

ISSN: 0258-2724

DOI : 10.35741/issn.0258-2724.55.3.41

Research article

Economics

DYNAMIC MODELLING AND FORECASTING OF DATA EXPORT OF AGRICULTURAL COMMODITY BY VECTOR AUTOREGRESSIVE MODEL

矢量自回归模型的农业商品数据出口动态建模与预测

L.M. Hamzah^a, S.U. Nabilah^b, E. Russel^c, M. Usman^b, E. Virginia^d, Wamiliana^{b,*}^a Department of Economic Development, Faculty of Economic and Business, Universitas Lampung
Jl. Prof. Dr. Soemantri Brojonegoro No. 1, Bandarlampung, Indonesia^b Department of Mathematics, Faculty of Mathematics and Sciences, Universitas Lampung
Jl. Prof. Dr. Soemantri Brojonegoro No. 1, Bandarlampung, Indonesia, wamiliana.1963@fmipa.unila.ac.id^c Department of Management, Faculty of Economic and Business, Universitas Lampung
Jl. Prof. Dr. Soemantri Brojonegoro No. 1, Bandarlampung, Indonesia^d Department of Accounting, President University, Jakarta, Indonesia
Jababeka Education Park. Jl. Ki Hajar Dewantara, Kota Jababeka, Cikarang Baru, Bekasi 17550, Indonesia.**Received: March 10, 2020 ▪ Review: May 20, 2020 ▪ Accepted: May 30, 2020**

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>)

Abstract

The Vector Autoregressive Model (VAR) is one of the statistical models that can be used for modeling multivariate time series data. It is commonly used in finance, management, business and economics. The VAR model analyzes the time series data simultaneously to arrive at the right conclusions while dynamically explaining the behavior of the relationship between endogenous variables, as well as endogenous and exogenous variables. From time to time, the VAR model is influenced by its own factors via Granger Causality. In this study, we will discuss and determine the best model to describe the relationship among data export value of Indonesia's agricultural commodities—coffee beans, cacao beans and tobacco—where the monthly data spans the years 2007-2018. Several models are applied to the data, such as VAR (1), VAR (2), VAR (3), VAR (4) and VAR (5) models. As a result, the VAR (2) model was chosen as the best model based on the Akaike's Information Criterion with Correction, Schwarz Bayesian Criterion, Akaike's Information Criterion and Hanna-Quinn Information Criterion for selecting statistical models. The dynamic behavior of the three export variables of Indonesian coffee beans, cacao beans and tobacco is explained by Granger Causality. Furthermore, the best model VAR (2) is used to forecast the next 10 months.

Keywords: Agricultural Commodity, Vector Autoregressive Model, Dynamic Behavior, Granger Causality, Forecasting

摘要 向量自回归模型 (VAR) 是可用于对多元时间序列数据进行建模的统计模型之一。它通常用

于金融，管理，商业和经济学领域。VAR 模型同时分析时间序列数据，以得出正确的结论，同时动态地解释内生变量之间以及内生变量和外生变量之间关系的行为。VAR 模型有时会通过格兰杰因果关系受到其自身因素的影响。在这项研究中，我们将讨论并确定最佳模型，以描述印尼农产品（咖啡豆，可可豆和烟草）的数据出口值之间的关系，其中每月数据跨越 2007-2018 年。多个模型应用于数据，例如 VAR (1)，VAR (2)，VAR (3)，VAR (4) 和 VAR (5) 模型。结果，VAR (2) 模型被选为最佳模型，该模型基于赤池的修正信息准则，施瓦兹贝叶斯准则，赤池的信息准则和汉娜·奎因信息准则来选择统计模型。格兰杰因果关系解释了印尼咖啡豆，可可豆和烟草这三个出口变量的动态行为。此外，最佳模型 VAR (2) 用于预测未来 10 个月。

关键词: 农业商品，向量自回归模型，动态行为，格兰杰因果关系，预测

I. INTRODUCTION

Data multivariate time series are commonly found in applied fields like finance, business and economics, and the environment. By using statistics, the data can be modeled accurately, effectively, and efficiently. Multivariate time series modeling includes model specifications, estimating the parameters, testing the parameters, model checking, and forecasting, while explaining the model of dynamic relationships between multivariate time series variables.

Time series data derived from economic variables are taken from time to time, and in some cases are not only influenced by themselves but also by other variables.

For example, when considering a single market, supply and demand functions together to determine the price balance [1]. The world market price of coffee in general is very dependent on coffee production in Brazil [2].

In addition, analyzing time series data are helps one to understand the dynamic relationship between variables over time, to get accurate forecasting, and to gain knowledge in order to obtain good forecasting results [3].

In multivariate time series data analysis, which involves more than one variable simultaneously, the analysis is carried out in order to obtain accurate conclusions without failing to consider other variables or rely on time factors alone. One method to analyze multivariate time series data is the Vector Autoregressive (VAR) Model. The application of the Vector Autoregressive (VAR) model has been carried out among others by Stock and Watson [4], Sharma et al. [5], Zuhroh et al. [6], and Warsono et al. [7], [8], [9].

In this study, we will find and discuss the best model that can describe the relationship among three variables, vector data time series, namely data export value of agricultural commodities of Indonesia, namely coffee beans, cacao beans, and tobacco, where data are monthly data from 2007 to 2018. As the basis of this study, the vector

autoregressive (VAR) model is used to explain the relationship among the export value data of agricultural commodities with the variable export value of Indonesian coffee beans, cacao beans, and tobacco from 2007 to 2018.

