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GARCH Model IBM Stock Forecasting of Price Volatility

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Abstract

Risk and volatility are two related factors in research regarding capital markets. Many factors influence the movement of shares and indices. Volatility is common and affects risk assessment. Stock price volatility is an important aspect of understanding market behavior, with high volatility reflecting rapid and unstable price fluctuations. This research investigates the GARCH model in assessing volatility on the IBM Stock Exchange. The method employed was the symmetric GARCH model. It focuses on univariate analysis using the GARCH econometric model. The GARCH model allows modeling stock price variance over time based on the assumption that the variance was influenced by past stock price variance. The stages of this research were (1) data collection, (2) data pre-processing, and (3) forecasting model implementation. The best model obtained was ARMA(4,2)-GARCH(5,6) with an AIC value of 4.1017. A lower AIC value indicates that the model explains the data better or more optimally. A diagnostic test found that the model was adequate because the residual distribution followed a straight line, which means it was normally distributed.

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INTRODUCTION

The financial market is dynamic and complex [1]. As an investment instrument in the financial market, share prices are greatly influenced by internal and external factors[2]. Internal factors include company performance, industry prospects, and policies[3]. External factors include macroeconomic conditions, political conditions, and global events. Volatility is one of the important characteristics of stock prices [4]. It measures how much stock prices fluctuate over time [5]. High volatility indicates that stock prices move quickly and erratically [6]. Risk and volatility are two things that are especially related in research regarding capital markets [7]. Many factors influence the movement of shares and indices. Volatility is common and affects risk assessment.

Conversely, low volatility indicates that stock prices tend to move more slowly and stably[8]. A deep understanding of stock price volatility is crucial for investors and analysts[9]. Investors can make more informed investment decisions and plan more effective risk management strategies by understanding volatility. One method that can be used to analyze stock price volatility is the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model.

ARCH/GARCH research by Sumiyati et al. shows that the Economic Policy Uncertainty (EPU) Index has no effect on stock volatility in Indonesia in the short term, but there is an influence in the long term[10]. This research contributes to developing event study literature on investor behavior in the capital market due to unpredictable events. The GARCH (0, 1) model is the most appropriate model for predicting Tokai Carbon share prices in this research. The MAPE value shows a low

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percentage, namely 4.949972%, which indicates that the ARCH/GARCH method is excellent in predicting Tokai Carbon share prices[11]. As well as responses to policies formulated by stakeholders to overcome economic uncertainty in the future. Another research showed the main findings suggest that the symmetric ARCH/GARCH models can capture characteristics of ASE and provide more evidence for both volatility clustering and leptokurtic.

In contrast, EGARCH output reveals no support for a leverage effect in the stock returns at the Amman Stock Exchange[12]. One of the usable methods to overcome the effect of heteroscedasticity is the GARCH model. This study aims to find the best model to estimate the parameters, predict the share price, and forecast the volatility of the data share price of Adaro Energy Tbk, Indonesia, from January 2014 to December 2016. The study also discusses Window Dressing. The best model that fits the data is AR(1)-GARCH (1,1). Applying this best model for forecasting the share price of Adaro Energy Tbk, Indonesia, for the next 30 days showed promising results, and the mean absolute percentage error was determined as 2.16%[13].

The parameters of ARIMA-type simple specifications are routinely anticipated by applying the OLS methodology, but it has two disadvantages when the volatility or ARCH effect is present. The first problem may be the autocorrelation in error terms. The lagged dependent variables can be incorporated as independent variables in the mean equation to handle this unwanted situation. The other problem may be the presence of the ARCH effect. This problem can be resolved by employing the ARCH or GARCH specifications, so we have taken advantage of such types of models in our study[14]. Based on the reviewed research, The GARCH model is a proper statistical model that can be used to model stock price variance over time. The GARCH model assumes that stock price variance is influenced by stock price variance in the past.

