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Causality test on gold prices and economic risk (VAR model application)

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ABSTRACT

The presence of gold as an investment asset has roots from the past to the present. The volatility of the value of economic risk can reflect the gold prices' volatility that can affect investors' decisions in investing amid uncertainty. This study aims to predict the reciprocal relationship between gold price volatility and economic risk proxied by BI 7-days Repo Rate. The Method applied in this study is the Vector Autoregression (VAR) model to dynamically express such causality. The result found that VAR (1) model is the best-fit model to analyse the causality between variables. In addition, VAR (1) model also is tested by Granger Causality as well as used in their respective impulse response. Finally, VAR (1) model is applied to forecast the next 12-month data for both variables and has high accuracy forecasting estimation with low MSE, RMSE, and MAPE. The study then can be used as one of considerations for gold investors in making investment decisions.

KEYWORDS

Gold Prices' Volatility; BI 7-Days Repo Rate; Dynamic Model; VAR Model; Economic Risk

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Introduction

The presence of gold as an investment asset has roots from the past to the present. However, Gold does not provide passive income like other investment instruments (Platias et al., 2020), like deposits, stocks, bonds, and properties that provide benefits in the form of coupons, interest, dividends and rent respectively. Profits from investing in precious metals can only be obtained from the difference in price, if the selling price is higher than the purchase price (Sari et al., 2010). The price of this shiny asset in the long term (> 5 years) has the potential to experience a fantastic increase, especially in a situation of economic crisis (Caballero et al., 2017). However, the price is relatively volatile in the short term, so there is a risk of losing gold investment if it is sold at any time (Jones & Sackley, 2016).

During the global crisis in 2013, gold prices experienced a significant decline. This is due to several factors, including growing confidence in the global economic recovery and the prospect of an interest rate hike by the US Federal Reserve (Ciner et al., 2013). At the start of 2013, gold was trading around $1700 an ounce. However, throughout the year the gold price continued to decline, touching a low of around $1180 per ounce in December 2013. This decline in gold prices was also supported by investors diverting their funds from gold to other assets that are expected to provide higher yields, such as stocks or bonds (Zhu et al., 2018). Thus, the 2013 global crisis showed that gold is not always considered a safe haven asset in a stable economic situation and the prospect of rising interest rates. However, we must also remember that stable global economic conditions and prospects for an increase in interest rates are not always a certainty, economic conditions may change and prospects for an increase in interest rates may change.

Additionally in 2018, the stock market experienced a challenging year, with both the Dow Jones Industrial Average and the S&P 500 seeing approximately a 10% decline in their value since the year's start (Yan & Wu, 2021). The Nasdaq also registered an approximately 8% drop. The significant losses mainly occurred from October onward, marking a downturn after the stock market had been on the longest bull run in history (Sumer & Ozorhon, 2020). December is poised to be the worst for the stock market since 1931; however, it's noteworthy that it also achieved record-breaking single-day gains on Wednesday, including a surge of over 1,000 points in the Dow.

The latest global crisis was marked by the outbreak of the Covid-19 virus which was declared a pandemic which had an impact on weakening the economy around the world. Specifically, the movement of gold prices during the Covid-19 pandemic was heavily influenced by changes in the global economic situation (Asaad, 2021). At the start of the pandemic, the price of gold experienced a significant increase as investors sought safe haven assets amid the economic uncertainty caused by the pandemic. Governments and central banks around the world are also taking aggressive monetary action to deal with the economic impact of the pandemic, which is also helping to prop up gold prices (Betz, 2021). In March 2020, the price of gold rose from around $1550 an ounce to over $1700 an ounce in a few weeks. However, in line with the global economic recovery and the prospect of an increase in interest rates, gold prices began to decline. At the end of 2020, the price of gold was trading around $1850 per ounce.

Therefore, the volatility of the value of economic risk can be a reflection of the business performance of gold companies that can affect investors decision in investing amid uncertainty (Badarau & Lapteacru, 2020). It is also

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important to predict the reciprocal relationship between gold price volatility and economic risk because it can have consequences for increasing and decreasing most economic and non-economic factors (Safari & Davallou, 2018). Models for causal relationship between gold price volatility and economic risk can be done by applying the Vector Autoregressive (VAR) model.

