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How To Forecast Islamic Bank Profitability?

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Abstract. *In governmental and private institutions, meticulous planning is paramount, given its pivotal role in affording a grace period for deliberation spanning years to hours. Forecasting is an indispensable tool in enhancing the efficacy and efficiency of such planning endeavors by projecting future occurrences through the meticulous analysis of historical data and its extrapolation into future contexts. Notably, forecasting provides a solid foundation for informed decision-making within economic planning. This study aims to address the following inquiries: 1) How is the liquidity ratio forecasting model developed using the ARIMA Box-Jenkins method at Bank Syariah Mandiri? 2) Based on the optimal forecasting model, What are the forecasted outcomes of the liquidity ratio utilizing the ARIMA Box-Jenkins method at Bank Syariah Mandiri for the forthcoming year? As a quantitative approach, the study utilizes secondary data from Bank Syariah Mandiri's financial statements from January 2017 to November 2020, comprising 47 data points. Subsequently, forecasting is conducted for the period December 2020 to November 2021, encompassing one year. The findings reveal that the optimal forecasting model for the liquidity ratio at Bank Syariah Mandiri is the ARIMA (11,1,1) model for the Cash Ratio, projecting a liquidity capability of 130%. This outcome underscores the robust health of Bank Syariah Mandiri's liquidity position. Moreover, the ARIMA (1,1,8) model for the financing-to-deposit ratio forecasts a liquidity capability of 77.4%, indicative of a healthy liquidity status. Finally, the ARIMA (3,1,3) model for the Loan to Asset Ratio forecasts a liquidity capability of 68.8%, affirming the institution's sound liquidity position.*

Keywords: *Bank Syariah Mandiri, Liquidity Ratio, ARIMA*

I. INTRODUCTION

Banking institutions represent pivotal economic entities, acting as conduits for financial intermediation. They function as business entities entrusted with the collection of funds from the public, primarily in the form of savings, which are subsequently channeled back into the economy through various lending activities. Individuals and businesses alike have direct access to loans from banks, contingent upon meeting the requisite eligibility criteria set forth by these institutions [1], [2].

Hence, the fundamental role of a bank lies in serving as an intermediary for the secure collection and dissemination of public funds. The inception of Islamic banking aims to offer interest-free services to its clientele by advocating and fostering Sharia principles. Islamic banks derive their compensation from customers through contracts or agreements established at the outset, subject to adherence to the terms and tenets of Sharia law [3], [4].

The primary principle embraced by Islamic banks is the prohibition of usury in transactions, business operations, and banking services. Sharia-compliant banks, when disbursing funds to clients, typically engage in profit-sharing or provide profit margins as part of their financial arrangements [4]–[6].

In the realm of banking activities, particularly within the context of Islamic banking in Indonesia, the presence of risks looms large, posing potential threats to banking stability and even precipitating the cessation of banking operations [7]–[9]. This scenario echoes the events of the 1997 monetary crisis, during which 16 banks in Indonesia had their licenses revoked. This revocation stemmed from severe liquidity challenges some banking entities face, consequently exerting adverse effects on the Indonesian economy, mainly through the Interbank Money Market (Pasar Uang Antar Uang - PUAB). Subsequently, certain banks failed to meet the Minimum Statutory Reserves (Giro Wajib Minimum - GWM) requirements mandated by Bank Indonesia, signifying the minimum savings thresholds that banks must maintain in the form of Bank Indonesia Clearing Accounts, as stipulated by the central bank.

During that period, certain banks faced challenges providing funds to meet public withdrawal demands, leading to panic-induced bank rushes. Consequently, trust in national banks waned, prompting individuals to shift their deposits to foreign banks. Despite efforts by Bank Indonesia, acting as the lender of last resort, to address the situation by tightening the Rupiah through interest rate hikes and government budget constraints, these measures resulted in a significant surge in interest rates and a contraction in banking liquidity. Consequently, banks encountered liquidity issues [10], [11].

Liquidity is a critical determinant for the viability and sustainability of banks, impacting their profitability and operational continuity. A deficient liquidity position significantly threatens a bank's solvency and profitability, rendering it unsafe and unhealthy. Within the asset and liability management framework, liquidity management constitutes an integral component for Islamic banks. Its objective is to uphold Islamic banks' liquidity, ensuring the seamless continuation of operational activities and preserving public trust. The liquidity ratio is a crucial benchmark within Islamic banking practices [12], [13].

Drawing upon the challenges encountered by banks in Indonesia, particularly Islamic banks, this research endeavors to conduct a forecasting analysis of the liquidity ratio. Utilizing the ARIMA Box-Jenkins method, the aim is to derive the optimal forecasting model for the liquidity ratio's evolution within Islamic banks, explicitly focusing on Bank Syariah Mandiri.

Objectives:

This study aims to develop a forecasting model for the liquidity ratios of Mandiri Syariah Bank using the ARIMA Box-Jenkins method. The aim is to generate forecasted liquidity ratio outcomes for Islamic Banks Mandiri for the upcoming year based on the optimal Box-Jenkins ARIMA Method.

II. METHOD

Forecasting methods can provide an analytical approach to a movement from past data to analyze the way of thinking, working, and solving systematically and pragmatically, as well as provide a higher level of confidence than forecasting results that have been made and can provide accuracy in a plan in the future [14].

This study adopts a quantitative research approach involving the analysis of numerical data using statistical methods. Specifically, it employs the time series forecasting technique known as the ARIMA Box-Jenkins method to identify the most practical forecasting methodology and generate forecasts for one year, from December 2020 to November 2021. The data source for this research comprises monthly reports from PT. Bank Syariah Mandiri, providing percentage-based data on liquidity ratios from January 2017 to November 2020.

The liquidity ratio is a crucial benchmark in Islamic banking, given its significant impact on a company's profitability, sustainability, and operational continuity. The Box-Jenkins ARIMA forecasting method is particularly suited for analyzing time series data, as it leverages historical patterns to generate accurate forecasts. While this method is effective for short-term forecasting, it may not yield satisfactory results for long-term forecasts, often resulting in flat or constant projections over extended periods [15]. Forecasting methods play a vital role in analyzing past data patterns, facilitating systematic and pragmatic approaches to decision-making, and instilling greater confidence in the accuracy of forecasted outcomes.

III. RESULT AND DISCUSSION

This study aims to identify the most practical forecasting method for liquidity ratios, encompassing the Cash Ratio, Financing to Deposit Ratio, and Loan to Asset Ratio at Bank Syariah Mandiri. The data analysis model employs calculations based on the ARIMA Box-Jenkins method to achieve this objective, utilizing the E-Views software.

