
Zero: Journal of Science, Mathematics, and Applied
E-ISSN: 2580-5754
P-ISSN: 2580-569X
Vol. 7, No. 1, Juni 2023
pp. 33-42

Application of Hybrid LSTAR-GARCH Model with Expected Taill Loss in Predicting the Price Movement of Bitcoin Cryptocurrency against Rupiah Currency

Yanna Rezki Fadillah[1] , Rina Widyasari[2] ,
[1,2]Department of Mathematics, Universitas Islam Negeri Sumatera Utara, Medan, Indonesia

Article Info

Article history:

Keywords:

Forecasting, Time series, Bitcoin, LSTAR, GARCH, Expected Taill Loss

ABSTRACT

Time series data from bitcoin has nonlinear data fluctuations so that a model is needed that can accommodate data with these conditions. The method that can be used for nonlinear time series data cases such as bitcoin is the LSTAR-GARCH model. LSTAR-GARCH is a combination of the LSTAR model and the GARCH model. Bitcoin investment also contains an element of risk. To find out the value of risk, the *Expected Tail Loss* risk measurement tool can be used. *Expected Tail Loss* (ETL). The data used in this study are historical daily bitcoin price data for the period April 1, 2022 to April 1, 2023. The modeling results obtained based on the MAPE value show that the LSTAR-GARCH model is the best model with the smallest MAPE value of 30% compared to the AR, LSTAR, or AR-GARCH models. The expected Taill loss value of bitcoin is -0.06784.

Corresponding Author:

Yanna Rezki Fadillah,
Department of Mathematics,
Universitas Islam Negeri Sumatera Utara, Medan, Indonesia
Email: yanna0703191063@uinsu.ac.id

1. INTRODUCTION

Cryptocurrencies garnered global attention toward the close of 2017, primarily due to Bitcoin being one of the digital currencies with an exchange rate exceeding 250 million Indonesia rupiahs for asingle unit. Bitcoin, cherished by many, stands as the foremost and most popular cryptocurrency globally, particularly resonating with the millennial generation. Shaid and Idris(2022) expond that Bitcoin, launched in January 2009, operates as a decentralized digital currenxy. The focal point of their research lies in the predicament of price volality, which undergoes daily fluctuations. Thus, the necessity for a mathematical model to prognosticate the future value of the Bitcoin cryptocurrency evident.

As time goes by, the development of technology and science continues to advance. The same applies to the field of learning *time series* data. The most commonly used time series model is the Box-Jenkins method. The model generated by the Box-Jenkins method is a linear model, but not all financial time series are liner (Tsay, 2005). Smooth Transition Autoregressive (STAR) is an extension of the autoregressive model for nonlinear time series data. According to Terasvirta (1994), STAR models include exponential STAR (ESTAR) and logistic STAR (LSTAR) models. In this case, the LSTAR method is used. The *Logistic Smoothing Transition Autoregressive* (LSTAR) model is a time series model that can be applied to data that follows a nonlinear model. Nonlinear time series models can be found in data that has fluctuations. The GARCH model is an improvement of the ARCH model where the volatility depends on yesterday's daily value along with the previous volatility value.

Besides being able to provide benefits, bitcoin investment also contains an element of risk. To find out the value of risk, the *Expected Tail Loss* (ETL) risk measurement tool or often also called *Conditional Value at Risk* (CVaR) can be used. ETL is the average of *tail losses* or *losses* that exceed VaR at a certain confidence level.

2. RESEARCH METHOD

This research uses the type of applied research, because it uses data based on historical data. The form of data used in this research is in the form of time series which is secondary data, where the author accesses bitcoin price data online through Yahoo Finance https://finance.yahoo.com. The data taken in this study is daily bitcoin price data in the period April 1, 2022 to April 1, 2023. The variables used in this study are bitcoin close price, bitcoin price return, and bitcoin volume. The stages in the data analysis process in this study include:

1. Data description
2. Stationary test with the results of the \unitroot test as well as the results of the ACF and PACF test
3. Testing the best AR model on bitcoin closing price data
4. Modeling with LSTAR
   In this LSTAR modeling, a nonlinearity test is carried out with a white test, and a transition test is also carried out to determine whether the transition function is correct.
5. Model parameter estimation
6. Modeling with Hybrid LSTAR-GARCH
7. Forecasting with Hybrid LSTAR-GARCH
   Forecasting bitcoin closing price data with the LSTAR-GARCH hybrid method.
8. Calculating the MSE value using variance forecasting and actual data
9. Estimating and calculating the Expected Taill Loss value of predicted bitcoin closing price returns
10. Interpretation of Expected Taill Loss value

3. RESULT AND ANALYSIS

1. Data Description

A graph of daily bitcoin closing price data for the period April 2022 to April 2023 can be seen in Figure 1.