Sims (1980) pioneered the use of the VAR model to examine macroeconomic data. Furthermore, Tsay (2014) proposed that the relationship between variables from financial markets and macroeconomics is quite evident, and that it is required to estimate them together in order to understand how they function dynamically. Thus, empirical research by Sharma et al. (2018) demonstrated that the VAR model plays a crucial role in advanced analytical procedures. Warsono et al. (2019) contributed to the literature by stating that the VAR model is an extension of the Autoregressive (AR) model, with the VAR model being more appropriate for usage in multivariate models. VAR modelling is thought to be capable of analysing two-way relationships between multivariate variables as well as forecasting data (Chuang & Wei, 1991). VAR modelling also includes parts of the Impulse Response Function (IRF) and the Granger Causality Test (GCT). This IRF serves to be able to measure how the influence of unexpected events (shock) of the economic situation at a commodity price (Hair et al., 2006), while GCT can model the price of gold which can be influenced by historical data on the price of gold itself and the historical data of the variables that influence it (Tsay, 2005).

In contrast, Umpusinga et al. (2020) discovered that Vector Autoregressive (VAR) modelling (1) is the best model to use in the analysis of the dynamic relationship between Islamic stock prices, Islamic stock indexes, and changes in the rupiah exchange rate against foreign currency in his empirical research. Their findings also revealed that each variable is only influenced by its own historical data and the results of the impulse response function, indicating that it is difficult for all variables to reach the zero point or balance point after a shock occurs in other variables in the short term. The VAR(1) modelling is then used as a model to predict the data for each variable for the next six months which shows the results of the Islamic stock variable data and currency exchange rates move stably, and the Islamic stock index is predicted to increase significantly.

However, according to observations, there has not been much research on forecasting the causal relationship between gold prices and economic risk values using the VAR approach in Indonesia. For this reason, the state-of-the-art study is to provide a causality relationship model of the gold price and the value of economic risk.

Methods

The variable analysed in this study is daily prices of gold for the last 5 years from 2018 to 2022, and economic risk variables that affect gold prices proxied by Bank Indonesia (BI) interest rates 7-days repo rate. Then gold prices and data from economic risk variables will be used as an input in the analysis of the causality relationship between each variable by applying Vector Autoregressive (VAR) model. VAR modelling can be done in several stages, as follows.

Stationary Data Testing

In analysing time series data, the first thing to do is check whether the data is in a stationary state or not. There are two ways of testing stationary data, the first by visually looking at the graphs of the time series data, and the second is statistically testing using the Augmented Dickey-Fuller Test (ADF Test) method (Brockwell & Davis, 1991), as following formula:

$$DF_\tau = \frac{\partial_i}{\widehat{Se}_{\partial_1}}$$

with the hypothesis:
H0 = 0 (not stationary)
H1 > 0 (stationary)

If it is less than -2.57 or the probability value is less than 5%, the null hypothesis is rejected (Brockwell & Davis, 2002).

VAR Modelling Estimation

VAR modelling at order p (VAR(p)) can be expressed mathematically as follows (Wei, 2006).

$$\theta_j = \beta + \sum_{k=0}^{p} \gamma_k \theta_{j-k} + \varepsilon_j$$

Where k is 1,2,3,…,p; θ is a k x k matrix; and can be described more detail below.

$$\begin{pmatrix} \theta_{1j} \\ \theta_{2j} \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} + \begin{bmatrix} \gamma_{11}^k & \gamma_{21}^k \\ \gamma_{12}^k & \gamma_{22}^k \end{bmatrix} \begin{pmatrix} \theta_{1j-k} \\ \theta_{2j-k} \end{pmatrix} + \varepsilon_j$$

Granger Causality Test

As an example, consider the bivariate VAR modelling of two variables (Ax and Bx) (Hair et al., 2014).

$$A_x = C_0 + \sum_{k=1}^{p} C_k A_{j-k} + \sum_{k=1}^{p} D_k B_{j-k} + \varepsilon_{1j}$$
$$B_x = N_0 + \sum_{k=1}^{p} N_k A_{j-k} + \sum_{k=1}^{p} M_k B_{j-k} + \varepsilon_{2j}$$

Bollerslev (1986) described a linear model of Granger causality, if Granger Ax causing Bx, then historical data Ax can predict Bx better than just historical data Bx Alone.

