How is the Modeling of the Relationship Between Food Inflation and the Agricultural Sector Composite Stock Price Index with the Statistical Analysis System?

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Abstract. The complex issue between inflation and stock indices makes it necessary for academic studies to examine related issues. Based on the previous explanation, this study attempts to model inflation and JCI in the context of the discussion of economic models, where inflation is represented by inflation in the food, beverage, and tobacco (IFBT) and JCI categories (RJKA). Then, the study will analyze how the two variables interact with each other to obtain the best model that establishes a short-term and long-term relationship between the two. The Vector Autoregressive (VAR) model will be utilized for the dynamic modeling in this study. Based on the investigation findings, the optimal model is the Vector Autoregressive model with the order 4 (p = 4), VAR (4).

Keywords: IFBT · RJKA · VAR

1 Introduction

Inflation is a skew of rising prices for products and services which is considered a price increase that lasts for a continuous period. If there is an increase in the price of goods and services in a country's territory, the inflation rate will rise. The rising cost of goods and services can reduce the currency's purchasing power (Baek & Koo, 2010). Consequently, inflation can also be regarded as a general decline in the value of money relative to the value of goods and services.

The role taken by inflation causes the emergence of the amount of contribution of each product that experiences price changes to inflation and or deflation that occurs in the coverage area of a country (national level) (Pratikto & Ikhsan, 2016). The amount of index benchmark results (inflation/deflation) that occurs every 30 days, becomes a combination of changes in a good and service that experience price fluctuations in the month concerned (bps.go.id).

Nairobi et al. (Eds.): ICEBE 2022, AEBMR 241, pp. 535–544, 2023.
https://doi.org/10.2991/978-2-38476-064-0_54

CPI (2012 = 100), which consists of seven groups, has changed to eleven groups in CPI (2018 = 100), namely: food, beverage, and tobacco groups; clothing and footwear; housing, water, electricity, and household fuel groups; class of household supplies, equipment, and routine maintenance; health groups; transport class; information, communication, and financial services; recreational, sports, and cultural groups; education; food, beverage/restaurant provision group and personal care and ophthalmic products group (Ismaya & Anugrah, 2018). Further research will only discuss inflation in the food, beverage, and tobacco (IFBT) group. The main discussion about IFBT is important because the price of food products has experienced a lot of inflation and or deflation. This is the reason for the general inflation movement (Rusono, n.d.).

Some of these policies are helping efforts to increase crop production in the country but there are still inflation figures sourced from IFBT which are still out of control also caused by limited food production itself and related food distribution problems. The distribution factor is a problem, among others, because the distribution process runs less smoothly which is characterized by economic disparities between regions. The lack of advice and distribution infrastructure as well as differences in geographical conditions in the archipelago area cause uneven production centers, difficulty in coordinating distribution implementation, unbalanced margins of implementation, the presence of illegal levies in their implementation and the dominance of certain parties contribute to the inflation rate in ifbt. This high inflation rate is certainly an issue that interferes with economic development.

The amount of information disseminated can affect investors' investment decisions. On the exchange, information about the development of the stock market is summarized in the stock market indices. Stock indices are an important indicator for investors to invest, because the strengthening or weakening of this index reflects the movement of the stock market (Agus Jumadil Akbar et al., 2016). One of the main goals of investors who consider stock indices when making investment decisions is to be able to determine the proportion of mutual fund allocations for the right investment vehicles. The Composite Stock Price Index (JCI) is Indonesia's most prominent and widely followed stock index. It is a composite index of all equities listed on the Indonesia Stock Exchange. Investors can use the JCI to determine if the stock market is sluggish or euphoric since the JCI is a stock price index figure that has been collated and calculated to predict future trends, allowing investors to compare changes in the behavior of stock price actors over time. The price of shares on the stock exchange is influenced by the capital market players' demand and supply for shares. Furthermore, the movement of stock indices will affect price movements in the market. This movement caused the JCI movement. Therefore, stock indices are used as indicators to see the development of a country's economy. This means that stock indices are an important change factor in assessing economic conditions.

