background to the issue or problem as well as the urgency and rationalization of activities (research or service).

2. Research Method

The data used in this research extended from January 2010 to July 2011. The variables listed are as follows:

Table 1
Research Variables

Variable	Definition	Source
PROF	Return on Assets	OJK
INF	Inflation rate	Bank Indonesia
INT	Interest proxied by the rate applied in the interbank money market	Bank Indonesia

Holt-Winters seasonality and SARIMA use autoregressive components for forecasting. These two models represented static forecasting method While regression with ARIMA errors would employ two independent variables namely INF and INT, hence the dynamic forecasting models, since it included independent variables to ensure accuracy. We compared the forecast accuracy and found out whether inflation and interest rate will enhance the forecasting power for predicting profitability of rural banks. The data were divided into two categories, training and test data. Training data extended from January 2010 to December 2020. The training data were used to derive the models necessary for forecasting. The second category of data is test data. Test data was used to compare the forecasts generated by Holt-Winters seasonality, ARIMA, and regression with ARIMA errors with the actual data. The accuracy was measured using Root Mean Squared Errors (RMSE) and Mean Absolute Percentage (MAPE). As the names suggest, RMSE results from taking the square root of the mean of squared errors. Errors were the difference between forecast and test data. MAPE proxies the mean of absolute error in percentage term. The lower the number of RMSE and MAPE, the better the forecast accuracy. The first model employed in this research was Holt-Winters seasonality or also called triple exponential smoothing. This model included coefficient estimates for level, trend, and seasonality. The general equation for Holt-Winters seasonality is as follows:

$$\hat{\mathbf{y}}_{\mathbf{t+h|t}} = \boldsymbol{\ell}_{\mathbf{t}} + \mathbf{hb}_{\mathbf{t}} + \mathbf{s}_{\mathbf{t+h-m(k+1)}}$$

The equation can be delved deeper into three equations that represent the level, trend, and seasonality equations. The level equation is $\ell_t = \alpha(y_t – s_{t-m}) + (1- \alpha)(\ell_{t-1} + b_{t-1})$. We can see that it is seasonally adjusted. The parameter α will be estimated from the equation. The trend equation is $bt = \beta(\ell_t - \ell_{t-1}) + (1- \beta)\ b_{t-1}$. The data testing will yield estimate for β parameter. The seasonality equation is $st = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1- \gamma)s_{t-m.}$ Again, the estimate for γ is our main concern. The SARIMA model would be written as SARIMA (P, D, Q)(p, d, q). P represents the autoregressive component. Therefore, it can also be written as $PROF_t = PROF_{t-1} + \textit{error}$. The value of ROA in a certain month might be influenced by the value of it in the previous month. The term D denotes the difference term. If D is equal 1 then the variable should be differenced once, $\Delta PROF= PROF_t - PROF_{t-1}$. Nonstationary data should be differenced before they can be further analysed. The term D denotes the moving average component. Moving average is the inclusion of the error terms in the SARIMA equation for forecasting. Errors from previous period could be assumed to impose influence on the value of current ROA. The term p denotes the seasonality component. Since this research used monthly data, seasonality is considered as the difference in the value of ROA 12 months before hence the equation PROFt = $PROF_{t-12}$ + *error* (for 1 lag operator). The term d is also the difference in seasonality component, ΔPROF= $PROF_t$ - $PROF_{t-12}$ (for 1 lag operator). The term q is the moving average component related to the seasonality. The third model is regression with ARIMA errors. Since it is a regression equation, then there will be independent and dependent variables. The independent variables are inflation (INF) and interest rate (INT). The general equation for regression with ARIMA errors is:

$$\hat{y}_t = \alpha + \beta_1 x_{1t} + \beta_2 x_{2t} + \xi_t$$

The term ξt will follow ARIMA pattern (P, D, Q). If one autoregressive component AR (1,0,0) the equation for error becomes $\xi_t = \xi_{t-1} + \lambda$.

3. Results and Discussion

3.1. Results

The analysis was first conducted to analyze the movement of profitability during the research period. The following figures depict the chart for profitability during research period.