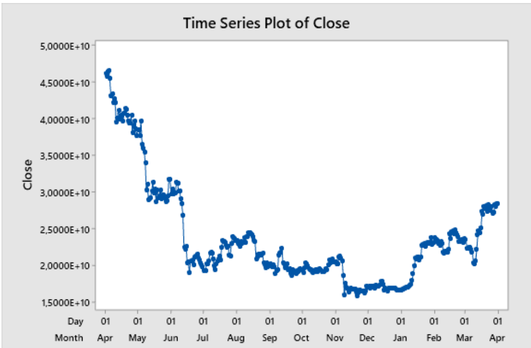

Figure 1 Plot of Bitcoin Closing Price Data

Figure 1 shows that the closing price of bitcoin is volatile over time. At some point, the closing price of bitcoin decreases and then increases again. This can be caused by price fluctuations.

2. Stationarity Testing

Data stationarity was tested using the Augmented Dickey Fuller (ADF) test.

Table 1 Uji ADF Test

Unit Root Test	t-statistic	Probability
Augmented Dickey Fuller Test	-1.7794	0.67

From table 1, it can be seen that the ADF test statistic value is -1.7794 with a p-value of 0.67>. α (0,05) which means accepting H_0 that there is a unit root or the data is not stationary. Because the data is not stationary, the data needs to be converted in the form of returns. The return plot data can be seen in Figure 3.2 below.

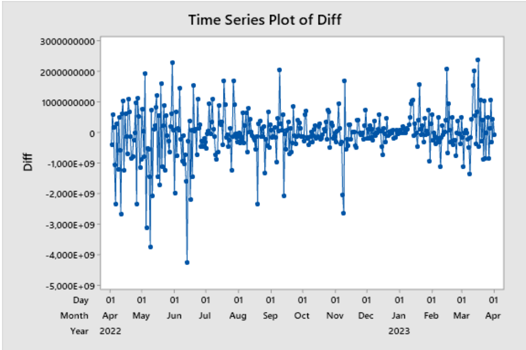

Figure 2 Plot of Bitcoin Price Return

Figure 2 shows that the data is stationary in terms of mean and variance. To ensure this, the Augmented Dickey Fuller (ADF) test will be conducted.

Table 2 Uji ADF Test

Unit Root Test	t-statistic	Probability
Augmented Dickey Fuller Test	-7.7699	0.001

From table 2, it can be seen that the ADF test statistic value is -7.7699 with a p-value of 0.001 <0.001, which means rejecting H , namely there is no unit root or stationary data. α (0,05) which means rejecting H_0 that there is no unit root or stationary data.

3. Model Identification

After the stationary assumption is met, a temporary model will be formed by looking at the ACF and PACF plots.

