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COMPARISON OF ARIMA, TRANSFER FUNCTION AND VAR MODELS FOR FORECASTING CPI, STOCK PRICES, AND INDONESIAN EXCHANGE RATE: ACCURACY VS. EXPLAINABILITY

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Abstract: The Consumer Price Index (CPI), stock prices and the rupiah exchange rate to the US dollar are important macroeconomic variables which their movements show the economic performance and can affect the monetary and fiscal policies of Indonesia. This makes forecasting effort of these variables become important for policy planning. While many previous studies only focus on examining the effect among macroeconomic variables, this study uses ARIMA (univariate method), transfer function and VAR (multivariate methods) to measure the forecasting accuracy and also observing the effect between these macroeconomic variables. The results showed that the multivariate methods gave better explanation about the relationship between variables than the simple one. Otherwise, the results of accuracy comparison showed that the multivariate methods did not always yield better forecast than the simple one, and these conditions in line with the results and conclusions of M3 and M4 competition.

1. INTRODUCTION

The Consumer Price Index (CPI), stock prices and rupiah exchange rate to US dollar are important macroeconomic variables which their movements show the economic performance of Indonesia. An increasingly open economic system causing more dynamic movement of these variables means that any changes in one variable can influence other variables of the countries involved. The dynamics of these three variables can affect the monetary and fiscal policies of Indonesia. This makes forecasting effort of these three variables becomes an important thing to do for policy planning.

Many previous studies only focus on examining the effect among macroeconomic variables empirically that can be grouped into two groups. First, studies that only focus on examining the effect of each macroeconomic variable on stock price, i.e. Nkoro & Uko (2016) and Okechukwu *et al.* (2019) used the Generalized Autoregressive Heteroscedasticity (GARCH) method to determine the effect of exchange rate, inflation, and interest rate on Nigerian stock prices, Wahyudi *et al.* (2017) used the Threshold Autoregressive Conditional Heteroscedasticity (TARCH) method to observe the effect of inflation, exchange rate, interest rate, GDP, crude oil price, primary commodity price, and wage in five ASEAN countries. Mgammal (2012) used multiple linear regression to determine the effect of inflation, exchange rate and interest rate on stock price of the United Arab Emirates and Saudi Arabia. Using the same method, Yogaswari *et al.* (2012) and Putra (2016) also observed the effect of the same macroeconomic variables on Indonesian stock price. In addition, Imran *et al.* (2014) and Firmansyah & Oktavilia (2017) used the Granger causality and Johansen cointegration test to observe the short-term and long-term relationship of macroeconomic variables to stock prices in Pakistan and in five ASEAN countries, respectively. Second, studies that examine the effect among macroeconomic variables not only focus on the effect on certain variable, including Liang *et al.* (2015), Parsva & Tang (2017) and Karim *et al.* (2018) who used the Granger causality test to find out the short-term relationship between the exchange rate and stock price in five ASEAN countries, four Middle Eastern countries and in Indonesia and also Pantas et al (2019) who used the Johansen cointegration test to find out the long-term relationship between exchange rate and stock price in Indonesia.

Empirical results from previous studies above indicate that there is no definite pattern of relationships between macroeconomic variables. For example, Yogaswari *et al.* (2012), Putra (2016) and Okechukwu *et al.* (2019) showed that inflation has a positive effect on stock price. Whereas in the study of Nkoro & Uko (2016) and Wahyudi *et al.* (2017), inflation has a negative effect on stock price. Similarly, the exchange rate variable showed a different effect on the stock price variable with a positive effect was obtained in the study of Okechukwu *et al.* (2019) and negative effect from the study of Yogaswari *et al.* (2012), Nkoro & Uko (2016) and Putra (2016). Furthermore, it turns out that using data with different frequencies can produce different conclusions as in the study of Mgammal (2012) where the exchange rate variable has a positive effect when using monthly data and has a negative when using quarterly data.

