Forecasting Stock Prices Using a Nonlinear Approach with the Exponential Smooth Transition Autoregressive (ESTAR) Model

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ABSTRAK

Peningkatan minat masyarakat Indonesia dalam berinvestasi pada aset keuangan tunggal telah mendorong pertumbuhan pasar modal secara signifikan. Namun, tingginya volatilitas pasar membawa risiko kerugian yang perlu diantisipasi. Salah satu model yang relevan dalam menangani permasalahan tersebut yaitu menggunakan model nonlinier *Exponential Smooth Transition Autoregressive* (ESTAR). ESTAR merupakan perluasan dari model *Autoregressive* (AR) yang menggunakan transisi lebih halus untuk menangani data deret waktu yang tidak linear. Penelitian ini bertujuan untuk memprediksi harga saham menggunakan model nonlinier ESTAR guna membantu investor menghadapi ketidakpastian pasar dan mengelola risiko jangka pendek. Data yang digunakan berupa harga penutupan harian saham PT Bank Central Asia Tbk, periode Januari 2022 hingga Desember 2024. Metodologi penelitian mencakup uji stasioneritas, estimasi parameter AR(p), estimasi parameter model ESTAR(p,d), hingga evaluasi akurasi prediksi menggunakan *Mean Absolute Percentage Error* (MAPE). Hasil penelitian menunjukkan bahwa model AR(1) merupakan model dengan orde terbaik dan model ESTAR(1,1) sebagai model akhir yang optimal. Evaluasi hasil prediksi untuk periode satu bulan ke depan, menunjukkan bahwa nilai MAPE sebesar 2,79% yang mengindikasikan performa model dalam memprediksi harga saham sangat baik.
Kata kunci: Deret waktu; ESTAR; Prediksi Saham

ABSTRACT

Increased interest among Indonesians in investing in a single financial asset has driven significant growth in the capital market. However, high market volatility brings the risk of loss that needs to be anticipated. One of the relevant models in dealing with these problems is using the nonlinear Exponential Smooth Transition Autoregressive (ESTAR) model. ESTAR is an extension of the Autoregressive (AR) model that uses smoother transitions to handle nonlinear time series data. This study aims to predict stock prices using the ESTAR nonlinear model to help investors deal with market uncertainty and manage short-term risk. The data used is the daily closing price of PT Bank Central Asia Tbk shares, for the period January 2022 to December 2024. The research methodology includes stationarity test, AR(p) parameter estimation, ESTAR(p,d) model parameter estimation, and prediction accuracy evaluation using Mean Absolute Percentage Error (MAPE). The results show that the AR(1) model is the best order model and the ESTAR(1,1) model is the final optimal model. Evaluation of the prediction results for the next one month period, shows that the MAPE value is 2.79% which indicates the model's performance in predicting stock prices is very good.
***Keywords**: Time Series; ESTAR; Stock Prediction*

INTRODUCTION

In recent years, the Indonesian stock market has often experienced significant fluctuations influenced by various economic, social and political sectors [1]. These fluctuations cause stock prices to become uncontrollable, resulting in increased stock market volatility, thus triggering an increased risk of loss to investors. Stock volatility is caused by overall uncertainty, such as the COVID-19 pandemic, unfavorable world trade activities, and changes in monetary policy [2]. Then, the phenomenon of declining purchasing power of the upper middle class is one of the reasons why stock prices will experience up and down movements every day [3]. This happens because instead of buying, people now have a tendency to save and the value of inflation is high [4].

This complex situation occurs in one of the company's shares in Indonesia, such as PT Bank Central Asia Tbk. The company is engaged in the financial services industry sector that focuses on commercial and consumer banking. BCA has a large influence in the Indonesian capital market which reflects investor confidence in national economic stability with the stock code BBCA.JK. The share price chart of PT Bank Central Asia Tbk over the past year shows a decline in April which does indicate a change in purchasing power. This volatile movement explains market conditions and can be one of the indicators that investors should pay attention to. Therefore, proper risk management is required by reducing losses and the uncertainty of stock price movements. The most important factor in making a risk management policy is to consider the stock price factor and the predicted risk of loss.