II. STATISTICAL MODEL

A. Vector Autoregressive Model (VAR)

VAR models are often used to find out the behavior of variables simultaneously over time [5]. The VAR model was introduced by Sims [2] as a tool for analyzing macroeconomic data. VAR models treat all the variables involved symmetrically. In the VAR model, a vector consists of two or more variables and on the right-hand side contains the lag vector of the dependent. VAR (p) models can be written as follows:

$$Y_t = \sum_{i=1}^p \phi_i Y_{t-1} + a_t \quad (1)$$

where Y_t is the vector of observation at the time t and has order $n \times 1$, ϕ_i is a matrix parameter with order $n \times n$, $i = 1, 2, \dots, p$, where p is lag length, and a_t is a vector shock.

The model (1) can be written as follows:

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) Y_t = a_t \quad (2)$$

where $B^j Y_t = Y_{t-j}$, $j = 1, 2, \dots, p$, $\phi_p = [\phi_{im}^s]$ is $k \times k$ matrix and $s = 1, 2, \dots, p$.

B. Estimation of Parameter VAR, Maximum Likelihood Estimation (MLE)

According to Tsay [10], if a_t in model VAR (p) has multivariate normal distribution and $Z_{h:q}$ is observation from $t = h$ to $t = q$, then the conditional likelihood function can be written as follows:

$$L(Y_{(p+1):T} | Y_{1:p}, \beta, \Sigma_a) = \prod_{t=p+1}^T p(Y_{(p+1):T} | Y_{1:p}, \beta, \Sigma_a) \quad (3)$$

where the Log-likelihood function is as follows:

$$\begin{aligned} \ell(\beta, \Sigma_a) &= c - \frac{T-p}{2} \log(|\Sigma_a|) - \frac{1}{2} \sum_{t=p+1}^T \text{tr}(a_t' \Sigma_a^{-1} a_t) \\ &= c - \frac{T-p}{2} \log(|\Sigma_a|) - \frac{1}{2} \text{tr} \left(\Sigma_a^{-1} \sum_{t=p+1}^T a_t a_t' \right) \end{aligned} \quad (4)$$

So that, the MLE of VAR(p) is:

$$\begin{aligned} L(\hat{\beta}, \hat{\Sigma}_a | z_{1:p}) &= \\ (2\pi)^{-k(T-p)/2} |\hat{\Sigma}_a|^{-(T-p)/2} \exp \left[-\frac{k(T-p)}{2} \right] \end{aligned} \quad (5)$$

C. Stationarity of Model

The main assumption that the VAR model can be formed is stationarity [7]. Stationary means there is no drastic change in the data. Data fluctuation is around a constant average value, not dependent on the time and variance of the fluctuation. Stationarity is divided into 2 namely:

1. Stationary in mean, and,
2. Stationary in variance [11].

There are some methods that commonly used to check the stationary databased on data plots or through the Augmented Dickey-Fuller test (ADF test) [12], [13], [14], [15]. If the data are nonstationary, then we can used differencing to attain stationary data.

III. RESULTS AND DISCUSSION

The data used in this study are data on the export of Indonesian coffee beans, cocoa beans and tobacco from January 2007 to December

2018. Data are obtained from the Economic Statistics Publication.

Figure 1 shows that the trend of export coffee slightly increases and fluctuate; export of cacao is increase from 2007 to 2010, then decrease from 2011 to 2018; while tobacco look fluctuate. In addition, the ACF and PACF values from the export value data coffee beans, cocoa beans and tobacco in Figures 2a, b and c. There is an exponential decrease that identifies that the data is not stationary in the means and variances. To make the data stationary for the needs of time series data analysis, the differencing process is carried out. The results differencing once ($d = 1$) shown in Table 1 ADF test shows that all data has been stationary and modeling using VAR models can be carried out.

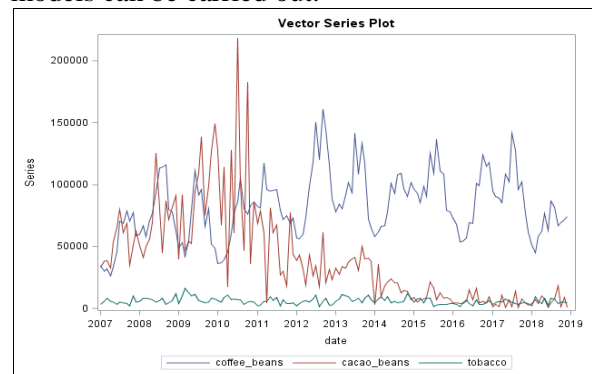


Figure 1. Plot of Indonesian export of coffee beans, cacao beans and tobacco from January 2007 - December 2018

Table 1.