According to this background, this study uses a forecasting method to measure the forecasting accuracy of macroeconomic variables, i.e. CPI, stock price and exchange rate of Indonesia and also observing the effect between these macroeconomic variables. Usually, the forecasting process of a macroeconomic variable generally uses the univariate method which means the process of forecasting a variable is done only by utilizing the information of variable itself in the past. In other words, the effects of other variables are not involved. Whereas in actual condition, the macroeconomic variables frequently affect each other which can be analyzed by multivariate methods. Therefore this study focus in term of accuracy and explainability by using univariate method, i.e. the Autoregressive Integrated Moving Average (ARIMA) method (Box & Jenkins, 1976) and multivariate method, i.e. the Transfer Function (Montgomery & Weatherby, 1980; Box *et al.* 1994; Wei, 2006) and Vector Autoregressive (VAR) method (Sims, 1980; Lutkepohl, 1993). By using multivariate methods, the forecasting accuracy for all three macroeconomic variables is expected to be improved as a result of Thomakos & Guerard (2004) and Stephani *et al.* (2015) that performance of multivariate methods, i.e. Transfer Function, and VAR method outperform univariate methods when forecasting the gas furnace, sales, Dow Jones Industrial Average (DJIA) and mergers-stock prices dataset and inflation rate of Indonesia respectively. Ogboghro (2017) used the same variables used in this study but only focus on examining the effect of inflation and exchange rate on Nigerian stock price using the VAR method.

2. LITERATURE REVIEW

2.1. Time Series Analysis

According to Box & Jenkins (1976), there are four important steps in modeling a time series data, i.e. model identification, model estimation, residual diagnostic checking, and forecasting.

2.2. ARIMA Model

The ARIMA model for time series data is a mix between Autoregressive (AR) process with p order and Moving Average (MA) process with q order or commonly abbreviated as ARIMA (p, d, q), with d is the differencing level. The general form is as follows:

$$\phi_p(B)(1 - B^d)\dot{Z}_t = \theta_q(B)a_t \tag{1}$$

where

$\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ is AR process (p), $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$ is MA process (q), $\dot{Z}_t = Z_t - \mu$ and a_t is a white noise process with $E(a_t) = 0$, $\text{Var}(a_t) = \sigma_\alpha^2$ and $\text{Cov}(a_t, a_{t+k}) = 0, k \neq 0$.

The stationary in variance can be checked using the lambda value (λ). If $\lambda \geq 1$, the data is already stationary in variance. However, if $\lambda < 1$, the data is not stationary in the variance and need to be transformed first. Nest, observe if there is any indication that the data do not yet satisfy the stationary condition in mean using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plot. If the significance of ACF or PACF plots decays very slowly then the data is non-stationary in mean and differencing process must be applied. When the data has satisfied the stationary condition, both in variance and mean, model identification can be done by looking at the plot of ACF and PACF to determine the ARIMA order as described by Wei (2006). The next process is model estimation. Once the significance requirement on the parameters is met then proceed with a diagnostic check to test whether the residuals a_t satisfy both assumptions (white noise and normal distribution).

2.3. Transfer Function Model

Time series data modeling with transfer function is categorized in the multivariate time series method since it utilizes the input series (x_t) to model the output series (y_t). The number of input series (x_t) used can be one (single input), or more than one (multi-inputs). The general form of single input and single output transfer functions is as follows:

$$y_t = v(B)x_t + n_t \tag{2}$$

Procedures for identification of transfer functions according to Wei (2006):

1. Prewhitening the input series x_t with the same procedure in ARIMA modeling, $\phi_x(B)x_t = \theta_x(B)\alpha_t$ and get the white noise series α_t:
$$\alpha_t = \frac{\phi_x(B)}{\theta_x(B)} x_t$$
2. Filtering the output series y_t using the ARIMA model obtained in the prewhitening process to obtain the non-white noise series β_t:
$$\beta_t = \frac{\phi_x(B)}{\theta_x(B)} y_t$$
3. Calculating Cross-Correlation Function (CCF), $\hat{\rho}_{\alpha\beta}(k)$, between α_t and β_t.
4. Identifying the values of *b*, *s*, and *r* based on significant CCF plots.