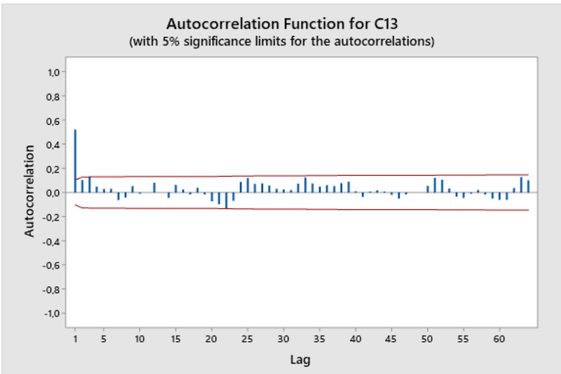

Figure 3 ACF plot of differencing data (d=1) Bitcoin price

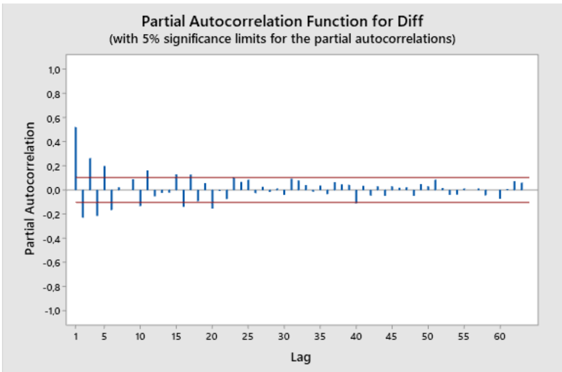

Figure 4 PACF plot of differencing data (d=1) Bitcoin price

Figure 3 above shows that the ACF plot *cuts off* at lag 1. While in Figure 4 shows that the PACF plot *cuts off* at lags 1, 2, 3, 4, and 5. So it can be estimated that the model parameter estimates are AR (1), MA (1), ARMA (1,1), ARMA (2,1).

4. AR Model Parameter Estimation and Testing

Furthermore, the ARMA model parameters are estimated using the *Least Square* method. The model parameter estimation results can be seen in table 3 below.

Table 3 Parameter Estimation of ARMA Model

Model		Coefficient	t-Statistic	Probability	Description	AIC
AR(1)	ϕ_1	-0.548413	-16.86301	0.0000	Significant	16.59391
AR(2)	ϕ_2	0.039085	0.937531	0.3491	Not Significant	16.95040
MA(1)	θ_1	-0.983344	-66.59147	0.0000	Significant	**16.23158**
ARMA	ϕ_1	-0.053309	-1.299214	0.1947	Not Significant	16.23401
(1,1)	θ_1	-0.981920	-64.72936	0.0000		
ARMA	ϕ_2	0.052386	1.111204	0.2672	Not Significant	16.23439
(2,1)	θ_1	-0.984589	-67.04732	0.0000		

Based on table 3, the parameters of the AR(1), MA(1) models are significant because they have a probability less than that of the AR(2), ARIMA(1,1), and ARMA(2,1) models. $\alpha = 0,05$. While AR(2), ARIMA(1,1), and ARMA(2,1) are not significant because they have a probability of more than $\alpha = 0,05$.

5. Best Model Selection

To determine the best model, it can be seen from the significant parameters that meet the statistical model test and have the smallest AIC, the smaller the AIC value the better the model. Based on Table 3 the MA (1) model is the best model because the model parameters are significant, fulfill the diagnostic model test and have the smallest AIC value of 16.23158. So the MA(1) model is written as

$$Y_t = -0.983344Y_{t-1} + e_t$$

6. Statistical Test

Before modeling LSTAR-GARCH, it is necessary to conduct an ARCH statistical test with the null hypothesis stating that there is no residual autocorrelation in the model.₀ is rejected if $p\ value < taraf\ signifikan$ 5% $atau\ \alpha = 0,05$

Table 4 Breusch-Godfrey *Statistical Test*

Breusch-Godfrey Autocorrelation Test			
F-statistic	0.831799	Prob.(1,362)	0.3624
Obs*R-squared	0.846098	Prob. Chi Square	**0.3577**

Based on the results of the *Breusch-Godfrey* statistical test, the result with a p value of 0.3577 is greater than the significant level of α = 0.05. This means H_0 accepted.

7. Linearity Test

To prove statistically, nonlinearity testing is carried out with the *White Test* method to see how the time series data pattern is formed

Table 5 White Test

White Test			
F-statistic	3.517018	Prob. F(7, 357)	0.0012
Obs*R-squared	23.54699	Prob. Chi-Square(7)	**0.0014**
SESS	74.71257	Prob. Chi-Square(7)	0.0000

Based on the results obtained, the p-value is 0.0014 which means less than $\alpha = 0,05$ so that bitcoin price data has a nonlinear pattern.

8. *Selection of Transition Variables and Transition Functions of STAR Model*

After proving nonlinear, the next step is the selection of the form of the transition function. The selection of the transition function is done by testing the hypothesized sequence of parameters β as follows.

H_{03} : $\beta_3 = 0$
H_{02} : $\beta_2 = 0 | \beta_3 = 0$
H_{01} : $\beta_1 = 0 | \beta_3 = \beta_2 = 0$
with conditions:

1. If $\beta_2 \neq 0$ then the model used is the LSTAR model
2. If $\beta_3 = 0$ but $\beta_2 \neq 0$ then the ESTAR model
3. If $\beta_3 = 0$ and $\beta_2 = 0$ but : $\beta_1 \neq 0$ then the model is LSTAR and if $\beta_1 = 0$ then the model is ESTAR.