Impulse Response Function (IRF)

Lutkepohl (2013) conducted a previous study that measured unexpected events (shocks) or the effects of non-zero residuals that can be studied to see the relationship between variables. This is because the VAR model translates shocks into the variable using a non-zero residual value if some previously considered structural constraints exist. Tsay (2014) defined IRF as a function for better understanding the impact of changes in each variable when analysing time series multivariate data.

Forecasting

The final stage of the VAR(p) model method is to predict the data value of the gold price and the variable risk value of each variable over a specific period, where the gold price value and the variable risk value variable are influenced not only by historical data of the commodity itself, but also by data from other historical variables, taking into account unexpected events during the research period.

The overall accuracy of any forecasting model including moving average, exponential smoothing or other can be explained by comparing the projected value with the actual value or the observed value. The level of forecasting accuracy can be measured from the following values (Engle & Bollerslev, 1986):

1. Mean Squared Error (MSE), defined as the average sum of the squared forecasting errors and with the following equation:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Y_t - Y_t')^2$$

2. Root Mean Square Error (RMSE), defined as the root of the value obtained in MSE, or with the equation as follows.

$$RMSE = \sqrt{MSE}$$

   The smaller the RMSE value, the better the prediction accuracy.

3. Mean Absolute Percentage Error (MAPE), defined as a calculating the average percentage of the first error from several periods, with the formula:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\frac{(Y_t - Y_t')}{Y_t}$$

   Where Y_t= Observation value; Y_t^'= Forecasting value. The smaller the MAPE value, the better the prediction accuracy.

Results and Discussion

Stationary Conditions

Before implementing the VAR model, the observed data series must be tested for stationarity. We check visual and statistical tests to get more valid results when running this test. Figure 1 depicts a data series plot for each variable. The graph clearly shows that no data series is stationary because the mean and variance are not close to zero.

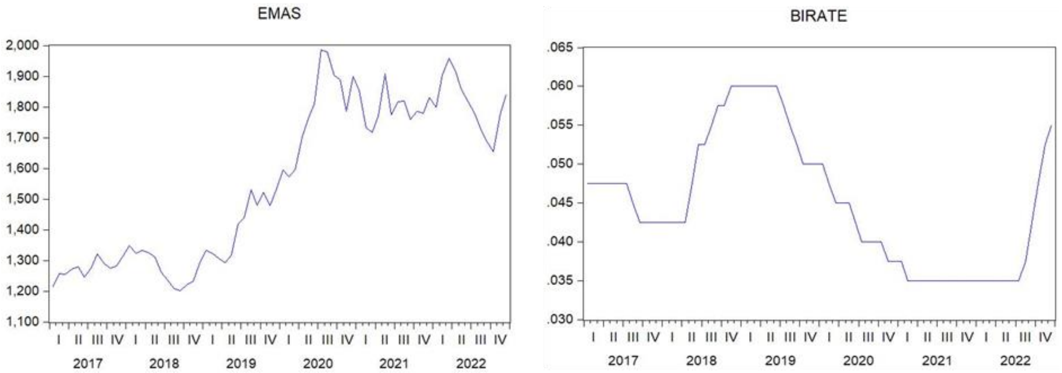

Figure 1. Plotting Graph of Daily Gold Prices and BI 7-days Repo Rate 2017 – 2022

Furthermore, we apply the ADF unit-root test based on the basic statistical test, as shown in Table 1, and all three data series have a probability value of more than 5%, indicating they have a unit-root, which is measured as a non-stationary data set.

Table 1. ADF Unit-root Test

Group unit root test: Summary
Series: EMAS, BIRATE
Date: 06/20/23 Time: 11:36
Sample: 2017M01 2022M12
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.06225	0.4752	2	141
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.30862	0.6212	2	141
ADF - Fisher Chi-square	2.09398	0.7185	2	141
PP - Fisher Chi-square	1.71027	0.7889	2	142

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Given that the average dataset is not stationary, the next step is to use the differencing method to transform it into a stationary dataset. The ADF statistical test with differencing 1 (d=1) is shown in Table 2. Because each p-value is less than 0.0001, the mean of the dataset is stationary after applying d=1. As a result, the VAR model can now be run statistically.

