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# Logistic Smooth Transition Autoregressive (LSTAR) and Exponential Smooth Transition Autoregressive (ESTAR) Methods in Predicting the Exchange Rate of Farmers in Lampung Province, Indonesia

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**ABSTRACT**: There are many time series forecasting techniques, one of which is Smooth Transition Autoregressive (STAR). STAR is an extension of the autoregressive model for nonlinear time series data. The STAR model consists of the Logistic STAR (LSTAR) model and the Exponential STAR (ESTAR) model. The aim of this research is to compare which model is more suitable for predicting farmer exchange rates in Lampung Province, Indonesia. The results of this research show that the ESTAR model outperforms the LSTAR model based on a smaller AIC.

**KEYWORDS**: Forecasting, Nonlinear, LSTAR ESTAR

## I. INTRODUCTION

Forecasting is an important tool for effective and efficient planning, especially in economics and business organizations where decision making is often significant (Brockwell & Davis, 2002; Oktafiani *et al*., 2012). Forecasting is often divided into three categories: short term, medium term, and long term. Short-term forecasting includes predictions for some period of time into the future, such as days, weeks, or months. Medium-term forecasting includes estimates for the next one to two years. Meanwhile, long-term forecasting covers several years into the future (Granger & Jeon, 2007; Aksan & Khalilah, 2020).

There are many time series forecasting techniques, one of which is Smooth Transition Autoregressive (STAR). STAR is a development of the autoregressive model for nonlinear time series data. According to Terasvirta (1994) and (Arnab *et al*., 2006), the STAR model consists of the logistic STAR (LSTAR) model and the exponential STAR (ESTAR) model.

The LSTAR model uses a logistic transition function to describe the change from one regime to another in a smooth transition. The logistic transition function is determined by parameters that control the speed and midpoint of the transition (Olukayode *et al*., 2006). The general form is:

$$G(s_t;\gamma;c) = \frac{1}{1+\exp(-\gamma(s_t-c))}, \gamma > 0$$

Exponential Smooth Transition Autoregressive (ESTAR) is another type of STAR model that uses an exponential transition function (Noman & Rahman, 2010). The exponential transition function describes a more gradual transition than the logistic function, with the general form:

$$Z_t = \phi_1' X_t(1-(1-\exp(-\gamma(s_t-c)^2)) + \phi_2' X_t(1-(1-\exp(-\gamma(s_t-c)^2)) + \varepsilon_t$$

The STAR model is a nonlinear model that can be applied to data with nonlinear patterns and very popular in applications in the field of agricultural economic. Agricultural economic is a sector that has an important role in the Indonesian economy. This sector is considered to have special abilities in combining growth and equity (growth with equity) or quality growth. As a tropical country, Indonesia has excellent agricultural potential, especially for tropical regions.

Farmer Exchange Rate is a ratio that compares the income from the sale of agricultural products with the cost of goods and services purchased by farmers. (Rachmat, 2013). Conceptually, Farmer Exchange Rate measures the extent to which farmers can exchange the agricultural products they produce for goods and services used by farming households as well as those needed to produce agricultural products.. Farmer Exchange Rate is presented in the form of an index in percentage. If the Farmer Exchange Rate value at a time is greater than 100 percent, it means that the exchange capacity of farmers at that time is better than the base year, and vice versa.

## II. MATERIAL AND METHODS

The data used in this research is secondary data taken from https://lampung.bps.go.id. The data form is monthly data on Farmer Exchange Rates for Lampung Province, Indonesia for the period January 2009 – April 2024 with n=184.