Then estimate the tentative transfer function model in Eq.(2). According to Montgomery & Weatherby (1980), the parameter estimation results in the tentative transfer model should not be significant because they are used to estimate residuals values n_t. Next, run diagnostic check whether residuals n_t white noise or not. If the residual is non-white noise, it will be modeled with ARIMA, so the transfer function becomes:

$$y_t = \frac{\omega_s(B)B^b}{\delta_r(B)} x_t + \eta_t \tag{3}$$

where $\omega_s(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s$, $\delta_r(B) = 1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r$ and $\eta_t = \frac{\theta_q(B)}{\phi_p(B)} a_t$. Then re-estimating the model, checking the significance of the parameters and diagnostic checking. According to Wei (2006), the general model for output series functions with more than one input series is:

$$y_t = \sum_{j=1}^{k} \frac{\omega_{sj}(B)B^{bj}}{\delta_{rj}(B)} x_{jt} + \frac{\theta_q(B)}{\phi_p(B)} a_t \tag{4}$$

with $v_j(B)$ is the transfer function for the input series x_{jt} assuming independent a_t for each input series $j = 1, 2, \ldots, k$ and the input series x_{it} and x_{jt} are not correlated for $i \neq j$.

2.4. Vector Autoregressive (VAR) Model

Time series data modeling with VAR is also categorized in the multivariate time series method. Unlike the transfer function model, the VAR model can explain the relationships between multiple sets of time series data and two-way or bidirectional relationships. The general model of VAR(p) is as follows:

$$\boldsymbol{\Phi}_p(B)\dot{\boldsymbol{Z}}_t = \boldsymbol{a}_t$$

$$(1 - \boldsymbol{\Phi}_1 B - \boldsymbol{\Phi}_2 B^2 - \cdots - \boldsymbol{\Phi}_p B^p)\dot{\boldsymbol{Z}}_t = \boldsymbol{a}_t$$

or

$$\dot{\boldsymbol{Z}}_t = \boldsymbol{\Phi}_1 \dot{\boldsymbol{Z}}_{t-1} + \boldsymbol{\Phi}_2 \dot{\boldsymbol{Z}}_{t-2} + \cdots + \boldsymbol{\Phi}_p \dot{\boldsymbol{Z}}_{t-p} + \boldsymbol{a}_t \tag{5}$$

After the time series data satisfy the stationary conditions in mean and variance then the next process is model identification or determine the number of lagged values based on Akaike Information Criterion (AIC) produced by VAR model as discussed by Lutkepohl (1993). The VAR(p) model, with p lagged values, will be used if this model produces minimum AIC value among other models. If each variable in the model satisfies the stationary condition then the VAR model is used. The co-integration test, i.e. two step Engel-Granger or Johansen cointegration test, need to be proceed when each variable does not satisfy the stationary condition or integrated in the same order (d) to find out long relationship among variables. If cointegration exists then Vector Error Correction Model (VECM) is used. Final step, proceed the diagnostic checking to ensure that the residuals a_t are white noise and satisfy multivariate normal distribution assumptions.

2.5. Consumer Price Index (CPI)

Consumer Price Index (CPI) is an index which calculates average price changes of a commodity package consisting of goods and services that people consumes in a certain period of time (BPS, 2018). This index is calculated based on the results of the Consumer Price Survey (SHK) in 82 cities in Indonesia covering 225-462 types of goods and services based on the result of Survey Cost of Living (SBH) 2012. The change in CPI over time indicates the rate of increase (inflation) or the rate of decline (deflation) of goods and services.

2.6. Exchange Rate

The exchange rate is one of the most important aspects in an open economy given the significant influence on the other macroeconomic variables that determined in the foreign exchange market, i.e. the market where a variety of different currencies traded. According to Bank Indonesia (2004), the exchange rate is the price of one unit of foreign currency in the domestic currency. For example, the exchange rate of the Rupiah against the US Dollar (USD) is the price of one US dollar (USD) in Rupiahs.

2.7. Composite Stock Price Index (CSPI)

According to Indonesia Stock Exchange (2010), the Composite Stock Price Index (CSPI) is the main indicator of stock price movement that assesses the general market situation or measuring the increase or decrease of the stock price by using all listed companies in Indonesia Stock Exchange (IDX). The CSPI was first introduced on April 1, 1983, as an indicator of stock price movements listed on the stock. The base day of the index calculation is August 10, 1982 with the first value is 100.

