A REPORT ON

ESTIMATION OF BETA USING CAPM MODEL AND ANALYSIS OF RETURNS OF UNDERLYING EQUITY USING ARIMA AND GARCH MODEL

By

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We would like to thank Prof. Nagaraju Thota for providing us this opportunity and letting us work under him. We got a great learning experience by working on real data and analysing it. We are immensely thankful for the chance to apply our academic knowledge to real-world scenarios, fostering our hands-on experience and professional development.

INDEX

1. PART -1 a) <u>INTRODUCTION</u>

TATA MOTORS:-

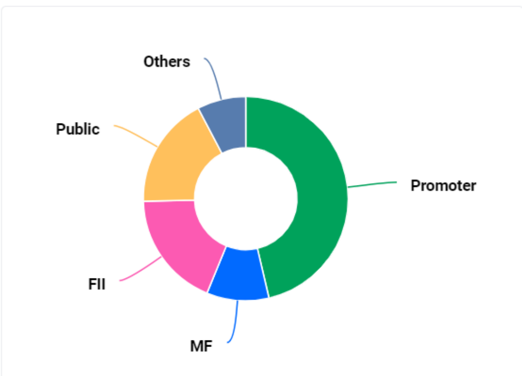
a) Nature of the Business:

Tata Motors is a renowned global automotive manufacturer that specialises in the design, production, and distribution of a wide range of vehicles. Operating within the manufacturing sector, the company focuses on automobiles, commercial vehicles, and utility vehicles. With its innovative approach and unwavering commitment to sustainability, Tata Motors has firmly established itself as a prominent player in the automotive market.

b) Public or Private Ownership:

Tata Motors Limited is a publicly traded company, listed on stock exchanges, which allows both individual and institutional investors to own shares in the company. As a publicly-owned entity, Tata Motors adheres to stringent transparency and regulatory standards in its financial reporting and corporate governance practices.
The shareholding pattern is shown below:-

SHAREHOLDING SUMMARY



c) Founding Circumstances:

Established in 1945 as Tata Engineering and Locomotive Co. Ltd, Tata Motors was founded with the visionary outlook of J.R.D. Tata. The company's inception aimed to introduce commercial vehicles to meet the growing transportation needs of post-independence India. Over the years, Tata Motors has evolved, expanded its product line, and emerged as a global player in the automotive industry.

d) Overall Greatness of the Company:

Tata Motors has earned a well-deserved reputation for excellence, innovation, and social responsibility. The company's commitment to quality and sustainability is evident in its diverse product portfolio, which encompasses.Passenger automobiles, multipurpose vehicles, and goods-carrying vehicles.Tata Motors has not only become a household name in India but has also expanded its global presence, penetrating various international markets. Its dedication to social and environmental causes, coupled with continuous research and development efforts, has contributed to its overall greatness and enduring success in the fiercely competitive automotive industry.

<u>**RUBYMILLS:-**</u>

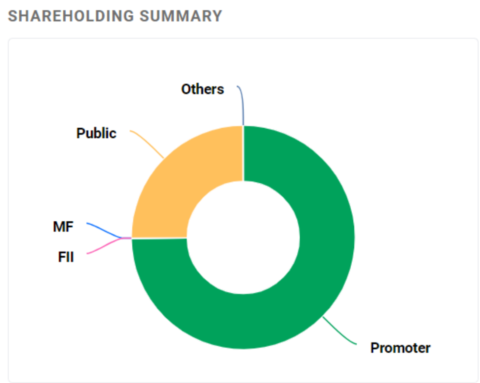
RUBY
SINCE 1917

a) Nature of the business:

Ruby Mills operates as a manufacturing company specialising in the production of various textile products, such as cotton, linen, and rayon fabrics. Additionally, the company manufactures fusible interlining and basic interlining.

b) Public or private ownership:

Ruby Mills is classified as a public limited company, indicating that its shares are available for public ownership and trading. The shareholding pattern is given below:-



c) Founding circumstances:

Established in 1917, Ruby Mills originated as a composite textile mill. Initially, it was owned by Hormusjee Ardeshir S. Goculdas and Co., Ltd. However, in 1946, the late C N Shah assumed management control of the company. Since then, Ruby Mills has consistently progressed and diversified its product range.

d) Overall greatness of the company:

Ruby Mills holds a prominent position as a leading textile manufacturer in India. Renowned for its commitment to quality and innovation, the company has earned a strong reputation. Moreover, Ruby Mills actively embraces social responsibility and prioritises environmental sustainability.

SPLIL:-

SPL Industries Limited

Established in 1994

a) Nature of the business:

SPL Industries Limited (SPLIL) is a prominent apparel export house in India. The company specialises in the design, production, and sale of cotton knitted garments and made ups. SPLIL operates through two distinct segments:

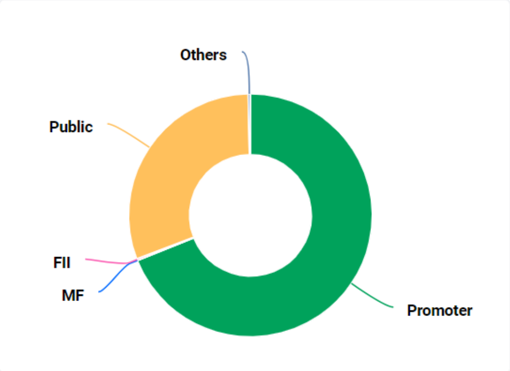
1. Manufacturing Cotton Knitted Garments and Made Ups: This segment encompasses the production of a diverse range of knitted garments, including T-shirts, polo shirts, sweatshirts, and tracksuits. Additionally, the company manufactures made-ups such as bedsheets, pillowcases, and towels.

2.Processing Charges: This segment provides dyeing, printing, and finishing services to other apparel manufacturers.

b) Public or private ownership:

Splil is a publicly listed company listed on the National Stock Exchange of India.(NSE).

SHAREHOLDING SUMMARY



c) Founding circumstances:

SPLIL's Journey from Humble Beginnings to Industry Leadership

Sure, here is a paraphrase of the sentence:

SPLIL's Journey from Humble Beginnings to Industry Leadership

1991: Shivalik Prints Private Limited - The Genesis of an Apparel Powerhouse

SPLIL's story began in 1991 as Shivalik Prints Private Limited. With a clear vision of manufacturing and exporting high-quality apparel, the company established its first textile unit, "SPL processing house." This unit focused on the printing and dyeing of cloth, initially with a daily capacity of 1,00,000 metres.

1994: SPL Industries Limited - A Publicly Traded Entity Emerges

In 1994, marking a significant milestone, the company underwent a name change to SPL Industries Limited and took the bold step of becoming a publicly traded entity. This decision opened up new avenues for growth and expansion, paving the way for SPLIL's remarkable journey in the apparel industry.

Today: A Vertically Integrated Knitwear Giant

Under the stewardship of astute leadership and a dedicated team, SPLIL has experienced exponential growth over the years. Today, it stands tall as one of

India's largest vertically integrated knitwear plants, a testament to its unwavering commitment to quality, innovation, and customer satisfaction.

SPLIL's comprehensive operations encompass the entire textile manufacturing process, from yarn procurement to knitting, dyeing, printing, stitching, and packaging. This vertical integration ensures complete control over quality and production efficiency, enabling SPLIL to consistently deliver exceptional products that meet the highest standards.

The company's unwavering focus on innovation has been a key driver of its success. SPLIL has continuously invested in cutting-edge technology and design expertise, allowing it to stay ahead of the curve and cater to the evolving demands of the global fashion industry.

As SPLIL continues to expand its reach and strengthen its position in the apparel sector, its commitment to sustainability remains paramount. The company has implemented eco-friendly practices across its operations, minimising its environmental footprint and contributing to a more sustainable future for the industry.