The complex problem between inflation and the stock price index makes it necessary to study academics for research on related issues. This study attempts to model the INF and JCI in a single discussion of economic models, with IFBT representing inflation and Return IDX Agriculture representing the JCI (RJKA). This study will examine the interrelationships between the two variables to determine the optimal model that describes their short- and long-term relationships. Next, an influence number will be obtained to determine how the two variables affect each other. This is the main discussion with the aim of providing an analysis of renewal with the latest model of economic variables. Finally, this study will explain how the policy reference that can be taken is related to the modeling results obtained with the title "How is the Modeling of the Relationship Between Food Inflation and the Agricultural Sector Composite Stock Price Index with a Statistical Analysis System?".

2 Literature Review

A. *Inflation (INF)*

Inflation is a holistic increase in prices. Inflation occurs when prices rise simultaneously. If the cost of products and services in a country rises, inflation will also rise. The increase in the price of this commodity decreased the purchasing power of money. Consequently, inflation can also be regarded as a general decline in the value of money relative to the value of goods and services. Inflation is measured by examining various goods and services and estimating the growth in homogenous pricing over many intervals. Inflation simplifies holistic biological standards using creating more expensive goods and services. This means that inflation reduces people's purchasing power (Syatira & Ekaria, 2022). During inflation many of the prices including input prices tend to rise simultaneously as well as input prices choose the income of workers as well as the income of the owners of capital and land.

The complex issue between inflation and stock indices makes it necessary for academic studies to examine related issues. This study attempts to model INF and ICI in the discussion of economic models, where INFFood represents INF and ICIFarm represents ICI. Then, the study will analyze how the two variables interact with each other to obtain the best model that establishes a short-term and long-term relationship between the two. Next, we obtain the effect number to determine how the two variables affect each other. This is the main discussion that aims to provide up-to-date analysis using the latest economic variable models. Finally, this study explains how policy references can be made in relation to the results obtained from modeling the two variables.

3 Research Methods

A. *Data Types and Sources*

This study utilizes secondary data in the form of secondary data collected from monthly data between January 2015 and April 2021. This research data is sourced from the id.investing website (id.investing.com) and from the website of the Ministry of Trade (satudata.kemendag.go.id).

B. *Statistical Modeling*

This paper presents a modeling analysis of Food Inflation (IFBT) and monthly JCI in the Agricultural Sector (RJKA) in Indonesia from 2015 to 2021. This study examined IFBT and RJKA data as vector time series observations: and suppose.

$$\mathrm{Z_t} = \begin{bmatrix} IFBTt \\ RJKAt \end{bmatrix}$$

is a vector measurement at time t. (1) This form of vector time series will be studied using the multivariate time series technique. Before modeling the data, multivariate time series analysis modeling assumptions will be investigated. In the study of time series modeling, it is assumed that static data are representative. Before constructing a model, it is required to determine whether the data satisfy the stationarity assumption. There are two methods for determining whether or not data are stationary: analyzing the behavior of the data plot and applying the Augmented Dickey–Fuller (ADF) test with the null hypothesis that the data were not stationary (Tsay, 2010; Virginia et al., 2018; Warsono et al., 2020). If the data is not stationary, a process of inferencing is used to transform it, so it becomes stationary (Wei, 2006). According to Brockwell and Davis (2002), the ADF testing procedure is as follows:

Suppose $x_1, x_2, \ldots, x_n$ is the time series data and $\{x_t\}$ follows the AR(p) model with *the mean* μ given by

$$x_t - \mu = \phi_1(x_{t-1} - \mu) + \ldots. + \phi_p(x_{t-p} - \mu) + \varepsilon_t \tag{1}$$

where is ε_t *white noise* and has a *mean* of 0 and *a variance* of σ^2, and ~ WN (0, $\sigma\ \varepsilon_t\ ^2$). Model (1) for the case of p = 4 can be written as

$$\nabla x_t = \phi_o^* + \phi_1^* x_{t-1} + \phi_2^* \nabla x_{t-1} + \phi_3^* \nabla x_{t-2} + \phi_4^* \nabla x_{t-3} + \varepsilon_t \tag{2}$$

Here, j = 2,3,4 and. $\phi_o^* = \mu(1 - \phi_1 - \ldots - \phi_p)\phi_1^* = \sum_{i=1}^{p} \phi_i - 1\phi_j^* = \sum_{i=j}^{4} \phi_i \nabla x_t = x_t - x_{t-1}$.