The Box-Jenkins model is a forecasting technique that relies on time series analysis, utilizing observed variable data collected over a specific time frame. Time series data refers to data monitored and recorded over successive intervals, allowing for studying data behavior over time.

The Box-Jenkins model, commonly called the Autoregressive Integrated Moving Average (ARIMA) model, is a prominent tool in time series analysis. This analytical approach aims to discern patterns and trends in past data, enabling the generation of predictive insights based on the inherent characteristics of the data. Central to this methodology is stationarity, wherein data exhibits consistent properties over time, allowing for accurate forecasting of future data trends. The rationale behind employing the Box-Jenkins method in this study lies in the complexity of explaining the movements of variables such as the cash ratio, financing-to-deposit ratio, and loan-to-asset ratio observed in Islamic banks using conventional economic theories.

The Box-Jenkins technique distinguishes itself from conventional forecasting models by its unique approach. Unlike many existing models, this technique does not rely on specific assumptions regarding past data in the time series. Instead, it adopts an iterative method to identify the best-fitting model. The selected model undergoes a validation process using historical data to assess its accuracy in describing the dataset. The optimal model is characterized by small, randomly distributed, independent residuals between the forecasted values and the

historical data. In cases where the chosen model fails to explain the data adequately, the iterative process of model selection is repeated until a satisfactory fit is achieved.

The Box-Jenkins model encompasses several sub-models, including Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA).

a) ***Autoregressive (AR) Models***

For instance, let Yt represent the Cash Ratio at time t. If we formulate a model for Yt as follows:

$$(Yt - \delta) = \alpha 1(Yt - 1 - \delta) + ut$$

Here, *δ* denotes the mean of *Y*, and *ut* represents the residual (error term), assumed to be uncorrelated with zero mean and constant variance (white noise). Thus, we can infer that *Yt* follows a stochastic first-order autoregressive or AR(1) process. The value of *Y* at time *t* is determined by the value of the previous period, adjusted by the error term. In other words, the forecasted value of *Y* at time *t* is a fraction (*α1*) of the *Y* value at time (*t-1*), along with a random shock or residual at time *t*. The model can represent this:

$$(Yt - \delta) = \alpha 1(Yt - 1 - \delta) + \alpha 2(Yt - 2 - \delta) + ut$$

A model where the value of *Y* at time *t* depends on the values of *Y* at the two preceding periods is referred to as a second-order autoregressive process or AR(2). Thus, the value of *Y* is expressed around the mean value *δ*. Generally, the autoregressive model can be expressed as:

$$(Yt - \delta) = \alpha 1(Yt - 1 - \delta) + \alpha 2(Yt - 2 - \delta) + \cdots + \alpha p(Yt - p - \delta) + ut$$

Here, *Yt* represents the value of the pth-order autoregressive process, denoted as AR(*p*).

b) ***Moving Average (MA) Models***

The MA model incorporates the white noise stochastic error term, denoted by u. Suppose the model for Y is as follows:

$$Yt = \mu + \beta 0ut + \beta 1ut - 1$$

Here, μ represents a constant, and Y at time t equals the constant plus the moving average of the current and past errors. Such a model is called Y following a first-order moving average process or MA(1). For a second-order moving average process or MA(2), the model is expressed as follows:

$$Yt = \mu + \beta 0ut + \beta 1ut - 1 + \beta 2ut - 2$$

In general, the moving average model of order p is represented by the following equation:

$$Yt = \mu + \beta 0ut + \beta 1ut - 1 + \beta 2ut - 2 + \cdots + \beta put - p$$

Thus, the moving average model can be understood as a linear combination of the white noise error term.

c) ***Autoregressive and Moving Average (ARMA) Models***

The ARMA model combines aspects of both autoregressive (AR) and moving average (MA) models to predict the value of Y, as it may exhibit characteristics of both. For instance, in the ARMA(1,1) model, the process is defined as follows:

$$Yt = \theta + \alpha 1Yt - 1 + \beta 0ut + \beta 1ut - 1$$

Here, θ represents a constant term, α1 denotes the autoregressive coefficient for lag 1, and β0 and β1 represent the coefficients for the white noise error terms at the current and lagged periods, respectively.

In general, an ARMA(p,q) model combines p autoregressive terms and q moving average terms to capture the dynamics of the data.

d) ***Autoregressive Integrated Moving Average (ARIMA) Model***

The autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models discussed earlier assume that the time series data under analysis is stationary, wherein the mean, variance, and covariance of the data remain constant over time.

However, many economic time series data are non-stationary or integrated. It is understood that if a time series data is integrated at the first level or order, denoted as I(1), then taking the first difference (i.e., the difference between consecutive observations) renders the data stationary, or I(0). Similarly, if the time series data is I(2), taking the differences yields stationary data or I(0). Consequently, it can be inferred that if the time series data is integrated at order d, denoted as I(d), then taking the difference d times will result in stationary data, or I(0).

Hence, if the time series data has been differenced d times to achieve stationarity, it can be applied to the ARMA(p,q) model, resulting in the ARIMA(p,d,q) model. Here, p represents the autoregressive component, d denotes the number of differencing operations required to attain stationarity, and q signifies the moving average component. Thus, for example, the ARIMA(2,1,3) model indicates a model where the data has been differenced once (d=1), includes two autoregressive components, and three moving averages. Similarly, the ARIMA(1,0,1) model is equivalent to the ARMA(1,1) model. An ARIMA model of the form ARIMA(p,0,0) is analogous to an AR(p) model, while an ARIMA(0,0,q) model is equivalent to an MA(q) model.

Table 1. Monthly data of Cash Ratio (CR), Financing to Deposit Ratio (FDR), Loan to Asset Ratio (LAR) at Bank Syariah Mandiri Period January 2017-November 2020