Table 6 Regression of Transition Variables Y_{t-1}

Parameters	Estimate	P-value
β_1	0.0755496	0.009119
β_2	0.9862862	<2.2e-16
β_3	-0.0037543	0.942472

Table 6 shows that the parameters β_2 is not significantly not equal to zero because it has a p-value (<2.2e-16). So the transition function that should be chosen is the LSTAR function.

9. *LSTAR Model*

The estimation results of the LSTAR(1,1) model using the *Nonlinear Least Square* (NLS) method are approximated by the *Gauss-Newton* iteration as follows.

Table 7 LSTAR(1,1) Model Estimation Result

	Estimate	Std.Error	t Value	Pr(>|z|)
Const. L	0.066762	0.054405	1.2271	0.21977
phiL.1	1.045669	0.058970	17.7231	<2e-16
phiL.2	-0.061077	0.059354	-1.0290	0.30346
Const.H	-0.167696	0.194759	-0.8610	0.38921
phiH.1	-0.385095	0.169660	-2.2698	0.02322
phiH.2	0.421138	0.182329	2.3098	0.02090
gamma	100	90.47	1.1053	0.26905
Th	4.477584	0.012315	363.5811	<.2e-16

Based on table 7 the LSTAR (1,1) model formed is:

$$Y_t = Y_{t-1} + (0.066762 + 1.045669 - 0.061077X_{t-1})\left(1 - \left(\frac{1}{1 + \exp\left(-(Y_{t-1} - 4.477584\right)}\right)\right) + (-0.167696 - 0.385095 + 0.421138X_{t-1})\left(1 - \left(\frac{1}{1 + \exp\left(-Y_{t-1} - 4.477584\right)}\right)\right) + a_1$$

Furthermore, the Residual Autocorrelation and Heteroscedasticity tests of the LSTAR model are conducted.

Table 8 Breusch-Godfrey Test

Breusch-Godfrey Test			
F-statistics	0.831799	Prob.(1,358)	0.3624
Obs*R-squared	0.846098	Prob. Chi Square	**0.3577**

The test criterion is to reject H_0 if the p-value is smaller than $\alpha = 0{,}05$. Table 8 shows that the *p-value of* 0.3577 > α (0,05) so that H_0 is accepted or it can be said that there is no autocorrelation in the residual model.

Table 9 ARCH-LM Test

ARCH-LM Test			
F-statistics	9.223651	Prob.(1,362)	0.0026
Obs*R-squared	9.044167	Prob. Chi Square(1)	0.0026

The test criterion is to reject H_0 if the p-value <0.05. α (0,05). In Table 9, the chi-square p-value is 0.0026 < . α (0,05) so H_0 is rejected or it can be said that there is a heteroscedasticity effect in the LSTAR model.

10. Modeling with LSTAR-GARCH

The identification of the LSTAR-GARCH model is done by looking at the ACF and PACF *correlograms* of the squared residuals of the LSTAR model. The ACF and PACF *correlogram* results are seen in Figure 3.5 below.

Date: 08/13/23 Time: 10:08
Sample (adjusted): 4/02/2022 4/01/2023
Included observations: 365 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.158	0.158	9.1372	0.003
		2	0.013	-0.012	9.1987	0.010
		3	0.103	0.106	13.152	0.004
		4	0.084	0.053	15.751	0.003
		5	0.104	0.088	19.797	0.001
		6	0.068	0.032	21.529	0.001
		7	0.084	0.063	24.191	0.001
		8	0.020	-0.023	24.336	0.002
		9	0.012	-0.005	24.387	0.004
		10	0.038	0.010	24.933	0.005
		11	-0.017	-0.043	25.047	0.009
		12	0.016	0.011	25.139	0.014
		13	0.042	0.028	25.806	0.018
		14	0.133	0.129	32.525	0.003
		15	0.003	-0.037	32.529	0.005
		16	-0.007	0.002	32.548	0.008
		17	-0.001	-0.032	32.548	0.013
		18	-0.020	-0.030	32.707	0.018
		19	-0.038	-0.060	33.262	0.022
		20	0.009	0.013	33.290	0.031
		21	0.099	0.095	37.117	0.016
		22	0.012	0.002	37.171	0.023
		23	0.023	0.043	37.376	0.030
		24	0.022	0.003	37.566	0.038