METHOD

Data Collection

In this research, the data used is International Business Machines Corporation (IBM) stock data. IBM is a multinational information technology company based in the United States. IBM is also one of the leading technology companies in the world and has been around since it was founded in 1911. IBM shares are traded on the stock market and can be bought and sold by investors. From the Yahoo finance website, IBM stock data used in GARCH modeling was taken from January 1, 2020, to November 30, 2023. This data consists of 5 columns, including 'Open,' 'High,' 'Low,' 'Close,' 'Volume,' and 'Adjusted. ' IBM's stock price fluctuates over time, influenced by various factors including the company's financial performance, industry events, global economic conditions, and other factors. Investors often buy shares in the hope that the value of the shares will increase so that they can profit from selling shares in the future.

Data Preprocessing

Data preprocessing serves as the foundation for valid data analyses. It is an indispensable step in building operational data analysis, considering the intrinsic complexity of building operations and deficiencies in data quality[15]. Data preprocessing refers to techniques for enhancing the quality of the raw data, such as outlier removal and missing value imputation[16]. Data pre-processing in Machine Learning is an essential process that plays a vital role in improving the data's quality, thereby facilitating the extraction of valuable insights. It involves preparing raw data, including cleaning and organizing, to ensure its suitability for constructing and training Machine Learning models. Data pre-processing in Machine Learning can be described as a data mining technique that converts raw data into an understandable and coherent format [17].

The data reprocessing process in this research was carried out to build a GARCH model. It is an important step to ensure that the data conforms to the model's assumptions and requirements. The following are some common preprocessing steps performed before applying a GARCH model.

There are several steps in data preprocessing. They are data cleaning, transformation, stationarity test, and checking Autocorrelation and Heteroscedasticity. Data cleaning ensures that the data does not have missing or invalid values. Data transformation is needed to fulfill the assumptions of the GARCH model by looking at the lambda value from the Boxcox test. Stationarity is used to ensure that the data is stationary. It has a constant mean and variance over time. If it is not stationary, the data needs to be differencing or other transformations to achieve stationarity. Then, checking Autocorrelation and Heteroscedasticity. Although GARCH models are designed to handle heteroscedasticity, understanding the data's autocorrelation patterns can help fit the model. The results will be explained more in the next results and discussion chapter.

Modelling

The processing process to answer the objectives begins with the model's specification, which detects stock data's ARCH effect using autocorrelation and ARCH tests [18]. This is followed by the average equation's appropriate specification. The next step is estimating the parameters and selecting the best variance model by simulating several models based on the Akaike Information Criterion (AIC) value. Furthermore, the variance model diagnostic test with error analysis includes the ARCH and normality tests.

ARCH Modelling

The ARCH (Autoregressive Conditional Heteroskedasticity) method is a statistical method used to analyze the volatility of time series data. The ARCH model is based on the assumption that the variance of data influences the variance of time series data in the past. The ARCH method analyzes IBM share price volatility[19]. Volatility measures how much stock prices fluctuate over time[20]. High volatility indicates that stock prices tend to move quickly and erratically. Conversely, low volatility indicates that stock prices move more slowly and stably.

The ARCH model consists of two parts, namely:

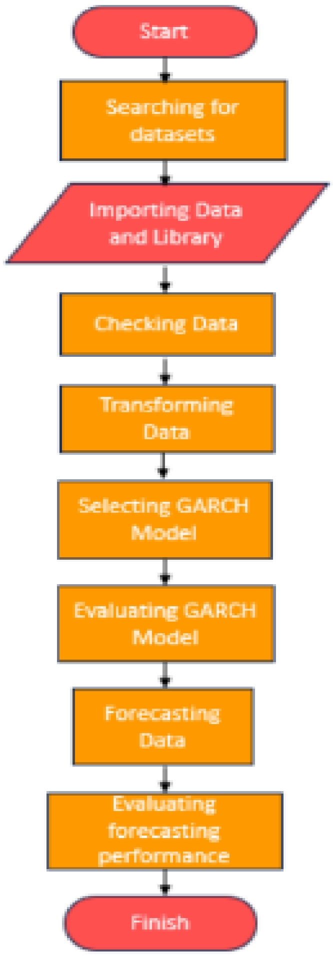
1. Mean model: The mean model predicts the average value of time series data. The mean model can be an AR (autoregressive), MA (moving average) model, or a combination of both (ARMA).
2. Variance model: The variance model predicts the variance of time series data. The ARCH variance model assumes that the variance of time series data is an autoregressive function of the squared error of the data in the past.