Under circumstances of stock market uncertainty, the linear approach is often unable to capture nonlinear changes. Therefore, a nonlinear approach that can capture better patterns and provide accurate predictions is needed as a solution to the problem. The data used is historical stock price data which is an important and difficult form of time series data in data science and machine learning because it requires accurate and reliable modeling for data that is very complex and changes over time [5], [6]. One of the time series models to predict stock prices is using the Threshold Autoregressive (TAR) model. Then the TAR model is generalized to get a smoother transition than Autoregressive (AR) or Smooth Transition Autoregressive (STAR). There are two types of STAR, the first is Exponential Smooth Transition Autoregressive (ESTAR) and the second is Logistic Smooth Transition Autoregressive (LSTAR) [7], [8]. Stock price data that has an up and down movement by showing a smooth non-linear pattern of change and experiencing symmetrical changes is more suitable for the ESTAR model. Meanwhile, LSTAR is more suitable for data that experience asymmetric changes.

Although many studies on stock price forecasting have been conducted, most of the existing studies use linear models, such as ARIMA, LSTM or non-linear approaches in general without utilizing the ESTAR model. Based on these problems, this study aims to forecast the stock price of PT Bank Central Asia Tbk (BBCA.JK) and fill the gap in the literature in applying nonlinear models, especially the ESTAR model. This approach is expected to make a significant contribution in helping investors face challenges in decision-making amid high market volatility.

METHOD

This study uses historical stock data on the company PT Bank Central Asia Tbk with the company code BBCA.JK. Data taken from January 2022 - December 2024 from the Investing website (www.investing.com), where the data for January 2022 - October 2024 is insample and the data for November - December 2024 is outsample. The historical stock price dataset used in this study is the closing price variable (close). In this research, Python is used to implement stock prediction using the ESTAR model. The following is a flowchart of the research to be carried out in Figure 1.

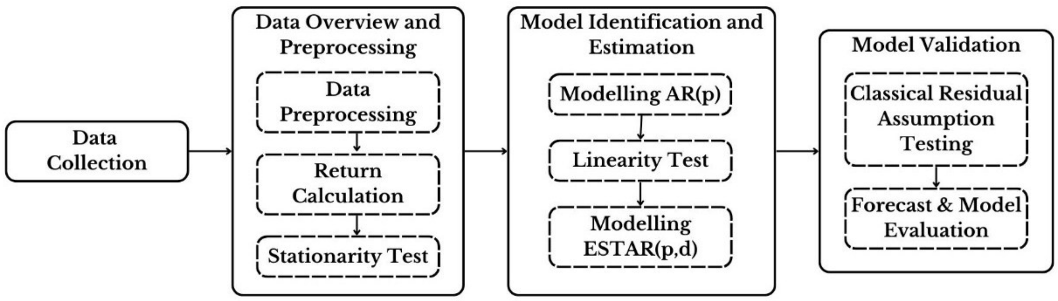

Figure 1. Flowchart of ESTAR modeling

1. Data Overview and Preprocessing

a. Data Preprocessing

Data preprocessing is an important process to improve data quality and data reliability [9]. This step has three processes, namely performing time stamp conversion, checking data type, checking missing values, checking duplicate data, and separating data as insample and outsample. After this process, it will be checked whether the time series data has stationary properties or not.

b. Return Calculation

Stock returns are defined as the returns that investors get from previous capital investments. Return can be done by calculating the natural logarithm, which is multiplied by the ratio between the price at time t and the price of the previous time period.

c. Stationarity Test

The characteristics of stationary data on variance have a lower limit and an upper limit that shows a number or $\lambda = 1$. Meanwhile, stationary data on the mean will fluctuate around the mean line which is close to 0. The purpose of the stationarity test is to fulfill the prerequisites of a time series model that has stationary properties, namely the average and variance do not change over time [10]. Augmented Dickey-Fuller (ADF) test is employed as a statistical method to formally test for the presence of unit roots [11].

2. Model Identification and Estimation

a. Model Selection and Parameter Estimation of AR(p)

Autoregressive model is a time series data regression modeling that relates the actual observation value to the previous observation value [12]. AR parameter estimates are obtained using the Least Square Method, which reduces the sum of the following residual squares:

$$\sum_{t=2}^{T} a_t^2 = SSE = \sum_{t=2}^{T} (X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p})^2 \quad (1)$$

Furthermore, to select the best model of the AR(p) order, we can use the Akaike Info Criterion (AIC) value [13]. According to Van Dijk (2000) [14], the AIC formula is as follows.

$$AIC = T \ln \hat{\sigma}_a^2 + 2k, \text{ where } \hat{\sigma}_a^2 = SSE = \sum_{t=1}^{T} \hat{a}_t^2 \qquad (2)$$

b. Linearity Test

The purpose of the LM_3 test is to detect whether or not the model is nonlinear in time series data. The linearity test can be conducted using the Lagrange Multiplier (LM) test method, specifically LM_3 [15], derived from auxiliary regression. The estimation of the auxiliary regression model is performed using Ordinary Least Squares (OLS). Testing using LM_3 is carried out as follows.