SPLIL's journey from humble beginnings to industry leadership is an inspiring tale of determination, innovation, and customer focus. The company's unwavering commitment to quality and sustainability has propelled it to the forefront of the apparel industry, making it a true Indian success story.

d) Overall greatness of the company:

SPLIL is widely regarded as a highly esteemed and prosperous company, boasting an impressive track record of expansion and profitability. Renowned for its superior quality products, unwavering customer focus, and commitment to sustainability, SPLIL has garnered recognition as one of the top-performing companies within the Indian textile industry.

SHANTIGEAR:-

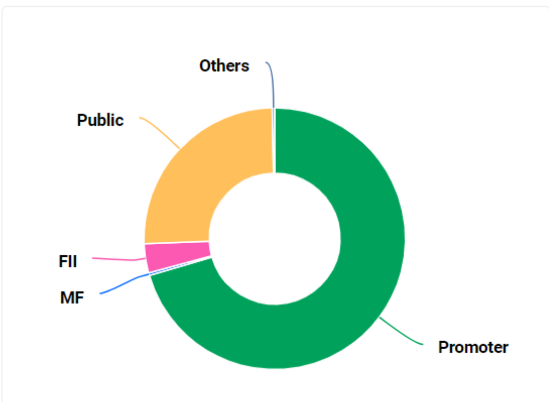
a) Nature of the business:

Shanthi Gears Limited is a prominent Indian manufacturer specializing in the production of industrial gears and gearboxes. The company's extensive product range includes gears, gearboxes, geared motors, and gear assemblies, catering to various industries such as power transmission, cement, steel, mining, sugar, and material handling. With a focus on quality and innovation, Shanthi Gears operates as a vertically integrated company,Priding itself on a top-notch manufacturing plant furnished with the latest advancements in technology. Additionally, the company places great emphasis on research and development, making substantial investments in new product development.

b) Public or private ownership:

Shanthi Gears Limited is a publicly listed company on the National Stock Exchange of India (NSE).

SHAREHOLDING SUMMARY



c) Founding circumstances:

Established in 1974, Shanthi Gears Limited originated as a joint venture between Shanthi Engineers and Nippon Seiko Kabushiki Kaisha (NSK). Initially, the company primarily manufactured gears for the automotive industry. However, in the 1980s, Shanthi Gears diversified its product portfolio to include gearboxes and geared motors. This expansion also facilitated the company's entry into international markets through product exports. In 1993, Shanthi Gears became a part of the esteemed Murugappa Group, a prominent business conglomerate in India, providing the company with access to extensive resources and expertise.

d) Overall greatness of the company:

Shanthi Gears Limited, a widely revered and prosperous company, has etched its name in the annals of industrial gear manufacturing with a remarkable history of growth and profitability. Renowned for its unwavering customer focus, commitment to technological advancements, and dedication to producing superior quality products, Shanthi Gears has established itself as a leading force in the industry. Its status as one of the largest industrial gear manufacturers in India, with a strong domestic market presence and a global export reach, further cements its position as a pioneer in the field.

VETO:-

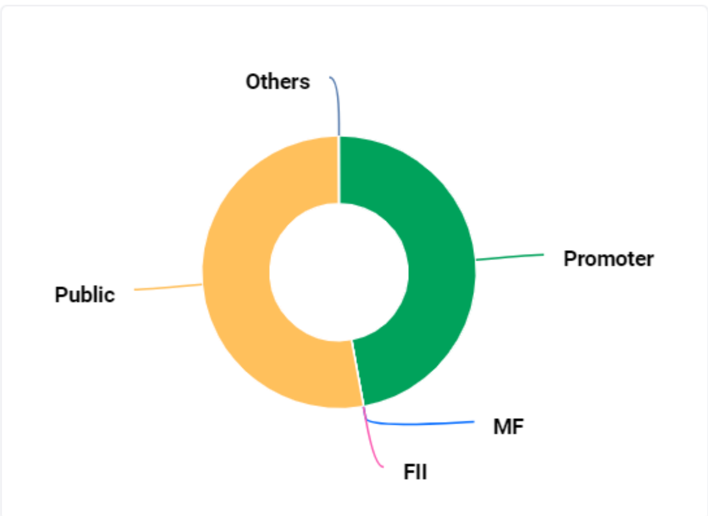
a) **Business Nature:**

Veto Switchgears and Cables Limited is a prominent manufacturer of wires and cables, electrical accessories, and lighting products in India. The company offers a diverse range of products for various applications, including power transmission, distribution, and control in industries such as power utilities, construction, and electrical equipment manufacturing. Veto's electrical accessories are renowned for their high quality and durability, while their lighting products, including LED lights, CFLs, and traditional incandescent lamps, are energy-efficient and eco-friendly.

b) **Ownership:**

Veto Switchgears and Cables Limited is a publicly listed company on the National Stock Exchange of India (NSE).

SHAREHOLDING SUMMARY



c) Founding Circumstances:

Founded in 1967, Veto Switchgears and Cables Limited owes its origins to the Gurnani Group, a well-established business conglomerate with diverse interests spanning wires and cables, electrical accessories, real estate, and hospitality. Veto's initial focus was on manufacturing wires and cables for the Indian market. However, its reputation for high-quality products propelled an expansion into electrical accessories and lighting products. The 1980s marked Veto's entry into the international export market, and currently, it commands a strong presence in over 50 countries worldwide

d) Company Reputation:

Veto Switchgears and Cables Limited is a highly respected and successful company with a proven track record of growth and profitability. The company is renowned for its commitment to quality and innovation, making it a leader in the industry.

TRIL:-

a) Nature of the business:

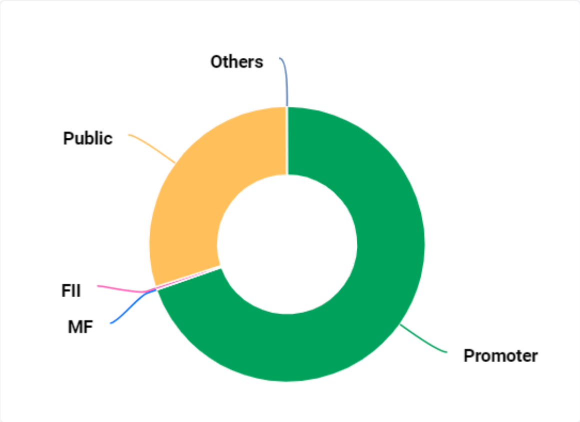
Transformers and Rectifiers (India) Limited (TRIL) reigns as a leading manufacturer of power transformers, distribution transformers, furnace transformers, rectifiers, reactors, and related equipment. The company's expertise extends to designing, manufacturing, and supplying a vast array of electrical equipment for various applications, encompassing:

- Power Transmission and Distribution: TRIL's power transformers are crucial components in the transmission and distribution of electricity, ensuring efficient and reliable power supply.
- Industrial Applications: TRIL's furnace transformers are widely used in industries like steel, aluminium, and ferroalloys, providing high-current power for melting and refining processes.
- Rectification and Conversion: TRIL's rectifiersChange alternating current (AC) into direct current (DC) to provide electrical power applications in electroplating, battery charging, and traction systems.
- Reactors: TRIL's reactors control the flow of current and voltage in electrical circuits, providing protection and stability in power systems.

b) Public or private ownership:

Transformers and Rectifiers (India) Limited (TRIL) is a public limited company listed on the Bombay Stock Exchange (BSE) and the National Stock Exchange of India (NSE). The shareholding pattern is given below:-

SHAREHOLDING SUMMARY



c) Founding circumstances:

Transformers and Rectifiers (India) Limited (TRIL) was incorporated in 1994 as Triveni Electric Company Limited. Initially, the company focused on manufacturing power transformers up to 220 kV. In 1995, the company's name was changed to Transformers and Rectifiers (India) Limited, reflecting its expanded product range.