Figure 5 *Correlogram of* ACF and PACF

The ACF *correlogram of* squared residuals shows that the *cut off is* at lag 1. Similarly, the PACF *correlogram of* squared residuals *cuts off* at lag 1. So the temporary conjecture based on the results of the ACF and PACF correlograms is the GARCH (0,1), GARCH (1,0), GARCH (1,1) model. In general, the LSTAR-GARCH model is in the form:

$$Y_t = X_t'b + \varepsilon_t$$
$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

with $X_t'b$ is the LSTAR model

a. GARCH (0,1) Model Estimation:

Table 10 Parameter Estimation of GARCH(0,1) Model Estimates

Parameters	Coefficient	Std.Error	z-Statistics	Prob.
ω	977882.8	1982466	0.493266	0.6218
β_1	-0.569888	3.181222	-0.179141	0.8578

The LSTAR-GARCH model obtained is:

$$Y_t = X_t'b + \varepsilon_t$$
$$\sigma_t^2 = 97788. - 0.569888\sigma_{t-1}^2$$

with $X_t'b$ as the LSTAR model

The p-value $\omega = 0.6218$ and $\beta_1 = 0.8578 > \alpha = 0{,}05$ so it can be said that the model parameters are not significant.

b. GARCH (1,0) Model Estimation

Table 11 Parameter Estimation of GARCH (1,0) Model Estimates

Parameters	Coefficient	Std. Error	z-Statistics	Prob.

ω	343903.5	23347.07	214.3505	0.0000
α_1	0.650699	0.101036	1.615504	0.0000

The LSTAR-GARCH model obtained is:

$$Y_t = X_t'b + \varepsilon_t$$
$$\sigma_t^2 = 343903.5 + 0.650699\varepsilon_{t-1}^2$$

with $X_t'b$ as the LSTAR model.

The p-value of each parameter = 0.0000 <0.0000. $\alpha = 0{,}05$ so it can be said that the model is significant.

c. GARCH (1,1) model estimation

Table 12 Parameter Estimation of GARCH (1,1) Model Estimates

Parameters	Coefficient	Std.Error	z-Statistics	Prob.
ω	29612.84	9167.844	3.230077	0.0012
α_1	0.224412	0.043173	5.197972	0.0000
β_1	0.762287	0.042087	18.11204	0.0000

The LSTAR model obtained is:

$$Y_t = X_t'b + \varepsilon_t$$
$$\sigma_t^2 = 29612.84 + 0.224412\varepsilon_{t-1}^2 + 0.762287\sigma_{t-1}^2$$

with $X_t'b$ as the LSTAR model

The p-value of each parameter = 0.0000 <0.0000. $\alpha = 0{,}05$ so it can be said that the model is significant.

Next, the *overfitting* stage is carried out to compare several parameters that have been estimated by paying attention to significant parameter values and having the smallest AIC and SIC values.

Table 13 GARCH Model Overfitting Results

Model	Description	AIC	SC
GARCH(0,1)	Not Significant	16.20378	16.24652
GARCH(4,0)	Significant	16.07404	16.11677
GARCH(1,1)	Significant	**16.00905**	**16.06247**

Table 3.12 shows that the GARCH (1,1) model is the best model with the smallest AIC value of 16.0095 and SC of 16.06247. The best LSTAR model obtained is:

$$Y_t = Y_{t-1} + (0.066762 + 1.045669 - 0.061077X_{t-1})\left(1 - \left(\frac{1}{1 + \exp\left(-(Y_{t-1} - 4.477584\right)}\right)\right) + (-0.167696 - 0.385095 + 0.421138X_{t-1})\left(1 - \left(\frac{1}{1 + \exp\left(-Y_{t-1} - 4.477584\right)}\right)\right) + a_1$$

$$\sigma_t^2 = 29612.84 + 0.224412\varepsilon_{t-1}^2 + 0.762287\sigma_{t-1}^2$$

11. Diagnostic Check of LSTAR-GARCH Model

Diagnostic checks to determine the presence or absence of heteroscedasticity effects are carried out by looking at the squared residual pattern from the *correlogram. The correlogram* value of the squared residuals of the LSTAR-GARCH Model can be seen in the appendix. The *correlogram* is detected until the 35th lag. The ACF and PACF *p-values of the* squared residuals of the LSTAR-GARCH model until the 35th lag are in the interval 0.677 to 0.241. This shows that all the ACF and PACF *p-values of the* squared residuals of the LSTAR-GARCH model > 0.677 to 0.241. α $(0{,}05)$ so it can be concluded that the model no longer contains the effect of heteroscedasticity.