This research was carried out through several steps. Starting by plotting farmer exchange rate data for Lampung Province, Indonesia to get a full picture of the data distribution. Then, carry out a stationarity test in the variance using the Box-Cox transformation and data stationarity in the average using the Augmented Dickey Fuller (ADF) test. If the data is not stationary with respect to the variance, transformation is carried out, and if it is not stationary with respect to the average, then a differentiation process is carried out. After the data is stationary regarding the variance and average, the best model is determined using the Box-Jenkins test. Next, the best model parameters were estimated by looking at the AIC value. Determining the best model is the model that has the smallest AIC value . AIC formula is:

$$AIC(M) = n \ln \hat{\sigma}_{\alpha}^{2} + 2M$$

Next, model diagnosis to test the fulfillment of model assumptions by carrying out autocorrelation tests, normality tests, heteroscedasticity tests, and nonlinear tests. The LSTAR and ESTAR models were identified by looking at the PACF plot, then LSTAR and ESTAR model parameters were estimated by looking at the smallest AIC value. Finally, forecasting using the best LSTAR and ESTAR models was carried out on farmer exchange rate data in Lampung Province, Indonesia for the next period.

## III. RESULTS AND DISCUSSION

The analysis of Farmer Exchange Rate in Lampung Province, Indonesia data using LSTAR and ESTAR is done first by checking the assumptions of the data, namely the stationary test in variety and stationary in average. Then the Ljung-Box test is carried out to see whether there is autocorrelation in the data. Besides that, a normality test is also carried out on the data as well as the test of nonlinearity. Identification of data stationarity is first done by plotting the raw data. From the observation data plot (Figure 1).

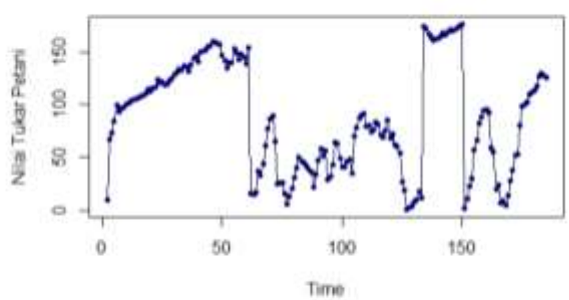


**Figure 1. Plot of Farmer Exchange Rate Data of Lampung Province**

From Figure 1 can be seen that the Farmer Exchange Rate data shows a graph that is not yet stationary. To ensure this, the Box-Cox test will be carried out to see the stationarity of the data on variance and the Augmented Dickey Fuller (ADF) test to test the stationarity of the mean.

The results of the stationarity of the variance data using the Box-Cox test obtained a lambda value of 0.65, which means the data is stationary in its variance, while for the stationarity test the mean obtained P-value = 0.1933 > 0.05, which means that the data has not stationary at the mean. So it is necessary to differentiate and based on the results of the differentiations, P-value = 0.01 < 0.05. It can be concluded that data is stationaryin the mean. Next, by using the Box-Jenkins model to get the ACF and PACF plots in order to obtain the possible ARIMA models. This step results in the ARIMA models (0,1,0), (0,1,17), (17,1,0), (17,1,17). The best model has the smallest AIC value compared to the other models and it is found that the model (17,1,0) has the smallest AIC value as can be seen in Table 1.

**Table 1. AIC Value of Each Model**

| Model | AIC |
|---|---|
| ARIMA (0,1,0) | 1783.66 |
| ARIMA (0,1,17) | 1688.18 |
| ARIMA (17,1,0) | 1684.9 |
| ARIMA (17,1,17) | 1695.92 |

Next, the ARIMA (17,1,0) model that has the smallest AIC value among other ARIMA models is tested for white noise assumptions, normality tests, and heteroscedasticity tests. The white noise assumption test can be carried out using the Ljung-Box test, the normality test can be carried out using the Kolmogorov-Smirnov test, while the heteroscedasticity test can be carried out using the Lagrange Multiplier test with the results are as follows.

**Table 2: Ljung-Box Test Results**

| Model | *X-squared* | df | *P-value* |
|---|---|---|---|
| ARIMA (17,1,0) | 13.199 | 37 | 0.9999 |

Ljung- Box Test as shown in Table 2. Has P-Value 0.9999 > 0.05, it means that $H_0$ was accepted. It cas be concluded that the Farmer Exchange Rate data does not have autocorrelation between residuals. In Addition, the normality data was tested using Kolmogorov-Smirnov test and the result is displayed in Table 3.