TRIL's establishment was driven by the growing demand for electrical equipment in India's rapidly developing power sector. The company's founders recognized the need for high-quality and reliable transformers to support India's infrastructure needs.

d) Overall greatness of the company:

Transformers and Rectifiers (India) Limited (TRIL) has established itself as a leading manufacturer of electrical equipment, earning its reputation through:

- Extensive Product Range: TRIL offers a comprehensive range of power transformers, distribution transformers, furnace transformers, rectifiers, reactors, and allied equipment, catering to diverse applications.
- Unwavering Commitment to Quality: TRIL adheres to stringent quality standards, ensuring that its products meet the highest expectations of customers worldwide.
- Strong Manufacturing Capabilities: TRIL possesses world-class manufacturing facilities equipped with advanced technology, enabling the production of high-quality electrical equipment.
- Robust Customer Base: TRIL has established a strong customer base in India and overseas, supplying its products to major power utilities, industrial companies, and electrical contractors.

- Commitment to Sustainability: TRIL is committed to environmental responsibility, adopting eco-friendly practices and developing energy-efficient electrical equipment.

Transformers and Rectifiers (India) Limited (TRIL) stands as a prominent player in India's electrical equipment manufacturing landscape, recognized for its unwavering commitment to quality, innovation, and customer satisfaction. The company's consistent growth and expansion demonstrate its ability to adapt to evolving technological trends and meet the diverse needs of its customers across various industries.

MODEL’S USED-

Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) is a tool that enables investors to examine the relationship between systematic risk and expected return on investment,equities and various financial instruments.

The expected return on an investment (ERi) can be calculated using the formula:

ERi = Rf + B(ERm-Rf),

Where,

- Rf represents the risk-free rate and ERm represents the expected return on the market.
- ERi is an acronym that represents the expected return on investment.
- B represents the investment beta, which is calculated by subtracting the risk-free rate of return (Rf) from the expected market return (ERm).

Beta measures the systematic risk or volatility of a portfolio in relation to the overall market returns. Beta is calculated using a linear regression model, where market returns are used as the predictor variable and securities returns are used as the response variable. The regression's slope is commonly known as the security's beta. This demonstrates the sensitivity of security returns to fluctuations in market returns.

ARIMA Model

The ARIMA models are commonly referred to as ARIMA with p, d, and q, where integer values are employed to denote the specific type of ARIMA model being utilised.

The following are the parameters:

- ‘p’ represents the lag order of the model, which corresponds to the overall number of lag observations.

- ‘d’ represents the degree of differencing, which indicates the number of times the raw observations may be differentiated.
- The variable ‘q’ represents the size of the moving average window, which is sometimes referred to as the order of the moving average.

The value of p, which represents the order of AR, is determined by the PACF correlogram. The value of d, which represents the count of differentiation, is determined by the differentiation process. The value of q, which represents the order of MA, is determined by the ACF correlogram.

The autoregressive (AR) and moving average (MA) coefficients of the security can be determined by analysing the autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs.

GARCH and EGARCH Model-

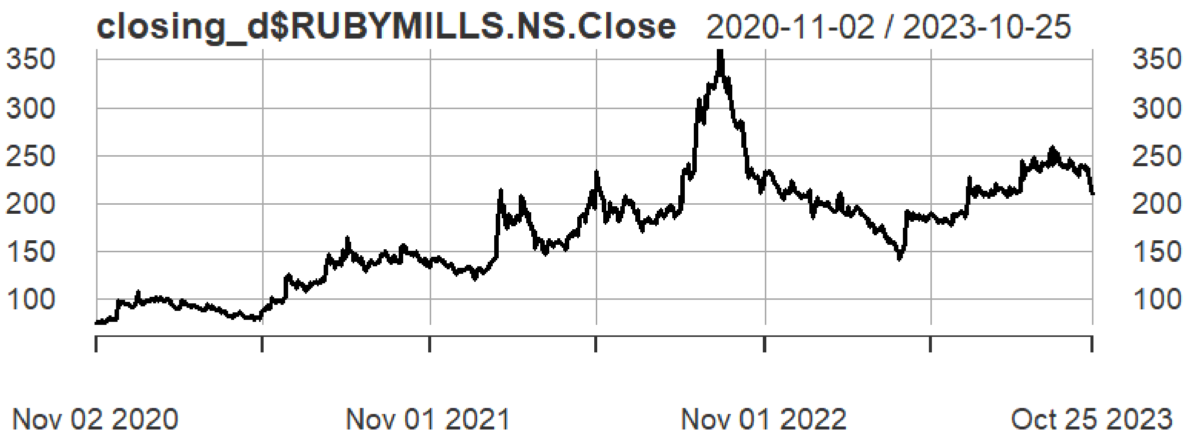
The GARCH (Generalised Autoregressive Conditional Heteroskedasticity) model is a statistical technique employed in finance for the purpose of modelling and predicting volatility in financial time series data. It postulates that the fluctuation in financial returns changes with time and may be forecasted using previous squared returns.
The EGARCH (Exponential GARCH) model is an expanded version that incorporates the concept of asymmetric volatility, wherein the impact of positive and negative shocks on volatility may differ. Both models are extensively utilised in risk management and option pricing, offering useful insights into the dynamic characteristics of volatility in financial markets.

PART 1 B) MODEL IMPLEMENTATION

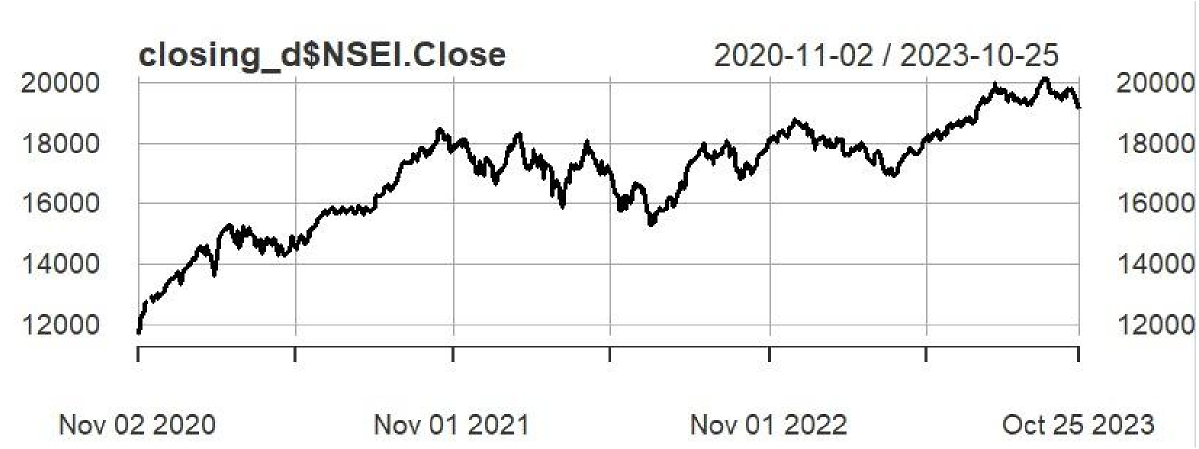
1. RUBYMILLS

SECTION 2: DAILY RETURNS ANALYSIS

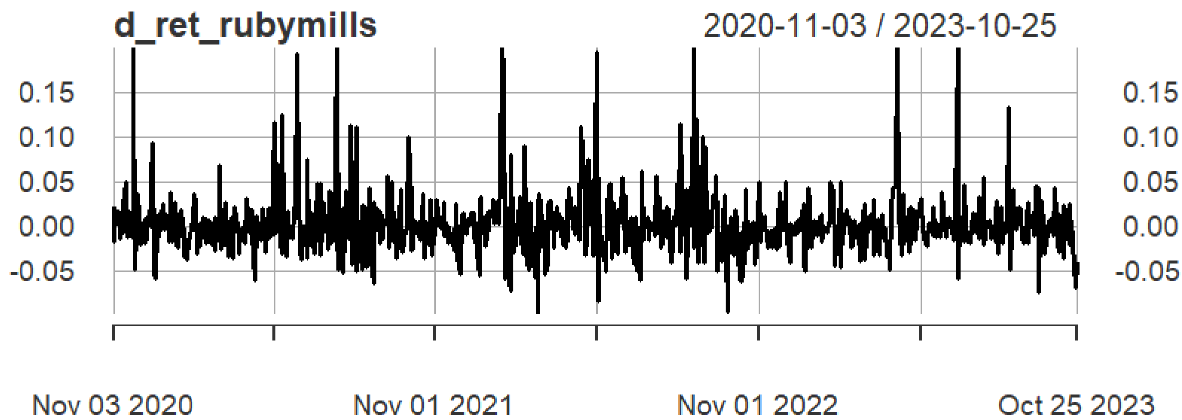
2.1 Estimating Beta Using CAPM Model



The provided figure illustrates the daily returns derived from RUBYMILLS stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the conclusion of 2022, followed by a subsequent correction. Over the course of a three-year period, there has been a more than twofold increase.



