MODELING AND FORECASTING CREDIT GROWTH USING ARIMA

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MODELING AND FORECASTING CREDIT GROWTH USING ARIMA

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A B S T R A C T

The Indonesia Financial Service Authority, namely OJK, projects that the credit growth disbursed by Indonesian banks increase to 9% up to 11% in 2018, which is triggered by the infrastructure development plan. As a bank which initial objective is to provide financing for the implementation of regional development efforts, and in accordance with the vision and mission of RDB) Regional Champion that is refined into RDB Transformation Program, Regional Development Bank (RDB) should have the ability as an Agent of Regional Champion by actively contribute to the regional development through credits. Based on this condition, RDB credit growth forecasting was performed using ARIMA which was compared to the situation analysis to minimize prediction errors caused by both global and domestic environment changes. The research results showed that in 2018, BPD credit growth tended to fluctuate with an increasing trend compared to the same period in the previous year.

***Keywords**: Regional Development Bank (RDB), ARIMA, Credit Growth, Situational Analysis.*

1. INTRODUCTION

Regional Development Bank (RDB) well known as *Bank Pembangunan Daerah/*BPD is a one of commercial bank whose of the shares are owned by the regional government. RDB is one of the banks which purpose of establishment based on the Law is to provide financing for the implementation of regional development business and provide loans for investment, expansion, and development projects purpose. It is expected to be able to contribute in the process of infrastructure development that will be promoted in 2018, in accordance with the vision and mission of RDB Regional Champion program that was refined into RDB Transformation program, namely the capability aspect as Agent of Regional Champion by actively contribute to the regional development through credit.

However, Lisdayanti et al. (2013) and Salim et al. (2015) show that RDB contribution to the regional economy is still relatively low. The low contribution of RDB to the regional economy is reflected in the performance of credit disbursement performance, which its growth is highly fluctuate ranging from 20% per year and tends to decline.

This research aimed to find out the growth performance of BPD credit disbursement based on the optimism of global and domestic economic conditions and the increase projection of banking credit growth in Indonesia in 2018 using the ARIMA method and situation analysis in response to dynamic economic conditions.

2. RELATED WORKS

The ARIMA prediction method is widely used to predict various phenomena such as predicting the economic Growth in Shengzheng, China (Wang, 2016), predicting the stock prices in India (Mondal, et, al, 2014), predicting the credit demand in Indonesia (Syarifuddin and Pratomo, 2013), and predicting credit disbursed by banking in Pakistan (Nooren, et al, 2017). 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).

3. RESEARCH METHODOLOGY

This section discusses the methodology stages used in this research. This research used credit total data disbursed to the non-bank third parties by conventional BPD in quarterly periods from 2007 to 2017. Data was obtained through Indonesia Financial Services Authorithy publication.

3.1 Descriptive Statistics and Difference Test

First, a descriptive statistical analysis was used to provide a general description of the data. As an additional analysis, difference test was used on the data by using the Mann-Whitney statistic test in which the criteria used were as follows:

H0 : RDB Transformation does not have a significant difference on the RDB credit growth;

H1 : RDB Transformation have a significant difference on RDB credit growth;

3.2 ARIMA Forecasting

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 var ance 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:

$$\emptyset_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t$$

ARIMA tentative model identification in predicting the RDB credit growth 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 credit disbursement.

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 homogen
H1 : The variance are not homogen
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 < $\alpha = 0.05$;
3. 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.

e) Selection of the Best Model
Selection of the best ARIMA model was performed by choosing a model with the smallest R-Squared value and AIC value.

3.3 Situational Analysis

Situation analysis in this research aimed to provide an alternative on the obtained prediction results. Situation analysis in this research consists of 4 (four) conditions described in the matrix with the following conditions:

1. International and national economic conditions are in good standing;
2. The condition of the global economy is good, the national economy tends to decline;
3. Global and national economic conditions have decreased;
4. The condition of the international economy has decreased, national economic conditions are in good standing;

Each prediction results obtained was then simulated in the four conditions, which every condition will provide different prediction results in accordance with the tolerance range of prediction value of each hypothesis.

4. RESULTS & DISCUSSION

4.1 Descriptive Statistics and Difference Test

Descriptive statistics of credit that distributed by RDB from 2007 to 2017 was presented on Table 1, Table 2, and Figure 1.