**Table 3: Kolmogorov-Smirnov Test Results**

| Model | $D_{count}$ | *P-value* |
|---|---|---|
| ARIMA (17,1,0) | 0.18108 | 0.00001227 |

Kolmogorov-Smirnov Test gives p-value 0.00001227 < 0.05. $H_0$ was rejected. It can be conclded that the Farmer Exchange Rate data is not normally distributed. According to Rosadi (2016), the normality test is not as important as the autocorrelation and heteroscedasticity test, so even if the normality test is not met the model is still suitable for use.

**Table 4: Lagrange Multiplier Test Results**

| Model | *Chi-squared* | *P-value* |
|---|---|---|
| ARIMA (17,1,0) | 0.76897 | 1 |

Furthermore, the heteroscedasticity was tested using Lagrange Multiplier, the result was shown in Table 4. Thos test gives P-Value: 1.000 > 0.05, it means it does not does not reject $H_0$. It can be concluded that the Farmer Exchange Rate data does not have heteroscedasticity. Last the linearity of the data was evaluated using terasvirtas nonlineaity test and the result is given in Table 5.

**Table 5: Terasvirta Nonlinearity Test Results**

| Data | Terasvirta Test | |
|---|---|---|
| | *F* | *P-value* |
| Farmer Exchange Rate | 3.0781 | 0.04847 |

Terasvirta Nonlinearity Test gives p-value: 0.04847 < 0.05, therefore $H_0$ is not rejected. It can be concluded that the Farmer Exchange Rate data is nonlinear

### Model Parameter Estimation

### Logistic Smooth Transition Autoregressive (LSTAR)

After conducting a model diagnostic check, the LSTAR model parameters are estimated. To estimate the parameters with LSTAR, first plot the data with PACF to identify the order of MA model. The result of PACF plot is seen in figure 2.

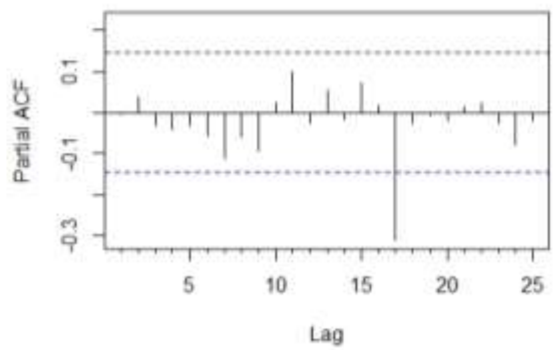


**Figure 2. Partial Autocorrelation Function (PACF) Plot**

To estimate the parameters with LSTAR, first plot the data with PACF to identify the order of MA model. The result of PACF plot is seen in figure 2.

As can be seen in Figure 2 that the PACF plot shows that the orde m is at lag 17. From this plot the LSTAR model parameter estimates are estimated using m = 17 and delay parameter = 1. The full estimation of LSTAR (17,1) model is shown in Table 6.

**Table 6: LSTAR Model Parameter Estimation (17,1)**

| Parameter | Estimation | $T_{count}$ | P-value | AIC |
|---|---|---|---|---|
| $\phi_{1,1}$ | 1.0227e+00 | 13.7744 | 2e-16 | 1045 |
| $\phi_{2,1}$ | 1.9059e-02 | 0.1797 | 0.85739 | |
| $\phi_{3,1}$ | -6.0280e-02 | -0.5708 | 0.56813 | |
| $\phi_{4,1}$ | 2.4266e-02 | 0.2312 | 0.81712 | |
| $\phi_{5,1}$ | -4.7233e-02 | -0.4926 | 0.62229 | |
| $\phi_{6,1}$ | -3.2974e-03 | -0.0395 | 0.96846 | |
| $\phi_{7,1}$ | -4.2930e-02 | -0.5158 | 0.60598 | |
| $\phi_{8,1}$ | 3.4253e-02 | 0.4149 | 0.67820 | |
| $\phi_{9,1}$ | -3.3788e-02 | -0.4105 | 0.68140 | |
| $\phi_{10,1}$ | 1.4372e-01 | 1.7507 | 0.08000 | |
| $\phi_{11,1}$ | 2.8908e-02 | 0.3495 | 0.72672 | |
| $\phi_{12,1}$ | -1.3792e-01 | -1.6673 | 0.09546 | |
| $\phi_{13,1}$ | 4.9113e-02 | 0.5890 | 0.55586 | |
| $\phi_{14,1}$ | -2.2112e-02 | -0.2652 | 0.79089 | |
| $\phi_{15,1}$ | 7.4237e-02 | 0.8940 | 0.37132 | |
| $\phi_{16,1}$ | -2.0651e-02 | -0.2514 | 0.80149 | |
| $\phi_{17,1}$ | -1.4518e-02 | -0.2478 | 0.80432 | |
| $\phi_{1,2}$ | -1.0721e+00 | -8.3844 | 2e-16 | |
| $\gamma$ | 5.0000e+01 | 0.0361 | 0.97120 | |
| $c$ | 1.5534e+02 | 84.3368 | 2e-16 | |

