Modelling and Forecasting Third Party Fund Growth using ARIMA

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ABSTRACT---Indonesian economy faces significant challenges in 2018, triggered by increasing global uncertainty. Even though the uncertainty and dynamics of the global economy are estimated to not be conducive enough in 2019, projections made by Bank Indonesia and the Ministry of Finance state that Indonesia's economic growth is expected to increase in the range of 5.0% - 5.4%. One of the factors for Indonesia's economic growth in 2019 is the increase in economic stability, supported by increased domestic demand both in terms of consumption and investment. In addition, increasing economic stability also has an impact on improving financial stability with a maintained risk. Therefore, Bank Indonesia projects that the performance of Third Party Funds (DPK) in 2019 will increase by 8% - 10%. In accordance with the objectives of the BPD Regional Champion (BRC) program, which was refined into the BPD Transformation program, where the composition of Non-Regional Third Party Funds (DPK) is at least 70%, with the projection of increasing deposits in 2019 and increasing economic stability, it is expected that BPDs can collect funds from especially the general public outside the Regional Government. Based on this, the BPD collected growth is forecast using ARIMA. The results of the study shows that, the growth of TPD will have increased but the growth is fluctuated and tended to be decline in the end of the year in 2019.

Index Terms— Third Party Fund, Regional Development Bank, Forecasting Growth, ARIMA.

I. INTRODUCTION

Third Party Funds (DPK) are important components of asset in maintaining business sustainability and the continuity of the bank's operational activities. If the performance of a DPK increases, the opportunity for banks to improve their business activities also increases, through spread management policies between interest deposits and loan interest, and optimizing idle funds to contribute to improving the regional economy.

As one of the regional financial institutions aiming to improve the regional economy, most of the operational activities of the BPD have so far been supported by regional governments, especially in the area of deposits collection. Based on data from the Association of Regional Development Banks (2015), the composition of DPK in all BPDs in Indonesia is dominated by regional government funds. This shows that in carrying out its operational activities, BPD is still dependent on local government funds. However, with the enactment of Minister of Finance Regulation Number 235 of 2015 on the Conversion of Distribution of Profit-Sharing Funds and/or Non-Cash General Allocation Funds, there is a possibility of a decrease in regional government funds deposited in the BPD. If BPD continues to be dependent on the regional government, they

will not be able to achieve the targets set out in the BPD Regional Champion program, which was refined into BPD Transformation program, as a bank acting as a regional development agent with a high competitiveness, and a leader in each area.

Through increasing economic stability in 2019, which has an impact on projections of increasing deposits by 8% - 10%, it is expected that BPD will be able to improve business performance especially in the funding sector by increasing the proportion of non-regional DPK by increasing CASA and diversifying non-regional funding products.

This study aims to find out how the growth performance of BPD deposits has been based on optimism for domestic economic conditions and projections of increased growth in banking deposits in Indonesia in 2019 using the ARIMA method.

II. RELATED WORKS

The ARIMA prediction method is widely used to predict various phenomena such as predicting ther growth of third parties fund in Indonesia (Kurniati, 2015), predicting the credit demand in Indonesia (Syarifuddin and Pratomo, 2013), predicting the economic Growth in Shengzheng, China (Wang, 2016), and predicting the stock prices in India (Mondal, et, al, 2014). From various works, known that the error rate of ARIMA prediction result is quite low. Additionally, ARIMA prediction method is also one of the prediction methods with high accuracy (Gao, et al, 2017; Tedorova, 2003; Omane-Adjepong, et al, 2013; Chen, et al, 200; Claveria, et al, 2013; Newaz, 2008).

III. RESEARCH METHODOLOGY

This section discusses the methodology stages used in this research. This research used total data third parties fund by conventional BPD in quarterly periods from 2007 to 2018. Data was obtained through Indonesia Financial Services Authorithy publication. To predict by using the ARIMA method, the following testing steps were performed (Cryer and Chan, 2008):

a) Variety and Average Stationarity Test

Time series data is stationary to the variance and mean if the probability value of Augmented Dickey-Fuller is significant;

b) ARIMA Model Identification

ARIMA forecast model in general is shows as below:

$$\emptyset\ ()(1-) \quad =_0 + \quad ()$$

ARIMA tentative model identification in predicting theRDB third parties fund was conducted by identifying each order in the model through Partial Autocorrelation Factor (PACF), Autocorrelation Factor (ACF), and differentiation degree performed on time series data of BPD third party fund.

c)Estimation of the ARIMA Model Parameter

The stage of estimation of the ARIMA tentative model parameter (p,d,q) was performed by using maximum likelihood method in which the significance of model parameters was tested using the following hypothesis:

H0: Model parameter is not significant

H1: Model parameter is significant

ARIMA model is considered significant if all model parameters are significant.

d)ARIMA Model Diagnostic

An ARIMA model free from white noise condition is a model which fulfils the assumptions that the residuals are free from autocorrelation, heteroscedasticity, and distributed normally. Every tentative model obtained was tested for feasibility using the following tests:

1. Homogeneity Assumption

Homogeneity assumption test was performed using the White Test with the following decision-making criteria:

H0 : The variance are homogeny

H1 : The variance are not homogeny

Residuals from time series data model considered to fulfil the homogeneity assumption if the probability of the white test statistic is $> \alpha = 0.05$;

2. Non-Autocorrelation Assumption Non-Autocorrelation assumption test was performed by comparing the probability value of the Ljung-Box Q Statistic test on each lag for every ARIMA tentative model obtained with the following decision-making criteria:

H0 : There is no autocorrelation

H1 : Autocorrelation occurs

Residuals from the time series data model considered as having no autocorrelation if the probability of Ljung-Box Q Statistics test is $< \alpha = 0.05$;

1. Normality Assumption

The normality assumption test was performed by using Jarque-Berra test with the following decision-making criteria:

H0 : Residual spreads normally

H1 : Residual does not spread normally

ARIMA tentative model suitable for predicting is ARIMA model free from white noise condition or fulfils these three assumptions.