The provided figure illustrates the daily closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The above graph illustrates the daily returns derived from RUBYMILLS. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

2.1.1 Interpretation of the regression

```
Call:
lm(formula = exrubymills_d ~ exnifty_d)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.075545 -0.016791 -0.004192  0.009141  0.198869 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.003557   0.002748   1.294    0.196    
exnifty_d   1.131123   0.135259   8.363 3.17e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03491 on 719 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.08864,	Adjusted R-squared:  0.08738 
F-statistic: 69.93 on 1 and 719 DF,  p-value: 3.174e-16
```

From the results of the regression, the beta came out to be 1.13, which implies that if index portfolio excess returns increase by 1%, then the returns of RUBYMILLS increase by 1.13%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.003557, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of RUBYMILLS are 0.003557%.

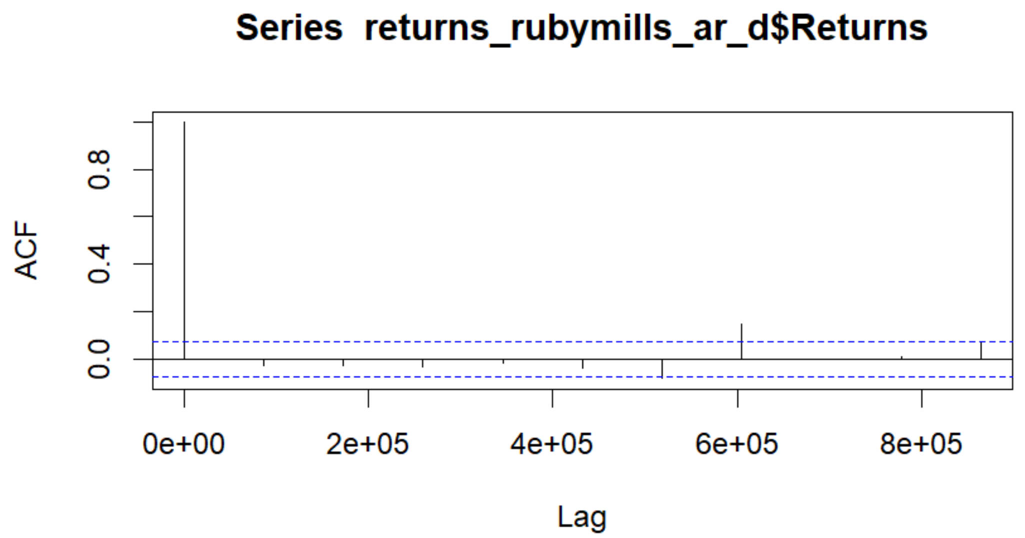
2.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
        Augmented Dickey-Fuller Test

data:  returns_rubymills_ar_d$Returns
Dickey-Fuller = -7.6611, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary
```

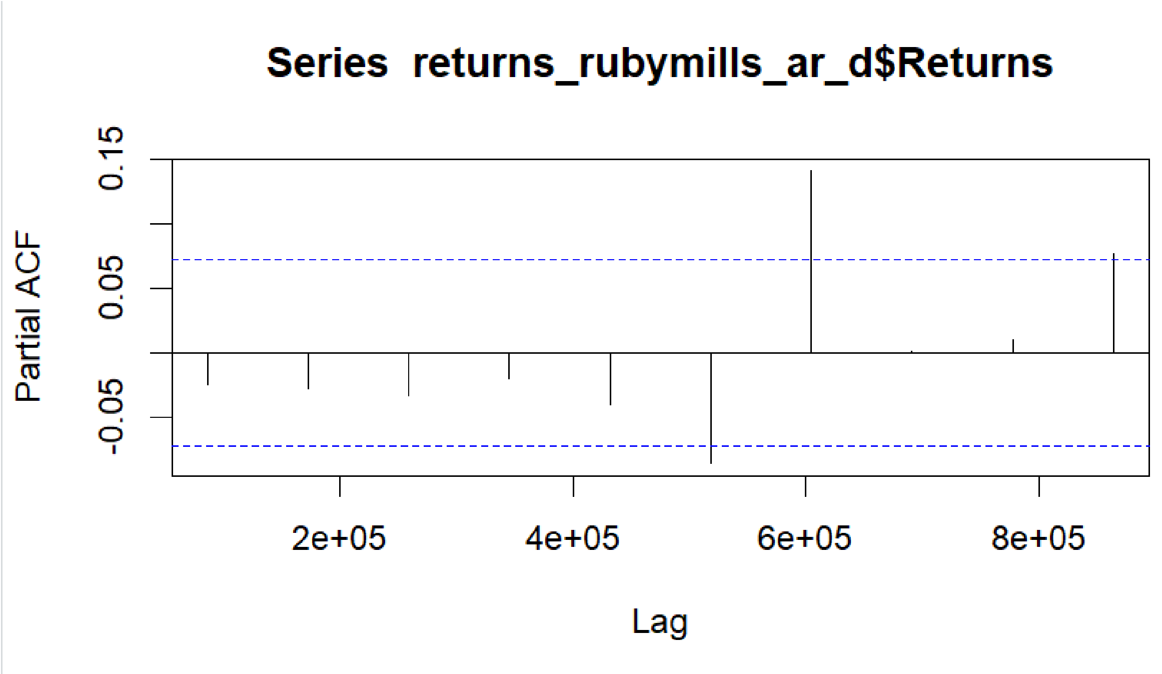
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -7.6611.

2.2.1 ACF Plot



From the above plot, it can be derived that the series is the MA(0) model since the initial lags are insignificant.

2.2.2 PACF plot



From the above plot it can be derived that the series is AR(0) model since the initial lags are insignificant.

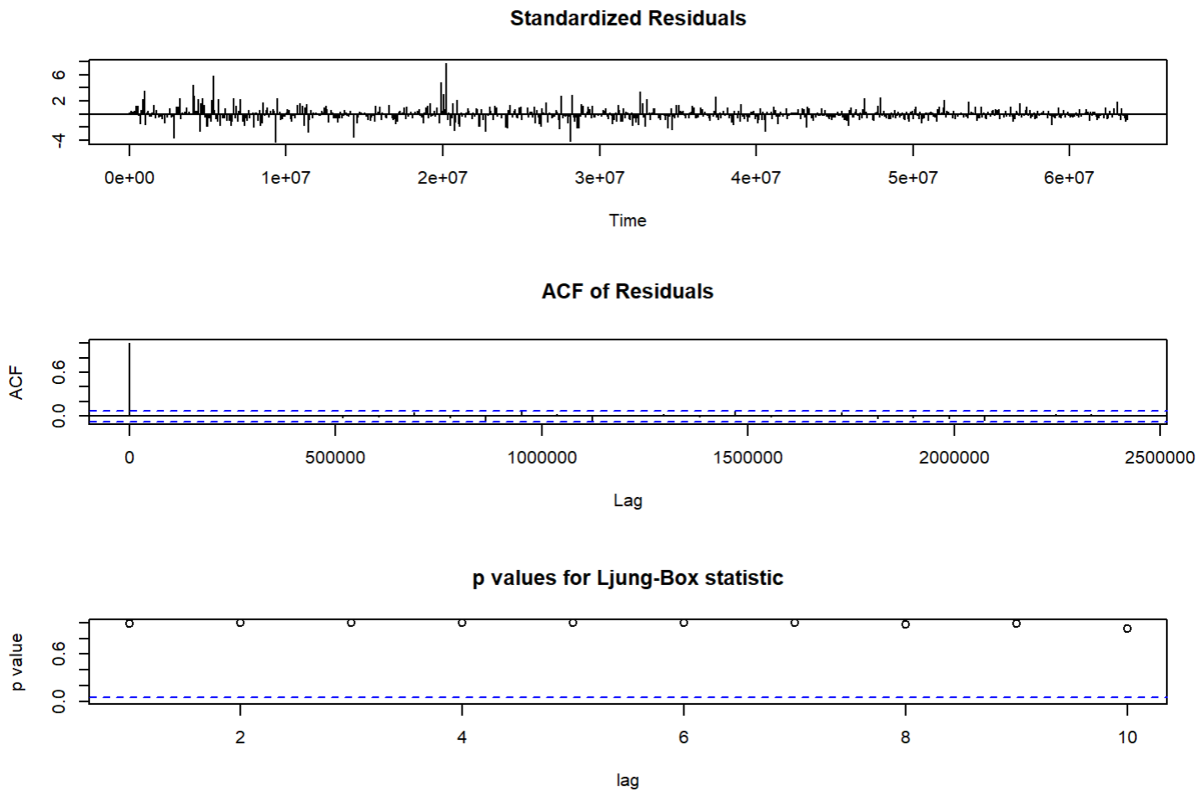
To finally interpret the correct model we use Auto.arima function as shown below-

2.2.3 Identification and interpretation of the ARIMA model