Table 1. Descriptive Statistics of RDB Credit from 2007 to 2017

Year	Quarter	Total Credit	Average Credit	Credit Growth (%)
2007	QTR I	58,816	57,111	5.11
	QTR II	65,088	63,101	10.66
	QTR III	70,900	68,900	8.93
	QTR IV	71,881	72,053	1.38
2008	QTR I	75,023	73,262	4.37
	QTR II	85,276	81,485	13.67
	QTR III	93,950	91,238	10.17
	QTR IV	96,385	96,545	2.59
2009	QTR I	100,880	98,565	4.66
	QTR II	111,057	107,444	10.09
	QTR III	119,667	116,953	7.75
	QTR IV	120,754	121,963	0.91
2010	QTR I	124,765	122,499	3.32
	QTR II	132,740	129,847	6.39
	QTR III	139,450	137,720	5.05
	QTR IV	143,707	143,234	3.05
2011	QTR I	149,427	146,256	3.98
	QTR II	161,654	157,115	8.18
	QTR III	170,352	167,579	5.38
	QTR IV	175,702	175,254	3.14
2012	QTR I	182,268	178,340	3.74
	QTR II	198,634	192,522	8.98
	QTR III	208,726	205,409	5.08
	QTR IV	218,851	216,200	4.85
2013	QTR I	227,278	222,856	3.85
	QTR II	244,815	238,811	7.72
	QTR III	257,175	252,924	5.05
	QTR IV	264,541	263,180	2.86
2014	QTR I	268,692	264,226	1.57
	QTR II	283,448	278,520	5.49
	QTR III	294,511	289,996	3.90
	QTR IV	301,456	300,405	2.36
2015	QTR I	303,530	300,201	0.69
	QTR II	315,633	311,253	3.99
	QTR III	324,803	320,729	2.91
	QTR IV	328,759	327,671	1.22
2016	QTR I	328,190	325,909	-0.17
	QTR II	344,896	338,645	5.09
	QTR III	354,953	350,537	2.92
	QTR IV	357,859	357,194	0.82
2017	QTR I	357,473	353,399	-0.11
	QTR II	371,780	365,931	4.00
	QTR III	380,997	376,899	2.48
	QTR IV	390,372	388,068	2.46

Figure 1. Chart of Credit Growth from RDB and Banking Industry

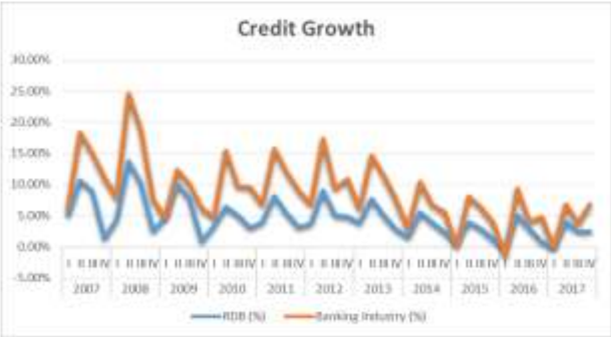

Table 2. Descriptive Statistics of RDB Credit from 2007 to 2017

Year	Quarter	**Total Credit RDB**	**Total Credit Banking**	***Market Share* RDB Credit (%)**
2007	QTR I	58,816	800,373	7.35
	QTR II	65,088	861,498	7.56
	QTR III	70,900	913,950	7.76
	QTR IV	71,881	1,002,012	7.17
2008	QTR I	75,023	1,036,065	7.24
	QTR II	85,276	1,148,356	7.43
	QTR III	93,950	1,246,146	7.54
	QTR IV	96,385	1,307,688	7.37
2009	QTR I	100,880	1,306,389	7.72
	QTR II	111,057	1,335,041	8.32
	QTR III	119,667	1,366,076	8.76
	QTR IV	120,754	1,437,930	8.40
2010	QTR I	124,765	1,456,114	8.57
	QTR II	132,740	1,586,492	8.37
	QTR III	139,450	1,659,145	8.40
	QTR IV	143,707	1,765,845	8.14
2011	QTR I	149,427	1,814,846	8.23
	QTR II	161,654	1,950,727	8.29
	QTR III	170,352	2,079,261	8.19
	QTR IV	175,702	2,200,094	7.99
2012	QTR I	182,268	2,266,175	8.04
	QTR II	198,634	2,452,856	8.10
	QTR III	208,726	2,555,839	8.17
	QTR IV	218,851	2,707,862	8.08
2013	QTR I	227,278	2,768,371	8.21
	QTR II	244,815	2,959,123	8.27
	QTR III	257,175	3,147,210	8.17
	QTR IV	264,541	3,292,874	8.03
2014	QTR I	268,692	3,334,011	8.06
	QTR II	283,448	3,494,968	8.11
	QTR III	294,511	3,592,087	8.20
	QTR IV	301,456	3,706,501	8.13
2015	QTR I	303,530	3,679,871	8.25
	QTR II	315,633	3,828,045	8.25
	QTR III	324,803	3,956,483	8.21
	QTR IV	328,759	4,057,904	8.10
2016	QTR I	328,190	4,000,448	8.20
	QTR II	344,896	4,168,308	8.27
	QTR III	354,953	4,212,377	8.43
	QTR IV	357,859	4,377,195	8.18
2017	QTR I	357,473	4,369,967	8.18
	QTR II	371,780	4,491,186	8.28
	QTR III	380,997	4,543,588	8.39
	QTR IV	390,372	4,737,944	8.24