H_0: $\phi_{1,i} = \phi_{2,i}$; the model is linear.

H_1: $\phi_{1,i} \neq \phi_{2,i}$; with at least one $i \in \{1,2,...,p\}$ nonlinear model.

Test statistic:

$$LM_3 = T \frac{(SSE_0 - SSE_1)}{SSE_0} \qquad (3)$$

Description:

SSE_0 : Sum of squares of AR(p) model residuals

SSE_1 : Sum of squares of model residuals from auxiliary regression

The test rejection criterion is if H_0 is rejected with a statistical value of $LM_3 > \chi^2_{3(p+1)}$

c. ESTAR Estimation and Modeling

The ESTAR model can be estimated using the Nonlinear Least Square (NLS) method which is suitable for the nonlinear structure of the ESTAR model because it can estimate the parameters γ (smoothness) and c (threshold). This method is carried out for the process of finding parameter values using numerical methods, namely the Gauss-Newton method to iterate on the estimation. According to Terasvirta (1994) [16], writing the function on the exponential transition as follows [17].

$$G(s_t; \gamma; c) = 1 - \exp(-\gamma(s_t - c)^2), \gamma > 0 \qquad (4)$$

So the following ESTAR model is obtained.

$$X_t = \boldsymbol{\phi}_1' \boldsymbol{Z}_t\left(1 - (1 - \exp(-\gamma(s_t - c)^2))\right) + \boldsymbol{\phi}_2' \boldsymbol{Z}_t(1 - \exp(-\gamma(s_t - c)^2)) + \varepsilon_t \qquad (5)$$

3. Model Validation

a. Classical Residual Assumption Testing

In the classical assumption testing of residuals, there are three types of tests that need to be conducted to ensure the validity of the model. First, the autocorrelation assumption test is carried out to determine whether the model exhibits a correlation between a period t and the previous period (t-1) [18], [19]. Second, the heteroscedasticity assumption test is performed to assess whether the regression model between observations shows differences in variances and residuals [20]. Third, the normality assumption test is conducted to evaluate whether the residual values in the model are normally distributed [21], [22].

b. Forecast and Model Evaluation

Stock price prediction involves forecasting future stock values using historical data and appropriate modeling techniques such as time series analysis or machine learning algorithms. To evaluate the performance of the prediction models, the Mean Absolute Percentage Error (MAPE) is utilized, providing a measure of the average deviation between the predicted and actual stock prices in percentage terms [23], [24], [25], [26].

RESULT AND DISCUSSION

Data Preprocessing

The following figure presents a graphical representation of the price trajectory of BBCA.JK shares.

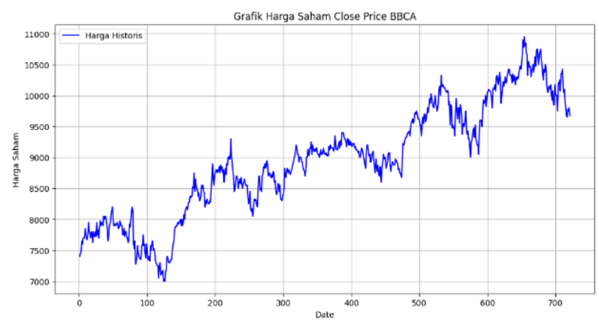

Figure 2. Close price plot line BBCA.JK

Figure 2 shows a plot line visualization of BBCA.JK stock closing price data. The figure shows the movement of the closing share price for the period January 2022 - December 2024. The smallest share price is 7000, the highest share price is 10950 and the average share price is 8954.29. In this process, check the date data type to datetime64[ns]. Then, after checking the data, the results do not occur missing values and duplicate data. Then, separating data in the January 2022 - October 2024 range as insample data and data in the November - December 2024 range as outsample data.

Return

In the picture below is the movement of BBCA.JK stock price returns.