Augmented Dicky-Fuller unit root tests

Variable	Type	Rho	P-value	Tau	P-value
coffee_beans	Zero mean	-1.69	0.3686	-0.84	0.3518
	Single mean	-28.26	0.0012	-3.91	0.0026
	Trend	-29.78	0.0062	-3.89	0.0149
cacao_beans	Zero mean	-7.19	0.0625	-1.91	0.0534
	Single mean	-15.97	0.0276	-2.75	0.0693
	Trend	-44.53	0.0005	-4.83	0.0007
tobacco	Zero mean	-7.53	0.0563	-1.93	0.0512
	Single mean	-80.26	0.0012	-6.27	<.0001
	Trend	-88.82	0.0005	-6.61	<.0001

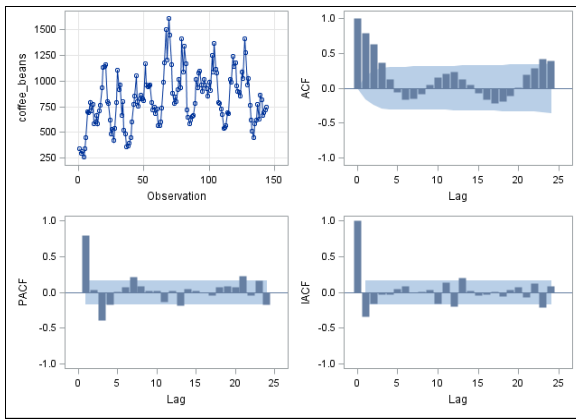


Figure 2a. Plots of trend, autocorrelation, partial autocorrelation function and inverse autocorrelation for data export of coffee beans

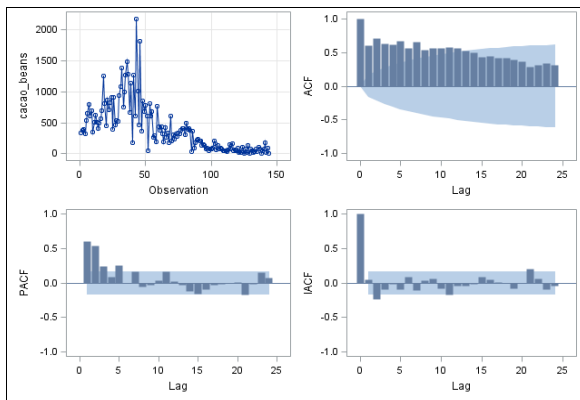


Figure 2b. Plots of trend, autocorrelation, partial autocorrelation function and inverse autocorrelation for data export of beans

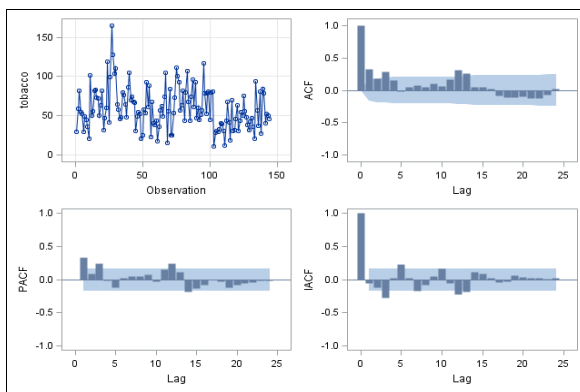


Figure 2c. Plots of trend, autocorrelation, partial autocorrelation function and inverse autocorrelation for data export of tobacco

A. VAR (p) Model

To get the best model that fits the data, several VAR (p) models are applied to the data export value of agricultural commodities such as VAR (1), VAR (2), VAR (3), VAR (4) and VAR (5). To select the best of these models are based on several criteria, namely the criteria: Akaike's Information Criterion with Correction (AICC), Hanna-Quinn Information Criterion (HQC), Akaike's Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). The best

model is the model that has the minimum value of these criteria. Based on Table 3, the 2 best models are the VAR (2) and VAR (3) models which has minimum values of AICC, HQC and SBC. In addition to seeing the selection criteria for the best model Schematic representation is displayed to convince the best model chosen. Table 4 shows the Schematic representation of VAR (2) and VAR (3) models.

Table 4 shows that there are 6 significant parameters in the VAR (2) and VAR (3) models, but also with the best minimum model selection criteria being considered. Model VAR (2) was chosen as the best model for modeling the export value of this agricultural commodity simultaneously.

The estimation results of model VAR (2) can be written as follows:

$$y_t = \begin{pmatrix} 2.714 \\ -6.157 \\ -0.177 \end{pmatrix} + \begin{pmatrix} -0.1002 & 0.0467 & -0.7534 \\ 0.0082 & -0.8053 & -0.90327 \\ -0.0223 & -0.007 & -0.522 \end{pmatrix} y_{t-1} + \begin{pmatrix} 0.2713 & 0.0146 & -0.052 \\ 0.1983 & -0.296 & -0.096 \\ -0.033 & -0.0067 & -0.4043 \end{pmatrix} y_{t-2} + \varepsilon_i \quad (6)$$

With the matrix covarians inovation is

$$\Sigma_{\varepsilon_i} = \begin{pmatrix} 26347.54 & 5353.90 & 714.985 \\ 5353.902 & 66866.35 & 231.466 \\ 714.9845 & 231.466 & 652.368 \end{pmatrix} \quad (7)$$