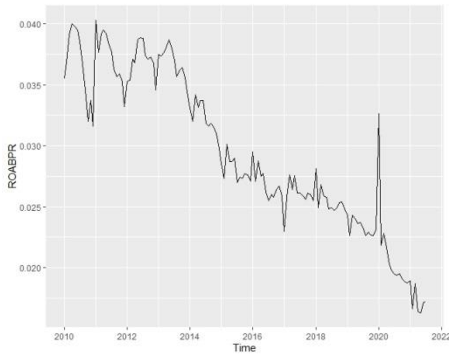

Figure 2 Plot of Profitability

The figure above depicts the development of rural banks' profitability. Overtime the trend is decreasing. The profitability always fluctuates. There are spikes and troughs along the research period. The decreasing trend begins in 2014. Since then, profitability keeps decreasing. However, approaching 2020, there is a massive increase in the profitability temporarily. Further analysis on the figure is conducted below:

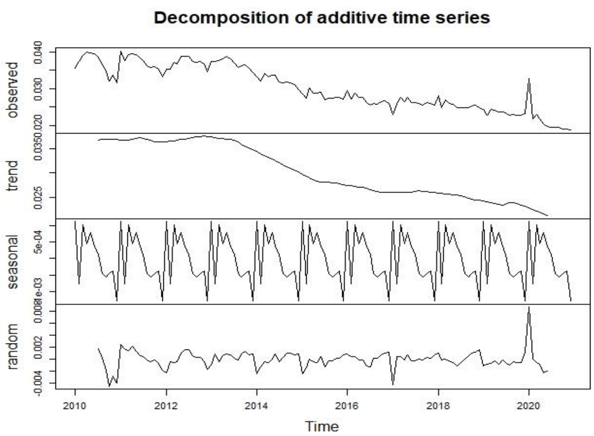

Figure 3 Decomposition of Profitability

The figure above shows the decomposition of profitability during research period. The first chart shows the real data. This has been shows on the previous figure. The second chart depicts the overall trend of the profitability. The trend has been smoothed to remove all the fluctuations so that the direction is clearly visible. The declining trend commences in 2014 and has still been going on until now. The third chard shows the seasonality. We can see that there is indeed seasonal pattern in the profitability. The year to year performance of the same month will be relatively similar. Therefore, we can predict the performance of rural banks in certain month by using the data of the same month at the previous year(s). The last chart shows the random errors component of the graph. The errors are up and down and fluctuate. Approaching the end of research period, the errors component surge drastically, representing the extraordinary circumstances we are experiencing now. The first estimation is Holt-Winters seasonality. The result of parameter estimation is as follows:

Table 2 Holt-Winters seasonality estimates

Holt-Winters Seasonality Estimates			
Parameters	**Alpha**	**Beta**	**Gamma**
	0.0393	0.0001	0.0453
	Initial States: l = 0.0393 b = -0.0001 s = -0.0012; -0.0004; -0.0002; -0.0004; -0.0002; -0.0004; 0.0004; 0.0008; 0.0007; 0.0012; -0.0003; 0.0001 Sigma: 0.0023 AIC = -943.0747; AICc = -937.7062		
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The table 2 shows that the Holt-Winters seasonality is able to estimate the level, trend, and seasonality. The coefficient of α, β, and γ are 0.0393, 0.0001, and 0.0453. This parameter would later be used to generate forecasts for the January-July 2021 period. The figure that shows the forecast result is as follows:

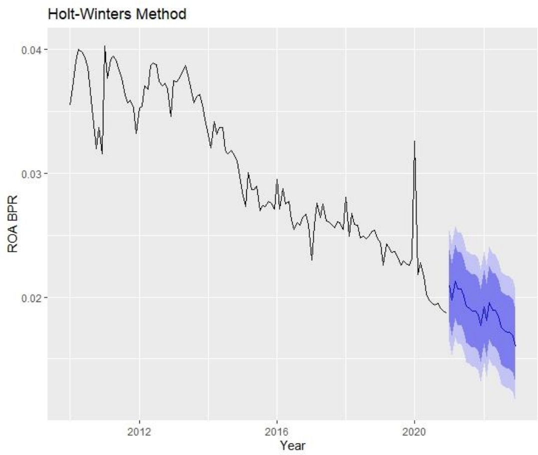

Figure 4 Holt-Winters seasonality forecasts

Figure 4 shows that the decreasing trend will continue in the near future. However, it will be interspersed with occasionally temporary increase. According to Holt-Winters seasonality seasonal component will also persist in the future. This seasonal component is the one which renders positive spikes. During the pandemic, there are public holidays and religious holidays that will drive positive economic activities in the economy. Consumption and production activities will continue to persist. At least during pandemic, micro, small, and medium enterprise can still market their product using online platform and gain sales. The second model tested was SARIMA model. Below is the the result of SARIMA model:

Table 3 SARIMA estimates

SARIMA(0,1,1)(2,0,1)			
ma1	**sar1**	**sar2**	**sma1**
-0.3952	-0.0640	0.6387	0.3421
(0.0874)	(0.1053)	(0.0857)	0.1086
AIC=-1314.93 AICc=-1314.45 BIC=-1300.55			

The table 3 shows that the appropriate model for prediction is SARIMA(0,1,1)(2,0,1). This model concerns no autoregressive component at level. However, the model should be differenced once to ensure stationarity. The error from previous period provides insight for forecasting of the current period. Regarding seasonality component, the autoregressive component is 2. This means the seasonal component from 24 months can still influence the seasonal component of the current period, together with seasonal component from previous year. No integrated component is necessary for the seasonality. The error in seasonality from previous year is necessary for prediction. Before moving on to the forecasting using SARIMA, we must first investigate whether the errors from SARIMA model is white noise as shown below.

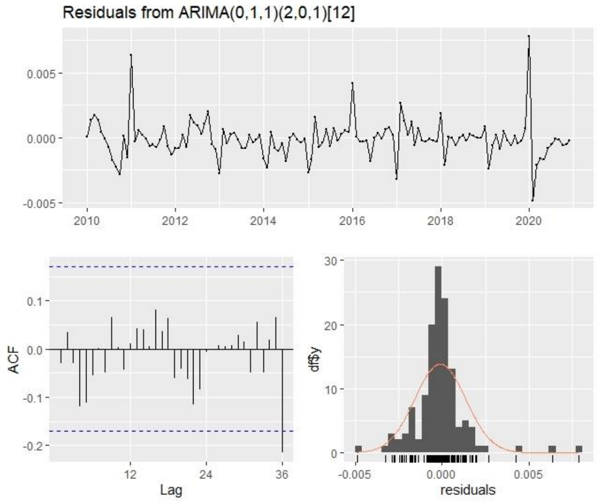

Figure 5 Residuals checks of SARIMA

The above figure presents the residual checks of SARIMA (0,1,1)(2,0,1). The first chart on top shows the residuals resulting from the model. The residuals seem stationary. They just revolve around a certain mean. The ACF figure shows that no correlation occurs from lag 1 until lag 35. The significant correlation occurs at lag 36. As long as, there is no correlation in residuals from lag 1 to lag 12, the residuals can be confirmed as white-noise. The last chart displays the distribution of the residuals. The residuals are normally distributed with the mean 0. Most residuals are concentrated near the mean, a typical feature of normal distribution. The forecast result of SARIMA is presented below:

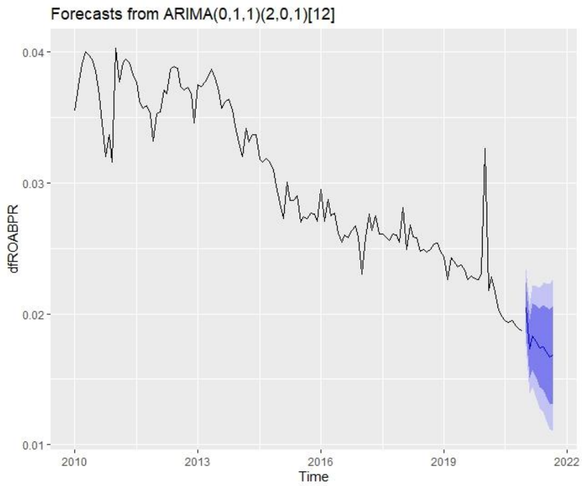

Figure 6 SARIMA Forecast Results

The forecasts derived from SARIMA model reveals little turbulence. There is not much fluctuation although the profitability is still volatile. The trend will continue to decline untul the end of research period. According to SARIMA, the ROA of rural banks will be more than 1.5%. So rural banks can still reap profits in the midst of the pandemic. The third and final observation is regression with ARIMA errors.

Table 4 Regression with ARIMA errors

Regression with ARIMA(1,1,0) errors		
Coefficients:		
ar1	**INF**	**INT**
-0.4205	0.0066	0.0002
(0.0777)	(0.0226)	(0.0004)
AIC=-1357.75 AICc=-1357.45 BIC=-1346.04		

Based on the table 4, the regression coefficients will include an autoregressive component of lag 1. This shows that current profitability is affected by previous month profitability. This is the essential feature of time series data in which high state will be followed by high state and lows state will be followed by low state. The variables INF and INT have parameter estimates that can be used for forecasting. The errors derived from this model follows the ARIMA (1,1,0). We first check the residuals diagnostics of the model as showsn below.

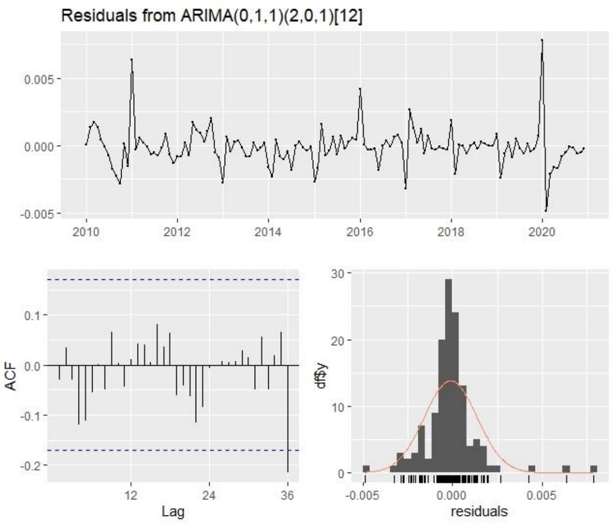

Figure 7 Residuals Diagnostics of Regression with ARIMA Errors

The above figure presents the residual checks of regression with ARIMA model. The first chart on top shows the residuals resulting from the model. The residuals also seem stationary, like residuals from SARIMA model. They just revolve around a certain mean. The ACF figure shows that no correlation occurs from lag 1 until lag 35, again just resemble the SARIMA model. The significant correlation occurs at lag 36. As the requirement, as long as, there is no correlation in residuals from lag 1 to lag 12, the residuals can be confirmed as white-noise. The last chart displays the distribution of the residuals. The residuals are normally distributed with the mean close to 0. Most residuals are concentrated near the mean, a typical feature of normal distribution. The forecast result of Regression with ARIMA Errors is presented below:

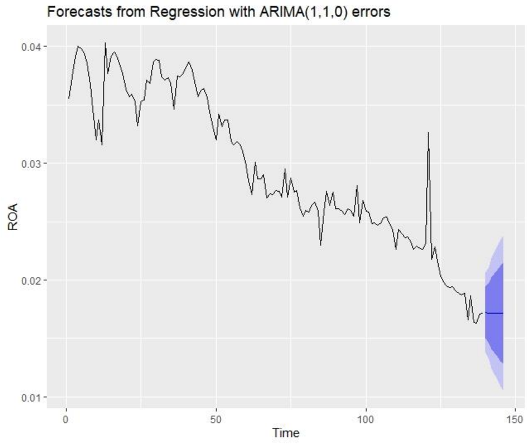

Figure 8 Regression with ARIMA Errors Forecasts Result

The above figure shows the forecasts results of Regression with ARIMA Errors. The profitability seems stable approaching the end. Actually, the data shows some volatility. However, the volatility is not visible by naked eyes. From the results, the ROA of rural banks will be around 1.7%. When the results are presented in the form of a table, we can clearly see the volatility I the results generated by regression with ARIMA errors. The following table displays forecast results and accuracy.