Table 2. ADF Unit-root Test After Differencing (d=1)

Group unit root test: Summary
Series: EMAS, BIRATE
Date: 06/20/23 Time: 11:39
Sample: 2017M01 2022M12
Exogenous variables: Individual effects
Automatic selection of maximum lags

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.94358	0.0000	2	140
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.25071	0.0000	2	140
ADF - Fisher Chi-square	42.3439	0.0000	2	140
PP - Fisher Chi-square	41.9905	0.0000	2	140

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

VAR Model Estimation

The determination of the optimal lag in the VAR model is a necessary preliminary test because it can more accurately explain the dynamics model for the VAR model. Because lag 1 is significant in the representation of the most schematic criteria, Table 3 measures the optimal lag 1.

Table 3. Estimation Parameter of Schematic Representation (Lag Optimum)

VAR Lag Order Selection Criteria
Endogenous variables: D(EMAS) D(BIRATE)
Exogenous variables: C
Date: 06/20/23 Time: 11:41
Sample: 2017M01 2022M12
Included observations: 67

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-42.60628	NA	0.012982	1.331531	1.397343	1.357573
1	-24.35833	34.86176*	0.008485*	0.906219*	1.103654*	0.984344*
2	-20.99322	6.227959	0.008651	0.925171	1.254229	1.055380
3	-18.40921	4.628089	0.009034	0.967439	1.428121	1.149732
4	-16.31786	3.620846	0.009580	1.024414	1.616719	1.258790

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

The optimal lag p for the VAR model is then stated to be 1 or VAR(1). As a result, VAR(1) can be written as follows.

$$\theta_j = \beta + \gamma_k \theta_{j-1} + \varepsilon_j$$

Where:

$\theta_j = \begin{bmatrix} EMAS_j \\ BIRATE_j \end{bmatrix}$; $\theta_{j-1} = \begin{bmatrix} EMAS_{j-1} \\ BIRATE_{j-1} \end{bmatrix}$; β = Constant; γ_k= 1 x 1 matrix parameters of AR1; dan ε_j= error.

The results of the VAR (1) statistical test are presented in Table 4 and it appears that there are parameters that are not significant. As Tsay (2014) explained, to overcome this problem, it is sufficient to remove the insignificant to improve the model.

Table 4. Estimate VAR(1) Model

Vector Autoregression Estimates
Date: 06/20/23 Time: 11:53
Sample (adjusted): 2017M03 2022M12
Included observations: 70 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(EMAS)	D(BIRATE)
D(EMAS(-1))	0.013413	-0,0000047
	(0.12284)	(2.9E-06)
	[0.10919]	[-1.61206]
D(BIRATE(-1))	-2401.618	0.624612
	(3991.26)	(0.09468)
	[-0.60172]	[6.59729]
C	8.421272	0.000100
	(7.20094)	(0.00017)
	[1.16947]	[0.58629]
R-squared	0.005756	0.418741
Adj. R-squared	-0.023923	0.401390
Sum sq. resids	238050.6	0.000134

S.E. equation	59.60700	0.001414
F-statistic	0.193938	24.13356
Log likelihood	-383.9367	361.5034
Akaike AIC	11.05533	-10.24296
Schwarz SC	11.15170	-10.14659
Mean dependent	8.357143	0.000107
S.D. dependent	58.90655	0.001828
Determinant resid covariance (dof adj.)		0.007101
Determinant resid covariance		0.006505
Log likelihood		-22.42043
Akaike information criterion		0.812012
Schwarz criterion		1.004741
Number of coefficients		6

From Table 4 it can be concluded that the VAR (1) estimation model is as follows:

D(BIRATE) = -0,0000047*D(EMAS(-1)) + 0.624612*D(BIRATE(-1))

The estimation results of the VAR (1) model on the EMAS and BIRATE variables show that only the BIRATE variable has significant results as an endogenous variable. This indicates that the BI 7-day repo rate is not only influenced by the volatility of the BI interest rate itself, but also by the volatility of world gold prices in lag 1.

Granger Causality Test

The hypothesis in the Granger causality test is to determine whether a variable's correlation value is influenced solely by itself and not by the historical values of other variables. The Granger causality test results from the VAR(1) model are shown below.