12. Forecasting the LSTAR-GARCH model

The LSTAR-GARCH model obtained is:

$$Y_t = Y_{t-1} + (0.066762 + 1.045669 - 0.061077X_{t-1})\left(1 - \left(\frac{1}{1 + \exp\left(-(Y_{t-1} - 4.477584\right)}\right)\right) + (-0.167696 - 0.385095 + 0.421138X_{t-1})\left(1 - \left(\frac{1}{1 + \exp\left(-Y_{t-1} - 4.477584\right)}\right)\right) + a_1$$

$$\sigma_t^2 = 29612.84 + 0.224412\varepsilon_{t-1}^2 + 0.762287\sigma_{t-1}^2$$

The next period forecast calculation, which is the forecast for the next 15 days, is presented in the following table.

Table 14 Forecasting results of the LSTAR-GARCH model for the period April 2-16, 2023

Date	Forecasting	Average point spread
02-04-2023	44.509.55	38,177
03-04-2023	44.484.70	38,512
04-04-2023	44.461.26	38,520
05-04-2023	44.439.05	38,528
06-04-2023	44.417.87	38,536
07-04-2023	44.397.56	38,543
08-04-2023	44.378.01	38,553
09-04-2023	44.359.11	38,552
10-04-2023	44.340.79	38,559
11-04-2023	44.323.00	38,567
12-04-2023	44.305.68	38,576
13-04-2023	44.288.80	38,584
14-04-2023	44.272.32	38,592
15-04-2023	44.256.21	38,600
16-04-2023	44.225.03	38,616

The measure of the accuracy of the forecasting value is seen from the *Mean Absolute Percentage Error* (MAPE). MAPE describes the average residual of the forecasting results with the actual value. The smaller the MAPE value, the better the model obtained. The MAPE value for each model is presented in table 13 below.

Table 15 Mean Absolute Percentage Error of each model

Model	MAPE
AR	57%
LSTAR	40%
AR-GARCH	72%
LSTAR-GARCH	**30%**

13. Interpretation of Expected Taill Loss (ETL) Value

In the calculation of ETL, Cornish-Fisher expansion is used. The level of confidence used to calculate ETL is 99% with a return of 366 transaction days. The calculation results can be seen in the following table.

Table 16 ETL Calculation Result

Expected Return	0,000373108
Standard Deviation	0,033019304
Average	-0,06784
$CVaR_{1\%}$	-0,06784
$CVaR_{5\%}$	-0,0998

From table 16 above, the Expected Taill Loss (CVaR) value is -0.06784, which means that if an investment of Rp. 100,000,000 is made with a 95% confidence level, the maximum loss that can occur borne by investors is Rp. 99,999.99 in a predicted time of one day.

4. CONCLUSIOON

From this research, the following conclusions were drawn:

1. The most appropriate LSTAR model to model the price of bitcoin against the rupiah is:

$$Y_t = Y_{t-1} + (0.066762 + 1.045669 - 0.061077X_{t-1})\left(1 - \left(\frac{1}{1 + \exp\left(-(Y_{t-1} - 4.477584\right)}\right)\right) + (-0.167696 - 0.385095 + 0.421138X_{t-1})\left(1 - \left(\frac{1}{1 + \exp\left(-Y_{t-1} - 4.477584\right)}\right)\right) + a_1$$

2. The most appropriate GARCH model to model the price of bitcoin against the rupiah is:
$$\sigma_t^2 = 29612.84 + 0.224412\varepsilon_{t-1}^2 + 0.762287\sigma_{t-1}^2$$
3. Forecasting based on the LSTAR-GARCH model shows that the price of bitcoin has increased. The MAPE value of the LSTAR-GARCH model has a small value which indicates that this model is the best model to use compared to the AR, LSTAR, or AR-GARCH models.
4. Based on the application of Expected Taill Loss in the LSTAR-GARCH model to determine the level of risk using bitcoin closing return data. It can be concluded that bitcoin has a high expected loss of 7%.