3. METHODOLOGY

3.1. Sources of Data

The data used in this study is secondary monthly data from January 2006 to March 2018. Monthly CPI (month to month) data are obtained from Statistics Indonesia (BPS). For stock prices, monthly composite index (CSPI) data of Indonesia Stock Exchange (IDX) that obtained from Yahoo Finance and monthly exchange rate (Rupiah/US$) data from Bank Indonesia are used. For simplicity, the three variables named as CPI, CSPI and exchange rate.

3.2. Analytical Procedures

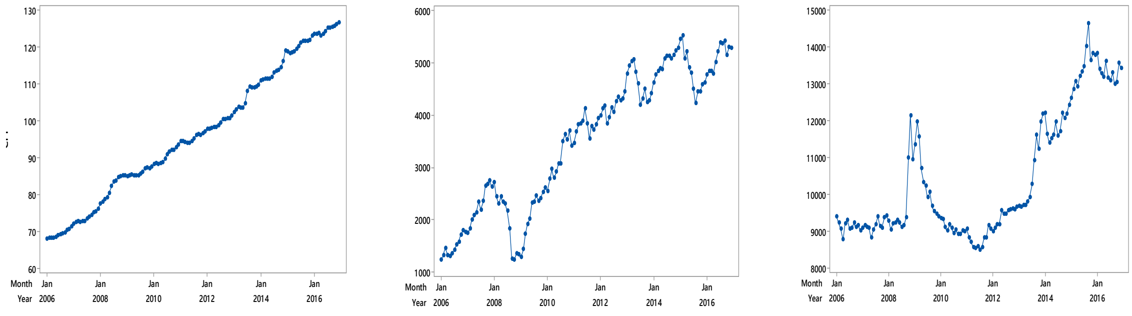
Firstly, the data are divided into in-sample data (training data), from January 2006 to December 2016 (132 months), for modeling and out-sample data, from January 2017 to March 2018 (15 months), for forecasting and selecting the best model. The analytical procedures used in this study are as follows:

1. Modeling the CPI, CSPI and exchange rate data using ARIMA, multi-input transfer function, and VAR methods.
2. Forecasting each series for several horizons ahead until 15 months using those three methods obtained from previous modeling process.
3. Choosing the best model for each series based on RMSE. Then calculate the reduction of RMSE for each variable from those three methods compared to mean-based forecasting as a benchmark.

4. RESULTS

4.1. ARIMA Method

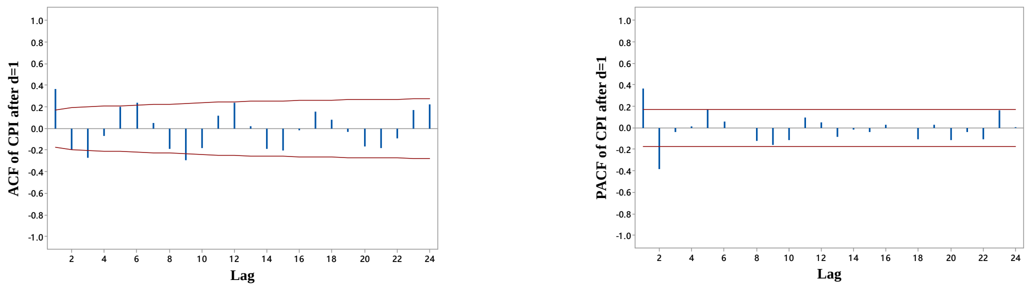
The estimate of λ for CPI, CSPI and exchange rate are 0.35, 0.87 and -1.89, respectively, indicated that the series of CPI and exchange rate need to be transformed first but not performed in this study since there are several issue in term of transformation as state by Hyndman & Athanasoposulos (2018), i.e. the effect on prediction intervals and the back-transformed forecast will not be the mean of forecast distribution. Figure 1 shows that there is a trend pattern on each time series plot.