Month/	CR				FDR				LAR			
Year	2017	2018	2019	2020	2017	2018	2019	2020	2017	2018	2019	2020
Jan	0.95173	1.14985	1.59843	2.44949	0.76957	0.75791	0.77111	0.75164	0.68187	0.67093	0.68497	0.66634
Feb	0.82670	0.97029	1.40473	1.69476	0.75688	0.74391	0.76389	0.72699	0.67018	0.65875	0.67544	0.64725
Mar	0.66343	0.77575	1.15126	1.45874	0.77798	0.73913	0.79343	0.74027	0.69070	0.65651	0.70166	0.65749
Apr	0.57382	0.73933	1.05100	1.36882	0.73895	0.74458	0.79966	0.74917	0.65720	0.66218	0.70676	0.66491
May	0.70202	0.95740	1.51182	1.47762	0.78701	0.75383	0.82397	0.75689	0.69375	0.66956	0.71702	0.66969
Jun	0.83287	1.00422	1.01939	1.02238	0.80091	0.75459	0.81567	0.74084	0.70701	0.67007	0.70539	0.65947
Jul	0.58461	0.65059	0.81743	0.90172	0.78648	0.77223	0.79062	0.75229	0.69831	0.68325	0.71383	0.66782
Aug	0.46050	0.56141	0.69055	0.86636	0.79485	0.78640	0.82189	0.77066	0.70527	0.69519	0.71657	0.68129
Sep	0.39869	0.46200	0.62702	1.24460	0.78332	0.79072	0.81336	0.74976	0.69634	0.69694	0.71612	0.66496
Oct	0.38317	0.46465	0.55707	0.60681	0.78880	0.79653	0.79198	0.76443	0.70013	0.70415	0.69890	0.67429
Nov	0.35559	0.41221	0.49539	0.60539	0.78583	0.80671	0.78684	0.78496	0.69862	0.71223	0.69267	0.69143
Dec	0.39776	0.45226	0.54406		0.77689	0.77229	0.75433		0.68822	0.68524	0.67044	

Modeling Liquidity Ratio of Cash Ratio (CR)

The Cash Ratio, a liquidity ratio, assesses the proportion of liquid assets relative to third-party funds collected by banks, which require immediate repayment. This ratio gauges a bank’s capacity to settle customer or depositor withdrawals using liquid assets.

The data utilized consisted of 47 observations from January 2017 to November 2020. Below are the findings from the ARIMA development stages:

1. ***Model Identification***
   a. ***Data Stationarity Test***

   For analysis with the Box-Jenkins model, the data must be stationary. Stationary data exhibits behavior with a variance that is not excessively large and tends to fluctuate around its mean value. Several ways to test the stationarity of data include:

   i. Graphical Method

   Development of Cash Ratio based on time series plot.

Figure 1. Time Series Plot of Cash Ratio

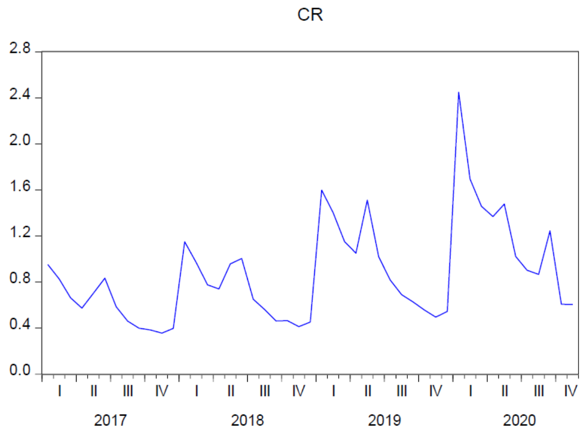


Figure 1 shows that the Cash Ratio does not exhibit a discernible seasonal pattern based on the time series plot. Additionally, the plot illustrates that the Cash Ratio does not fluctuate consistently around a constant average, and there are noticeable variations in variance over time. Consequently, it can be concluded that the pattern of Cash Ratio development is non-stationary. Notably, from January 2020 to May 2020, there appears to be a higher Cash Ratio value, indicating that Bank Syariah Mandiri held a more significant proportion of current assets relative to third-party funds during this period than others.

ii. ***Test Autocorrelation Function (ACF) and Correlogram***

Subsequently, testing is conducted to validate further the assertion that the Cash Ratio development is non-stationary, employing the Autocorrelation Function (ACF) and correlogram.

Figure 2. Testing AC and PAC on Correlogram CR

Sample: 2017M01 2020M11
Included observations: 47

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.531	0.531	14.099	0.000
		2	0.252	-0.042	17.337	0.000
		3	0.140	0.032	18.364	0.000
		4	0.080	0.000	18.705	0.001
		5	-0.173	-0.303	20.351	0.001
		6	-0.247	-0.047	23.784	0.001
		7	-0.126	0.109	24.693	0.001
		8	0.078	0.213	25.049	0.002
		9	-0.046	-0.203	25.179	0.003
		10	0.051	0.156	25.339	0.005
		11	0.306	0.279	31.325	0.001

Based on the correlogram of data from Figure 2 above, it can be observed that the data is not stationary. From the autocorrelation chart, the first lag is outside the Bartlett line and decreases exponentially or slowly gets smaller. If it continues, it will come out from the Bartlett line. In general, the correct number of lags in the model identification process is a maximum of n, where n is the amount of data. This study's data is 47, so the number of lags is 11. The statistical value of Q up to the 11th lag is 31.325. This value is far greater than the statistical value of the distribution of chi-squares X2 with degrees of freedom (df) of 11 with $\propto$ = 5%, namely 19.675. The value of the Q statistic is greater than the statistical value of the distribution of chi-squares X2, so the data is not stationary.

iii. ***Unit Root Test***

Figure 3. Augmented Dickey-Fuller (ADF) CR Test Results

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.971640	0.9998
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

*MacKinnon (1996) one-sided p-values.

The results of the Augmented Dickey-Fuller (ADF) test above indicate that the null hypothesis, stating that the Cash Ratio (CR) possesses a unit root or that the data is non-stationary, cannot be rejected, shown by a probability value of 0.999, which exceeds the significance level of 0.05. Consequently, the findings from the ADF test corroborate the conclusions drawn from the graphical analysis and correlogram, suggesting that the CR data is indeed non-stationary at zero degrees.

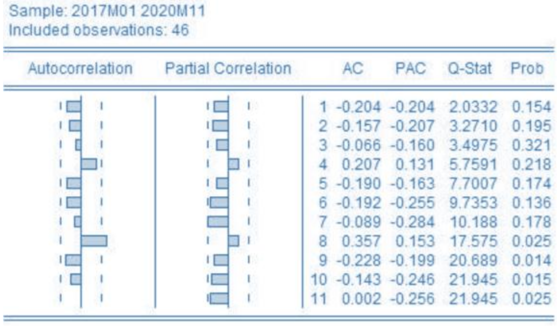
b. ***Transformation of Non-Stationary Time Series Data into Stationary***

It is essential to transform the non-stationary time series data to mitigate the spurious or pseudo regression resulting from regressing non-stationary time series data into stationary form through differencing, which involves computing the first difference, whereby CRt is reduced to CRt-1. Therefore, for the first difference:

$$\mathrm{Dt} = \Delta\,\mathrm{CRt} = (\mathrm{CRt} - \mathrm{CRt} - 1)$$

i. ***First Difference on Correlogram***

Figure 4. Stationarity Test Results on Correlogram CR



	AC	PAC	Q-Stat	Prob
1	-0.204	-0.204	2.0332	0.154
2	-0.157	-0.207	3.2710	0.195
3	-0.066	-0.160	3.4975	0.321
4	0.207	0.131	5.7591	0.218
5	-0.190	-0.163	7.7007	0.174
6	-0.192	-0.255	9.7353	0.136
7	-0.089	-0.284	10.188	0.178
8	0.357	0.153	17.575	0.025
9	-0.228	-0.199	20.689	0.014
10	-0.143	-0.246	21.945	0.015
11	0.002	-0.256	21.945	0.025