ARCH Modelling

The GARCH method is used to model IBM stock price variance using the GARCH (5,6) model. The GARCH (5,6) model is a GARCH model that has five autoregressive coefficients and six quadratic autoregressive coefficients.

The GARCH model consists of two parts, namely:

1. Mean model: The mean model predicts the average value of time series data. The mean model can be an AR (autoregressive), MA (moving average) model, or a combination of both (ARMA).
2. Variance model: The variance model is used to predict the variance of time series data. The GARCH variance model is based on the assumption that the variance of time series data is an autoregressive function of the past squared error of the data. The flowchart of this research is shown in Pigure 1.



Pigure 1. Material and Methods Process Flowchart[21]

RESULTS AND DISCUSSION

Data Exploratory Transformation and Analysis

Stock prices are reoriented in graphical form into a time series that allows visualization of changes in stock prices over time. With this process, we can identify and understand trends, volatility, and stationarity with ADF testing. The time series plot in Figure 2 depicts the International Business Machines (IBM) stock price. It shows that the stock price pattern increases over time even though the price shows volatility, so the stock price is not stationary over time due to changes in the mean and variance from time to time. Before entering the modeling stage, the first thing you need to know about the data is to check the stationarity of the data regarding the mean and variance, as shown in Figure 2, where the x-axis is time and the y-axis is the close price of the IBM Stock.

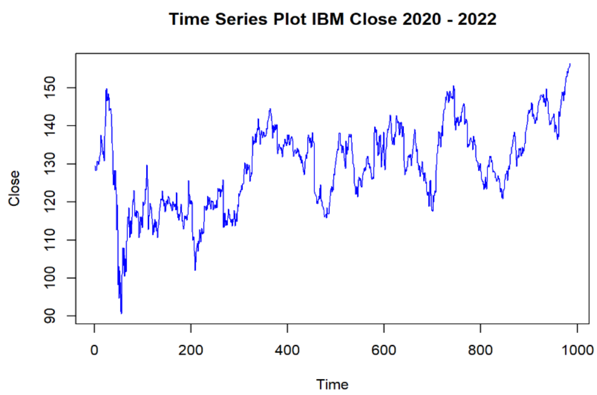


Figure 2. Stationarity of the Plot Data of IBM Stock 2020-2023

Based on Figure 3, the ACF plot of IBM stock data is moving downwards, and there is a tails-off pattern, so it can be concluded that the data is not stationary with respect to the mean. Meanwhile, when checking the stationary variance using the Box.cox test, a lambda value of 0.9289157 was obtained, which means the data is stationary regarding the variance because it has a lambda value close to 1.

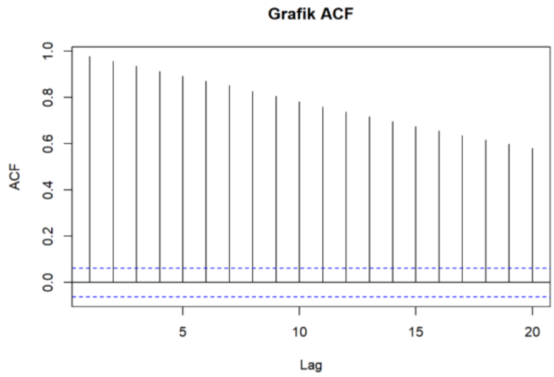


Figure 3. ACF Plot

Figure 4 shows the ACF plot after differencing once, and it can be seen that the plot is stationary concerning the mean.

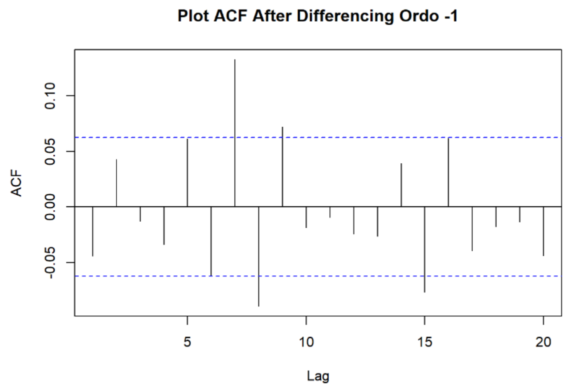


Figure 4. ACF Plot after Differencing Once

Figure 5 indicates a plot of IBM stock data after differencing the data 1 time.