Using the ADF test or the tau test (τ), the model (2) was tested for nonstationary data as follows:

Ho: (nonstationary data) $\phi_1^* = 0$

His opponentHa: (stationary data) $\phi_1^* < 0$.

Test statistics are (ADF test)

$$\tau = \frac{\hat{\phi}_1^*}{\hat{S}e_{\phi_1^*}} \tag{3}$$

For significance levels ($\alpha = 0.05$), Reject Ho if $\tau <$ -2.57 or if the p-value < 0.05 (See Brockwell and Davis, 2002, p.195).

4 Research Results

The data used in this study is Idx Agriculture (RJKA) Return data sourced from id.investing (2022) and Food, Beverage and Tobacco Inflation (IFBT) from the Ministry of Trade (2022) from January 2015 to April 2021 with a total of 75 observations.

The AICC information criteria with the smallest AICC value are utilized to establish the optimal lag while picking the best model. Several VAR(p) models will be assessed to identify the optimal VAR(p) model. The AICC VALUE is computed as follows:

$$AICC = \log(|\widehat{\Sigma}|) + 2r/(N - r/k)$$

where r represents the number of estimated parameters, N represents the number of observations, k represents the number of dependent variables, and denotes the maximum likelihood estimate of Σ (Tsay, 20 $\widehat{\Sigma}$ 10).

A. *VAR Form Representation*

The VAR process of order p (denoted VAR(p)) is expected to create stochastic XT:

$$Y_T = \Phi_1 Y_{T-1} + \Phi_2 Y_{T-2} + \ldots + \Phi_p Y_{T-p} + \varepsilon_T$$

where (i = 1,…, p) is the kxk parameter matrix, and the error process is a white noise process with a zero mean and a dimension k with a covariance matrix In short, $\Phi_i \varepsilon_t = (\varepsilon_{1T}, \ldots, \varepsilon_{KT})' E(\varepsilon_t, \varepsilon_t') = \Sigma_\varepsilon . \varepsilon_t \sim$ i.i.d. The VAR(p) process is stable if for $|z| \leq 1$, $(0, \Sigma_\varepsilon) \det(I_K - \Phi_1 z - \ldots - \Phi_p z^p) \neq 0$

that is, if all the roots of the determinant polynomial are in a circle of units.

B. *Normal Distribution Test*

To check the normality of the error (residual) there are several methods that can be used, namely: first, checking the histogram of the residual; second, checking the Q-Q plot from the data; and the third, using the Jarque-Fallow (JB) test with the hypothesis of zero normal distributed data (Tsay, 2010). In this study to check whether the error (residual) is normally distributed will use two methods, namely checking the histogram of the residual and checking the Q-Q plot from the data.

Figure 1 demonstrates that RJKA data varies about 0 from the first observation period to the final observation period, 2015 to 2021. Meanwhile, IFBT data from the initial period or from January 2015 to December 2019 (the 60th observation period) fluctuated around 0.5 and tended to decrease slightly, while the next period, namely in January to the end of the observation period (April 2021) the data tended to fluctuate very