REFERENCES

[1] F. Chana, D. Marinovab, and M. Mcaleera, "STAR-GARCH Models of Ecological Patents in the USA," pp. 526–531, 1997.

[2] M. A. Maliki, I. Cholissodin, and N. Yudistira, "Prediksi Pergerakan Harga Cryptocurrency Bitcoin terhadap Mata Uang Rupiah menggunakan Algoritme LSTM," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 6, no. 7, pp. 3259–3268, 2022.

[3] G. Kresnawati, B. Warsito, and A. Hoyyi, "Peramalan Indeks Harga Saham Gabungan Dengan Metode Logistic Smooth Transition Autoregressive (Lstar)," *J. Gaussian*, vol. 7, no. 1, pp. 84–95, 2018, doi: 10.14710/j.gauss.v7i1.26638.

[4] A. H. A. Zili, Derick Hendri, and S. A. A. Kharis, "Peramalan Harga Saham Dengan Model Hybrid Arima-Garch dan Metode Walk Forward," *J. Stat. dan Apl.*, vol. 6, no. 2, pp. 341–354, 2022, doi: 10.21009/jsa.06218.

[5] M. Odelia, D. A. I. Maruddani, and H. Yasin, "PERAMALAN HARGA SAHAM DENGAN METODE LOGISTIC SMOOTH TRANSITION AUTOREGRESSIVE (LSTAR) (Studi Kasus pada Harga Saham Mingguan PT. Bank Mandiri Tbk Periode 03 Januari 2011 sampai 24 Desember 2018)," *J. Gaussian*, vol. 9, no. 4, pp. 391–401, 2020, doi: 10.14710/j.gauss.v9i4.29403.

[6] U. Azmi and W. H. Syaifudin, "Peramalan Harga Komoditas Dengan Menggunakan Metode Arima-Garch," *J. Varian*, vol. 3, no. 2, pp. 113–124, 2020, doi: 10.30812/varian.v3i2.653.

[7] N. Salwa, N. Tatsara, R. Amalia, and A. F. Zohra, "Peramalan Harga Bitcoin Menggunakan Metode ARIMA (Autoregressive Integrated Moving Average)," *J. Data Anal.*, vol. 1, no. 1, pp. 21–31, 2018, doi: 10.24815/jda.v1i1.11874.

[8] I. G. M. H. PRATAMA, I. W. SUMARJAYA, and N. L. P. SUCIPTAWATI, "Peramalan Harga Bitcoin Dengan Metode Smooth Transition Autoregressive (Star)," *E-Jurnal Mat.*, vol. 11, no. 2, p. 100, 2022, doi: 10.24843/mtk.2022.v11.i02.p367.

[9] N. B. Yolanda, N. Nainggolan, and H. A. H. Komalig, "Penerapan Model ARIMA-GARCH Untuk Memprediksi Harga Saham Bank BRI," *J. MIPA*, vol. 6, no. 2, p. 92, 2017, doi: 10.35799/jm.6.2.2017.17817.

[10] N. F. F. Rizani, M. Mustafid, and S. Suparti, "Penerapan Metodeexpected Shortfallpada Pengukuran Risiko Investasi Saham Dengan Volatilitas Model Garch," *J. Gaussian*, vol. 8, no. 1, pp. 184–193, 2019, doi: 10.14710/j.gauss.v8i1.26644.

[11] D. M. H. Ilmawan, B. Warsito, and S. Sugito, "Penerapan Artificial Neural Network Dengan Optimasi Modified Artificial Bee Colony Untuk Meramalkan Harga Bitcoin Terhadap Rupiah," *J. Gaussian*, vol. 9, no. 2, pp. 135–142, 2020, doi: 10.14710/j.gauss.v9i2.27815.

[12] G. A. M. A. Putri, N. P. N. Hendayanti, and M. Nurhidayati, "Pemodelan Data Deret Waktu Dengan Autoregressive Integrated Moving Average Dan Logistic Smoothing Transition Autoregressive," *J. Varian*, vol. 1, no. 1, p. 54, 2017, doi: 10.30812/varian.v1i1.50.