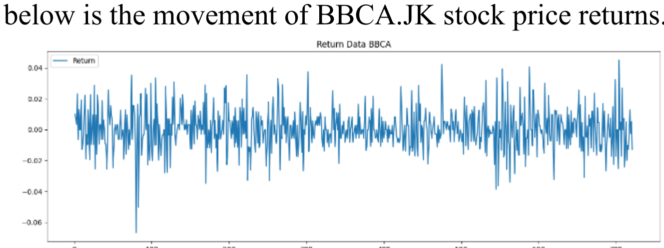

Figure 3. BBCA.JK stock return chart

Figure 3 shows that the return value of BBCA.JK shares has a stationary condition which can then be tested using the ADF test.

Stationarity Test

The results of stationarity testing using the ADF test at the 5% significance level can be seen in the following table.

Table 1. Stasionerity Test with ADF

ADF-statistic	p-value	Critical value
-21.7301	0.00	-2.865568

Based on the table, it can be concluded that the ADF statistic value is smaller than the critical values and the ADF test p-value is smaller than $\alpha = 0.05$, which means that it succeeds in rejecting H_0, namely the data does not have unit roots or stationary data.

Estimating and Testing AR (p) Model Parameters

The process of building an ARIMA model is done from the previous return data. Then the visualization of ACF and PACF is done to determine the order (lag) of the optimal AR model by eliminating the influence of the lag between previous values, as follows.

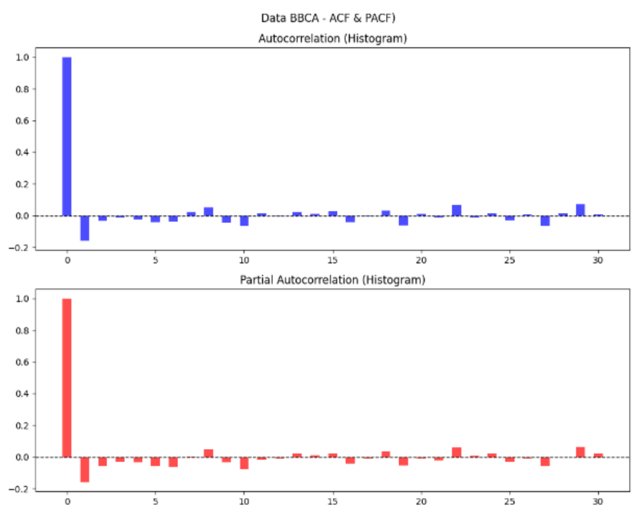

Figure 4. ACF and PACF plots

Then to build an AR model using the library from statsmodels.tsa.arima.model import ARIMA and identify the best AR(p) model with the AIC method. The result is that the AR(1) model is the best model. Furthermore, estimation of the model is carried out using the OLS method.

Table 2. AR(1) Model parameter identification and estimation

AR Model	AIC	Significant Test
(1,0)	**-3995.362**	Yes
(2,0)	-3994.998	No
(3,0)	-3993.991	No
⋮	⋮	⋮

Based on this table, the transition variable used in the STAR model is obtained from the AR(1) model with an AIC value of -3995.362 and a p-value that is less than $\alpha = 0.05$.

Linearity Test

Furthermore, linearity testing is carried out to determine whether the model requires a linear or nonlinear model using the LM_3 test with auxiliary regression. The estimation of the auxiliary regression model is done using OLS. The following are the estimation results of the auxiliary regression model with the transition variable $s_t = X_{t-1}$.

Table 3. Auxiliary regression model estimation with transition variable

Parameter	Coefficient	t-value	Probability
Intercept	0.0001	10.482	0.000
$\boldsymbol{\beta_{1,1}}$	-0.0022	-1.730	0.084
$\boldsymbol{\beta_{2,1}}$	0.1233	2.964	0.003
$\boldsymbol{\beta_{3,1}}$	2.2336	1.965	0.050

The following is the LM_3 test table with a significance level of 5%

Table 4. LM_3 test result

LM-statistic	p-value	Critical value (Chi-Square)
680.596	0.0000	12.591

Based on these results, it can be obtained that the LM-statistic value is greater than the critical value and which means that it succeeds in rejecting H_0 so that the model is nonlinear.

ESTAR Estimation and Modeling

The best model estimation result is AR(1) so that the following form is obtained.

$$Y_t = -0.1582 Y_{t-1} + e_t$$

After knowing the order used is 1, to determine the delay value for the ESTAR model using AIC and obtained the best delay is d = 1. ESTAR (1,1) using the Nonlinear Least Square method is as follows.