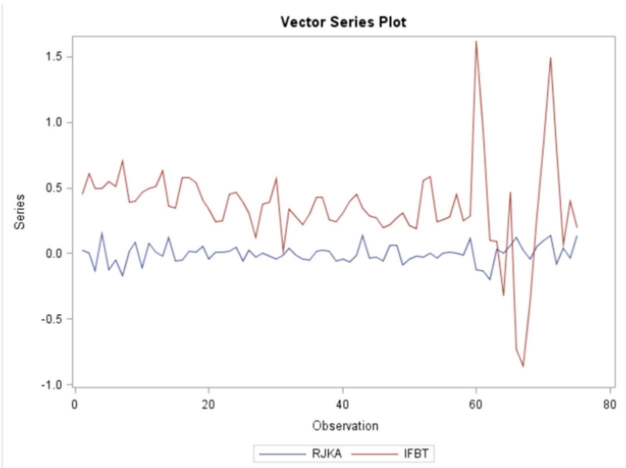

Fig. 1. Data plot of Return IDX Agriculture (RJKA) and Food, Beverage and Tobacco Inflation (IFBT) from 2015 to 2021.

diversely. Figure 1 demonstrates that the two data series share a common characteristic, namely that the data is not stationary, necessitating the following step of differencing data, which seeks to make the data conform to stationary assumptions (Wei, 2006). In this case, analytical approaches such as the ADF (Augmented Dickey Fuller) test can be used to check the stability of the data (Russel et al., 2020; Nairobi et al., 2020).

To create stationary data, the differencing method and the first differencing (d = 1) result are used (Table 1). The ADF test for RJKA and IFBT data is a Tau test = 9.34 with P = 0.0001, a Tau test = -7.71 with P = 0.0001. Following the initial differentiation, we may therefore conclude that the data are stationary.

Table 2 shows that the + or – sign indicates a marked difference from 0; in other words, there is a cross-correlation between the RJKA and IFBT variables. Therefore, the modeling process must involve autoregressive vector modeling (VAR) (Tsay, 2010) for RJKA and IFBT.

This study uses Akaike's Information Criterion corrected (AICC) as one of the factors for determining the optimal lag. The optimal lag value occurs in Vector Autoregressive

Table 1. ADF (Augmented Dickey Fuller) Test for RJKA and IFBT data After Diffrencing lag = 1 (d = 1)

Variables	**Type**	**Rho**	**Pr < Rho**	**Know**	**Pr < Tau**
RJKA	Zero Mean	-179.76	0.0001	-9.40	<.0001
	Single Mean	-179.74	0.0001	-9.34	0.0001
	Trend	-179.77	0.0001	-9.27	<.0001
IFBT	Zero Mean	-124.50	0.0001	-7.77	<.0001
	Single Mean	-124.58	0.0001	-7.71	0.0001
	Trend	-124.59	0.0001	-7.66	<.0001

Table 2. Representation schematic of cross-correlation

Variable/Lag	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
RJKA	+ -	..	..	..	..	..	..	..	..	..	..	..	..
IFBT	- +	..	..	..	..	..	.-	..	..	..	..	..	..
+ is > 2*std error, - is < -2*std error,. is between													

Table 3. Optimum lag test using AICC

Lag	**AR0**	**AR1**	**AR2**	**AR3**	**AR4**	**AR5**
	-6.592537	6.813624	-6.841914	-6.964016	**-7.170863**	-7.091318

Note: AR4 has the smallest AICC value

(VAR) models with order 4, as seen in Table 3. (4). As a result, the VAR(4) model will be utilized for following analyses.

VAR(4) model estimate,

$$\begin{pmatrix} RJKA_t \\ IFBT_t \end{pmatrix} = \begin{pmatrix} 0.00374 \\ -0.00162 \end{pmatrix} + \begin{bmatrix} -0.80744 & -0.03215 \\ 0.41948 & -0.21183 \end{bmatrix} \begin{pmatrix} RJKA_{t-1} \\ IFBT_{t-1} \end{pmatrix}$$
$$+ \begin{bmatrix} -0.62527 & -0.02445 \\ -0.03915 & -0.24732 \end{bmatrix} \begin{pmatrix} RJKA_{t-2} \\ IFBT_{t-2} \end{pmatrix} + \begin{bmatrix} -0.62545 & -0.05696 \\ -0.97206 & -0.23298 \end{bmatrix}$$
$$\begin{pmatrix} RJKA_{t-3} \\ IFBT_{t-3} \end{pmatrix} + \begin{bmatrix} -0.44683 & -0.04858 \\ -0.37755 & -0.25404 \end{bmatrix} \begin{pmatrix} RJKA_{t-4} \\ IFBT_{t-4} \end{pmatrix}$$

With Covariance of Innovation.