From Table 6. The equation of LSTAR (17.1) with an AIC value of 1045 can be written as :

$$Y_t = (1.0227X_{t-1} + 0.019059X_{t-2} - 0.060280X_{t-3} + 0.024266X_{t-4} - 0.047233X_{t-5} - 0.0032974X_{t-6} - 0.042930X_{t-7} + 0.034253X_{t-8} - 0.033788X_{t-9} + 0.14372X_{t-10} + 0.028908X_{t-11} - 0.13792X_{t-12} + 0.049113X_{t-13} - 0.022112X_{t-14} + 0.0074237X_{t-15} - 0.020651X_{t-16} - 0.014518X_{t-17})\left(1 - \left(\frac{1}{1+\exp(-50(X_{t-1}-155.34))}\right)\right) - 1.0721X_{t-1}\left(1 - \left(\frac{1}{1+\exp(-50(X_{t-1}-155.34))}\right)\right)$$

**Exponential Smooth Transition Autoregressive (ESTAR)**

Using the same PACF plot in figure 2, we get that The ESTAR model is ESTAR (17,1). The full estimation of ESTAR (17,1) model is shown in Table 7.

**Table 7: ESTAR Model Parameter Estimation (17,1)**

| Parameter | Estimation | $T_{count}$ | P-value | AIC |
|---|---|---|---|---|
| $\phi_{1,1}$ | 9.9433e-01 | 13.3850 | 2e-16 | |
| $\phi_{2,1}$ | 2.3814e-02 | 0.2276 | 0.81994 | |
| $\phi_{3,1}$ | -6.0125e-02 | -0.5773 | 0.56374 | |
| $\phi_{4,1}$ | 2.6924e-02 | 0.2601 | 0.79476 | |
| $\phi_{5,1}$ | -4.9762e-02 | -0.5262 | 0.59876 | |
| $\phi_{6,1}$ | 2.2958e-04 | 0.0028 | 0.99777 | |
| $\phi_{7,1}$ | -4.3688e-02 | -0.5322 | 0.59455 | |
| $\phi_{8,1}$ | 2.8067e-02 | 0.3445 | 0.73044 | |
| $\phi_{9,1}$ | -3.8137e-02 | -0.4697 | 0.63855 | |
| $\phi_{10,1}$ | 1.3710e-01 | 1.6923 | 0.09058 | 1044 |
| $\phi_{11,1}$ | 2.9197e-02 | 0.3579 | 0.72041 | |
| $\phi_{12,1}$ | -1.3548e-01 | -1.6605 | 0.09682 | |
| $\phi_{13,1}$ | 4.5298e-02 | 0.5507 | 0.58182 | |
| $\phi_{14,1}$ | -2.3345e-02 | -0.2838 | 0.77653 | |
| $\phi_{15,1}$ | 7.4854e-02 | 0.9140 | 0.36071 | |
| $\phi_{16,1}$ | -2.2391e-02 | -0.2764 | 0.78224 | |
| $\phi_{17,1}$ | -3.9474e-02 | -0.6709 | 0.50226 | |
| $\phi_{1,2}$ | -1.0425e+00 | -9.1012 | 2e-16 | |
| $\gamma$ | 5.0000e+01 | 0.0024 | 0.99809 | |
| $c$ | 1.5534e+02 | 1.0480 | 0.29464 | |

