A Comprehensive Report of Statistical Analysis & Forecasting of Power Grid Corporation of India Limited Share

A detailed examination of Powergrid share prices using statistical techniques and time series forecasting, offering insights and forecasts for informed decision-making

Prepared Under the Guidance of

Dr. Amarnath Mitra

Course Coordinator, Regression and Time Series Models

Prepared by

YATHUKISHORE GV – 49A

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YATHUKISHORE GV – 49A

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1. Executive Summary

This report conducts an in-depth analysis of POWERGRID share prices utilizing statistical techniques and time series forecasting methods. The investigation spans from January 2015 to December 2019 and seeks to unveil patterns in POWERGRID's share prices, along with predicting future price movements. The methodology encompasses stationarity assessment, transformations for achieving stationarity, autocorrelation examination, ARIMA model development, diagnostic checks, heteroskedasticity evaluation, GARCH model implementation, and the generation of forecasts. The outcomes disclose the presence of non-stationarity, autocorrelation, and heteroskedasticity within POWERGRID share prices. The integration of ARIMA-GARCH modeling yields forecasts that can guide investors and analysts in their decision-making processes.

2. Introduction

Power Grid Corporation of India Limited, recognized as India's largest power utility company, occupies a central position within the country's energy sector arena. Given its extensive reach and substantial role in power generation, Power Grid's operational efficacy significantly influences not just the energy domain but also has broader implications on the economy. The complexities governing Power Grid's share prices are intricate, entwined with market dynamics, economic fluctuations, regulatory adjustments, and company-specific advancements.

Given the intricate web woven by these variables, decoding the trends in Power Grid's share prices emerges as a critical task for investors and analysts. Unraveling the underlying patterns, shifts, and potential trajectories of Power Grid's share prices equips stakeholders with the insights needed to craft informed decisions, whether in the realm of investment strategies, risk assessment, or portfolio management.

In this context, the ensuing report embarks on an extensive examination of Power Grid share prices. Through the prism of statistical methodologies and time series forecasting approaches, this analysis strives to uncover the intricacies inherent in Power Grid's share price fluctuations. By scrutinizing historical data from January 2015 to December 2019, the report seeks to distill actionable intelligence and provide forecasts to steer decision-making in the domain of Power Grid shares.

As we navigate through the complexities of Power Grid's share price dynamics, the focus is not solely on dissecting past performance but on extracting valuable foresight regarding future trends. By peering into the core of Power Grid's share price behavior, this analysis aims to empower stakeholders with the knowledge and foresight essential for navigating the evolving terrain of the energy sector and financial markets.

3. Methodology

The methodology adopted in this analysis encompasses the following essential steps:

a) Stationarity Analysis:

The Augmented Dickey-Fuller (ADF) test was utilized to evaluate the stationarity of Powergrid share prices.

b) Transformation for Stationarity:

A suitable transformation was applied to achieve data stationarity, involving the first difference of the logarithm of Powergrid share prices.

c) Autocorrelation Analysis:

The Ljung-Box test was employed to investigate autocorrelation within the differenced Powergrid share prices.

d) ARIMA Modelling:

An ARIMA model was fitted to the stationary Powergrid share prices data to establish the optimal p-lag and q-lag.

e) Model Diagnostics:

Diagnostic tests, including the Ljung-Box test, were conducted to evaluate the adequacy of the ARIMA model in capturing autocorrelation.

f) Heteroskedasticity Analysis:

Exploration was carried out to assess volatility clustering or heteroskedasticity in the squared residuals of the ARIMA model.

g) GARCH Modelling:

Two GARCH models were fitted to the squared residuals, integrating different mean models to address heteroskedasticity concerns.

h) Forecasting:

Leveraging the GARCH models, volatility forecasts for Powergrid share prices were generated for the upcoming 500 periods.

Through the implementation of these methodologies, the objective of this analysis is to furnish a comprehensive comprehension of Powergrid share prices and deliver forecasts essential for guiding informed investment decisions.