$Var(\varepsilon_t) = \Sigma = \begin{bmatrix} 0.00501 & -0.00604 \\ -0.00604 & 0.11937 \end{bmatrix}.$

The above VAR model can alternatively be expressed as the following univariate regression equation:

$$\begin{aligned} RJKA_t &= 0.00374 - 0.80744\, RJKA_{t-1} - 0.03215 IFBT_{t-1} - 0.62527 RJKA_{t-2} \\ &-0.02445 IFBT_{t-2} - 0.62545 RJKA_{t-3} - 0.05696\, IFBT_{t-3} \\ &-0.44683 RJKA_{t-4} - 0.04858 IFBT_{t-4} + \varepsilon_{1t} \end{aligned}$$

$$\begin{aligned} RJKA_t &= 0.00162 + 0.41948\, RJKA_{t-1} - 0.21183 IFBT_{t-1} - 0.03915 RJKA_{t-2} \\ &-0.24732 IFBT_{t-2} - 0.97206 RJKA_{t-3} - 0.23298\, IFBT_{t-3} \\ &-0.37755 RJKA_{t-4} - 0.25404 IFBT_{t-4} + \varepsilon_{1t} \end{aligned}$$

Estimation and testing of model parameters are given in Table 4.

Table 4 shows the effect of $RJKA_{t-1}$, $RJKA_{t-2}$, $RJKA_{t-3}$, $RJKA_{t-4}$ on $RJKA_t$ is negative, with the estimated values for the parameters being 0.80744, 0.62527, 0.62545 and 0.44683 for $RJKA_{t-1}$, $RJKA_{t-2}$, $RJKA_{t-3}$, $RJKA_{t-4}$, respectively. With an estimated parameter value of 0.80744, $RJKA_{t-1}$ has a negative effect on $RJKA_t$. This indicates that the value of $RJKA_t$ will decrease by 0.80744 units for each unit rise in $RJKA_{t-1}$, provided all other values remain constant; while the influence of $RJKA_{t-2}$ on QEWCt is negative, with an estimated value of 0.62527 for the parameter. Consequently, the QEWCt value will fall by 0.62527 for each unit rise in $RJKA_{t-2}$, provided all other variables remain constant. This is also true for $RJKA_{t-3}$, and $RJKA_{t-4}$, as it has a negative effect. The effect of $IFBT_{t-1}$, $IFBT_{t-2}$, $IFBT_{t-3}$, and $IFBT_{t-4}$ on $RJKA_t$ was negative, with parameter estimates of 0.03215, 0.02445, 0.05696, and 0.4858 for $IFBT_{t-1}$, $IFBT_{t-2}$, and $IFBT_{t-4}$, respectively. Therefore, the influence of $IFBT_{t-1}$ on $RJKA_t$ is negative; with the parameter estimation value of 0.03215, this indicates that the value of $RJKA_t$ will decrease by 0.03215 for each increase in the unit of $IFBT_{t-1}$, assuming that all other variables remain constant. This also applies to $IFBT_{t-2}$, $IFBT_{t-3}$, and $IFBT_{t-4}$ because they have a negative influence.

Table 4. Model parameters Estimation and testing for VAR models(4)

