Forecasting the farmers’ terms of trade in Yogyakarta using transfer function model

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Abstract. The transfer function model is one of the forecasting models that predicts future values from a time series based on its past values and the other variables. In this paper, the transfer function model is utilized to forecast the farmers’ terms of trade in Yogyakarta province. The farmers’ term of trade (FTT) is one indicator of farmers’ welfare. The variables included in the model inputs are the inflation and exchange rate in Yogyakarta. The procedure for transfer function modeling is through two stages, those are building a single input transfer function model for each input based on the autoregressive integrated moving average model, and then building the transfer functions simultaneously for all variables. The result demonstrates that the transfer function can predict farmers’ terms of trade accurately with the mean absolute percentage error value of 0.841%.

1. Introduction

Indonesia is an agrarian country that has vast agricultural land and a large population involved in agricultural activities. Therefore, the agricultural sector is one of the sectors that have an important contribution to national development [1]. In the last decade, the contribution of the agricultural sector, especially in Yogyakarta has decreased from year to year [2]. The percentage of the gross regional domestic product of Yogyakarta for the agricultural sector in 2007 of 13.58% to only 9.12% in 2016. The change in the contribution of the agricultural sector affects the number of workers in the agricultural sector tends to decrease. The agricultural sector tends to have a lower labor income average than the non-agricultural sector.

The implementation of agricultural development basically aims to improve people's welfare, especially the farmers’ welfare. Through various agricultural development policies and programs implemented, the government has sought to improve the farmers’ welfare. One measure that describes the level of farmers’ welfare is farmers’ term of trade (FTT)[1].

The FTT is time series data. The typical forecasting methods that can be used is the Autoregressive Integrated Moving Average (ARIMA) method. It only runs a single variable FTT. Various methods have been developed for FTT forecasting. The univariate methods to forecast FTT have been proposed using the Artificial Neural Network (ANN) Backpropagation [3] and Autoregressive Conditional Heteroscedasticity (ARCH) or Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model [4].
In fact, there are several factors that influence FTT such as inflation and exchange rate [5]. The transfer function is a time series model that accommodates the effects of other variables besides its past values. The transfer function model combines the characteristics of the univariate ARIMA model and regression analysis [6]. The works using transfer function models have accurately predicted atmospheric temperature with input atmospheric CO$_2$ emission [7], Naira exchange rate on us dollar the Swiss Franc [8], and natural rubber in India [9]. It is also effective in modeling residential building costs in New Zealand [10]. In this study, the transfer function model is used to forecast the FTT in Yogyakarta Province. Since it is assumed that the inflation and the exchange rate affect the FTT, the transfer function is built based on the ARIMA models of inflation and the exchange rate.

2. Research methods

2.1. Data source

FTT is a percentage of the price index received by farmers over the price index paid by farmers. It measures the ability of the agricultural commodities exchange values or the price received by farmers towards the cost of household consumption and agricultural production. The FTT calculation includes the sectors’ food crops (rice, maize, beans, and tubers) and plantation crops (sugar cane, coffee, pepper, tobacco, rubber, coconut, tea, cloves, vanilla, vegetables, fruits, and flowers). To predict FTT ($Y_t$) with the transfer function model to predict the FTT involves the inflation ($X_{1t}$) and the exchange rate (USD to Rupiah) ($X_{2t}$) as the input variables. The data are published every month by the Statistic Centre Bureau in Yogyakarta Province in the period from January 2008 to December 2017 [2].

2.2. Model Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a univariate time series model. An autoregressive term corresponds to the regression model with previous values of the series in the independent position. A moving average deals with the dependency of the series to the past error. ARMA model combines the autoregressive and moving average terms. A nonstationary series is converted to a stationary series by differencing. A nonstationary autoregressive integrated moving average (ARIMA) with $d$ amount of differentiating, $p$ order of autoregressive, and $q$ order of moving average is denoted as ARIMA $(p,d,q)$ and written as [11]:

$$\phi_p(B)(1-B)^dX_t = \mu + \theta_q(B)e_t$$  \hspace{1cm} (1)

with AR($p$) operator:

$$\phi_p(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$$  \hspace{1cm} (2)

and MA($q$) operator:

$$\theta_q(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$$  \hspace{1cm} (3)

The seasonal ARIMA provides a model for the data which exhibits periodic behavior. The notation of a seasonal ARIMA is SARIMA $(p,d,q)(P,D,Q)^S$ model. It is defined as [12]:

$$\phi_p(B)\Phi_p(B^S)(1-B)^d(1-B^S)^D X_t = \theta_q(B)\Theta_q(B^S)e_t$$  \hspace{1cm} (4)

with AR($P$) seasonal operator:

$$\Phi_p(B^S) = (1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdots - \Phi_p B^{pS})$$  \hspace{1cm} (5)

with MA($Q$) seasonal operator:

$$\Theta_q(B^S) = (1 - \Theta_1 B^S - \Theta_2 B^{2S} - \cdots - \Theta_q B^{qS})$$  \hspace{1cm} (6)