Selection of the Best Model

Selection of the best ARIMA model was performed by choosing a model with the smallest AIC value.

IV. RESULT & DISCUSSION

a) Stastionary Test

The results of stationary tests on the total data of BPD third partie fund are not stationary against variety or average. Therefore, a transformation was performed on the total data of BPD third party fund. The stationary test result on the transformation result data fulfils the assumption of variance and average stationarity after 1 differentiation.

Table 1. Augmented Dickey Fuller Test

Condition	ADF	Conclusion
WithoutDifferentiation	0.5708	Notfulfilledtheassumption
First Differentiation	0.0053	Fulfilledtheassumption

b) Model Identification

Based on the correlogram results, it is found that time series data is significant in the first lag for autocorrelation (ACF) and partial autocorrelation (PACF). Therefore, the possible ARIMA prediction model with 2 differentiation is ARIMA (1,1,1).

Table 2.Correlogram Test

Lag	Q-Statistic Probabilistic	Conclusion
Lag ke-1	0.047	Significant
Lag ke-2	0.000	Not significant
Lag ke-3	0.026	Significant
Lag ke-4	0.000	Significant
Lag ke-5	0.000	Significant

c) Parameter Model Estimation

Table 3. Signification Test of Parameter Model

Tentative Model	Significancy Level
ARIMA (4,1,4)	Not Significant
ARIMA (4,1,3)	Not Significant
ARIMA (4,1,2)	Not Significant
ARIMA (4,1,1)	Not Significant
ARIMA (4,1,0)	Not Significant
ARIMA (3,1,4)	Not Significant
ARIMA (3,1,3)	Significant
ARIMA (3,1,2)	Not Significant
ARIMA (3,1,1)	Not Significant
ARIMA (3,1,0)	Not Significant
ARIMA (2,1,4)	Not Significant
ARIMA (2,1,3)	Not Significant
ARIMA (2,1,2)	Not Significant
ARIMA (2,1,1)	Not Significant
ARIMA (2,1,0)	Not Significant
ARIMA (1,1,4)	Not Significant
ARIMA (1,1,3)	Not Significant
ARIMA (1,1,2)	Significant
ARIMA (1,1,1)	Significant
ARIMA (1,1,0)	Not Significant
ARIMA (0,1,4)	Not Significant
ARIMA (0,1,3)	Not Significant
ARIMA (0,1,2)	Not Significant
ARIMA (0,1,1)	Not Significant

QTR III 2019	562.893	-2,33%
QTR IV 2019	475.804	-15,47%

d) Model Diagnostic

ARIMA tentative model diagnostic was performed by homoscedasticity, non-autocorrelation, and normality assumption test. The results of ARIMA tentative model diagnostic is as follows:

Table 8. ARIMA Model Diagnostic Test

Tentative Model	Heteros Assumption	Autocorr Assumption	Normality Assumption
ARIMA (3,1,3)	√	√	X

Tentative Model	Heteros Assumption	Autocorr Assumption	Normality Assumption
ARIMA (1,1,2)	√	√	X
ARIMA (1,1,1)	√	√	X

e) Best Model Selection

The best ARIMA model selected by choosing tentative models with the smallest Akaike info Criterion (AIC).

Table 9. Best ARIMA Model Selection

Tentative Model	AIC	R-Square
ARIMA (3,1,3)	-2,388953	67,40%
ARIMA (1,1,2)	-1,641232	20,46%
ARIMA (1,1,1)	-1,496594	4,62%

Based on Table 9, the best ARIMA model to forecast RDB third parties funds growth is ARIMA (3,1,3). The equation is:

$$= \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \emptyset_3 Y_{t-3} - \theta_1 e_{t-1} - \theta_2 e_{t-2}$$
$$- \theta_3 e_{t-3} +$$
$$= -1.04_{-1} - 1.04_{-2} - 1.02_{-3} + 1.09_{-1}$$
$$1.07_{-2} + 0.92_{-3}$$

f) Forecasting using ARIMA Model

Table 10 shows the forecast result of RDB third party fund growth using ARIMA (3,1,3). Based on the projection result, third party fund of RDB will have increased but the growth is fluctuated and tended to be decline in the end of the year. From the projection result, we can say that RDB Transformation Program is not give significant impact to increase the performance of RDB.

Table 10. Forecast Result

Period	ProjectionResult	Projection RDBThird PartyFund Growth
QTR I 2019	567.678	18,89%
QTR II 2019	576.334	1,52%

V. CONCLUSION

Based on the projections results obtained, the best ARIMA predicting method is ARIMA (3,1,3) although the normality assumption are not fulfilled to all significant tentative models. The result shows that third party fund of RDB will have increased but the growth is fluctuated and tended to be decline in the end of the year.

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