Table 5 Forecast Results and Accuracy

Time	Actual Data	HW Seasonality	SARIMA	Regression ARIMA
January 2021	0.01890000	0.02090200	0.020474	0.01722830
February 2021	0.01661000	0.01979640	0.017330	0.01717006
March 2021	0.01867000	0.02126010	0.018272	0.01716250
April 2021	0.01637000	0.02065934	0.017900	0.01716768
May 2021	0.01628000	0.02068058	0.017378	0.01718401
June 2021	0.01712106	0.02013808	0.017427	0.01716370
July 2021	0.01719881	0.01927662	0.017113	0.01718088
RMSE		**0.003208315**	**0.000985769**	**0.00098825**
MAPE		**18.08%**	**4.74%**	**4.44%**

The table 5 shows the comparison of various forecasting method and actual data. The actual data shows that the ROA of rural banks will extend from 1.6 to 1.8%. Holt-Winters seasonality with RMSE 0.003208315 and MAPE 18.08% predicts the data will be around 1.9% to 2.1%. Holt-Winters seasonality consistently over predicts the profitability of the rural banks. The SARIMA (0,1,1)(2,0,1) predicts that the profitability will extend from 1.7% to 2%. SARIMA model has RMSE of 0.000985769 and MAPE of 4.74%. Lastly, the regression with ARIMA errors predicts that the profitability will hover around 1.7%. When presented in numbers, we can see that the number are actually fluctuating. This model has the best accuracy with lowest value of RMSE and MAPE. Therefore, the best model for prediction is regression with ARIMA errors followed by SARIMA. The Holt-Winters seasonality is the least accurate.This section presents research results. Research results can be supplemented by tables, graphs (figures), and / or charts.

3.2. Discussion

Apparently due to COVID pandemic, the profitability does not last long. It begins decline sharply. In 2014, the profitability was about 0.036 or 3.6%. At the end of the research period, the profitability becomes less than 1%. It is steadily decreasing. During pandemic, the rural banks remain profitable although the profit is decreasing. This is a sign of how good rural banks can withstand extraordinary circumstances. Rural banks profitability can stay within the positive area. Rural banks' customers are mainly micro, small, and medium enterprise. This enterprise has proven capable of enduring hardships. This posits influence to rural banks. Rural banks can weather bad economic condition. Profitability forecasting is particularly important for rural banks and regulators alike. By forecasting profitability rural banks and the parties involved can anticipate bad economic condition and be prepared for obtaining additional capital. The models prove accurate for forecasting profitability is regression with ARIMA errors followed by SARIMA. Holt-Winters seasonality is the least accurate. All the models can pick up the seasonality and trend existing in the data and predict forecasts. The addition of Inflation and interest rate in the regression with ARIMA errors will provide additional valuable insights for enhancing forecast accuracy.

4. Conclusion

The purpose of this research is to find the best model for forecasting rural banks' profitability. Two kinds of forecasting were used, dynamic and static forecasting. Dynamic forecasting was represented by regression with ARIMA errors and static forecasting is represented by Holt-Winters seasonality and SARIMA. The result shows that regression with ARIMA errors is the most accurate model followed by SARIMA. The Holt-Winters seasonality is the least accurate. Based on the results, inflation and the prevailing interest rate can be used to forecast rural banks profitability. The increase in general price together with interest rate in the market provide valuable insights concerning the performance of rural banks. Therefore, regulators and government can predict when rural banks might experience distress that can jeopardize the economy and take prevention measures to anticipate the circumstances. Future research can attempt to forecast profitability by using machine learning or deep learning model and include another independent variable such as exchange rate.

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