Table 5. Parameter estimation of ESTAR(1,1) model

Parameter	Coefficient	t-value	Probability
$\boldsymbol{\varphi_{1,0}}$	-0.000930	-0.013671	0.989097
$\boldsymbol{\varphi_{1,1}}$	-0.114007	-0.028132	0.977565
$\boldsymbol{\varphi_{2,0}}$	0.915124	0.083459	0.933511
$\boldsymbol{\varphi_{2,1}}$	17.929593	0.085525	0.931870
$\boldsymbol{\gamma}$	6.525581	0.091928	0.926783
$\boldsymbol{c}$	0.013083	0.036304	0.971051

So that the ESTAR(1,1) model obtained is as follows:

$$\mathrm{X_t} = (-0.000930 - 0.114007\mathrm{X_{t-1}})\big(1-(1-\exp(6.525581(X_{t-1}-(0.013083))^2))\big) + (0.915124 + 3.064531\mathrm{X_{t-1}})(1-\exp(6.525581(X_{t-1}-(0.013083))^2)) + \varepsilon_t$$

Classical Residual Assumption Test

1. Autocorrelation Assumption Test

Testing autocorrelation in this study uses the Ljung Box-Pierce test. The following are the test results:

Table 6. Residual autocorrelation test results

Lag	Q-Stats	p-value
1	0.018032	0.893179
2	3.240676	0.197832
⋮	⋮	⋮
19	21.561696	0.306610
20	21.566417	0.364494

The test uses a significance level of 5% and shows that at the 1st to 20th lag there is no significant autocorrelation in the model.

2. Heteroscedastisity Assumption Test

In testing heteroscedasticity using the Lagrange Multiplier test where the results show that using a significance level of 5%, the LM value = 2.7457 and p-value = 1.0000 which is more than the $\alpha = 0.05$ value so that the residual data model is homogeneous or there is no heteroscedasticity and there is no ARCH effect in the residuals.

3. Normality Assumption Test

Next, conduct a normality test using the Kolmogorov-Smirnov test. Based on this test using a 5% significance level, the results obtained are the statistical value of $D = 0.0431$ and the p-value = 0.1549 where the p-value is more than $\alpha = 0.05$. This means that the residual data of the ESTAR(1,1) model is proven to be normally distributed.

Stock Price Prediction and MAPE Calculation

The ESTAR (1,1) model used is as follows:

$$\mathrm{X_t} = (-0.000930 - 0.114007\mathrm{X_{t-1}})\big(1-(1-\exp(6.525581(X_{t-1}-(0.013083))^2))\big) + (0.915124 + 3.064531\mathrm{X_{t-1}})(1-\exp(6.525581(X_{t-1}-(0.013083))^2)) + \varepsilon_t$$

The prediction results of the daily stock price of PT Bank Central Asia Tbk for the next four months are as follows.

Table 7. Comparison of stock price prediction results with original data

Date	Data Original	Data Prediction
01/11/2024	10425	10290.33
04/11/2024	10375	10281.69
⋮	⋮	⋮
30/12/2024	9800	10311.11

31/12/2024	9675	10311.88

In the prediction results of the model, further prediction evaluation is carried out using Mean Absolute Percentage Error (MAPE). The MAPE value shows a fairly small result of 2.79% in the model so that the model can be very good at predicting. Based on the prediction results, the ESTAR(1,1) model produces a relatively constant and small BBCA stock return prediction. This shows that the model is able to capture the gradual nonlinear transition characteristics in accordance with the basic characteristics of the model that accommodates nonlinear transitions smoothly between regimes. So that the model provides an indication that in the final period of 2024, the BBCA.JK stock market tends to experience volatility that is not extreme and is in a relatively stable adjustment phase. This situation reflects the attitude of investors who are still cautious in making decisions because the economic conditions after the pandemic have not fully stabilized.

CONCLUSION

This research successfully developed a stock price prediction model using the ESTAR approach to overcome the complexity of financial time series data. By applying the ESTAR model, this study achieved a MAPE of 2.79%, which indicates a high level of accuracy in forecasting stock price movements. This finding emphasizes the effectiveness of incorporating nonlinear dynamics in financial forecasting, which allows for better alignment between forecasted prices and actual market behaviour. However, the model has an important limitation in that it does not account for external economic shocks or the influence of global financial indicators, both of which can have a significant impact on stock prices. As a result, its predictive performance is limited under highly dynamic market conditions. To improve its robustness, future research could integrate the ESTAR model with hybrid approaches, such as artificial neural networks (ANN), to improve its adaptability to complex and nonlinear patterns. In addition, exploring multi-asset forecasting could expand the applicability of this model in the broader context of portfolio analysis.

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