The VAR (2) model can also be written in the form of three univariate regression models as follows:

$$Coffe_{beans_t} = 2.714 - 0.1002coffe_{beans_{t-1}} + 0.0467cacao_{beans_{t-1}} - 0.7534tobacco_{t-1} + 0.2713coffe_{beans_{t-2}} + 0.0146cacao_{beans_{t-2}} - 0.052tobacco_{t-2} + \varepsilon_1 \quad (8)$$

$$cacao_{beans_t} = -6.157 - 0.0082coffe_{beans_{t-1}} - 0.8053cacao_{beans_{t-1}} - 0.90327tobacco_{t-1} + 0.1983coffe_{beans_{t-2}} - 0.2966cacao_{beans_{t-2}} - 0.096tobacco_{t-2} + \varepsilon_2 \quad (9)$$

$$Tobacco_t = -0.177 - 0.0223coffe_{beans_{t-1}} - 0.007cacao_{beans_{t-1}} - 0.522tobacco_{t-1} - 0.033coffe_{beans_{t-2}} - 0.0067cacao_{beans_{t-2}} - 0.4043tobacco_{t-2} + \varepsilon_2 \quad (10)$$

Statistical test for parameters of the above models are given in Table 6 and univariate model test is given in Table 7. Based on statistical test model 8 is very significant with $F = 3.07$ and $p = 0.0075$. The degree of determination of R-square is 0.121. Based on statistical test model 9 is very significant with the value of $F = 20.49$ and the value of $p < 0.0001$ with the degree of determination of R-square is 0.4784. Based on statistical test model 10 is very

significant with a value of $F = 11.15$ and p value < 0.0001 with the degree of determination of R-square is 0.3329. Model 10 also explained that the export value of cacao beans had a positive effect and the value of tobacco exports had a negative effect on lag 1 (t-1) and lag 2 (t-2) on the export value of coffee beans. In model 1.2 the

export value of coffee beans and tobacco has a negative effect on lag 1 (t-1) and lag 2 (t-2) on the export value of cacao beans. Whereas in the 1.3 model the export value of cacao beans and coffee beans at lag 1 (t-1) and lag 2 (t-2) had a negative effect on the value of tobacco exports.

Table 2.
Augmented Dicky-Fuller unit root tests after differencing

Variable	Type	Rho	P-value	Tau	P-value
coffee_beans	Zero mean	-91.35	<.0001	-6.71	<.0001
	Single mean	-91.43	0.0012	-6.69	<.0001
	Trend	-92.03	0.0005	-6.69	<.0001
cacao_beans	Zero mean	-421.38	0.0001	-14.41	<.0001
	Single mean	-421.62	0.0001	-14.37	<.0001
	Trend	-422.74	0.0001	-14.33	<.0001
tobacco	Zero mean	-456.76	0.0001	-15.15	<.0001
	Single mean	-456.72	0.0001	-15.1	<.0001
	Trend	-456.81	0.0001	-15.04	<.0001

Tabel 3.
Criteria AICC, HQC, AIC and SBC for VAR (1), VAR (2), VAR (3), and VAR (4)

Variable	Type	Rho	P-value	Tau	P-value
coffee_beans	Zero mean	-91.35	<.0001	-6.71	<.0001
	Single mean	-91.43	0.0012	-6.69	<.0001
	Trend	-92.03	0.0005	-6.69	<.0001
cacao_beans	Zero mean	-421.38	0.0001	-14.41	<.0001
	Single mean	-421.62	0.0001	-14.37	<.0001
	Trend	-422.74	0.0001	-14.33	<.0001
tobacco	Zero mean	-456.76	0.0001	-15.15	<.0001
	Single mean	-456.72	0.0001	-15.1	<.0001
	Trend	-456.81	0.0001	-15.04	<.0001

Table 4.
Schematic representation estimation of parameter for VAR (2) and VAR (3)

Model	Variable/Lag	C	AR1	AR2	AR3
VAR(2)	coffee_beans	+..	
	cacao_beans	.	..-	..-	
	tobacco	.	..-	..-	
VAR(3)	coffee_beans	+	..
	cacao_beans	.	..-	..-	..
	tobacco	.	..-	..-	..

Granger Causality is used to test several null hypotheses. Test 1 - Test 6 tests the hypothesis that the coffee beans, cacao beans and tobacco are influenced by themselves and the alternative hypothesis is that the coffee beans, cacao beans and tobacco are influenced by other variables. In Table 2 of the Granger Causality Test, Test 1, the Chi-Square value = 7.27 and the value of $P = 0.0264$, consequently we reject the Null

hypothesis. Therefore, it is concluded that the value of tobacco exports is not only influenced by itself but is also influenced by the export value of coffee beans and the export value of cacao beans. In test 2 Chi-Square value = 2.5 and P value = 0.2862 as a result we did not have enough evidence to reject H_0 and concluded that the export value of coffee beans was only influenced by itself and was not influenced by the value of tobacco exports. Test 3-Test 6 in Table 2 shows a P-value > 0.05 so we do not have enough evidence to reject H_0 . As a result, it was concluded that the value of tobacco exports was not influenced by the export value of cacao beans. The export value of coffee beans is not influenced by the export value of cacao beans. The export value of Cacao Beans is not influenced by the export value of coffee beans and tobacco.