2.3. Transfer function model

The transfer function model is a model that describes the time series prediction based on the past values of the series itself and one or more variables related to the series [13]. The uniqueness of the transfer function method is that there is a regression element in the model. The concept of the transfer function
model consists of an input series \( (x_t) \), an output series \( (y_t) \) and all other influences called the noise series \( (n_t) \). The bivariate transfer function model is [6]:

\[
y_t = v(B)x_t + n_t
\]

where

\[
v(B) = \frac{\omega_j(B)B^b}{\delta_j(B)} \quad \text{and} \quad n_t = \frac{\theta_j(B)}{\phi_p(B)} a_t .
\]

So, it can be written as

\[
y_t = \frac{\omega_j(B)B^b}{\delta_j(B)} x_t + \frac{\theta_j(B)}{\phi_p(B)} a_t
\]

where

\[
\omega_j(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s
\]

\[
\delta_j(B) = 1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_f B^f
\]

The transfer function can involve two or more input variables that affect the output variable. Such transfer functions are called multivariate or multi-input transfer functions. The multivariate transfer function model can be expressed as [14]:

\[
y_t = \sum_{j=1}^{u} \frac{\omega_j(B)B^b}{\delta_j(B)} x_{jt} + \frac{\theta_j(B)}{\phi_p(B)} a_t
\]

where \( x_{jt} \) is the \( j \)th input variable, \( j = 1, 2, \ldots, u \), \( \omega_j(B) \) is the moving average operator for the \( j \)th variable with order \( s_j \), \( \delta_j(B) \) is the autoregressive operator for the \( j \)th variable with order \( r_j \) order, and \( a_t \) is random noise.

2.4. Procedure for forming a multivariate transfer function model

The method used to forecast the FTT in the Yogyakarta Province is the multivariate transfer function. The procedure for developing a multivariate transfer function model is carried out in two steps, those are developing a single input transfer function model of each input and then developing the transfer functions simultaneously for all variables. The steps to develop a multivariate transfer function model are described below

Step 1: Identify the single input transfer function model

The ARIMA model is constructed in each series of inputs and output. The prewhitening on the input and output series are employed based on the ARIMA model. Furthermore, the cross correlation between prewhitened input and output series is identified by using cross correlation function (CCF)

\[
r_{\alpha \beta}(k) = \frac{\sum_{t=1}^{n} (\alpha_t - \bar{\alpha})(\beta_{t+k} - \bar{\beta})}{\sqrt{\sum_{t=1}^{n} (\alpha_t - \bar{\alpha})^2 \sum_{t=1}^{n} (\beta_{t+k} - \bar{\beta})^2}}
\]

The single input transfer function parameters \( (b, r, s) \) are identified by observing the CCF pattern. Then, we can calculate the weights of the impulse response and build the noise series and the ARMA model on the noise series.

Step 2: Estimating the parameters of the single input transfer function model

The parameter of the transfer function model can be estimated using the conditional least squares method [14]. The parameters of this single input transfer function model are determined based on the value of the transfer function parameter \( (b, r, s) \).

Step 3: Diagnostic check

The model diagnostic is necessary to check the model fit. The diagnostic check is done by investigating the error behavior \( (\alpha_t) \) and the cross correlation between the transfer function error \( (\alpha_t) \) and the prewhitening input \( (\alpha_t) \). The model is fit if the autocorrelation of the \( \alpha_t \) and the cross correlation
between the $\alpha_t$ and $\alpha_t$ at any lag are not significant. Those requirements are tested using the Box-Pierce Q Test [14].

Step 4: Developing multivariate transfer function models
The multivariate transfer function model is developed by estimating the transfer function model for all variables simultaneously. After the stages have been completed, we can calculate the forecast using the yielded model.

3. Results and discussions
The first step in modeling the transfer function is identifying the ARIMA model for each input series. The inputs inflation and exchange rate have nonstationary patterns. We conduct the difference process at lag 24 and lag 1 to inflation and exchange rate to make stationary series. The results of the time series, ACF, and PACF plots of the stationary inflation and exchange rate are depicted in Figure 1, Figure 2, and Figure 3, sequentially.