From the diagram, it is evident that the data is stationary. This observation is supported by the correlogram diagram, where each lag is positioned around the zero line. The appearance of the correlogram indicates that the autocorrelation coefficient is close to zero, except for lag 8, which exhibits a relatively high autocorrelation coefficient, which signifies that the Cash Ratio (CR) data is stationary at the first difference level.

ii. ***First Difference on Augmented Dickey-Fuller***

Next, we will employ the Unit Root Test to bolster further the conclusions regarding the first difference observed in the correlogram.

Figure 5. Stationarity Test Results on ADF CR

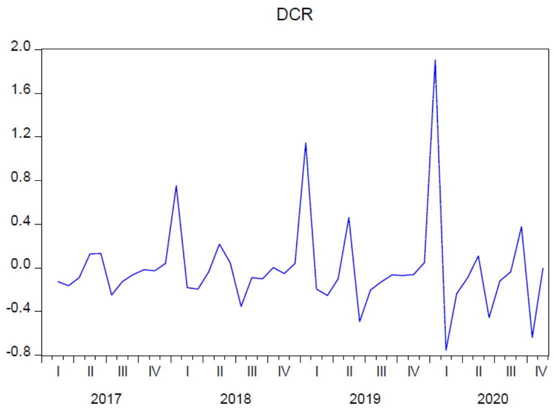
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.068453	0.0000
Test critical values:	1% level	-3.584743	
	5% level	-2.928142	
	10% level	-2.602225	

*MacKinnon (1996) one-sided p-values.

The Augmented Dickey-Fuller (ADF) test results indicate that the ADF t-statistics value of -8.068 exceeds (in absolute terms) the critical value, and the associated p-value is 0.000, which is less than the significance level. Thus, it can be concluded that the Cash Ratio (CR) data is stationary at the first difference level (d=1). Therefore, the CR data is suitable for forecasting using ARIMA estimation at level 1.

iii. ***First Difference in Graphics***

Figure 6. Stationarity Test Results on Graphs



The image above illustrates that the Cash Ratio (CR) at level 1 (DCR) data no longer exhibits a trending pattern, indicating that it has become stationary. Furthermore, from the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots in Figure 4.6, it is evident that all data exhibit stationarity in terms of both variance and mean, as the initial lags have been eliminated.

Following the attainment of stationary data, the subsequent step is determining the suitable prediction model. Based on the abovementioned analysis, the ARIMA model selected for use is the ARIMA (8,1,0) model. However, it is worth noting that alternative ARIMA models may be considered. The ARIMA models deemed potentially suitable for the time series data of Bank Syariah Mandiri's Cash Ratio are as follows:

a. ARIMA (8,1,0)
b. ARIMA (0,1,8)
c. ARIMA (2,1,2)
d. ARIMA (6,1,1)
e. ARIMA (6,1,6)
f. ARIMA (11,1,1)

After identifying potential ARIMA models, the subsequent step involves estimating the parameters.

2. Parameter Estimation

Next, after obtaining the tentative model, the subsequent step is to estimate the parameters of the provisional model. The following is the parameter estimation output from the EViews 10 software.

Table 2. Parameter Estimation Results of the Temporary ARIMA Model CR

Model	Parameter Model	Koefisien	Probability
ARIMA (8,1,0)	$\emptyset 8$ $\theta 0$	0,338774	0,0515
ARIMA (0,1,8)	$\emptyset 0$ $\theta 8$	0,384185	0,0183
ARIMA (2,1,2)	$\emptyset 2$ $\theta 2$	-0,992419 0,930480	0,0000 0,0043
ARIMA (6,1,1)	$\emptyset 6$ $\theta 1$	-0,425429 -0,718778	0,0260 0,0001
ARIMA (11,1,1)	$\emptyset 11$ $\theta 1$	0,564018 -0,89055	0,0000 0,0000

The model's parameters were estimated using the Exact Maximum Likelihood Estimation method with the help of EViews 10 software. The subsequent step involves testing the significance of the parameters with the following hypotheses:

$H0: \theta = 0$

$H0: \theta \neq 0$

The model passes the significance test if the model probability is <0.05.

3. Diagnostic Checking

Diagnostic examination assesses whether the model is adequate or suitable for forecasting. This examination evaluates whether the residuals and variance of the model's residuals satisfy the assumptions of white noise and are typically distributed. With the assistance of EViews 10 software, residual diagnostics can be conducted using the statistical Q correlation test for each model.

The assumption of white noise and regular distribution of the residual results signifies that the model has addressed its autocorrelation issue. This condition is met if the results of the Q-statistical correlogram test do not yield any significant Q-statistic values at each lag. A Q-statistic value is deemed insignificant if its associated probability is > 0.05.

Based on the Q-statistical correlogram residual test results conducted on five provisional ARIMA models, only 2 ARIMA models have fulfilled the assumption of white noise and normal distribution. These ARIMA models are ARIMA (8,1,0) and ARIMA (11,1,1).

Table 3. Criteria for the Best ARIMA Model (p,d,q) in CR

Model	AIC	BIC	SSR
ARIMA (8,1,0)	1.046556	1.126062	6.883747
ARIMA (11,1,1)	**1.032113**	**1.151372**	**5.895073**

Table 3 shows that the ARIMA model (11,1,1) exhibits the smallest AIC, BIC, and SSR values. Therefore, the ARIMA model is optimal for forecasting the Cash Ratio at Bank Syariah Mandiri for the next 12 months (11,1,1). Below are the parameter estimation results for this model:

Table 4. ARIMA Parameter Estimation Results (11,1,1) in CR

Variable	Coefficient	t-Statistics	Probability
C	0.015066	2.712891	0.0096
AR(11)	0.564018	5.244104	0.0000
MA(1)	-0.890225	-9.772566	0.0000

From these results, it can be seen that the values of AR (11) and MA (1) have a probability of <0.05, so they are significant and can be used in the ARIMA equation. Therefore, the equation formed from the ARIMA model (11,1,1) is as follows:

$$DCRt = 0.015066 + 0.564018DCRt - 11 - 0.890225DCRt - 1$$

This equation means that the Cash Ratio value at the first difference has a coefficient of 0.015066 plus 0.564018 times the Cash Ratio value at the first difference in the previous 11 periods and minus 0.890225 times the error during the last period.