```
ARIMA(0,0,0) with non-zero mean

Coefficients:
        mean
      0.0020
s.e.  0.0013

sigma^2 = 0.001316:  log likelihood = 1400.95
AIC=-2797.91   AICc=-2797.89   BIC=-2788.7
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



2.3 GARCH and EGARCH models

Running GARCH on daily return of RUBYMILLS yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model                : sGARCH(1,1)
Variance Targeting         : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model                 : ARFIMA(1,0,1)
Include Mean               : TRUE
GARCH-in-Mean              : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The daily returns of RUBYMILLS were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
-----------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
-----------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model      : sGARCH(1,1)
Mean Model       : ARFIMA(1,0,1)
Distribution     : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error     t value Pr(>|t|)
mu      0.001950    0.001192  1.6358e+00 0.101888
ar1     0.631901    0.217830  2.9009e+00 0.003721
ma1    -0.670547    0.207256 -3.2354e+00 0.001215
omega   0.000001    0.000000  1.1667e+01 0.000000
alpha1  0.000000    0.000164  8.0000e-06 0.999994
beta1   0.999000    0.000006  1.8118e+05 0.000000

Robust Standard Errors:
        Estimate  Std. Error     t value Pr(>|t|)
mu      0.001950    0.001287  1.5154e+00 0.129674
ar1     0.631901    0.155272  4.0696e+00 0.000047
ma1    -0.670547    0.132744 -5.0514e+00 0.000000
omega   0.000001    0.000000  1.2457e+01 0.000000
alpha1  0.000000    0.000264  5.0000e-06 0.999996
beta1   0.999000    0.000059  1.6991e+04 0.000000

LogLikelihood : 1404.107
```

```
Information Criteria
------------------------------------

Akaike       -3.7838
Bayes        -3.7464
Shibata      -3.7839
Hannan-Quinn -3.7694

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1156 0.73382
Lag[2*(p+q)+(p+q)-1][5]    0.4413 1.00000
Lag[4*(p+q)+(p+q)-1][9]    7.8968 0.06289
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic  p-value
Lag[1]                      9.115 0.002535
Lag[2*(p+q)+(p+q)-1][5]    10.379 0.007355
Lag[4*(p+q)+(p+q)-1][9]    11.025 0.030023
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.3242 0.500 2.000  0.5691
ARCH Lag[5]    0.3560 1.440 1.667  0.9250
ARCH Lag[7]    0.9360 2.315 1.543  0.9237
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  109.2387
Individual Statistics:
mu      0.12844
ar1     0.08057
ma1     0.08277
omega   1.14472
alpha1  0.17351
beta1   0.20792

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                    t-value     prob sig
Sign Bias           0.05827 0.953553
Negative Sign Bias  0.74212 0.458251
Positive Sign Bias  2.99599 0.002828 ***
Joint Effect       10.87376 0.012428  **