From Table 7. The equation of ESTAR (17.1) with an AIC value of 1044 can be written as :

$$Z_t = (0.99433X_{t-1} + 0.023814\,X_{t-2} - 0.060125X_{t-3} + 0.026924X_{t-4} - 0.049762X_{t-5} + 0.00022958X_{t-6} - 0.043688X_{t-7} + 0.028067X_{t-8} - 0.038137X_{t-9} + 0.13710X_{t-10} + 0.029197X_{t-11} - 0.13548X_{t-12} + 0.045298X_{t-13} - 0.023345X_{t-14} + 0.074854X_{t-15} - 0.022391X_{t-16} - 0.039474X_{t-17}(1 - (1 - \exp(-50(X_{t-1} - 155{,}34)^2)) - 1.0425X_{t-1}(1 - (1 - \exp(-50\,(X_{t-1} - 155{,}34)^2) + \varepsilon_t$$

From the parameter estimation results above, it can be seen that the LSTAR model has a larger AIC value compared to the ESTAR model. This means that ESTAR is a better model in predicting Farmer Exchange Rates in Lampung Province, Indonesia.

By using the best ESTAR (17,1) model, the Farmer Exchange Rate of Lampung province, Indonesia was forecasted for the next 8 months from May to December 2024. The results are presented in table 8 and figure 3

**Table 8: Forecasting Estar Farmer Exchange Rate for Lampung Province for the next 8 months**

| Month | Forecasting |
|---|---|
| May | 122.5782 |
| Juni | 127.9499 |
| July | 128.2447 |
| August | 129.5103 |
| September | 130.9720 |
| October | 131.5592 |
| November | 132.3873 |
| December | 133.6444 |

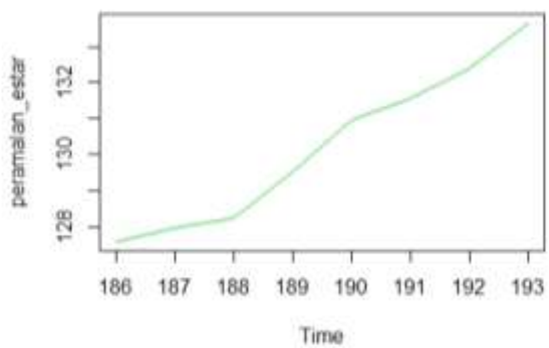


**Figure 3. Forecasting Farmer Exchange Rate Lampung Province for the next 8 months.**

From Table 8 and Figure 3 it can be seen that there is an increase in the Farmer Exchange Rate every month based on the ESTAR model. This shows that farmers income is increasing and automatically the agricultural economy in Indonesia is getting better.

## IV. CONCLUSION

From the results of the analysis of farmer exchange rate data in Lampung province, Indonesia in 2024, It can be concluded that the ESTAR model is superior to the LSTAR model in terms of balance between model suitability to data and model complexity based on smaller AIC value. The best ESTAR model is ESTAR (17,1) with an AIC value of 1044 as follows:

$$Z_t = (0.99433X_{t-1} + 0.023814\,X_{t-2} - 0.060125X_{t-3} + 0.026924X_{t-4} - 0.049762X_{t-5} + 0.00022958X_{t-6} - 0.043688X_{t-7} + 0.028067X_{t-8} - 0.038137X_{t-9} + 0.13710X_{t-10} + 0.029197X_{t-11} - 0.13548X_{t-12} + 0.045298X_{t-13} - 0.023345X_{t-14} + 0.074854X_{t-15} - 0.022391X_{t-16} - 0.039474X_{t-17}(1 - (1 - \exp(-50(X_{t-1} - 155{,}34)^2)) - 1.0425X_{t-1}(1 - (1 - \exp(-50 (X_{t-1} - 155{,}34)^2) + \varepsilon_t$$

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