4. ***Do Forecasting***

Based on the outcomes of the best-performing ARIMA model, specifically the ARIMA model (11,1,1), the forecasted Cash Ratio liquidity ratio for the upcoming 12 months spans from December 2020 to November 2021.

Figure 7. Cash Ratio Forecasting Results for Twelve Months

Figure 8. Forecasting Results and Their Confidence Interval Values

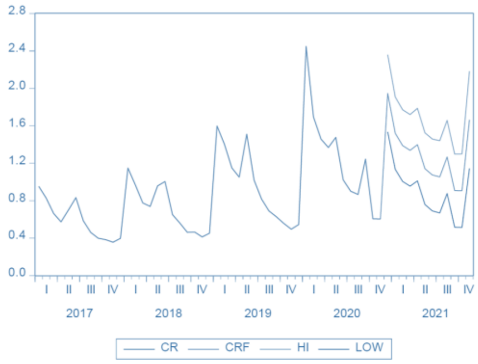


Table 5. Cash Ratio Forecasting Results

Month	Cash Ratio
Dec-20	1.94745
Jan-21	1.52176
Feb-21	1.38865
Mar-21	1.33793
Apr-21	1.39929
May-21	1.14253
Jun-21	1.07448
Jul-21	1.05453
Aug-21	1.26787
Sep-21	0.90814
Oct-21	0.90734
Nov-21	1.66428
Average	**1.30119**

Table 5 presents the forecasted movement of the Cash Ratio from December 2020 to November 2021. The highest forecasted value is observed in December 2020, reaching 1.94745 or 194.7%, while the lowest is recorded in October 2021, amounting to 0.90734 or 90.7%. On average, the forecasted Cash Ratio yields 130%. These values indicate that the bank's liquidity remains notably healthy, as evidenced by the very high Cash Ratio values.

Modeling of the Financing to Deposit Ratio (FDR) Liquidity Ratio

The Financing to Deposit Ratio (FDR) liquidity ratio is an indicator that illustrates the future availability of funds and sources of funds for banks and the public. The progression of FDR is crucial for ensuring that banks can meet immediate payment obligations.

Below is the process for developing the ARIMA model for the Financing to Deposit Ratio:

1. Model Identification

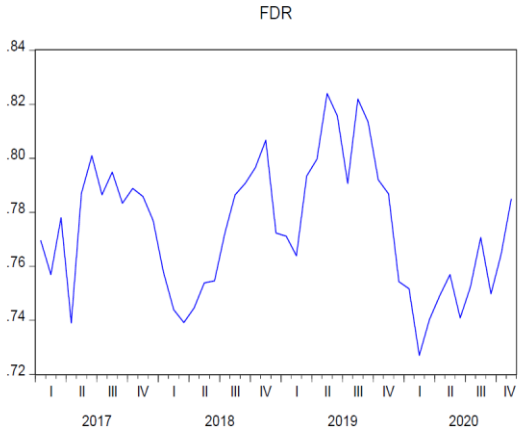
a. Data Stationarity Test

There are several ways to test the stationarity of data, including:

i. Graphical Method

Development of Financing to Deposit Ratio based on time series plot.

Figure 9. Identify Time Series Plots



According to an objective assessment in Figure 4.9, a time series plot is formed, showing that the development of the financing-to-deposit ratio is still found to have a change in variance. In addition, it is found that the time series plot fluctuates around a constant average, so it can be said that the development of the financing-to-deposit ratio is not stationary in variance and mean. In addition, a glance at the plot's movement illustrates the bank's condition, having a relatively higher financing-to-deposit ratio in May 2019 and August 2019. Then, the financing-to-deposit ratio decreased in February 2020, when the change showed that the bank had a higher total financing, lower than the funds held.

ii. Test Autocorrelation Function (ACF) and Correlogram

Figure 10. Testing AC and PAC on the FDR Correlogram

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.715	0.715	25.592	0.000
		2	0.549	0.078	41.038	0.000
		3	0.354	-0.133	47.579	0.000
		4	0.113	-0.251	48.261	0.000
		5	-0.026	-0.025	48.298	0.000
		6	-0.161	-0.080	49.758	0.000
		7	-0.234	-0.027	52.899	0.000
		8	-0.310	-0.146	58.570	0.000
		9	-0.286	0.060	63.541	0.000
		10	-0.217	0.075	66.474	0.000
		11	-0.158	-0.007	68.074	0.000

From Figure 10 above, it can be observed that ACF (autocorrelation) ACF decreases slowly, and in PACF, after the first lag, it decreases dramatically. Thus, the characteristics show that the Financing to Deposit Ratio data is not stationary at zero degrees.

iii. Unit Root Test

Figure 11. FDR Augmented Dickey-Fuller (ADF) Test Results

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.675867	0.0859
Test critical values:	1% level	-3.581152	
	5% level	-2.926622	
	10% level	-2.601424	

*MacKinnon (1996) one-sided p-values.

The results of the Augmented Dickey-Fuller test above show the null hypothesis that the financing-to-deposit ratio has a unit root or non-stationary data. It cannot be rejected, as indicated by the t-statistic value of -2.6758, which is still smaller than the critical value at α=5%, which is -2.9266. In addition, the probability value of 0.0859 is more significant than 0.05. ADF test results strengthen the graph and correlogram analysis by showing that the financing-to-deposit ratio data is not stationary at zero degrees.

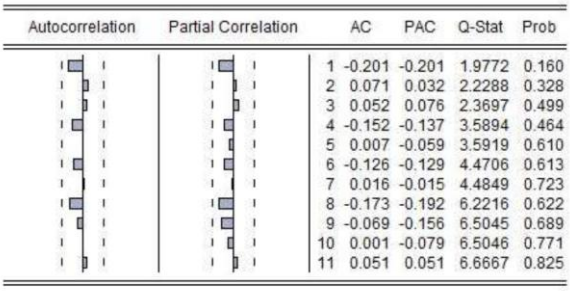
b. Transformation of Non-Stationary Time Series Data into Stationary

To avoid spurious regression problems from regressing non-stationary time series data. So, it is necessary to transform non-stationary time series data into stationary data through differencing, namely, reducing FDRt with FDRt-1 for the first difference. So for a difference of one:

$$\mathrm{Dt} = \Delta\,\mathrm{FDRt} = (\mathrm{FDRt} - \mathrm{FDRt} - 1)$$

i. First Difference on Correlogram

Figure 12. Correlogram FDR Stationarity Test Results



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.201	-0.201	1.9772	0.160
		2	0.071	0.032	2.2288	0.328
		3	0.052	0.076	2.3697	0.499
		4	-0.152	-0.137	3.5894	0.464
		5	0.007	-0.059	3.5919	0.610
		6	-0.126	-0.129	4.4706	0.613
		7	0.016	-0.015	4.4849	0.723
		8	-0.173	-0.192	6.2216	0.622
		9	-0.069	-0.156	6.5045	0.689
		10	0.001	-0.079	6.5046	0.771
		11	0.051	0.051	6.6667	0.825