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     155.0    2.376e-23
2    30     180.9    6.751e-24
3    40     174.4    4.884e-19
4    50     195.0    2.571e-19
```

2.3.1 Interpretation

• The Log Likelihood obtained from the model is 1404.168.

• GARCH(1,1) is the best-fit model for RUBYMILLS daily returns.

• The optimal parameters omega and beta have significant value while alpha is insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that only alpha is insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values less than 0.05, indicating that the null hypothesis should be rejected. This suggests a significant disparity between the observed and predicted values.

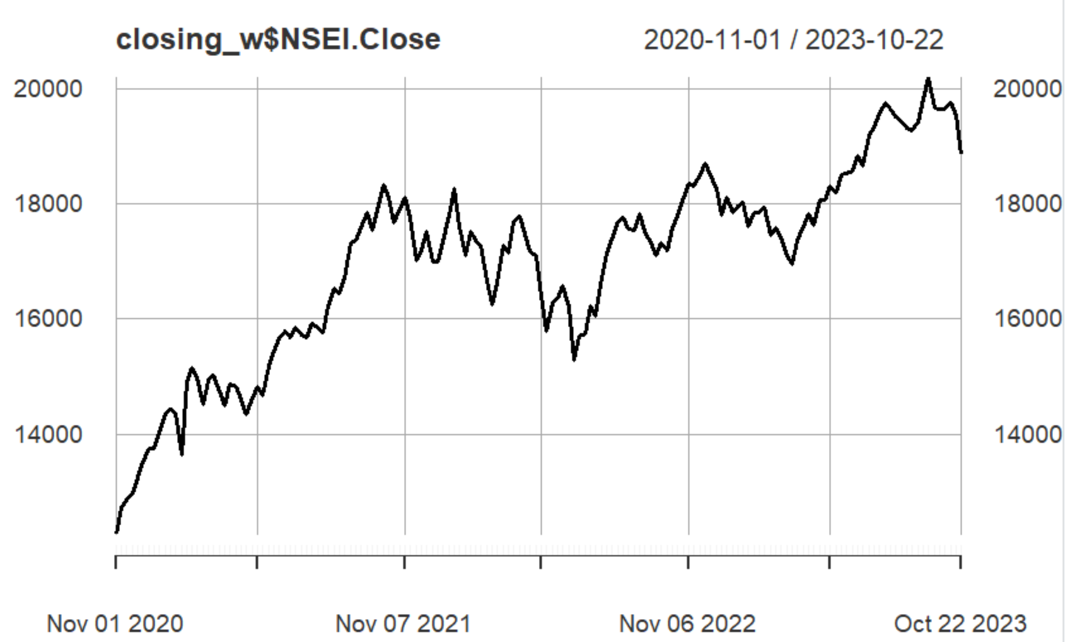
2.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-day period are expected to be positive, with an approximate value of 0.3%, accompanied with a standard deviation in close proximity to 3.5%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of RUBYMILLS within the subsequent 10-day period, aligning with the forecast provided by the ARIMA model.

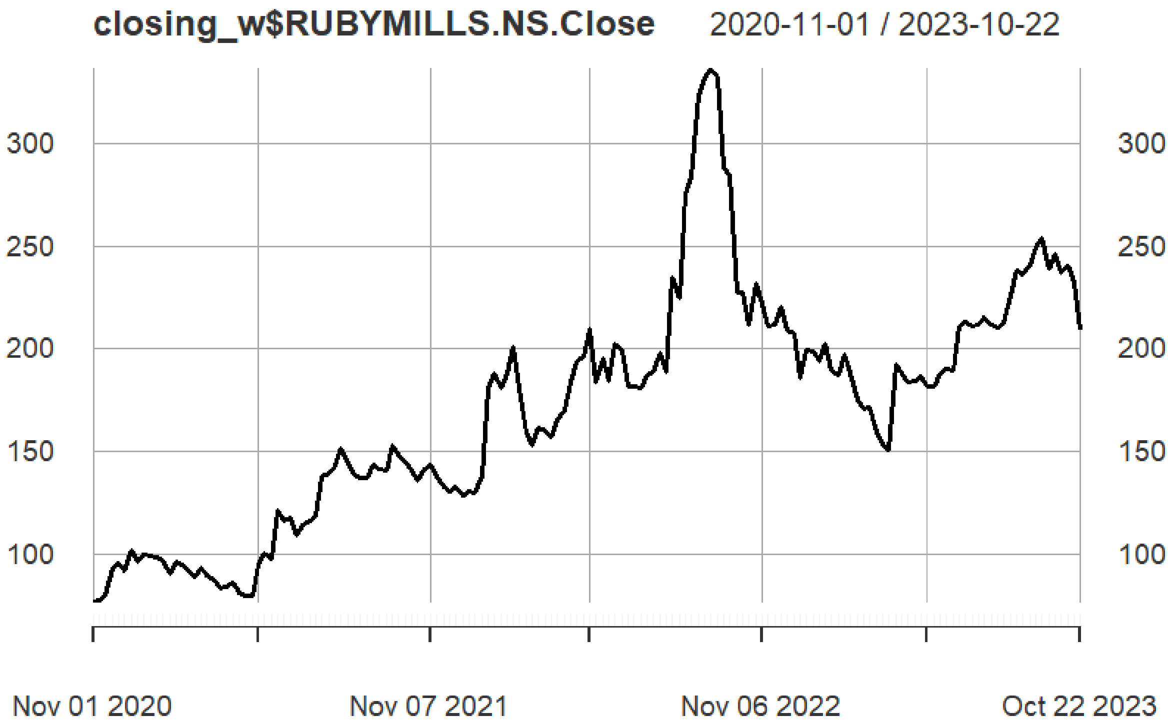
```
*---------------------------------------*
*       GARCH Model Forecast            *
*---------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1   0.005868 0.03501
T+2   0.004425 0.03501
T+3   0.003514 0.03501
T+4   0.002938 0.03501
T+5   0.002574 0.03501
T+6   0.002345 0.03501
T+7   0.002199 0.03500
T+8   0.002107 0.03500
T+9   0.002049 0.03500
T+10  0.002013 0.03500
```

SECTION 3: WEEKLY RETURNS ANALYSIS

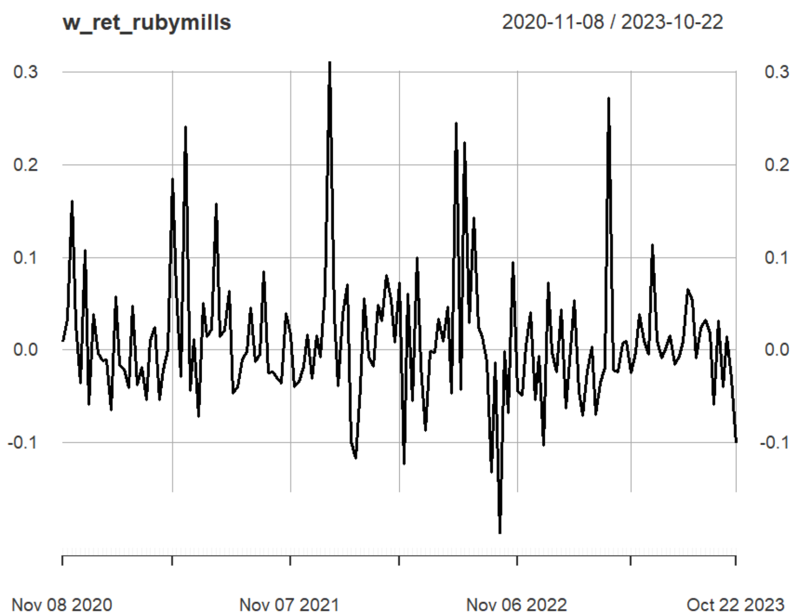
3.1 Estimating Beta Using CAPM Model



The Provided figure illustrates the weekly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the weekly returns derived from RUBYMILLS stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the conclusion of 2022, followed by a subsequent correction. Over the course of a three-year period, there has been a more than twofold increase.



The above graph illustrates the weekly returns derived from RUBYMILLS. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

3.1.1 Interpretation of the regression

```
> #Running the regression model
> regression_w<-lm(exrubymills_w~exnifty_w)
> #slope parameter is beta in CAPM model
> summary(regression_w)