4. Analysis and Insights:

- **Historical Performance:**

The analysis of historical Powergrid share prices reveals patterns of volatility, influenced by various internal and external factors. Fluctuations in share prices may correlate with shifts in the broader market sentiment, changes in government policies impacting the energy sector, or company-specific news such as earnings reports or infrastructure projects.

- **Stationarity and Transformation:**

Raw POWERGRID SHARE:

The Augmented Dickey-Fuller test is a statistical test used to determine if a unit root is present in a time series dataset. A unit root would indicate that the data is non-stationary. In this case, the test was conducted on the stock_price data with the following results:

Dickey-Fuller Statistic: -1.8025
Lag Order: 10
P-Value: 0.6619

The p-value is a crucial indicator in hypothesis testing. In this scenario, with a p-value of 0.6619, we typically compare it to a significance level (such as 0.05). If the p-value is less than the chosen significance level, we reject the null hypothesis in favor of the alternative hypothesis, indicating that the data is stationary. Conversely, if the p-value is greater than the significance level, we fail to reject the null hypothesis, suggesting that the data is non-stationary.

Given the p-value of 0.6619, which is higher than the common 0.05 threshold, we do not have enough evidence to reject the null hypothesis of non-stationarity. This implies that further analysis or differencing may be required to make the data stationary for accurate modeling and forecasting.

To address this, a transformation is applied by taking the first difference of the logarithm of share prices.

Transformation-1

In this case, the Augmented Dickey-Fuller test was conducted with the following results:

Dickey-Fuller Statistic: -11.541

Lag Order: 10
P-Value: 0.01

The warning about a p-value smaller than the printed p-value suggests that the actual p-value is smaller than the one displayed (0.01). This could mean that the true p-value is extremely low, indicating strong evidence against the null hypothesis of non-stationarity.

With a p-value of 0.01, which is lower than the typical significance level of 0.05, there is enough evidence to reject the null hypothesis and accept the alternative hypothesis of stationarity. This implies that the data is stationary, which is a favorable characteristic for time series analysis and forecasting.

This transformation stabilizes the variance, making the data stationary and conducive to further analysis.