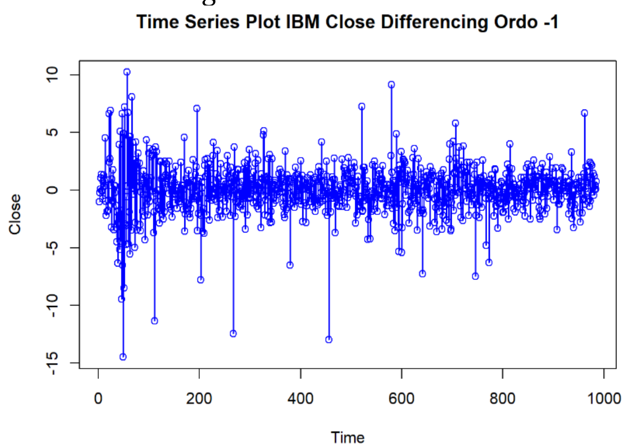


Figure 5. IBM Stock Data Plot

ARIMA Model

The ARIMA model is formed by looking at the ACF, PACF, and EACF plots as in Figures 6 and 7. Based on the plot above, the models formed are ARMA (1, 1), AR (1), and ARMA (4, 2). Then, from the three models, the smallest AIC value was obtained by the ARMA (4, 2) model, which was 4283.457. Apart from using ACF, PACF, and EACF plots, there is a method with the auto.arima function to get the best model automatically. The model obtained is ARIMA (0, 0, 0) when applied. If we look at it based on the AIC comparison value obtained from the 'Arima' function with the ML method, we get the ARMA (4,2) = 4274.261 model with the smallest AIC value compared to other models. For this reason, the 'auto.arima' function was used to strengthen the analysis, which produced the best model, namely ARIMA (0,0,0) = 4298.13. If we compare the AIC values with the ML and Auto.arima methods, we get the best model, namely the ARMA (4, 2) model with an AIC value of 4274.261, smaller than the other models.

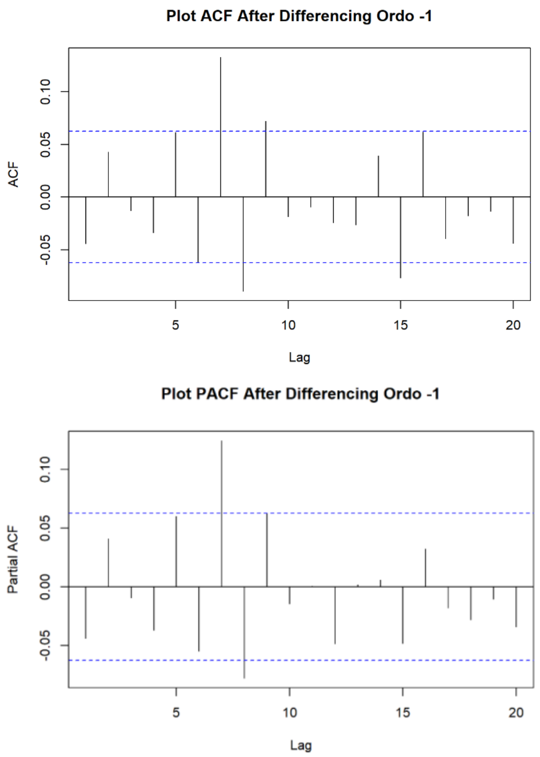


Figure 6. ACF and PACF Plots

```
## AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 o o o o o o o x x x o o  o  o
## 1 x o o o o o o x o o o o  o  o
## 2 x x o o o o o x o o o o  o  o
## 3 x x x o o o o o o o o o  o  o
## 4 x x o o o o o o o o o o  o  o
## 5 x x o x x o o o o o o o  o  o
## 6 x x o x x x o o o o o o  o  o
## 7 x x x o x x o o o o o o  o  o
```

Figure 7. EACF Plot

Model Diagnostics

After initial modeling has been carried out, the next step, namely Figure 8, shows the model diagnostic test using the QQ plot, residual plot, and ACF tests. It can be seen that the model is significant based on the p-value obtained based on the assumption test. From the results released, it can be seen that the p-value is > 0.05, so it can be said that the data are independent.