Based on Table 1, RDB credit disbursement are continuously increased. However, the credit actually not growing. Figure 1, shows that the trend of credit disbursement of RDB and commercial banks in Indonesia has similar pattern, which are fluctuated and tended to decline. Table 2, shows the market share of RDB credit disbursement compared to total credit that disbursed by commercial banks in Indonesia are fluctuated. This dynamic economic condition caused by the dynamic of global economic that is affects to domestic economy.

Table 3. Difference Test of RDB Credit Growth

Period	**Median**	**Mann-Whitney Test**
Before RDB Transformation Program	4.85%	0.0041
After RDB Transformation Program	2.48%	

Table 4. Difference Test of RDB Market Share

Period	**Median**	**Mann-Whitney Test**
Before RDB Transformation Program	8.13%	0.0381
After RDB Transformation Program	8.24%	

Based on Table 3, BPD Transformation program have different growth performance and maket share of RDB credit disbursement. The median value of the growth performance of BPD credit disbursement before BPD transformation is lower when compared to the growth performance of BPD credit disbursement after BPD Transformation. The decline in the BPD credit disbursement after BPD Transformation is also experienced by Indonesian banks in general. During the same period, the growth performance of national banking credit disbursement also declining compared to the growth performance of credit disbursement before the BPD Transformation period.

The declining performance of banking credit disbursement, in general, is caused by a weakening of domestic economic growth as well as a decrease in supply due to standard credit increase as a response of the bank on the increasing non-performing credit ration (Central Bank of Indonesia, 2015).

In terms of market share, BPD credit after the BPD Transformation period has increased compared to before the BPD Transformation Period. Table 4 shows that the median value of a market share of BPD credit after BPD Transformation is bigger compared to before BPD Transformation period. This shows that the BPD Transformation program has a quite positive impact on the development of BPD credit performance.

4.2 Forecasting Credit Growth using ARIMA

a) Stastionary Test

The results of stationary tests on the total data of BPD credit disbursement are not stationary against variety or average. Therefore, a transformation was performed on the total data of BPD credit disbursement. The stationary test result on the transformation result data fulfils the assumption of variance and average stationarity after 2 differentiation.

Table 5. Augmented Dickey Fuller Test

Condition	**Augmented Dickey Fuller**	**Conclusion**
Without Differentiation	0.9908	Not fulfilled the assumption
First Differentiation	0.3550	Not fulfilled the assumption
Second Differentiation	0.0291	Fulfilled the assumption

b) Model Identification

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

Table 6. Correlogram Test

Lag	**Q-Statistic Probabilistic**	**Conclusion**
Lag ke-1	0.431	Not significant
Lag ke-2	0.000	Significant
Lag ke-3	0.000	Significant
Lag ke-4	0.000	Significant
Lag ke-5	0.000	Significant

c) Parameter Model Estimation

Table 7. Signification Test of Parameter Model

MODEL	**RESULTS**
ARIMA(2,2,2)	Not significant
ARIMA(2,2,1)	Not significant
ARIMA(2,2,0)	Significant
ARIMA(1,2,2)	Not significant
ARIMA(0,2,2)	Significant
ARIMA(1,2,1)	Not significant
ARIMA(1,2,0)	Not significant
ARIMA(0,2,1)	Significant
ARIMA(3,2,3)	Significant
ARIMA(3,2,2)	Significant
ARIMA(3,2,1)	Significant
ARIMA(3,2,0)	Significant
ARIMA(0,2,3)	Not significant
ARIMA(2,2,3)	Not significant
ARIMA(1,2,3)	Significant
ARIMA(4,2,4)	Not significant
ARIMA(4,2,3)	Not significant
ARIMA(4,2,2)	Not significant