Figure 1. (a) Time series plot of inflation after differencing lag 24 and (b) Time series plot of exchange rate after differencing lag 1

Figure 2. (a) The ACF and (b) the PACF plots of inflation after differencing lag 24

Figure 3. (a) The ACF and (b) the PACF plots of exchange rate after differencing lag 1

Figure 2 exhibits that the autocorrelation and partial autocorrelation coefficients at lag 1, 2, and 24 are significantly different from zero. Figure 3 exhibits that the autocorrelation and partial autocorrelation...
coefficients at lag 1 are significantly different from zero. These results indicate several possible tentative models. After examining the model based on the least Akaike information criterion (AIC) value, the best models are SARIMA\((0,0,1)(0,1,1)^{24}\) for inflation and ARIMA \((0, 0, 1)\) for the exchange rate (see Table 1).

**Table 1.** ARIMA models for inputs.

| Input Series   | ARIMA Model | Equation |
|----------------|-------------|----------|
| Inflation      | \((0,0,1)(0,1,1)^{24}\) | \((1 - B^{24})x_{1t} = (1 + 0.4940B)(1 - 0.4255B^{24})\alpha_{1t}\) |
| Exchange Rate  | \((0,1,1)\) | \((1 - B)x_{2t} = (1 + 0.31737B)\alpha_{2t}\) |

The prewhitening for each input series is assigned using the ARIMA model in Table 1. The prewhitening for output series is adjusted to the prewhitened input series. The notations are \(\alpha_{jt}\) for input series and \(\beta_{jt}\) for output series \(j=1, 2\). The prewhitening results are delivered in Table 2 and the CCF plots between prewhitened input and output are illustrated in Figure 4.

**Table 2.** Model of prewhitened input and output series.

| Input Series   | Equation |
|----------------|----------|
| Inflation      | \(\alpha_{1t} = x_{1t} - x_{1t-24} - 0.4940\alpha_{1t-1} + 0.4255\alpha_{1t-24} + 0.210\alpha_{1t-25}\) |
|                | \(\beta_{1t} = y_{1t} - y_{1t-24} - 0.4940\beta_{1t-1} + 0.4255\beta_{1t-24} + 0.210\beta_{1t-25}\) |
| Exchange Rate  | \(\alpha_{2t} = x_{2t} - x_{2t-1} - 0.31737\alpha_{2t-1}\) |
|                | \(\beta_{2t} = y_{2t} - y_{2t-1} - 0.31737\beta_{2t-1}\) |

![Figure 4](image)

**Figure 4.** (a) The CCF plot of prewhitened inflation and FTT and (b) CCF plot of prewhitened exchange rate and FTT

The value of \((b, r, s)\) can be determined from the CCF plot of each input series. The lags that are positive do not show a clear pattern. The values of \(r\) and \(s\) for inflation inputs and exchange rate input are all 0. However, after calculation, the appropriate \(r\) and \(s\) values for exchange rate input are 2 and 0. The first lag that significantly influences inflation input is the second lag, so the delay value or the value of \(b\) is identified as 2. However, the second lag does not meet the assumptions. The value of \(b\) that meets the assumption for inflation input is 3. The initial value of \(b\) for exchange rate input is 0. But it is switched to 2 which is met the assumptions. The order \((b, r, s)\) for each input and the parameter estimator are provided in Table 3. Table 3 shows that all parameters of the single input transfer function are significant. The diagnostic check results for single input transfer function are presented in Table 4 and Table 5.
Table 3. Parameter estimator of a single input transfer function.

| Input Series       | b | r | s | Parameters | Estimator | p – value |
|--------------------|---|---|---|------------|-----------|-----------|
| Inflation          | 2 | 0 | 0 | $\theta_1$ | 0.86172   | 0.0001    |
|                    |   |   |   | $\omega_0$ | 0.47439   | 0.0308    |
| Exchange Rate      | 2 | 2 | 0 | $\theta_1$ | 0.75754   | 0.0001    |
|                    |   |   |   | $\omega_0$ | 0.0004    | 0.0028    |
|                    |   |   |   | $\delta_1$ | -1.4876   | 0.0001    |
|                    |   |   |   | $\delta_2$ | -0.975    | 0.0001    |

Table 4. The Box Pierce test result for error autocorrelation for the univariate transfer function

| Lag | p – value | Inflation ($X_1$) | Exchange Rate ($X_2$) |
|-----|-----------|-------------------|-----------------------|
| 12  | 0.7916    | 0.9054            |
| 18  | 0.9448    | 0.9616            |
| 24  | 0.9745    | 0.9719            |
| 30  | 0.9726    | 0.9525            |

Table 5. The Box Pierce test result for error cross-correlations for the univariate transfer function

| Lag | p – value | Inflation ($X_1$) | Exchange Rate ($X_2$) |
|-----|-----------|-------------------|-----------------------|
| 11  | 0.1058    | 0.5148            |
| 17  | 0.2094    | 0.6932            |
| 23  | 0.2449    | 0.7469            |
| 29  | 0.4395    | 0.9285            |

Table 4 and Table 5 demonstrate that all p-values $> \alpha = 0.05$. It can be concluded that the error autocorrelations and the correlations between the prewhitened input series $\alpha_t$ and model error $\alpha_t$ from each model are not significant.