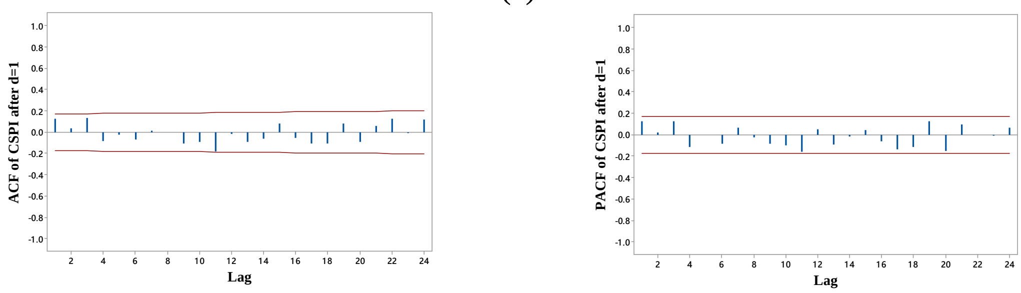
(a) (b) (c)

Figure 1 Time Series Plot of CPI (a), CSPI (b) and Exchange Rate (c) 2006-2016

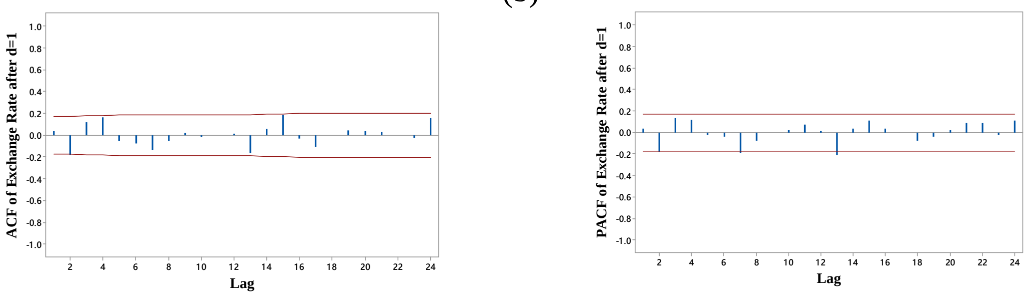
After regular differencing ($d = 1$), the ACF and PACF for each variable has indicated stationary condition as shown in Figure 2.



(a)



(b)



(c)

Figure 2 ACF and PACF of CPI (a), CSPI (b) and Exchange Rate (c) after Regular Differencing

After estimating parameter coefficients, the significance of all parameter and white noise assumption for residuals are checked. The best ARIMA models for CPI, CSPI and exchange rate with $\alpha = 0.05$ significance level and white noise residuals based on Ljung-Box statistic Q until lags 36 are ARIMA([1,2,5],1,[1,3,5,6]), ARIMA(0,1,0) and

ARIMA(0,1,[15]), respectively. The normality test using Kolmogorov-Smirnov test shows that all residuals are not normally distributed.

4.2. Multi-input Transfer Function Method

Each variable will be modeled with the multi-input transfer function method. CPI as the output variable will be modeled with the CSPI and exchange rate as input variables. The same process will be applied to other variables. The prewhitening processes for input variables to find the best ARIMA models are already done in the previous section which produces white noise residuals a_t (or α_t in term of transfer function method). These ARIMA models will be applied for output variables to generate non-white noise residuals β_t.Then from residuals α_t and β_t, the CCF plot will be generated to identify the transfer function models. This study only focuses with significant CCF at positive lags in order to elaborate effect of input variable to output variable.

CPI Model

According to the CCF plot, the identified value of $b = 0$, $s = 1$ and $r = 0$ for CSPI and CPI and $b = 9$, $s = 0$ and $r = 0$ for exchange rate and CPI. The Ljung-Box statistic Q shows that the residuals $n_{1,t}$ are not white noise. The final estimate of multi-input transfer function model for CPI is as follows:

$$Z_{1,t} = Z_{1,t-1} - 0.0007Z_{2,t} + 0.0002Z_{2,t-1} + 0.0005Z_{2,t-2} - 0.0003Z_{3,t-9} \quad (6)$$
$$+0.0003Z_{3,t-10} + \frac{(1 - 0.2558B^2)}{(1 - 0.5753B - 0.3560B^5)} a_{1,t}$$

where residuals $a_{1,t}$ are white noise and normally distributed.