Based on the above level 1 FDR data correlogram, the image produced differs from the one at level zero. The diagram shows that the residuals are random, shown by a bar graph inside the Bartlett line, indicating that the FDR data is stationary at level one.

ii. First Difference in Unit Root Test

Figure 13. FDR Augmented Dickey-Fuller (ADF) Test Results

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.013139	0.0000
Test critical values:	1% level	-3.584743	
	5% level	-2.928142	
	10% level	-2.602225	

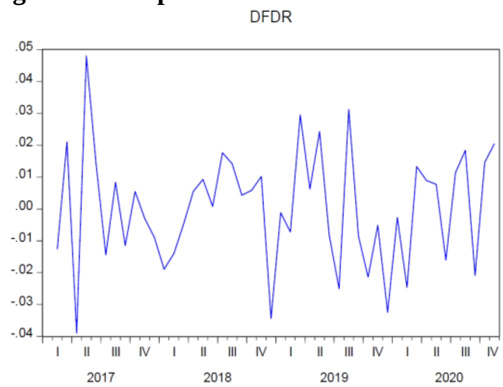
*MacKinnon (1996) one-sided p-values.

The ADF test results above show that the ADF t-statistic value is -8.012990 greater (absolute) than the critical value and significance with a probability value 0.0000. Therefore, it can be concluded that the financing-to-deposit ratio data is stationary at degree 1 (d=1), meaning that the FDR data that can be used to forecast ARIMA estimates is level 1.

iii. Graph at First Difference

Furthermore, after being differentiated once, you can verify the stationary level 1 data by looking at the line graph. The results are as follows:

Figure 14. Graph of FDR Data after Stationary



The picture above shows that level 1 FDR data (DFDR) no longer shows a trending pattern or is already stationary. Temporary ARIMA models that are suitable for the forecasting process are:

a. ARIMA (0,1,4)
b. ARIMA (1,1,8)

Next, the parameters of the temporary ARIMA model will be estimated.

2. ***Parameter Estimation***

Table 6. FDR Temporary ARIMA Model Estimation Results

Model	Model Parameter	Coefficient	Probability
ARIMA (0,1,4)	$Ø_0$		
	θ_4	-0,306245	0,0486
ARIMA (1,1,8)	$Ø_1$	-0,284972	0,0491
	θ_8	-0,390503	0,0436

Table 6 above is a temporary ARIMA model because it fulfills a probability of <0.05.

3. ***Diagnostic Checking***

Based on the results of the Q-statistical residual correlogram test that has been carried out on two temporary ARIMA models and from these two models, namely ARIMA (0,1,4) and ARIMA (1,1,8) fulfill the assumption of white noise and are typically distributed.

Table 7. Criteria for the Best ARIMA Model in FDR

Model	AIC	BIC	SSR
ARIMA (0,1,4)	-5,095337	-4,976078	0,014356
ARIMA (1,1,8)	-5,130813	-4,971801	0,012977

The results of the BIC and SSR values, which are the smallest, show that they are owned by the ARIMA model (1,1,8). Thus, it can be concluded that the best model for forecasting the financing-to-deposit ratio at Bank Syariah Mandiri for the next 12 months is the ARIMA model (1,1,8) with the following parameter estimation results:

Table 8. ARIMA Parameter Estimation Results (1,1,8) on FDR

Variable	Coefficient	t-Statistic	Probability
C	4,19E-05	0,030861	0,9755
AR(1)	-0,284972	-2,026830	0,0491
MA(8)	-0,390503	-2,081100	0,0436

From these results, it can be seen that the coefficient value of the constant has a probability > 0.05, so the constant is not significant and cannot be used in the ARIMA equation. But this in-significant is allowed because, in the ARIMA model, the most important are the coefficients θ and $\emptyset$. From that, the equation formed from the ARIMA model (1,1,8) is as follows:

$$\mathrm{DFDRt} = \mu - 0.284972\mathrm{DFDRt} - 1 - 0.390503\mathrm{DFDRt} - 8$$

4. ***Do Forecasting***

Next, we will forecast from the best ARIMA model, namely the ARIMA model (1,1,8), thus forecasting the Financing to Deposit Ratio liquidity ratio for the next 12 months, December 2020 to November 2021.

Figure 15. FDR Forecasting Results for Twelve Months

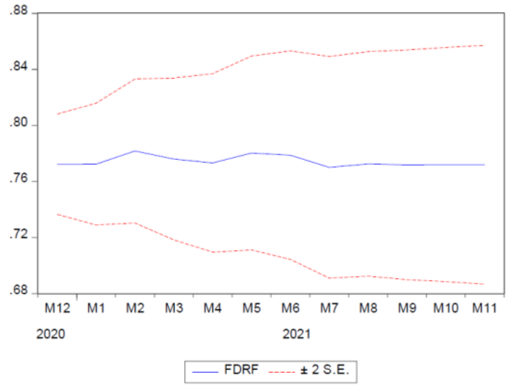


Figure 16. Forecasting Results and their Confidence Intervals

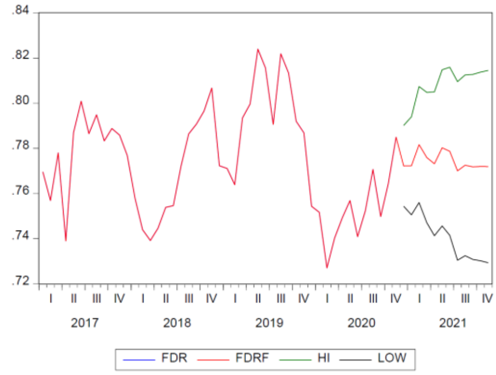


Table 9. Forecasting Results of Financing to Deposit Ratio

Month	FDR
Dec-20	0.77222
Jan-21	0.77226
Feb-21	0.78167
Mar-21	0.77593
Apr-21	0.77317
May-21	0.78023
Jun-21	0.77870
Jul-21	0.77000
Aug-21	0.77248
Sep-21	0.77177
Oct-21	0.77197
Nov-21	0.77191
Average	**0.77436**

Based on table 9 shows that the results of the forecast for the movement of the Financing to Deposit Ratio at Bank Syariah Mandiri for the period December 2020 to November 2021 obtained the highest forecast result obtained in February 2021, namely 0.78167 or 78.2%, and the lowest forecast result is owned in July 2021 with a value of 0.77000 or 77% with an average value of 77.4%. Forecasting results show that the bank's liquidity capacity is healthy when viewed from the perspective of developing the financing-to-deposit ratio soundness predicate.