Multivariate transfer function modeling is done after a single input transfer function model has been built, that is by modeling simultaneously all variables that have been identified previously. Orders $(b, r, s)$ on each input series are modeled simultaneously to obtain the estimated parameter values of the multivariate transfer function model. While the ARIMA model for noise multivariate transfer functions is ARIMA(0,0,0)(0,0,1)$^{12}$.

Table 6 provides the parameter estimation result of the multivariate transfer function model. We can infer from table 6 that all parameters of the multivariate transfer function model are significant because the p-value for each parameter is less than the significance level 0.05. Then a diagnostic check of the multivariate transfer function model is carried out and the results are given in Table 7 and Table 8. It can be observed from table 7 that the error autocorrelations are not significant because the p-values for all lags are more than $\alpha = 0.05$. From table 8, it can be concluded that the correlation between the error model and the prewhitened input series is not significant because the p-values for all lags are more than $\alpha = 0.05$.
Table 6. Parameter estimation result of multivariate transfer function

| Parameter | Estimator | p – value |
|-----------|-----------|-----------|
| $\Theta_1$ | 0.91687 | 0.0001 |
| $\omega_{0,1}$ | 0.56971 | 0.0087 |
| $\omega_{0,2}$ | $-0.00006$ | 0.0235 |
| $\delta_{1,2}$ | 1.6314 | 0.0001 |
| $\delta_{2,2}$ | $-0.90335$ | 0.0001 |

Table 7. The Box Pierce test result for error autocorrelation for the multivariate transfer function models.

| Lag | p – value |
|-----|-----------|
| 12  | 0.7949    |
| 18  | 0.9427    |
| 24  | 0.9694    |
| 30  | 0.9843    |

Table 8. The Box Pierce test result for error cross-correlations for the multivariate transfer function

| Lag | Inflation ($X_1$) | Exchange Rate ($X_2$) | p – value |
|-----|-------------------|-----------------------|-----------|
| 11  | 0.1423            | 0.1398                |           |
| 17  | 0.2887            | 0.3349                |           |
| 23  | 0.3459            | 0.6721                |           |
| 29  | 0.5354            | 0.8582                |           |

The fit multivariate transfer function with the parameter values displayed in table 6 has been developed. The multivariate transfer function model for FTT in Yogyakarta can be formulated in the following equation

$$Y_t = 2.6314Y_{t-1} - 2.5348Y_{t-2} + 0.90335Y_{t-3} + Y_{t-12} + 2.5348Y_{t-14} - 2.6314Y_{t-13} - 0.90335Y_{t-15} + 0.56971(X_1)_{t-3} - 0.9294(X_1)_{t-4} + 0.5146(X_1)_{t-5} - 0.56971(X_1)_{t-27} + 0.9294(X_1)_{t-28} - 0.5146(X_1)_{t-29} + 0.00006(X_2)_{t-2} - 0.00006(X_2)_{t-3} + \alpha_t - 1.6314\alpha_{t-1} - 0.90335\alpha_{t-2} - 0.91687\alpha_{t-12} + 1.4958\alpha_{t-13} - 0.8283\alpha_{t-14}. $$

Figure 5 compares the FTT actual data and the forecast result from 2008 to 2017 in Yogyakarta using the multivariate transfer function method. It reveals that the fluctuation of the multivariate transfer function forecasts is very similar to that of the actual data. The plot time series in Figure 5 demonstrates that the FTT data decrease drastically at the end of 2011. The forecasts also decrease drastically at that year. The accuracy of the multivariate transfer function method to forecast FTT is assured by the very small MAPE (Mean Absolute Percentage Error) value 0.841%. The proposed method is competitive compared to the previous methods backpropagation neural network [3] with MAPE more than 1 % and ARCH [4] with MAPE more than 3 %.
4. Conclusion

In this study, we develop the multivariate transfer function to forecast the FTT in the Yogyakarta Province. The model includes two inputs: inflation and USD exchange rate to rupiah. The data indicate the nonstationary series. The differencing is performed to get the stationary condition. The steps of the multivariate transfer function can be implemented to forecast the FTT. From the computational results, it can be concluded that the multivariate transfer function delivers very high performance in forecasting FTT in Yogyakarta.

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