Table 5. Granger Causality Test for VAR (1) Model

VAR Granger Causality/Block Exogeneity Wald Tests Date: 06/20/23 Time: 12:09 Sample: 2017M01 2022M12 Included observations: 69			
Dependent variable: D(EMAS)			
Excluded	Chi-sq	df	Prob.
D(BIRATE)	2.293777	2	0.3176
All	2.293777	2	0.3176
Dependent variable: D(BIRATE)			
Excluded	Chi-sq	df	Prob.
D(EMAS)	7.261690	2	0.0265
All	7.261690	2	0.0265

From the results of the Granger causality test, only the BIRATE variable has a probability value of less than 0.05. This means that the BIRATE variable is not only influenced by its own historical data, but also by the EMAS variable's historical data. The results of this Granger causality test validate the results of the parameter estimation of the VAR(1) model, where only variable D(BIRATE) has significant results.

This result of causality Granger test which has a probability level of less than 0.05 on the BIRATE variable. While the gold variable in this case is not significant when tested as an endogenous variable also proven through the Granger test which has a probability level of more than 0.05. This Granger Causality test supports what we have on the VAR(1) estimation.

Impulse Response Factors

Figure 2 shows the response relationship between variables if a variable occurs shock. Variable D(BIRATE) will respond negatively to shocks that occur in variable D(EMAS) over the next 10 periods with a tendency to approach the convergent line, which is shown in the Response of D(EMAS) to D(BIRATE) graph. The same thing happens to the D(EMAS) variable which responds negatively to the shocks that occur in the D(BIRATE) variable for the next 10 periods (shown in the Response of D(BIRATE) to D(EMAS) graph, with the movement approaching the line converge, even over a second period experienced a significant negative response.

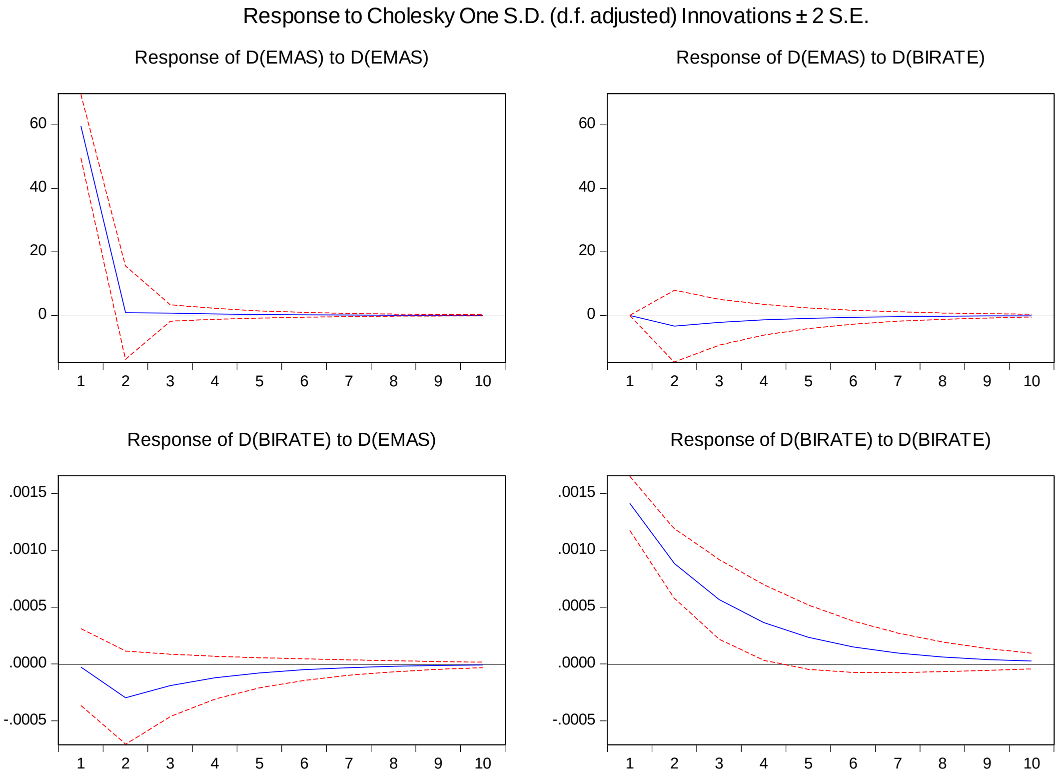

Figure 2. IRF Graphs for D(EMAS) and D(BIRATE) for the next 10 periods

Meanwhile, the shock that occurs in variable D(EMAS) will be responded positively by D(EMAS) itself, which at the beginning of the shock period makes a large response to variable D(EMAS), but significantly the response returns to approach the convergent line in the period- next period. The same thing happened to the variable D(BIRATE), where at the start of the shock D(BIRATE) gave a high positive response, but slowly in the next period it approached the convergent line.