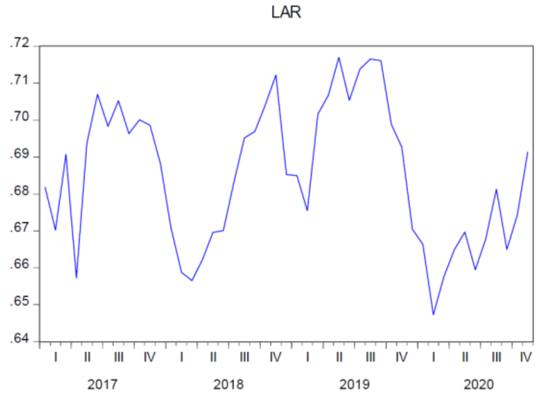
Modeling Loan to Asset Ratio (LAR) Liquidity Ratio

The Loan to Asset Ratio liquidity ratio is a ratio that displays a comparison of the company's assets with total financing. This ratio aims to assess the ability of the company's assets to meet short-term financing requirements.

The following is the development of the ARIMA Loan to Asset Ratio stages, namely:

1. ***Model Identification***
   a. ***Data Stationarity Test***
   The stages of testing the stationarity of the data include:
      i. ***Graphical Method***

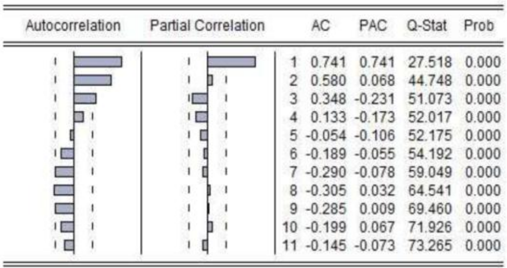
Figure 17. Identify Time Series Plots



The time series plot in Figure 17 shows that there are still changes in variance in the time series plot, and the movement of the plot has not fluctuated around a constant mean. The movement of the time series plot also shows that there has been a significant change in the development of the loan-to-asset ratio in May 2019 compared to the previous month's period, which then the bank's Loan to Asset Ratio value is relatively higher after May 2019 to September 2019 compared to other months, which means that the condition of the bank has total financing or total credit that is higher to total money assets held compared to other months.

      ii. ***Test Autocorrelation Function (ACF) and Correlogram***

Figure 18. Testing AC and PAC on Correlogram LAR



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.741	0.741	27.518	0.000
		2	0.580	0.068	44.748	0.000
		3	0.348	-0.231	51.073	0.000
		4	0.133	-0.173	52.017	0.000
		5	-0.054	-0.106	52.175	0.000
		6	-0.189	-0.055	54.192	0.000
		7	-0.290	-0.078	59.049	0.000
		8	-0.305	0.032	64.541	0.000
		9	-0.285	0.009	69.460	0.000
		10	-0.199	0.067	71.926	0.000
		11	-0.145	-0.073	73.265	0.000

From Figure 18 above, the autocorrelation graph shows a gradual decline, and the partial autocorrelation graph shows a drastic decrease after the first lag. After the first lag, all chart bars fall between two dashed boundary lines called Bartlett lines. Thus, it can be concluded that the Loan to Asset Ratio data is not stationary at zero degrees.

      iii. ***Unit Root Test***

Figure 19. LAR Augmented Dickey-Fuller (ADF) Test Results

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.540558	0.1128
Test critical values:	1% level	-3.581152	
	5% level	-2.926622	
	10% level	-2.601424	

*MacKinnon (1996) one-sided p-values.

The ADF test results above show the null hypothesis that the loan-to-asset ratio has a unit root or the data is not stationary, and it cannot be rejected as demonstrated by the t-statistic value of -2.5405 which is still smaller than the critical value at an alpha of 1%, 5%, and even 10%. In addition, the probability value of 0.1128 is more significant than 0.05. Augmented Dickey-Fuller (ADF) test results strengthen the graph and correlogram analysis that Loan to Asset Ratio data is not stationary at zero degrees.

b. Transformation of Non-Stationary Time Series Data into Stationary

Furthermore, the transformation of non-stationary time series data to be stationary is carried out by differentiating, namely reducing LARt with LARt-1 for the first difference. So for a difference of one:

$$Dt = \Delta LARt = (LARt - LARt - 1)$$

i. First Difference on Correlogram

Figure 20. Correlogram LAR Stationarity Test Results

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.181	-0.181	1.6143	0.204
		2	0.154	0.125	2.8008	0.247
		3	-0.059	-0.013	2.9801	0.395
		4	-0.032	-0.065	3.0326	0.552
		5	-0.087	-0.097	3.4356	0.633
		6	-0.078	-0.100	3.7689	0.708
		7	-0.161	-0.182	5.2404	0.631
		8	-0.064	-0.122	5.4801	0.705
		9	-0.118	-0.145	6.3091	0.709
		10	0.047	-0.022	6.4472	0.776
		11	0.032	0.017	6.5116	0.837

Based on the correlogram of the data, the first difference between the loan and asset Ratios above is that the data differs from the data at zero degrees. The residuals are random from the diagram, indicated by a bar graph inside the Bartlett line. Thus, the Loan to Asset Ratio data is stationary at level one.

ii. First Difference in Unit Root Test

Figure 21. Stationarity Test Results on ADF LAR

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.853498	0.0000
Test critical values:	1% level	-3.584743	
	5% level	-2.928142	
	10% level	-2.602225	

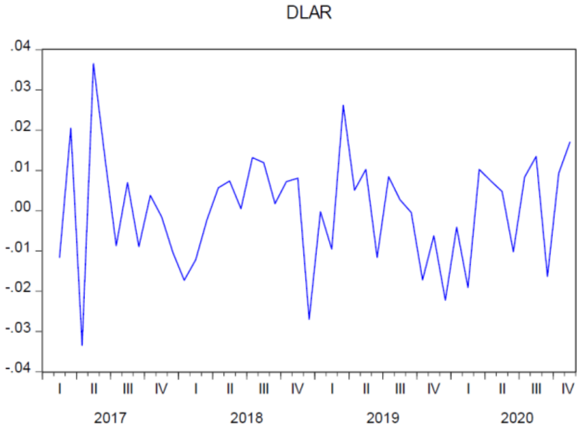
*MacKinnon (1996) one-sided p-values.