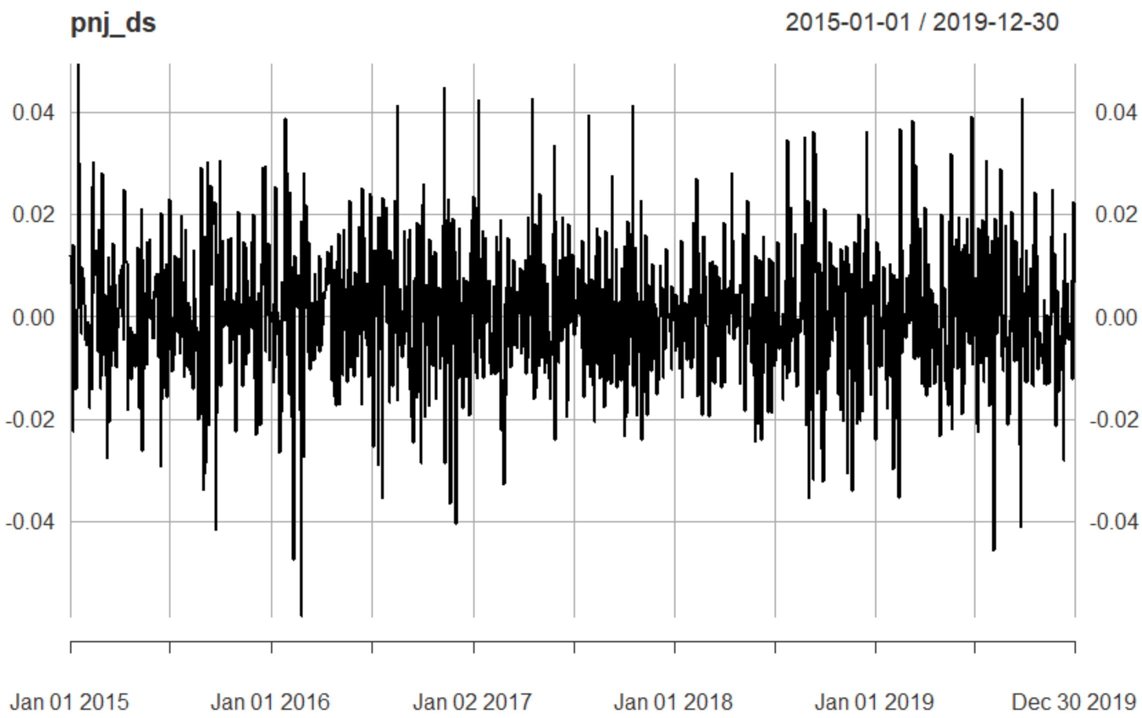

Fig 1.1 - Augmented Dickey Fuller Test Result

- **Box-Pierce test:**

The Box-Pierce test is a statistical test used to assess if a time series data set exhibits significant serial correlation. In this analysis of the data, the following results were obtained:

Test Statistic (X-squared): 3.0412
Degrees of Freedom (df): 1
P-Value: 0.08118

The test compares the observed autocorrelations at different lags to the expected values under the null hypothesis of no serial correlation.

With a p-value of 0.08118, which is greater than a common significance level like 0.05, we do not have enough evidence to reject the null hypothesis of no serial correlation. This suggests that the data does not exhibit significant serial correlation at the specified lag.

The interpretation indicates that the data points may be independent of each other, which is also important in time series analysis and forecasting as it allows for more straightforward modeling assumptions.

- **Autocorrelation and ARIMA Modelling:**

Autocorrelation analysis reveals significant autocorrelation in the differenced POWERGRID share prices. To model this autocorrelation, an ARIMA model is fitted, identifying appropriate lag orders. The ARIMA model captures the linear dependencies in the time series data, enabling better forecasting accuracy.