CSPI Model

The value of $b = 0$, $s = (3)$ and $r = 0$ for CPI and CSPI. But, since there are no significant CCF at positive lags for exchange rate and CSPI so the tentative transfer function model only has one input. Based on Ljung-Box statistic Q, the residuals $n_{2,t}$ are not white noise at lag 24. The final estimate of single input transfer function model for CSPI is

$$Z_{2,t} = Z_{2,t-1} - 83.8096Z_{1,t} + 83.8096Z_{1,t-1} - 123.7102Z_{1,t-3} \quad (7)$$
$$+123.7102Z_{1,t-4} + \frac{(1 - 0.9354B)}{(1 - 0.9997B)} a_{2,t}$$

with residuals $a_{2,t}$ are white noise but not normally distributed.

Exchange Rate Model

The CCF plot shows that the value of $b = 4$, $s = 0$ and $r = 0$ for CPI and exchange rate (significant CCF at lags 21 and 27 are not included) and $b = 1$, $s = (1,6)$ and $r = 0$ for CSPI and exchange rate. Based on Ljung-Box statistic Q, the residuals $n_{3,t}$ are not white noise at lag 6 and 18. The final estimate of single input transfer function model for the exchange rate is

$$Z_{3,t} = Z_{3,t-1} + 114.2284Z_{1,t-4} - 114.2284Z_{1,t-5} - 0.8238Z_{2,t-1} \quad (8)$$
$$+0.5321Z_{2,t-2} + 0.2917Z_{2,t-3} + 0.3617Z_{2,t-7} - 0.3617Z_{2,t-8}$$
$$+ \frac{1}{(1 + 0.2727B^2)} a_{3,t}$$

with residuals $a_{3,t}$ are white noise and normally distributed.

4.3. VAR Method

First, the VAR model is identified according to the minimum value of AIC from Minimum Information Criterion. The minimum value of AIC, 20.3875, was generated by VAR(4) model. Although there are cointegration according to the two step Engle-Granger test, in this study the VAR model is still used rather than VECM. From the estimation result of VAR(4) model, there are a lot of non-statistically significant parameter estimate. So, non-statistically significant parameter with the highest p-value is restricted one by one until all significant parameters remained ($\alpha = 0.15$) in the model. The final models are:

$$\begin{aligned} Z_{1,t} &= 1.6964Z_{1,t-1} - 0.9266Z_{1,t-2} + 0.2302Z_{1,t-3} + 0.2660Z_{1,t-4} \\ &\quad -0.2660Z_{1,t-5} + 0.0006Z_{2,t-4} - 0.0006Z_{2,t-5} + a_{1,t} \end{aligned} \tag{9}$$

$$\begin{aligned} Z_{2,t} &= 76.7711Z_{1,t-2} - 209.4420Z_{1,t-3} + 180.6872Z_{1,t-4} \\ &\quad -48.0161Z_{1,t-5} + 1.1777Z_{2,t-1} + 0.0346Z_{2,t-2} - 0.0789Z_{2,t-3} \\ &\quad -0.2638Z_{2,t-4} + 0.1304Z_{2,t-5} + 0.1005Z_{3,t-1} - 0.1005Z_{3,t-2} + a_{2,t} \end{aligned} \tag{10}$$

and

$$\begin{aligned} Z_{3,t} &= 95.4044Z_{1,t-2} - 95.4044Z_{1,t-3} + 118.8361Z_{1,t-4} \\ &\quad -118.8361Z_{1,t-5} - 0.8852Z_{2,t-1} + 0.4748Z_{2,t-2} \\ &\quad +0.1421Z_{2,t-3} + 0.2683Z_{2,t-4} + 0.8484Z_{3,t-1} - 0.1324Z_{3,t-2} \\ &\quad +0.2840Z_{3,t-3} + a_{3,t} \end{aligned} \tag{11}$$

The minimum AIC, 19.8247, is obtained from Vector AR(0) and MA(0) model of residuals, indicated that the residuals of VAR(4) model are white noise. While, multivariate normality test using Mardia's test (Korkmaz, Goksuluk, & Zararsiz, 2014) shows that the variables are not multivariate normally distributed.