The Augmented Dickey-Fuller (ADF) test results show that the ADF t-statistic value of -7.8534 is more excellent (absolute) than the critical alpha values of 1%, 5%, and 10%. The ADF value has a probability of 0.0000. Thus, it can be concluded that the Loan to Asset Ratio data is stationary at degree 1 (d=1), which means that the Loan to Asset Ratio data that can be used in forecasting ARIMA estimates is level 1.

iii. First Difference in Graphics

Furthermore, after being differentiated once, you can verify the stationary level 1 data by looking at the line graph. The results are as follows:

Figure 22. LAR Data Graph after Stationary



The figure above shows that the Loan to Asset Ratio level 1 (DLAR) data no longer shows a trending pattern or is stationary. The temporary ARIMA models that are suitable for the forecasting process are as follows:

a. ARIMA (3,1,3)
b. ARIMA (11,1,11)

2. ***Parameter Estimation***

Table 10. ARIMA Model Estimation Temporary Results of LAR

Model	Model Parameter	Coefficient	Probability
ARIMA (3,1,3)	$\emptyset_3$	-1,000000	0,0000
	θ_3	0,999973	0,0000
ARIMA (11,1,11)	$\emptyset_{11}$	-1,000000	0,0000
	θ_{11}	0,999934	0,0000

Table 10 above is a temporary ARIMA model because they have a probability <0.05.

3. ***Diagnostic Checking***

Based on the results of the Q-statistical correlogram residual test that was carried out on two temporary ARIMA models, these models fulfill the assumption of white noise and are typically distributed.

Table 11. Criteria for the Best ARIMA Model in LAR

Model	AIC	BIC	SSR
ARIMA (3,1,3)	-5,583326	-5,424314	0,008063
ARIMA (11,1,11)	-5,595768	-5,436756	0,007269

The results of AIC and BIC, which are the smallest values, show that they are owned by the ARIMA model (3,1,3), concluded that the best model for forecasting the Loan to Asset Ratio at Bank Syariah Mandiri for the next 12 months is the ARIMA model (3,1,3) with the following parameter estimation results:

Table 12. ARIMA Parameter Estimation Results (3,1,3) in LAR

Variable	Coefficient	t-Statistic	Probability
C	0,000138	0,070231	0,9443
AR(3)	-1,000000	-3404,509	0,0000
MA(3)	0,999973	10629,99	0,0000

From the results of Table 12 above, the constant coefficient value has a probability > 0.05, so the continuous is insignificant and cannot be used in the ARIMA equation. This insignificant is allowed because the most essential ARIMA models are the coefficients $\emptyset$ and θ. Therefore, the equation formed from the ARIMA model (3,1,3) is:

$$\text{DLARt} = \mu - 1.000000\text{DLARt} - 3 + 0.999973\text{DLARt} - 3$$

4. ***Do Forecasting***

The next stage is forecasting from the best ARIMA model, namely the ARIMA model (3,1,3), thus forecasting the Loan to Asset Ratio liquidity ratio for the next 12 months, from December 2020 to November 2021.

Figure 23. LAR Forecasting Results for Twelve Months

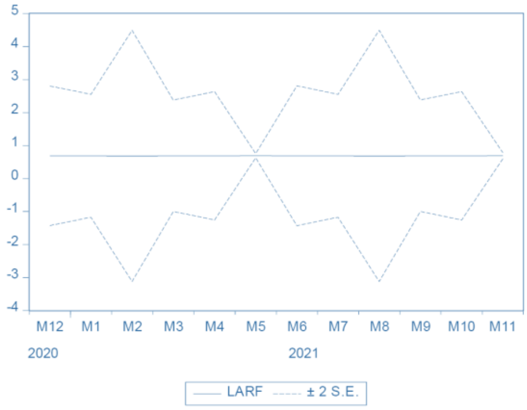


Figure 24. Forecasting Results and Their Confidence Interval Values

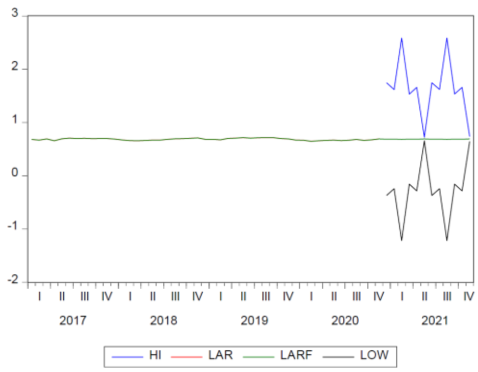


Table 13. Forecasting Result of Loan to Asset Ratio

Month	LAR
Dec-20	0.68777
Jan-21	0.68820
Feb-21	0.68484
Mar-21	0.68850
Apr-21	0.68806
May-21	0.69143
Jun-21	0.68777
Jul-21	0.68820
Aug-21	0.68484
Sep-21	0.68850
Oct-21	0.68806
Nov-21	0.69143
Average	**0.68813**

Based on Table 13, it can be seen that the results of the Loan to Asset Ratio forecast at Bank Syariah Mandiri from December 2020 to November 2021 obtained the forecast value with an average of 0.68813 or 68.8%, with the highest forecast value occurring in November 2021 of 69.1 %. The lowest forecast value is 68.4% in February 2021. The forecasting results obtained from the average results show that the bank's liquidity capability is considered healthy in developing the Loan to Asset Ratio predicate.

IV. CONCLUSION

The conclusions that can be drawn from the research results on developing banking liquidity ratios are as follows. First, the best forecasting model obtained based on the ARIMA Box-Jenkins method in the study of each liquidity ratio of Bank Syariah Mandiri is ARIMA (11,1,1) for Cash Ratio, ARIMA (1,1,8) for Financing to Deposit Ratio and ARIMA (3,1,3) for Loan to Asset Ratio. Second, forecasting the liquidity ratio of Bank Syariah Mandiri shows the development of the bank's liquidity capacity from December 2020 to November 2021, namely the development of the Cash Ratio with the predicted results of the liquidity capacity of 130% by showing that the liquidity capacity of Bank Syariah Mandiri is considered very healthy. The financing-to-deposit ratio was obtained by obtaining the predicted result of a liquidity capacity of 77.4%, indicating that Bank Syariah Mandiri's liquidity capacity is considered healthy. The Loan to Asset Ratio obtains the expected outcome of liquidity capacity of 68.8%, indicating that Bank Syariah Mandiri's liquidity capability is considered healthy.

V. SUGGESTION

We realize there is still much to improve and add to this research. Further research is recommended to use Bank Syariah Indonesia so that there are more comparisons and can better assess how good it is for future planning.

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