Figure 9 shows the residual distribution. It presents a normal distribution and a stationary error graph with a constant mean and variance. Thus, the model is suitable and meets the requirements.

The test was carried out using the ArchTest function on the residual values , and a p-value of 3.334e-11 was obtained. Because the p-value is lower than α, the residual data has an ARCH effect, and the modeling can be done using GARCH.

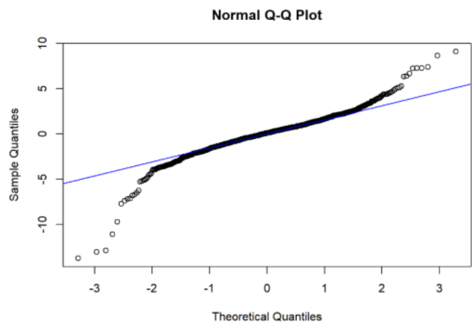


Figure 8. Q-Q Plot, Residual Plot, ACF Plot, Histogram

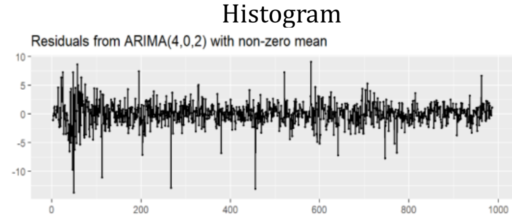


Figure 9. Q-Q Plot, Residual Plot

L-jung-Box on standard residuals and standard squared residuals shows no significant serial autocorrelation. The ARCH LM test also shows no heteroscedasticity remaining in the model. This shows that the GARCH (1,1) model with a standard distribution is proper at capturing the effects of fluctuating volatility over time. It can be seen from the model diagnostic test on the QQ-norm plot that the residual distribution follows a straight line so it can be concluded that the residuals are distributed normally in Figure 10.

Then, it is strengthened by the p-value in the L-jung Box test which is greater than α = 0.05.

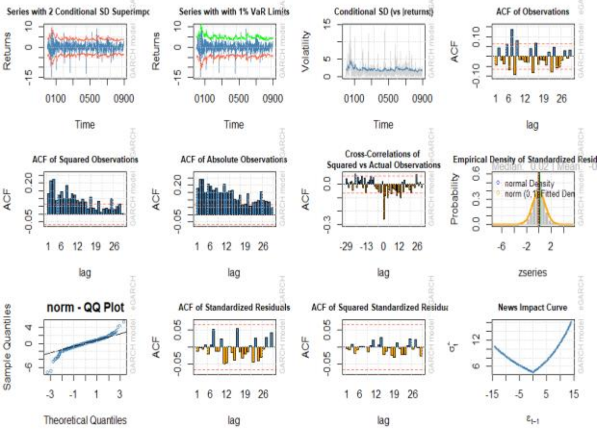


Figure 10. Diagnostic Test of ARMA (4,2) –GARCH (1,1) Model with Normal Distribution

The normal distribution results of the plot were not satisfying compared to the standard t-student distribution because the standard t-student distribution is more flexible than the normal distribution. After all, it can adjust the degrees of freedom that affect the shape of the tail of the distribution. However, the p-value results in the L-jung Box test are still greater than α = 0.05.

The plot of the same ARMA model but with a different GARCH model obtained from the analysis of the ACF and PACF plots shows in Figure 10 that the results of the model diagnostic test on the QQ-norm plot show that the residual distribution follows a straight line, so it can be concluded that the residuals are distributed normally. Then, it is strengthened by the p-value in the L-Jung Box test, greater than α = 0.05.