Call:
lm(formula = exrubymills_w ~ exnifty_w)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.191669 -0.040918 -0.008649  0.018003  0.274954 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.03295    0.02849   1.157    0.249    
exnifty_w    1.21252    0.21928   5.529 1.36e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0671 on 153 degrees of freedom
Multiple R-squared:  0.1666,	Adjusted R-squared:  0.1611 
F-statistic: 30.57 on 1 and 153 DF,  p-value: 1.356e-07
```

From the results of the regression, the beta came out to be 1.21, which implies that if index portfolio excess returns increase by 1%, then the returns of RUBYMILLS increase by 1.21%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.003295, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of RUBYMILLS are 0.003295%.

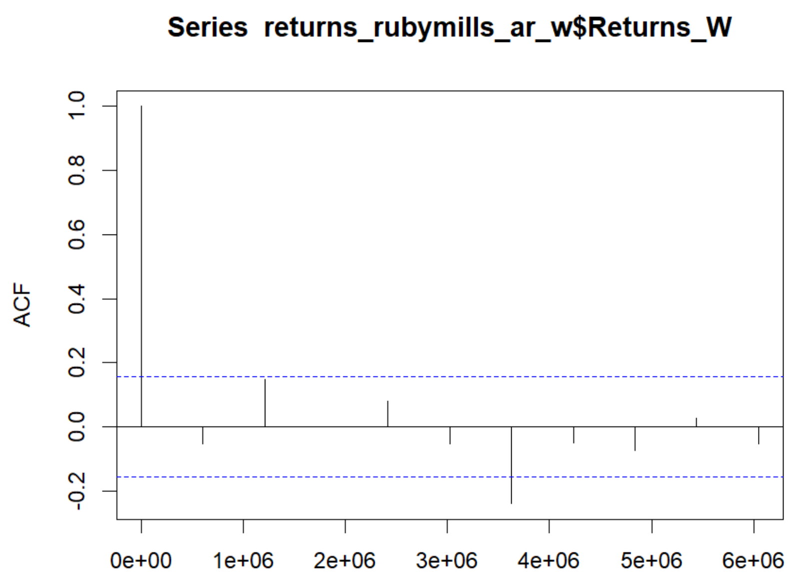
3.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_rubymills_ar_w,alternative=c("stationary"))

	Augmented Dickey-Fuller Test

data:  returns_rubymills_ar_w
Dickey-Fuller = -6.2019, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

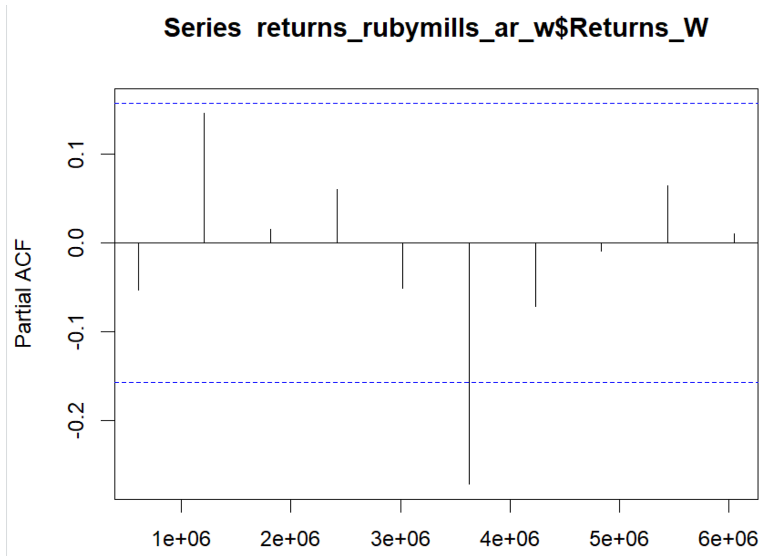
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -6.2019.

3.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(0) model since the initial lags are insignificant.

3.2.2 PACF plot



From the above plot it can be derived that the series is an AR(0) model since initial lags are insignificant.

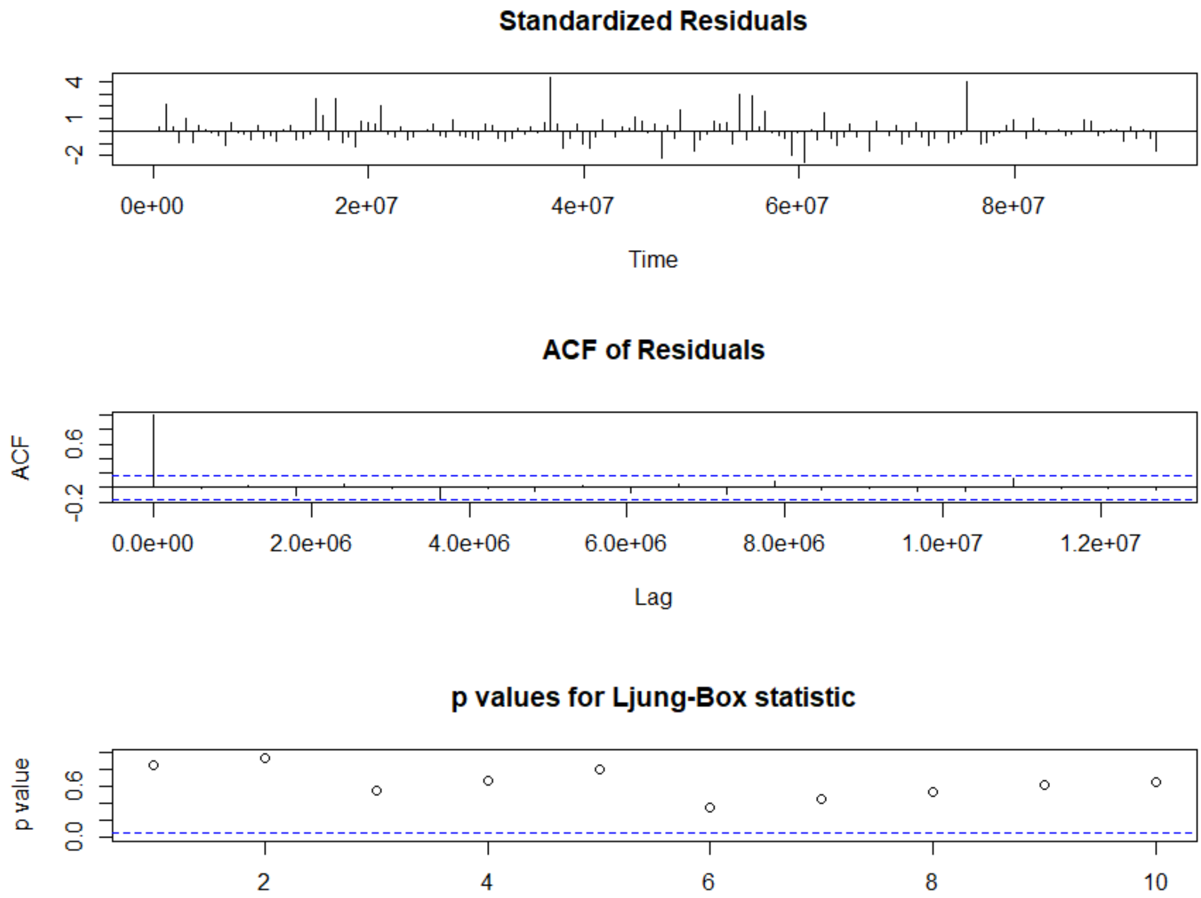
To finally interpret the correct model we use Auto.arima function as shown below-

3.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_rubymills_ar_w$Returns)
Series: returns_rubymills_ar_w$Returns
ARIMA(2,0,2) with zero mean

Coefficients:
         ar1      ar2      ma1     ma2
      0.9727  -0.5810  -1.0390  0.8064
s.e.  0.2127   0.1284   0.1589  0.0814

sigma^2 = 0.004861:  log likelihood = 194.66
AIC=-379.32   AICc=-378.91   BIC=-364.1
```

The ARIMA function recommended a (2,0,2) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



3.3 GARCH and EGARCH models

Running GARCH on weekly return of RUBYMILLS yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
-----------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
-----------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The weekly returns of RUBYMILLS were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
-----------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
-----------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.008682    0.005418   1.602425 0.109062
ar1    -0.632159    0.249235  -2.536397 0.011200
ma1     0.546327    0.263329   2.074692 0.038015
omega   0.000004    0.000044   0.091432 0.927149
alpha1  0.000000    0.004172   0.000001 1.000000
beta1   0.998999    0.003468 288.070760 0.000000

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.008682    0.005724   1.516756  0.12933
ar1    -0.632159    0.121056  -5.222056  0.00000
ma1     0.546327    0.100062   5.459905  0.00000
omega   0.000004    0.000104   0.038349  0.96941
alpha1  0.000000    0.007507   0.000000  1.00000
beta1   0.998999    0.005814 171.840081  0.00000

LogLikelihood : 192.0216
```

```
Information Criteria
------------------------------------

Akaike       -2.3849
Bayes        -2.2676
Shibata      -2.3877
Hannan-Quinn -2.3372

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.3296 0.56591
Lag[2*(p+q)+(p+q)-1][5]    2.1237 0.93020
Lag[4*(p+q)+(p+q)-1][9]    8.0036 0.05751
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.8082  0.3686
Lag[2*(p+q)+(p+q)-1][5]    1.6281  0.7084
Lag[4*(p+q)+(p+q)-1][9]    2.1971  0.8802
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]  0.009518 0.500 2.000  0.9223
ARCH Lag[5]  0.457677 1.440 1.667  0.8961
ARCH Lag[7]  0.732220 2.315 1.543  0.9528
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  15.5872
Individual Statistics:
mu     0.1314
ar1    0.1512
ma1    0.1396
omega  0.1135
alpha1 0.1030
beta1  0.1481

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.6457 0.5195
Negative Sign Bias  0.5750 0.5662
Positive Sign Bias  0.3407 0.7338
Joint Effect        0.9410 0.8155