[13] M. S. M. Dadan Kusnandar, "Pemodelan Dan Peramalan Volatilitas Saham Menggunakan Model Integrated Generalized Autoregressive Conditional Heteroscedasticity," *Bimaster Bul. Ilm. Mat. Stat. dan Ter.*, vol. 9, no. 1, pp. 79–86, 2020, doi: 10.26418/bbimst.v9i1.38669.

[14] A. S. G. Models, "On Evaluating the Volatility of Nigerian Gross Domestic Product Using Smooth Transition," vol. 9, no. 3, pp. 102–106, 2021, doi: 10.12691/ajams-9-3-4.

[15] P. Kartikasari and H. Kuswanto, "MODEL LSTAR (LOGISTIK SMOOTHING TRANSITIONAUTOREGRESSIVE) UNTUK PEMODELAN RETURN SAHAMPADA PT . BANK RAKYAT INDONESIA DAN PT . BANK NEGARA INDONESIA (LSTAR MODEL (LOGISTIK SMOOTHING TRANSITION AUTOREGRESSIVE) FOR MODELLINGSTOCK MARKET RETURN AT PT . BANK RAKYAT INDONESIA AND PT . BANK NEGARAINDONESIA)," no. November, pp. 132–144, 2014.

[16] P. Kartikasari and H. Kuswanto, "Model Lstar (Logistik Smoothing Transitionautoregressive) Untuk Pemodelan Return Sahampada Pt . Bank Rakyat Indonesia Dan Pt . Bank Negara Indonesia (Lstar Model (Logistik Smoothing Transition Autoregressive) for Modellingstock Market Return At Pt .," *Pros. Semin. Nas. Mat. Univ. Jember*, no. November, pp. 132–144, 2014.

[17] B. N. Chandra, N. N. Debataraja, and N. Imro'ah, "Model Logistic Smooth Transition Autoregressive Pada Produksi Kelapa Sawit," *Bul. Ilm. Mat. Stat. dan Ter.*, vol. 10, no. 3, pp. 369–378, 2021.

[18] P. H. RS Faustina, A Agoestanto, "Model Hybrid ARIMA-GARCH Untuk Estimasi Volatilitas harga Emas," *UNNES J. Math.*, vol. 6, no. 1, pp. 11–24, 2017.

[19] S. N. Brilliantya, K. Nisa, S. Saidi, and E. Setiawan, "Model EGARCH dan TGARCH untuk Mengukur Volatilitas Asimetris Return Saham," vol. 03, no. 02, pp. 45–52, 2022.

[20] I. Indriyanti, N. Ichsan, H. Fatah, T. Wahyuni, and E. Ermawati, "Implementasi Orange Data Mining Untuk Prediksi Harga Bitcoin," *J. Responsif Ris. Sains dan Inform.*, vol. 4, no. 2, pp. 118–125, 2022, doi:

10.51977/jti.v4i2.762.
[21] S. Setyowibowo, M. As'ad, S. Sujito, and E. Farida, "Forecasting of Daily Gold Price using ARIMA-GARCH Hybrid Model," *J. Ekon. Pembang.*, vol. 19, no. 2, pp. 257–270, 2022, doi: 10.29259/jep.v19i2.13903.
[22] M. Bildirici, I. Şahin Onat, and Ö. Ö. Ersin, "Forecasting BDI Sea Freight Shipment Cost, VIX Investor Sentiment and MSCI Global Stock Market Indicator Indices: LSTAR-GARCH and LSTAR-APGARCH Models," *Mathematics*, vol. 11, no. 5, 2023, doi: 10.3390/math11051242.
[23] N. Ben Cheikh, Y. Ben Zaied, and J. Chevallier, "Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models," *Financ. Res. Lett.*, vol. 35, pp. 0–13, 2020, doi: 10.1016/j.frl.2019.09.008.
[24] C.-U. Lstargarchlstm, "Analyzing Crude Oil Prices under the Impact of," pp. 1–18, 2020.
[25] E. P. Setiawan, "Analisis Potensi dan Risiko Investasi Cryptocurrency di Indonesia," *J. Manaj. Teknol.*, vol. 19, no. 2, pp. 130–144, 2020, doi: 10.12695/jmt.2020.19.2.2.