Table 5.
Causality test variabel coffee beans, cacao beans and tobacco

Test	Group	DF	Chi-square	P-value
Test 1	Group 1 variables: tobacco	2	7.27	0.0264

	Group 2 variables: coffee_beans			
Test 2	Group 1 variables: coffee_beans	2	2.5	0.2862
	Group 2 variables: tobacco			
Test 3	Group 1 variables: tobacco	2	1.51	0.4693
	Group 2 variables: cacao_beans			
Test 4	Group 1 variables: coffee_beans	2	0.84	0.6559
	Group 2 variables: cacao_beans			
Test 5	Group 1 variables: cacao_beans	2	4.68	0.0964
	Group 2 variables: coffee_beans			
Test 6	Group 1 variables: cacao_beans	2	2.9	0.2341
	Group 2 variables: tobacco			

Table 6.
Model dynamic parameter estimates

Equation	Parameter	Estimate	Standard error	t -value	Pr > t	Variable
coffee_beans	CONST1	2.71433	13.676	0.2	0.843	1
	AR1_1_1	-0.10019	2.7823	-0.04	0.9713	coffee_beans(t-1)
	AR1_1_2	0.04665	0.3704	0.13	0.9	cacao_beans(t-1)
	AR1_1_3	-0.75344	0.4906	-1.54	0.1269	tobacco(t-1)
	AR2_1_1	0.2713	0.1248	2.17	0.0315	coffee_beans(t-2)
	AR2_1_2	0.01462	0.0533	0.27	0.7842	cacao_beans(t-2)
cacao_beans	AR2_1_3	-0.05218	0.4949	-0.11	0.9162	tobacco(t-2)
	CONST2	-6.15753	21.788	-0.28	0.7779	1
	AR1_2_1	0.00825	0.1386	0.06	0.9526	coffee_beans(t-1)
	AR1_2_2	-0.80535	0.0826	-9.75	0.0001	cacao_beans(t-1)
	AR1_2_3	-0.90327	0.7819	-1.16	0.2501	tobacco(t-1)
	AR2_2_1	0.19829	0.1333	1.49	0.1391	coffee_beans(t-2)
Tobacco	AR2_2_2	-0.2966	0.0815	-3.64	0.0004	cacao_beans(t-2)
	AR2_2_3	-0.09591	0.7882	-0.12	0.9033	tobacco(t-2)
	CONST3	-0.17793	2.1520	-0.08	0.9342	1
	AR1_3_1	-0.02233	0.0133	-1.68	0.095	coffee_beans(t-1)
Tobacco	AR1_3_2	-0.00751	0.0089	-0.84	0.4029	cacao_beans(t-1)
	AR1_3_3	-0.52261	0.0772	-6.77	0.0001	tobacco(t-1)
	AR2_3_1	-0.03311	0.0132	-2.51	0.0132	coffee_beans(t-2)
	AR2_3_2	-0.00669	0.0087	-0.77	0.4413	cacao_beans(t-2)
	AR2_3_3	-0.4043	0.0779	-5.19	0.0001	tobacco(t-2)

Table 7.
Univariate model ANOVA diagnostics

Variable	R-square	Standard deviation	F value	Pr > F
coffee_beans	0.121	162.31926	3.07	0.0075
cacao_beans	0.4784	258.58529	20.49	<.0001
Tobacco	0.3329	25.5415	11.15	<.0001

Table 8.
Forecasting data export coffe beans, cacao beans and tobacco

Variable	Obs	Time	Forecast	Standard error	95% confidence limits	
Coffee beans	145	Jan-19	749.3877	162.3193	431.2479	1067.528
	146	Feb-19	757.2463	218.3110	329.3645	1185.128
	147	Mar-19	761.1371	292.1964	188.4427	1333.832
	148	Apr-19	766.3663	347.9699	84.35781	1448.375
	149	May-19	769.4453	401.3438	-17.1741	1556.065
	150	Jun-19	772.9451	448.0753	-105.266	1651.157
	151	Jul-19	776.4663	491.6744	-187.198	1740.130
	152	Aug-19	779.6407	531.3977	-261.879	1821.161
	153	Sep-19	782.8851	568.7539	-331.852	1897.622
Cacao beans	154	Oct-19	786.1952	603.7236	-397.081	1969.472
	145	Jan-19	56.162	258.5853	-450.656	562.9799
	146	Feb-19	40.0592	265.0968	-479.521	559.6394
	147	Mar-19	34.9492	307.387	-567.518	637.4166
	148	Apr-19	41.8329	335.8254	-616.373	700.0385
	149	May-19	32.6469	356.8796	-666.824	732.1181
	150	Jun-19	33.6007	383.0271	-717.119	784.3200
	151	Jul-19	31.2501	403.8903	-760.360	822.8606

	152	Aug-19	28.03985	424.6323	-804.224	860.3038
	153	Sep-19	26.6377	444.8403	-845.233	898.5087
	154	Oct-19	24.10017	463.5352	-884.412	932.6126
Tobacco	145	Jan-19	48.21995	25.5415	-1.84046	98.28037
	146	Feb-19	48.14474	28.14352	-7.01555	103.3050
	147	Mar-19	46.49559	29.97266	-12.2498	105.2409
	148	Apr-19	47.15844	34.12272	-19.7209	114.0377
	149	May-19	47.10839	36.73515	-24.8912	119.1080
	150	Jun-19	46.56503	38.89852	-29.6747	122.8047
	151	Jul-19	46.65699	41.44829	-34.5802	127.8942
	152	Aug-19	46.54855	43.67686	-39.0566	132.1537
	153	Sep-19	46.32782	45.71704	-43.2759	135.9316
	154	Oct-19	46.24915	47.77437	-47.3869	139.8852