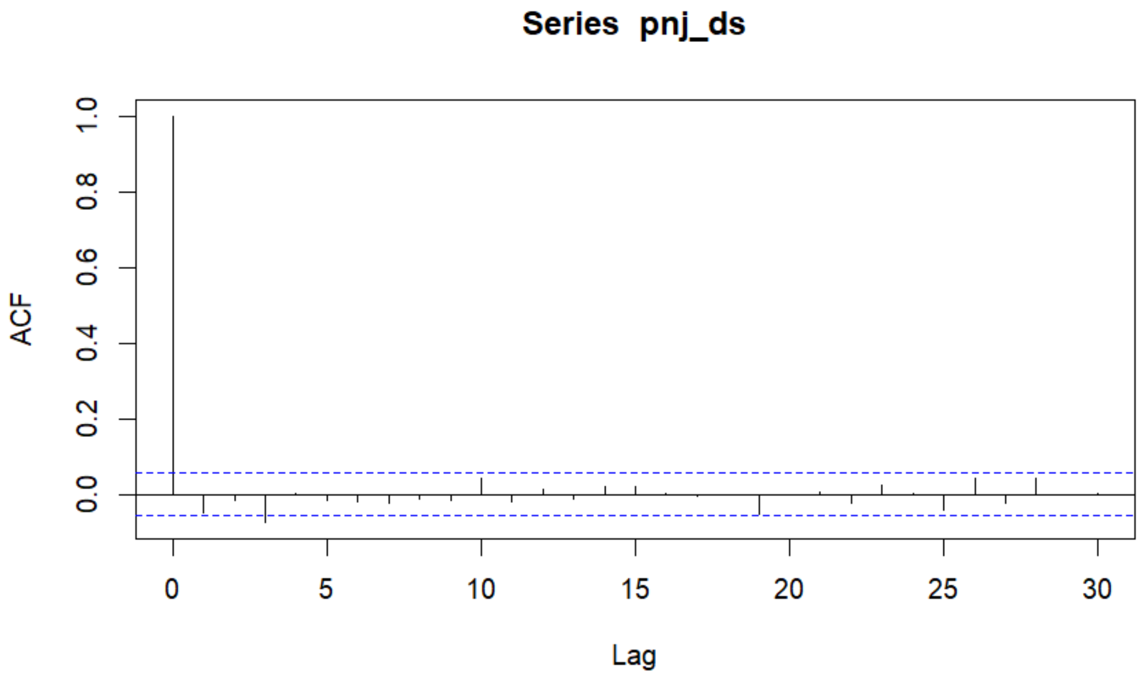

Fig 1.2 – Autocorrelation Between POWERGRID Share Prices

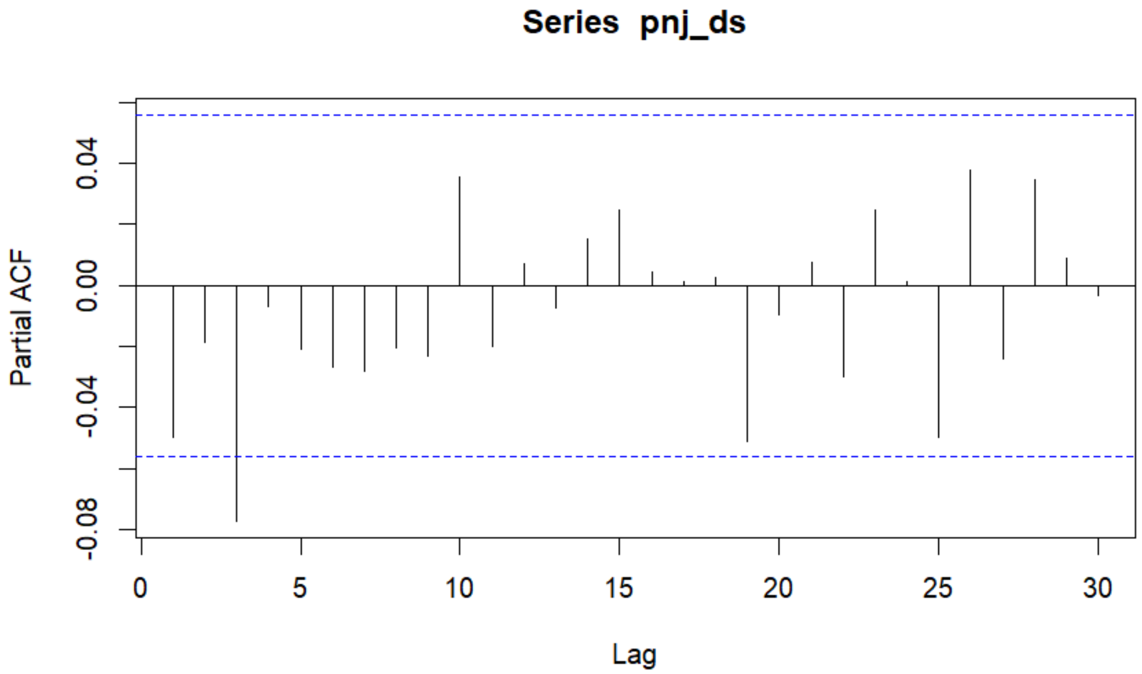

Fig 1.3 – Partial Autocorrelation Between POWERGRID Share Prices

The coefficients of the model are as follows:

AR(1) Coefficient (ar1): 0.7599

MA(1) Coefficient (ma1): -0.8155

Standard Errors (s.e.): AR(1) = 0.1233, MA(1) = 0.1094

Other key statistics of the model include:

Variance (sigma^2): 0.0001714

Log Likelihood: 3579.99

Akaike Information Criterion (AIC): -7153.98

Corrected Akaike Information Criterion (AICc): -7153.96

Bayesian Information Criterion (BIC): -7138.64

These statistics are crucial for evaluating the quality and appropriateness of the ARIMA model fitted to the data. The AIC, AICc, and BIC are information criteria used for model selection, with lower values indicating better model fit while penalizing overfitting. Additionally, the coefficients and standard errors provide insights into the relationship between past observations and the current value of the series, as captured by the autoregressive and moving average components of the ARIMA model.