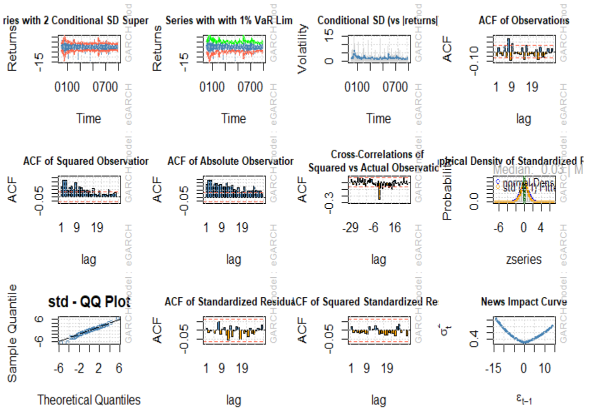


Figure 10. The Diagnostic Test of ARMA Model (4,2)-GARCH(5,6) with t-Student Standard Distribution

After displaying the plot, the AIC value that has been obtained will also be displayed. Each model used can be measured or compared by looking at the Akaike Information Criterion (AIC) in Figure 11. AIC is a general method for determining how well a model fits the data. The smallest AIC value is the best-fitting model. When comparing the three models, the lowest AIC is ARMA(4,2)-GARCH(5,6), with an AIC value of 4.1017. Therefore, the GARCH model above will be used for forecasting. The AIC (Akaike Information Criterion) value given, namely 4.1017, indicates the magnitude of the AIC value of a statistical model. AIC is one of the criteria used in statistical modeling, especially to compare several different models. A lower AIC value indicates that the model is better or more optimal in explaining the data, considering the trade-off between model suitability (fit) and its complexity.

```
## Information Criteria
## ------------------------------------
##
## Akaike       4.1017
## Bayes        4.2369
## Shibata      4.1002
## Hannan-Quinn 4.1534
```

Figure 11. AIC Value of the Best Model

Forecasting

Based on the best GARCH model obtained, namely the ARMA(4,2)-GARCH(5,6) from the Figure 10 model with a standard t-Student distribution, the forecast results for the next ten days are obtained in Figure 12. The results show that the ARCH and GARCH have a significant effect in forecasting IBM Stock market volatility, which means that the past volatility of the IBM Stock market affects its current volatility. It also shows that bad and good news can significantly affect the conditional volatility of all IBM Stock market returns, and it is supported by research doing Bashar et al. This study contributes to the investors' understanding of the dynamics of the cryptocurrency market, which enhances the ability to make informed decisions based on a scientific approach[22], and found homogeneous clusters of industries in terms of the impact of COVID-19 on US stock market volatility [23].

```
##
## *------------------------------------*
## *        GARCH Model Forecast        *
## *------------------------------------*
## Model: eGARCH
## Horizon: 10
## Roll Steps: 10
## Out of Sample: 10
##
## 0-roll forecast [T0=0886-01-01]:
##          Series Sigma
## T+1   0.1791733 2.295
## T+2  -0.0150281 1.834
## T+3   0.1095469 1.226
## T+4  -0.0203224 1.744
## T+5   0.1375804 1.977
## T+6   0.0007563 1.555
## T+7   0.1224547 1.794
## T+8   0.0147007 1.587
## T+9   0.1088667 1.485
## T+10  0.0264765 2.144
```

Figure 12a. Forecasting Results

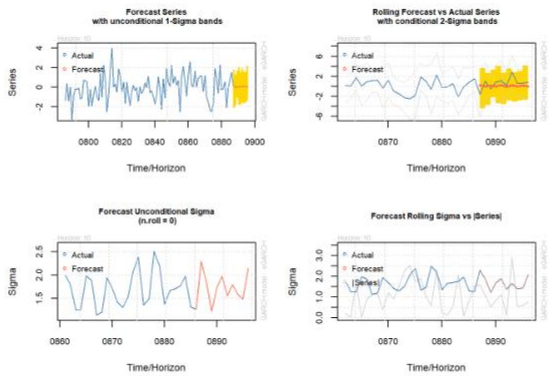


Figure 12b. Forecasting Results

CONCLUSION

Based on the results and discussion above, using the ARCH model is still significant. Therefore, several GARCH models were tried, and compared values such as AIC and parameter significance; the GARCH (5,6) model will be used, which has a small AIC value and parameters that are almost all significant. We get the Mean, ARMA (4,2), and the Variant, GARCH (5,6). With the following equation:

$$\sigma_t{}^2 = 0.281 - 0.029\epsilon^2{}_{t-1} - 0.562\sigma^2{}_{t-1} - 0.790\sigma^2{}_{t-2}$$

GARCH (5,6) Model Variant: The forecast from the GARCH (5,6) model follows the pattern of the existing data. So, the model is suitable for modelling variance/risk in the future.

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