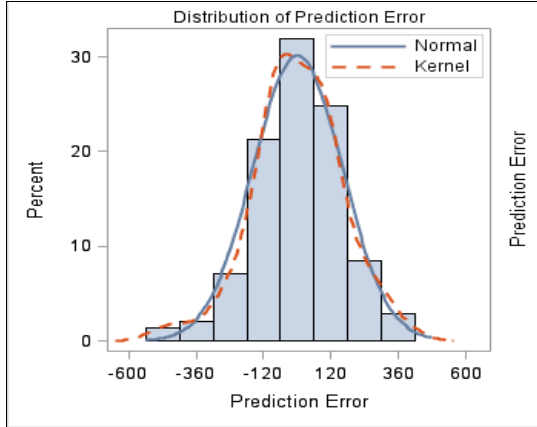


Figure 3a. Distribution of error for data coffee beans

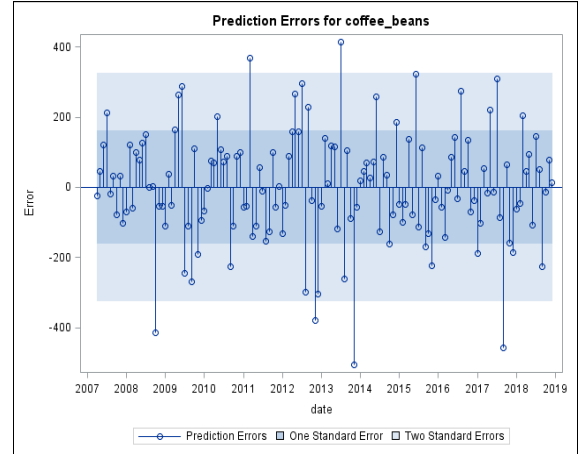


Figure 4a. Prediction errors based on model VAR (2) for data coffee beans

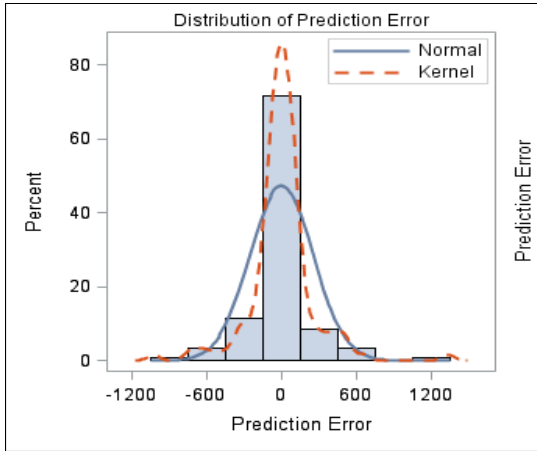


Figure 3b. Distribution of error for data cacao beans

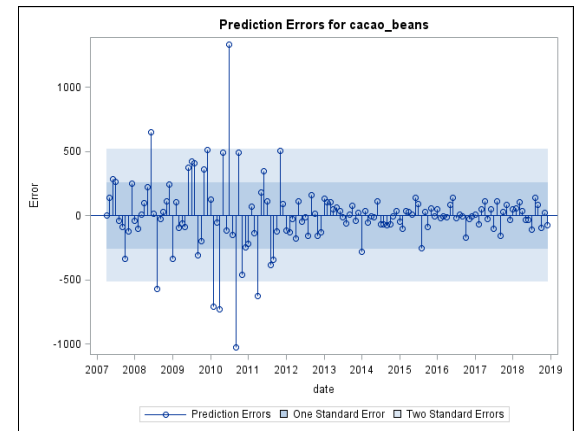


Figure 4b. Prediction errors based on model VAR (2) for cacao beans

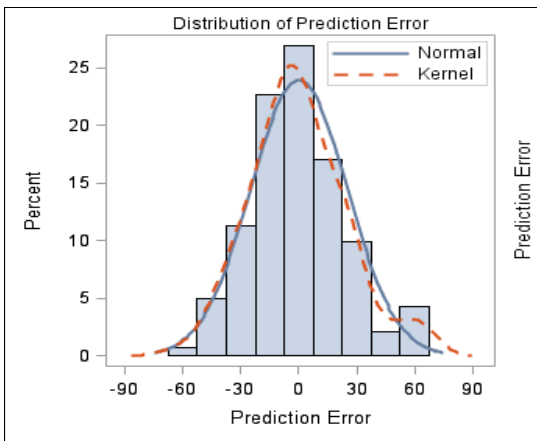


Figure 3c. Distribution of error for tobacco

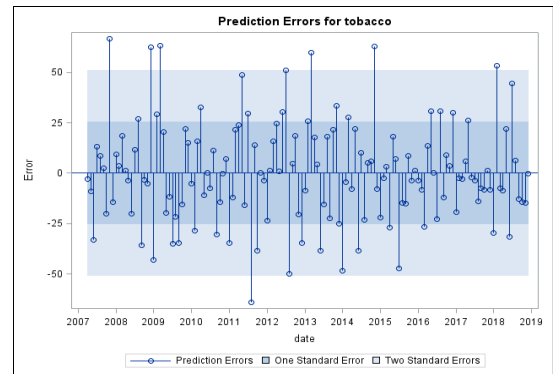


Figure 4c. Prediction errors based on model VAR(2) for data tobacco

From Figures 3a, 3b and 3c the pattern of the error distribution for the export value data of coffee beans, cacao beans and tobacco is very close to the normal distribution. In Figures 4a, 4b and 4c the prediction error from coffee bean data shows that the prediction error from year to year fluctuates and is between two standard error values. This indicates that the export value of coffee beans is unstable in this time frame (2007–2018). Different from the prediction error pattern, the export value of cacao beans shows the instability of fluctuation error in 2007 to 2011 and is at two standard error values, while from 2012–2018 the fluctuation of error is stable and shows a homogeneous error and is only within the range of one standard error. This is supported by Figure 1, which showed unstable fluctuations (2007–2011) and tended to decrease but was stable between 2012 and 2018. The predicted error from the tobacco data showed unstable fluctuations from year to year (2007–2008). This unstable fluctuation is also supported by the graph of the data presented in Figure 1.

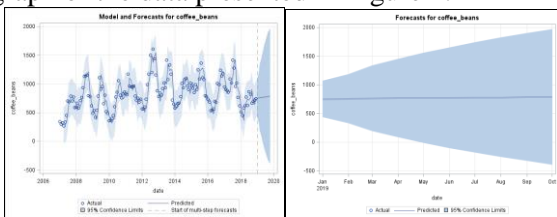


Figure 5. Model and forecasting for the next 10 months of data export coffee beans

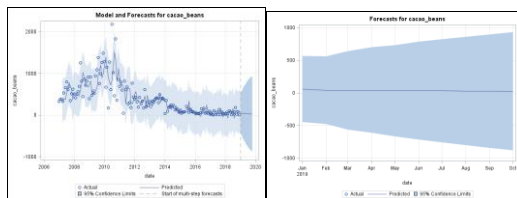


Figure 6. Model and forecasting for the next 10 months of data export cacao beans

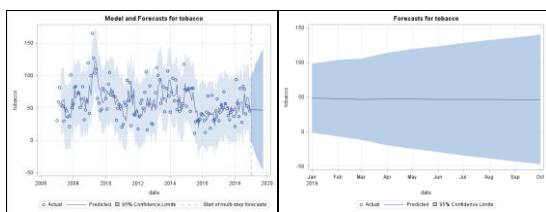


Figure 7. Model and forecasting for the next 10 months of data export tobacco

The graph of the model VAR(2) for the export values of coffee beans, cacao beans, and tobacco, are shown in Figures 5, 6, and 7, which show the predicted data and real data are close to each other, this indicating that the given model fit the data well. The predictions in Table 8 showed that the forecast for coffee bean data started at 749.3877 in the first prediction period and