Equation	Parameters	Estimate	StandardError	t Value	Pr > |t|	Variables
RJKA	**CONST1**	0.00374	0.00847	0.44	0.6605	1
	AR1_1_1	-0.80744	0.11231	-7.19	0.0001	RJKA(t-1)
	AR1_1_2	-0.03215	0.02629	-1.22	0.2259	IFBT(t-1)
	AR2_1_1	-0.62527	0.12945	-4.83	0.0001	RJKA(t-2)
	AR2_1_2	-0.02445	0.02522	-0.97	0.3362	IFBT(t-2)
	AR3_1_1	-0.62545	0.12920	-4.84	0.0001	RJKA(t-3)
	AR3_1_2	-0.05696	0.02612	-2.18	0.0331	IFBT(t-3)
	AR4_1_1	-0.44683	0.11437	-3.91	0.0002	RJKA(t-4)
	AR4_1_2	-0.04858	0.02755	-1.76	0.0828	IFBT(t-4)
IFBT	**CONST2**	-0.00162	0.04137	-0.04	0.9688	1
	AR1_2_1	0.41948	0.54845	0.76	0.4473	RJKA(t-1)
	AR1_2_2	-0.21183	0.12836	-1.65	0.1040	IFBT(t-1)
	AR2_2_1	-0.03915	0.63215	-0.06	0.9508	RJKA(t-2)
	AR2_2_2	-0.24732	0.12316	-2.01	0.0491	IFBT(t-2)
	AR3_2_1	-0.97206	0.63093	-1.54	0.1286	RJKA(t-3)
	AR3_2_2	-0.23298	0.12755	-1.83	0.0727	IFBT(t-3)
	AR4_2_1	-0.37755	0.55849	-0.68	0.5016	RJKA(t-4)
	AR4_2_2	-0.25404	0.13453	-1.89	0.0637	IFBT(t-4)

5 Model Diagnostic Check

Table 5 shows that univariate ANOVA models for models with independent variable RJKA, enormously significant models with p-values < 0.0001 and R-square = 0.4996 which means 49.96% of The model explains RJKA diversity; IFBT has an R-square value of 0.2001 for models with independent variables which means that 20.01% of IFBT diversity is explained by the model, but the significance value is above 5% which is 0.0751 which means that the model is insignificant. The error distribution and Q-Q plot for Fig. 2, show a deviation that is not too far from the normal distribution, but the error distribution graph is close to normal.

Table 5. Univariate Model ANOVA Diagnostics

Univariate Model ANOVA Diagnostics				
Variables	**R-Square**	**StandardDeviation**	**F Value**	**Pr > F**
RJKA	0.4996	0.07075	7.61	<.0001
IFBT	0.2001	0.34550	1.91	0.0751

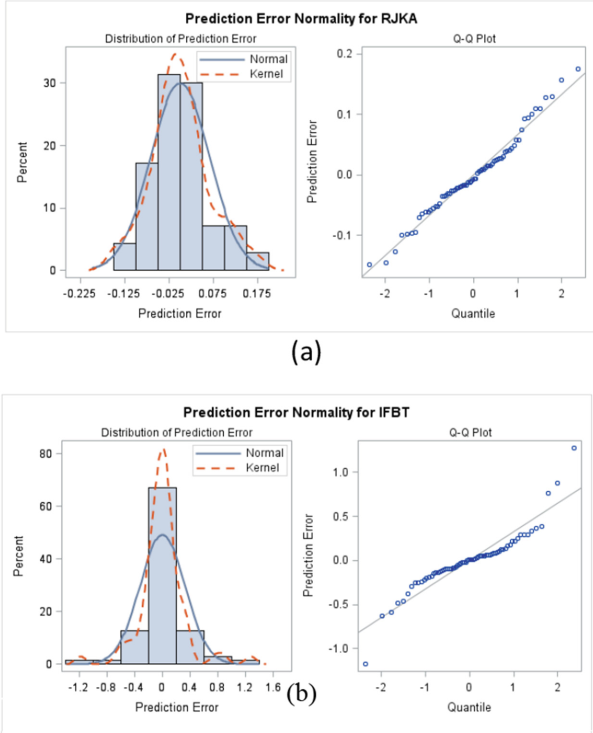

Fig. 2. Prediction Error Normality for Data (a) RJKA and (b) IFBT

6 Conclusion

From the results of the analysis of RJKA and IFBT data using the AICC method, estimation and hypothesis testing were performed on the compared models to identify the model that best describes the dynamic relationship between the RJKA and IFBT data, the best model was obtained was the Vector Autoregressive model with order p = 4 (VAR (4)).

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