4.4. The Relationship between Variables

Figure 3 summarizes the relationships between variables from the results of modeling in subsection 4.1 to 4.3. The relationship between variables from transfer function models are different with VAR models except for bidirectional relationship between CPI and CSPI. The relationships in Figure 4(a) are equal with the result of VAR model from Ogboghro (2017) although this previous study only focused on examining the effect of inflation and exchange rate on Nigerian stock price.

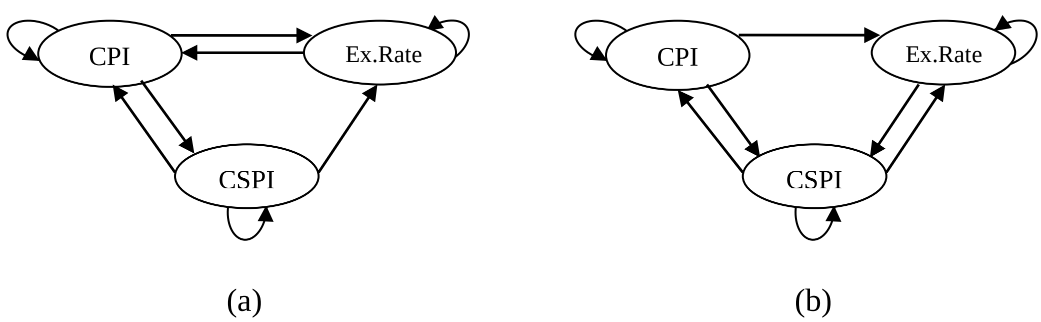


Figure 5 Relationships of Variables from Transfer Function (a) and VAR (b) Models

4.5. The Best Model for CPI, CSPI, and Exchange Rate

The forecasting performance using RMSE for in-sample and out-sample data are presented in Table 1. For in-sample data, the best model for CPI is ARIMA model. While the best model for CSPI and exchange rate is VAR model. This result is different with result for out-sample data. The best forecasting performance for out-sample data of each variable has a consistent result across 5 horizons except for the exchange rate. In the case of CPI and CSPI, whether for short or long-term forecast, the best model for CPI and CSPI are ARIMA and transfer function respectively. For exchange rate, the model with minimum error measures across 1 to 3 until 1 to 12 horizons is transfer function model but for 1 to 15 horizons, the best model is VAR. So, for the short-term forecast, the best model for the exchange rate is transfer function whereas for the long-term forecast the best model is VAR. Generally, the RMSE value increases as the forecasting period increases, means that the forecasting results are getting inaccurate, except for ARIMA model of CPI and VAR model of exchange rate. The later model has a RMSE with a descending pattern after the 1-9 horizons.

Table 1 RMSE of ARIMA, Transfer Function, and VAR Across Various Horizons

Output	Model	In-sample Data	Out-sample Data by Horizons				
			1-3	1-6	1-9	1-12	1-15
CPI	ARIMA	0.4588*	0.5950*	0.5856*	0.4956*	0.4619*	0.4275*
	Transfer Function	0.4733	1.0442	1.2015	1.3668	1.5179	1.9143
	VAR	0.5158	1.0335	1.2083	1.5256	1.7809	2.3855
CSPI	ARIMA	172.9692	280.8845	412.2664	496.5749	676.9604	752.2826
	Transfer Function	158.2929	223.6880*	303.2731*	340.0051*	484.7531*	523.7564*
	VAR	157.4181*	263.4915	392.7047	474.7299	653.1621	727.1346
Exchange Rate	ARIMA	326.2368	142.4404	183.2218	260.9508	372.6271	455.1592
	Transfer Function	260.0099	106.9873*	81.5349*	94.9699*	150.6836*	339.8894
	VAR	255.1595*	159.5745	237.5309	258.7142	242.2023	233.9288*