The results of impulse response also supports the parameter estimation results of the VAR(1) model, where when shocks occur in one variable, other variables will respond with a negative response but will tend to approach the convergence line until the 10th period.

Forecasting

Table 6. Forecasting Evaluation Estimate

Forecast Evaluation
Date: 06/20/23 Time: 12:34
Sample: 2017M01 2023M12
Included observations: 84

Variable	Inc. obs.	RMSE	MAE	MAPE	Theil
BIRATE	71	0.013072	0.010745	19.80171	0.132596
EMAS	71	139.4184	107.2273	6.848282	0.044312

RMSE: Root Mean Square Error
MAE: Mean Absolute Error
MAPE: Mean Absolute Percentage Error
Theil: Theil inequality coefficient

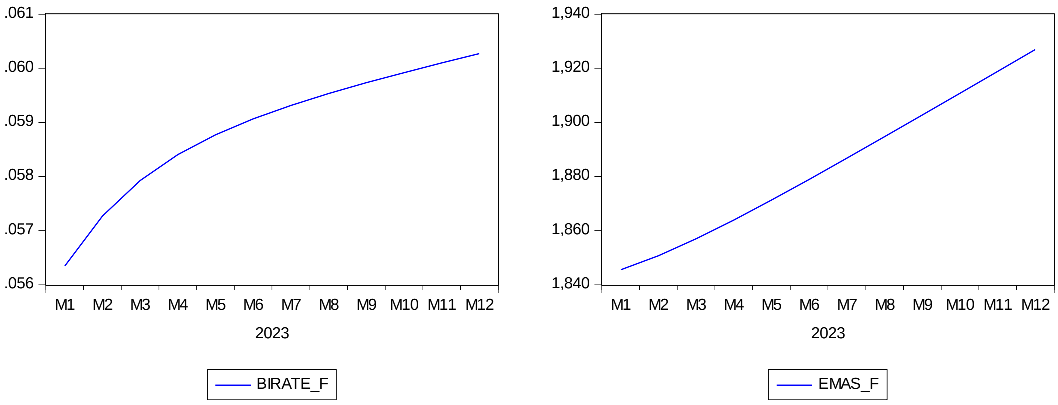

Figure 2. Forecasting Graph for variable BIRATE and Emas for the Next 12 Months

Figure 3 illustrates the graph of the forecasting results of the BIRATE data showing a significant increase in the BIRATE variable for the first 6 months and continues to increase but slowly until the end of the 12th month. The results of this forecasting are accurate, supported by forecast evaluation estimates on the low RMSE and MAE (Table 6). Meanwhile, the gold price forecasting chart shows a significant increase in the EMAS variable over the next 12 months, with low forecast evaluation estimates for the MAPE and Theil components (Table 6).

Conclusion

This study examined the causal relationship between volatility of gold prices and economic risk proxied by BI 7-days Repo Rate in the last five years by applying VAR model. As far as we know previous studies have not put concern in gold prices related to its main factor of volatility in Indonesia which is BI rate by applying VAR model. Therefore, before estimating VAR model, we run stationary check to ensure that the time series has been stationary. By implementing differencing 1 (d=1) we obtained the stationary condition. This is required to have best fit estimates for modelling VAR. The VAR(1) model was found to be the best-fit model for estimating dynamic causality between variables in this study. Granger Causality and Impulse Response Function were also used to test the VAR(1) model. The estimation VAR(1) model revealed that only the BIRATE variable was significant as an endogenous variable, indicating that the BI 7-day repo rate was influenced not only by the volatility of the BI interest rate, but also by the volatility of world gold prices. Finally, the VAR(1) model is used to forecast for the next 12 months and has a high level of accuracy as evidenced by low RMSE, MAE, and MAPE values.

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