continued to increase until the tenth prediction period. The forecast for the cacao bean data started at 56.162 in the first period and decreased until the third period, showing a value of 34.94917. The cacao bean data then rose by the fourth period with a value of 41.83285, followed by a downward trend to the tenth period, where the prediction number reached 24.10017. Furthermore, the forecast for tobacco data started at 48.21995 in the first period and continued to decline until the tenth period, reaching a value of 46.24915. For all the predicted values, the export values of coffee beans, cacao beans, and tobacco entered the 95% confidence interval, which can be seen in Figures 5, 6, and 7. The confidence interval for forecasting the next ten periods are increase (Figure 5, 6 and 7). This indicates that, although the VAR model (2) is suitable for modeling agricultural commodity export value data, if used to make long-term predictions, the prediction results will not be stable. This can be seen based on the confidence intervals in Figures 5, 6, and 7, which became bigger over the 10 periods.

IV. CONCLUSION

Based on the research and studies that have been carried out, where this study focused on determining the best model for modeling export value data of some agricultural commodities from 2007–2018, we can conclude that the best model that can be formed to model the data export values of coffee beans, cacao beans and tobacco is the VAR (2) model. The best model was chosen based on several selection criteria, namely AICC, AIC, SBC, and HQC, where there are six significant variables in the model and the rest are not significant but can still be included in the model by considering the meaningfulness of the estimate obtained. Forecasting results showed that the standard error value increases from time to time, where the standard error value of the first month was relatively smaller than the following months. This demonstrated that the model can present forecasting results in a short period, but the forecasting results will be unstable when the period is long.

ACKNOWLEDGMENT

The authors would like to thank BI (Bank of Indonesia) for providing the data in this study.

REFERENCES

- [1] KIRCHGASSNER, G. and WOLTERS, J. (2007) *Introduction to*

Modern Time Series Analysis. Berlin: Pearson Education Inc.