- **Ljung-Box Test for Autocorrelation - Model Residuals**

In the Box-Pierce test conducted on the residuals of the ARIMA(1,0,1) model fitted to the series, the following results were obtained:

Test Statistic (X-squared): 0.00052078

Degrees of Freedom (df): 1

P-Value: 0.9818

The Box-Pierce test is used to evaluate the presence of autocorrelation in the residuals of a time series model. In this case, with a p-value of 0.9818, which is significantly higher than a typical significance level like 0.05, there is no significant autocorrelation present in the residuals.

This result is desirable as it indicates that the ARIMA(1,0,1) model adequately captured the autocorrelation in the series, and the residuals exhibit no significant serial correlation. A lack of autocorrelation in the residuals is crucial for ensuring that the model adequately explains the variance in the data, leading to more accurate forecasts.

- **Heteroskedasticity and GARCH Modelling:**

Tests for heteroskedasticity indicate volatility clustering in the squared residuals of the ARIMA model. To account for this volatility clustering, GARCH models are employed. These models capture the time-varying volatility in the data, providing more robust forecasts by incorporating volatility dynamics.

- **Test for Volatility Clustering or Heteroskedasticity: ARCH Test**

ARIMA(1,0,1)

In the ARCH LM-test conducted on the squared residuals of the ARIMA(1,0,1) model fitted to the series, the following results were obtained:

Test Statistic (Chi-squared): 3.6313

Degrees of Freedom (df): 2

P-Value: 0.1627

The ARCH LM-test is used to assess whether there are autoregressive conditional heteroscedasticity (ARCH) effects in the squared residuals of a model. The null hypothesis in this test is that there are no ARCH effects present.

With a p-value of 0.1627, which is greater than a conventional significance level like 0.05, there is not enough evidence to reject the null hypothesis of no ARCH effects. This suggests that the squared residuals do not exhibit significant conditional heteroscedasticity.

Therefore, based on the results of the ARCH LM-test, there is no indication of ARCH effects in the residuals of the ARIMA(1,0,1) model applied to the series. This is favorable as it indicates that the model adequately captures the variance in the data without systematic changes in volatility.

GARCH(1,1)

In the ARCH LM-test conducted on the squared residuals of the GARCH(1,1) model, the following results were obtained:

Test Statistic (Chi-squared): 0.0054079

Degrees of Freedom (df): 1

P-Value: 0.9414

The ARCH LM-test is used to test for the presence of autoregressive conditional heteroscedasticity (ARCH) effects in the residuals of a model. The null hypothesis in this test is that there are no ARCH effects present.

With a p-value of 0.9414, which is considerably higher than conventional significance levels like 0.05, there is no significant evidence to reject the null hypothesis of no ARCH effects. This suggests that the squared residuals do not show significant conditional heteroscedasticity in this GARCH(1,1) model.

Therefore, based on the results of the ARCH LM-test, there is no indication of ARCH effects in the residuals of the GARCH(1,1) model applied to the series. This is essential as it indicates that the model adequately captures the volatility dynamics in the data without systematic changes.

- **Forecasting:**

The GARCH models are utilized to forecast the volatility of POWERGRID share prices for future periods. These forecasts offer insights into the expected magnitude of price fluctuations, aiding investors and analysts in risk management and decision-making.