MODEL	RESULTS
ARIMA(4,2,1)	Not significant
ARIMA(4,2,0)	Significant
ARIMA(0,2,4)	Significant
ARIMA(3,2,4)	Not significant
ARIMA(2,2,4)	Not significant
ARIMA(1,2,4)	Not significant

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	Hetero-scedas-ticity	Auto-correla-tion	Nor-mality
ARIMA (0,2,2)	X	X	✓
ARIMA (0,2,1)	✓	X	✓
ARIMA (2,2,0)	✓	X	✓
ARIMA (3,2,3)	✓	✓	✓
ARIMA (3,2,2)	✓	✓	✓
ARIMA (3,2,1)	✓	✓	✓
ARIMA (3,2,0)	✓	X	✓
ARIMA (1,2,3)	✓	X	✓
ARIMA (4,2,0)	✓	✓	✓
ARIMA (0,2,4)	X	X	✓

e) Best Model Selection

The best ARIMA model selected by choosing tentative models with the largest R-Square value and the smallest Akaike info Criterion (AIC).

Table 9. Best ARIMA Model Selection

Tentative Model	AIC
ARIMA (3,2,3)	-5.952636
ARIMA (3,2,2)	-5.896710
ARIMA (3,2,1)	-5.820456
ARIMA (4,2,0)	-6.066265

Based on Table 9, the best ARIMA model to forecast RDB credit growth is ARIMA (4,2,0). The equation is:

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \emptyset_3 Y_{t-3} + \emptyset_4 Y_{t-4} + \varepsilon$$

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \emptyset_3 Y_{t-3} + \emptyset_4 Y_{t-4} + \varepsilon$$

f) Forecasting using ARIMA Model

Table 10 shows the forecast result of RDB credit growth using ARIMA (4,2,0). Based on the projection result, credit disbursement of RDB will have increased but the growth is fluctuated. From the projection result, RDB Transformation Program is not give significant impact to increase credit performance of RDB.

Table 10. Forecast Result

Period	Actual Value	Projected Results	Actual Credit Growth	Project-ed RDB Credit Growth
QI ‘18	390,679	394,903	0.08%	0.99%
QII ‘18	400,768	410,464	2.58%	4.12%
QIII ‘18	412,041	420,932	2.81%	2.55%
QIV ‘18	-	432,230	-	2.68%

4.3 Situational Analysis

To minimize the prediction error of ARIMA model caused by the dynamic condition of economic, the forecast results are compared to situation analysis that describes the domestic and foreign economic into four conditions. Situational analysis for RDB credit disbursement and RDB credit growth are shows on Table 11 and Table 12.

Table 11. RDB Credit Disbursement based on Situational Analysis

3rd Quad-rant	2nd Quad-rant	4th Quad-rant	1st Quad-rant
342,249 – 356,361	356,361 – 371,055	371,055 – 386,354	394,239
356,334 – 371,027	371,027 – 386,325	386,325 – 402,255	410,464
365,422 – 380,489	380,489 – 396,178	396,178 – 412,513	420,932
375,230 – 390,702	390,702 – 406,811	406,811 – 423,585	432,230

Table 12. RDB Credit Growth based on Situational Analysis

3rd Quad-rant	2nd Quad-rant	4th Quad-rant	1st Quad-rant
0.86% - 0.89%	0.89% - 0.93%	0.93% - 0.97%	0.99%
3.58% - 3.72%	3.72% - 3.88%	3.88% - 4.04%	4.12%
2.21% - 2.30%	2.30% - 2.40%	2.40% - 2.50%	2.55%
2.33% - 2.42%	2.42% - 2.52%	2.52% - 2.63%	2.68%

5. CONCLUSION

Based on the projections results obtained, the growth performance of credit disbursement and BPD credit growth has not experienced a significant increase after the implementation of the BPD Regional Champion program or BPD Transformation program. In terms of credit disbursement, BPD credit growth is far below the target set in both programs. Therefore, improvement efforts are necessary to improve the BPD performance as a whole, especially in the credit sector.

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