Note: *) the minimum value

The formulas for percentage of reduction when using ARIMA, transfer function and VAR are $\frac{(S1-S2)}{S1} \times 100\%$, $\frac{(S1-S3)}{S1} \times 100\%$ and $\frac{(S1-S4)}{S1} \times 100\%$, respectively. Where $S1$ or standard deviation is the error measures from mean-based forecasting as a benchmark, $S2$, $S3$, and $S4$ are RMSE from ARIMA, transfer function, and VAR, respectively. From Table 2, the RMSE reduction decreases as the forecasting period increases for all methods and all variables except for ARIMA model of CPI that the RMSE reduction increases slightly as the forecasting period increases. By using criteria RMSE reduction between in-sample data and out-sample data, the short-term forecasting (1 to 3 horizons) is the best horizon to forecast CPI and CSPI because the RMSE reduction for out-sample data is still higher than in-sample data. Whereas for exchange data, the long-term forecasting (1 to 15 horizons) is still give higher RMSE reduction for out-sample data than in-sample data.

Table 2. RMSE Reduction by Using ARIMA, Transfer Function and VAR Models

Output	Model	In-Sample Data (%)	Out-Sample Data by Horizons (%)				
			1-3	1-6	1-9	1-12	1-15
CPI	ARIMA	97.39*	98.1218*	98.1754*	98.4792*	98.5994*	98.7267*
	Transfer Function	97.31	96.7038	96.2567	95.8057	95.3971	94.2988
	VAR	97.06	96.7376	96.2356	95.3183	94.5997	92.8956
CSPI	ARIMA	86.96	86.2809	81.0677	78.0446	71.9314	69.7549
	Transfer Function	88.07	89.0745*	86.0729*	84.9671*	79.9009*	78.9426*
	VAR	88.14*	87.1304	81.9660	79.0105	72.9182	70.7659
Exchange Rate	ARIMA	80.92	95.0705	93.6430	91.0088	87.3782	84.8254
	Transfer Function	84.79	96.2974*	97.1711*	96.7278*	94.8960*	88.6684
	VAR	85.08*	94.4775	91.7587	91.0859	91.7960	92.2010*

Note: *) the highest reduction

5. CONCLUSIONS

This study elaborates two aspects, i.e. the causal explanation and the forecasting accuracy of CPI, CSPI and exchange rate. First, the aspect of causal explanation tries to capture relationships between input (predictor) variable and output (dependent) variable from the best model obtained in the previous section. From multivariate methods, both transfer function and VAR concluded that CPI and CSPI affect the exchange rate significantly. Whereas, CPI is affected by exchange rate and CSPI based on transfer function and only affected by CSPI in VAR model. For CSPI, this variable is affected by both CPI and exchange rate in VAR model but only CPI in transfer model.

Second, from the aspects of forecasting accuracy, that more complex methods, i.e. transfer function and VAR, do not always yield better forecasting performance for out-sample of each variable. It has been proved empirically that for CPI the best forecasting model is the simple method, ARIMA. This conclusion is in agreement with the results of M3-Competition (Makridakis & Hibon, 2000) and still relevant to the current condition, confirmed by M4-Competition (Makridakis, Spiliotis, & Assimakopoulos, 2018b). Generally, the models are only suitable for short term forecasting indicated by the increasing of RMSE values and the decreasing of RMSE reduction as longer the horizons. Therefore, the recommendation is to perform short-term forecasting (1 to 3 horizons) and update the forecasting values with the actual values after three horizons.

The forecasting performance from three models for in-sample data outperforms the performance for 1 to 15 horizons of out-sample data indicates that there is an over-fitting problem that can decrease the accuracy of forecasting performance for out-sample data as concluded by the previous study (Suhartono & Subanar, 2005; Makridakis, Spiliotis, & Assimakopoulos, 2018a). For the future study, incorporate outlier as exogenous variable in ARIMA, transfer function and VAR is important given that there are non-normally distributed residual from the models. In addition, considering the important findings from M4-Competition (Makridakis *et al.*, 2018b) that hybrid approaches and combinations of statistical and machine learning methods are the way forward for improving the forecasting accuracy, especially for out-sample data, also needed since it yields the 1st and 2nd most accurate forecast in this competition.

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