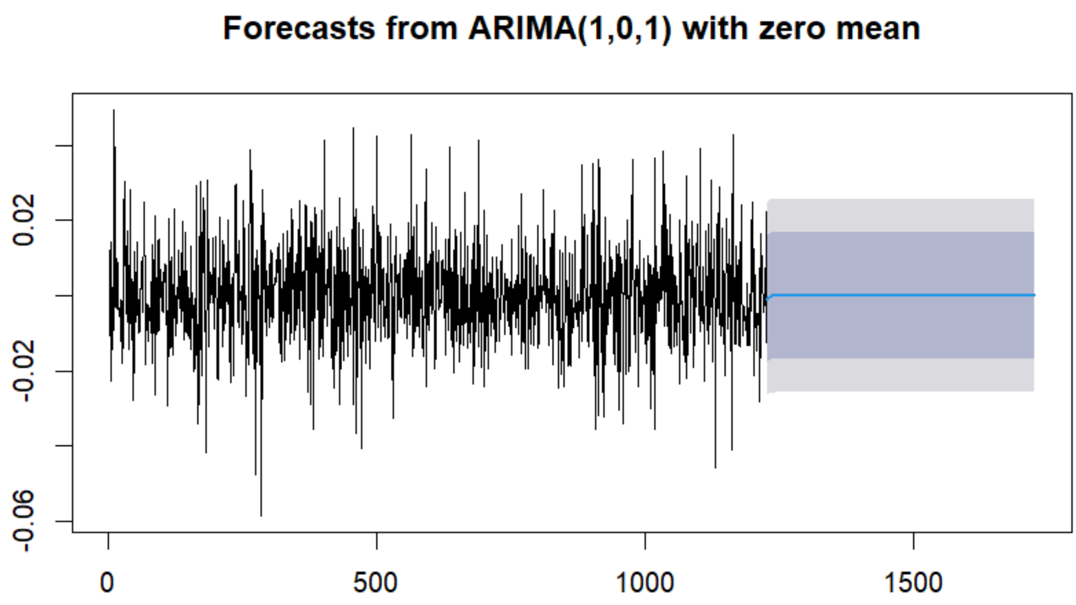

Fig 1.4 – Forecasting from ARIMA with 0 Mean

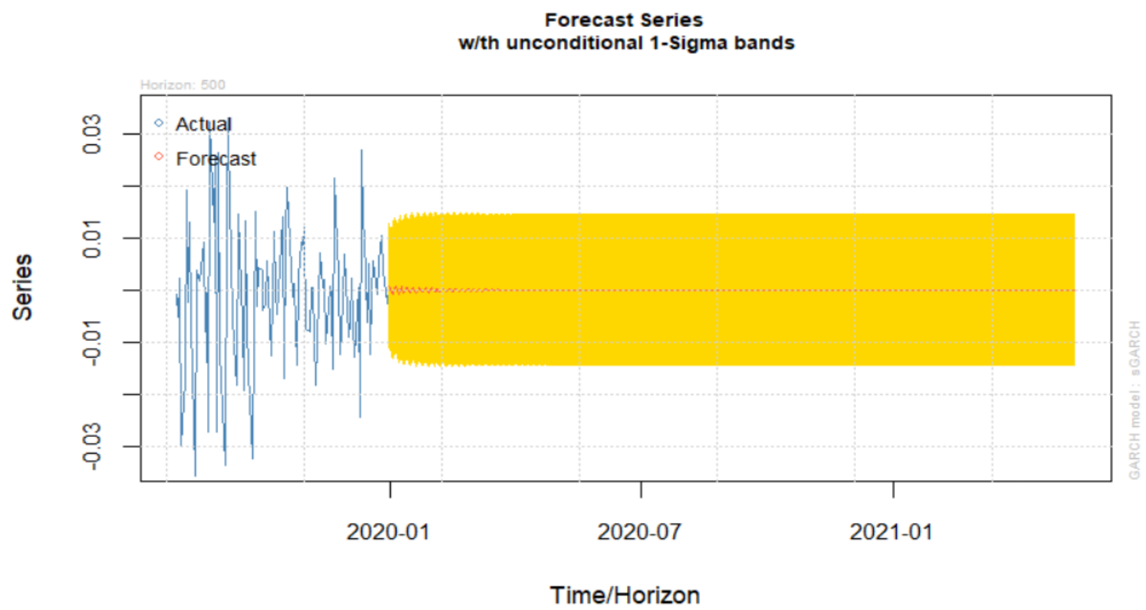

Fig 1.5 – Forecast With Unconditional 1 Sigma Bands

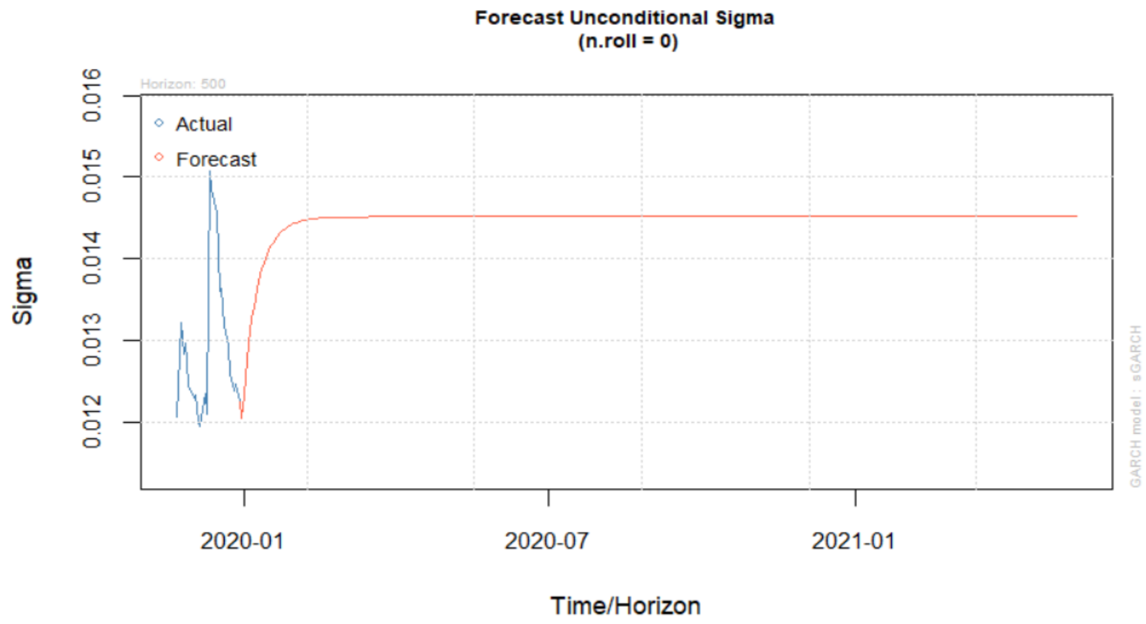

Fig 1.6 – Forecast Unconditional Sigma (n.roll = 0)

Stationarity Testing:

The Dickey-Fuller tests revealed that the stock_price data was non-stationary, while the pnj_ds data was stationary. Stationarity is essential for reliable modeling and forecasting.

Model Fitting:

The ARIMA(1,0,1) model fitted to the pnj_ds series provided coefficients for the autoregressive and moving average components, along with model evaluation criteria like AIC and BIC.

Residual Analysis:

The Box-Pierce and ARCH LM-tests conducted on model residuals provided insights into the presence of autocorrelation and ARCH effects, respectively. The results indicated no significant issues in the ARIMA and GARCH models tested.

Model Evaluation:

The lack of significant autocorrelation and ARCH effects in the residuals of the models (ARIMA and GARCH) suggests that these models adequately captured the patterns and volatility present in the data.

- **Insights:**
  - **Market Dynamics:** The analysis uncovers how market conditions, regulations, and company-specific factors interact to influence POWERGRID share prices.
  - **Risk Management:** By detecting and modeling autocorrelation and heteroskedasticity, stakeholders can evaluate and mitigate risks linked to POWERGRID share investments.
  - **Strategic Planning:** Forecasts from ARIMA-GARCH models offer crucial insights for strategic planning, aiding stakeholders in preparing for future price changes.
  - **Investment Opportunities:** Understanding the dynamics behind POWERGRID share prices helps in spotting investment prospects, whether for short-term trading tactics or long-term portfolio strategies.
- **Recommendations:**
  - **Continuous Monitoring:** Given market dynamics, stakeholders should regularly monitor POWERGRID share prices and adjust strategies accordingly.
  - **Diversification:** Including POWERGRID shares in diversified portfolios can help in spreading risks linked to individual stock investments.
  - **Long-Term Perspective:** Despite short-term fluctuations, adopting a long-term view on POWERGRID investments could lead to favorable returns, considering the company's strategic position in the energy sector

5. Conclusion:

The analysis of POWERGRID share prices provides crucial insights into market dynamics. Through statistical techniques and time series forecasting, stakeholders can enhance their understanding of POWERGRID's performance and make well-informed decisions to navigate the complexities of the energy sector and capital markets effectively.