- [2] SIMS, C.A. (1980) Macroeconomics and reality. *Econometrica*, 48 (1), pp. 1-48.
- [3] PENA, D. and TIAO, G.C. (2001) Introduction. In: PENA, D., TIAO, G.C., and TSAY, R.S. (eds.) *A Course in Time Series Analysis*. New York: John Wiley and Sons.
- [4] STOCK, J.H. and WATSON, M.W. (1999) Forecasting Inflation. *Journal of Monetary Economics*, 44 (2), pp. 293-335.
- [5] SHARMA, A., GIRI, S., VARDHAN, H., SURANGE, S., SHETTY, R., and SHETTY, V. (2018) Relationship between crude oil prices and stock market: Evidence from India. *International Journal of Energy Economics and Policy*, 8 (4), pp. 331-337.
- [6] ZUHROH, I., KUSUMA, H., and KURNIAWATI, S. (2018) An Approach of Vector Autoregression Model for Inflation Analysis in Indonesia. *Journal of Economics, Business & Accountancy Ventura*, 20 (3), pp. 261-268.
- [7] WARSONO, W., RUSSEL, E., WAMILIANA, W., WIDIARTI, W., and USMAN, M. (2019) Vector autoregressive with exogenous variable model and its application in modeling and forecasting energy data: Case study of PTBA and HRUM energy. *International Journal of Energy Economics and Policy*, 9 (2), pp. 390-398.
- [8] WARSONO, W., RUSSEL, E., WAMILIANA, W., WIDIARTI, W., and USMAN, M. (2019) Modeling and Forecasting by the Vector Autoregressive Moving Average Model for Export of Coal and Oil Data (Case Study from Indonesia over the Years 2002-2017). *International Journal of Energy Economics and Policy*, 9 (4), pp. 240-247.
- [9] WARSONO, W., RUSSEL, E., PUTRI, A.R., WAMILIANA, W., WIDIARTI, W., and USMAN, M. (2020) Dynamic Modeling Using Vector Error-Correction Model: Studying the Relationship among Data Share Price of Energy PGAS Malaysia, AKRA, Indonesia, and PTT PCL-Thailand. *International Journal of Energy Economics and Policy*, 10 (2), pp. 360-373.

- [10] TSAY, R.S. (2014) *Multivariate Time Series Analysis: With R and Financial Applications*. New York: John Wiley.
- [11] WEI, W. (2006) *Time Series Analysis: Univariate and Multivariate Methods*. 2nd ed. New York: Pearson Inc.
- [12] WEI, W. and WILLIAM, W.S. (1990) *Time Series Analysis: Univariate and Multivariate Methods*. Reading, Massachusetts: Addison Wesley.
- [13] DICKEY, D.A. and FULLER, W.A. (1979) Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74, pp. 427-431.
- [14] BROCKWELL, P.J. and DAVIS, R.A. (2002) *Introduction to Time Series and Forecasting*. New York: Springer.
- [15] TSAY, R.S. (2005) *Analysis of Financial Time Series*. Hoboken, New Jersey: John Wiley and Sons, Inc.

参考文献:

- [1] KIRCHGASSNER, G. 和 WOLTERS, J. (2007) 现代时间序列分析导论。柏林：培生教育公司
- [2] SIMS, 加拿大 (1980) 宏观经济学与现实。计量经济学, 48 (1), 第 1-48 页。
- [3] PENA, D. 和 TIAO, G.C. (2001) 简介。在：华盛顿特区 PENA, TIAO, G.C. 和 TSAY, R.S. (合编) 时间序列分析课程。纽约：约翰·威利父子。
- [4] STOCK, J.H. 和 WATSON, M.W. (1999) 预测通货膨胀。货币经济学杂志, 44 (2), 第 293-335 页。
- [5] SHARMA, A., GIRI, S., VARDHAN, H., SURANGE, S., SHETTY, R., 和 SHETTY, V. (2018) 原油价格与股市之间的关系：来自印度的证据。国际能源经济与政策杂志, 8 (4), 第 331-337 页。
- [6] ZUHROH, I., KUSUMA, H. 和 KURNIAWATI, S. (2018) 印尼通货膨胀分析的矢量自回归模型。文图拉经济, 商业与会计杂志, 20 (3), 第 261-268 页。

- [7] WARSONO, W., RUSSEL, E., WAMILIANA, W., WIDIARTI, W., 和 USMAN, M. (2019) 带外生变量模型的向量自回归及其在建模和预测能源数据中的应用：案例研究 PTBA 和人力资源能量。国际能源经济与政策杂志, 9 (2), 第 390-398 页。
- [8] WARSONO, W., RUSSEL, E., WAMILIANA, W., WIDIARTI, W., 和 USMAN, M. (2019) 通过向量自回归移动平均模型对煤炭和石油数据的出口进行建模和预测 (案例) 印度尼西亚的研究 (2002-2017 年)。国际能源经济与政策杂志, 9 (4), 第 240-247 页。
- [9] WARSONO, W., RUSSEL, E., PUTRI, AR, WAMILIANA, W., WIDIARTI, W., 和 USMAN, M. (2020) 使用矢量错误校正模型的动态建模：研究数据共享之间的关系能源 PGAS, 马来西亚阿克拉, 印度尼西亚和一键通-泰国的价格。国际能源经济与政策杂志, 10 (2), 第 360-373 页。
- [10] TSAY, R.S. (2014) 多元时间序列分析：R 和金融应用。纽约：约翰·威利 (约翰·威利)。
- [11] WEI, W. (2006) 时间序列分析：单变量和多变量方法。第二版。纽约：培生公司。
- [12] WEI, W. 和 W.W.S. (1990) 时间序列分析：单变量和多变量方法。马萨诸塞州雷丁：艾迪生·韦斯利。
- [13] DICKEY, D.A. 和 FULLER, W.A. (1979) 具有单位根的自回归时间序列的估计量分布。美国统计协会杂志, 74, 第 427-431 页。
- [14] PROCK 的 BROCKWELL 和 R.A.的 DAVIS. (2002) 时间序列和预测简介。纽约：施普林格。
- [15] TSAY, R.S. (2005) 金融时间序列分析。新泽西州霍博肯：约翰·威利父子公司。