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     40.15     0.003123
2    30     42.46     0.051012
3    40     60.41     0.015509
4    50     70.28     0.024724
```

3.3.1 Interpretation

• The Log Likelihood obtained from the model is 192.0216.

• GARCH(1,1) is the best-fit model for RUBYMILLS weekly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values less than 0.05, indicating that the null hypothesis should be rejected. This suggests a significant disparity between the observed and predicted values.

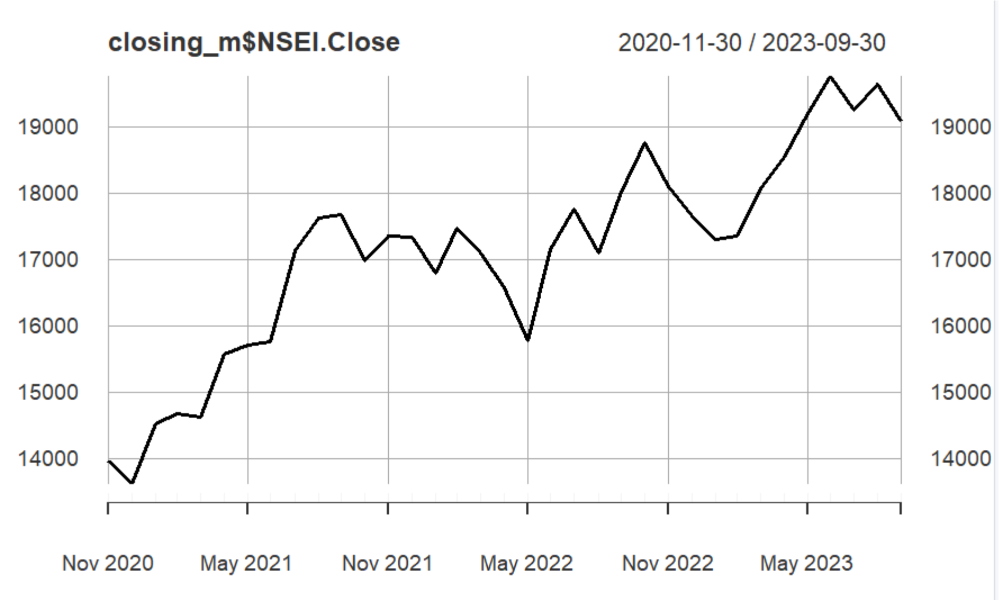
3.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-week period are expected to be positive, with an approximate value of 0.8%, accompanied with a standard deviation in close proximity to 6.96%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of RUBYMILLS within the subsequent 10-week period, aligning with the forecast provided by the ARIMA model.

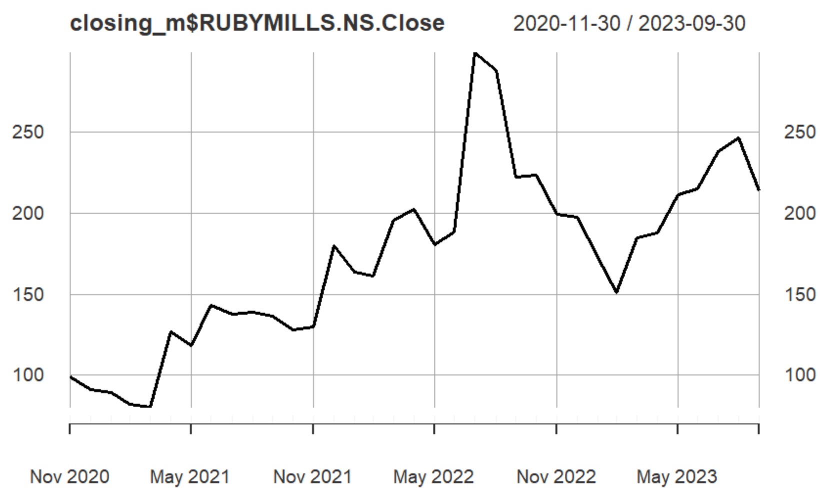
```
> #Forecasting
> ugforecast_w=ugarchforecast(ugfit_w,n.ahead = 10)
> ugforecast_w

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1  0.015343 0.06963
T+2  0.004471 0.06963
T+3  0.011344 0.06962
T+4  0.006999 0.06962
T+5  0.009745 0.06961
T+6  0.008009 0.06960
T+7  0.009107 0.06960
T+8  0.008413 0.06959
T+9  0.008852 0.06958
T+10 0.008574 0.06958
```

SECTION 4: MONTHLY RETURNS ANALYSIS

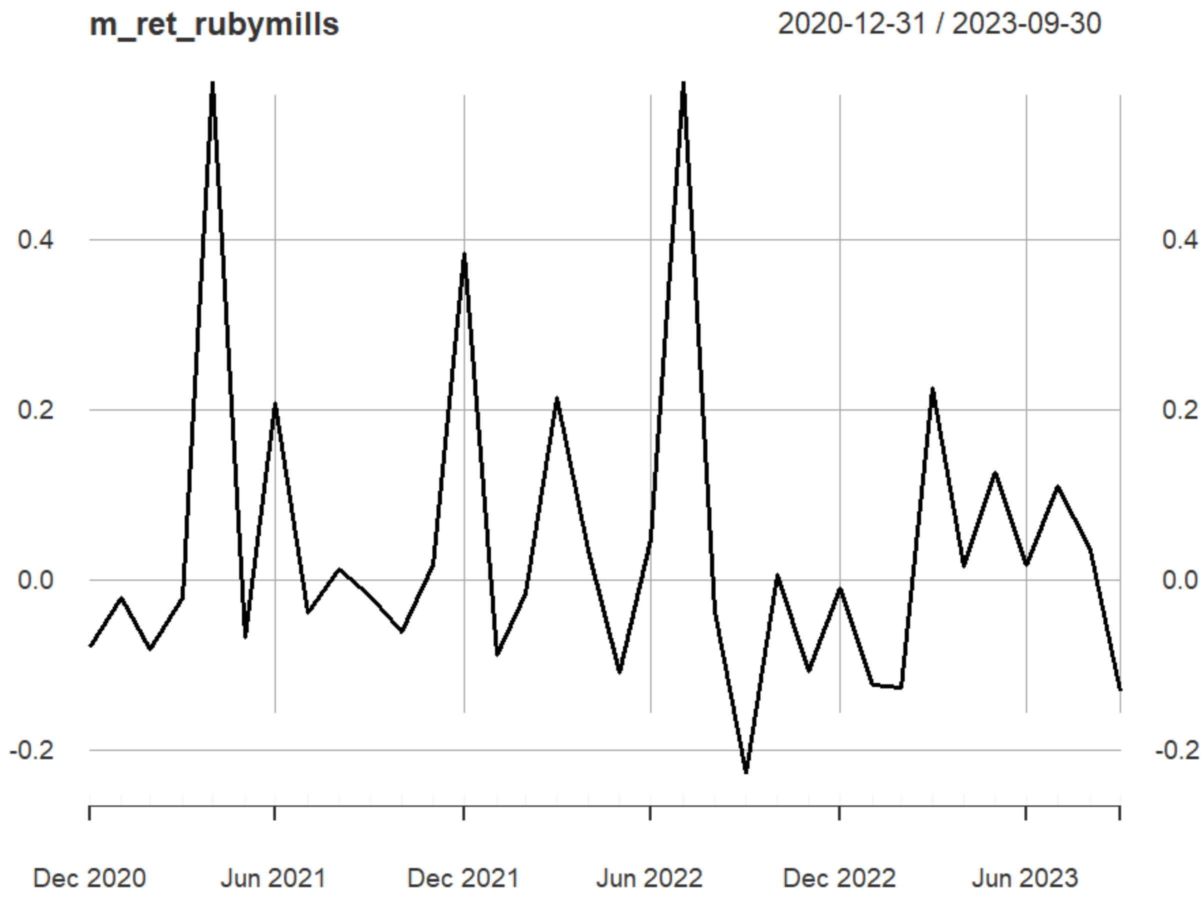
4.1 CAPM Model – Estimating Beta of the company



Provided figure illustrates the monthly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the monthly returns derived from RUBYMILLS stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the conclusion of 2022, followed by a subsequent correction. Over the course of a three-year period, there has been a more than twofold increase.



The above graph illustrates the monthly returns derived from RUBYMILLS. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

4.1.1 Interpretation of the regression

```
> summary(regression_m)

Call:
lm(formula = exrubymills_m ~ exnifty_m)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.30645 -0.09273 -0.05673  0.04991  0.52429 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)   0.2021     0.2765   0.731   0.4702  
exnifty_m     1.3129     0.4901   2.679   0.0116 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1788 on 32 degrees of freedom
Multiple R-squared:  0.1832,	Adjusted R-squared:  0.1576 
F-statistic: 7.176 on 1 and 32 DF,  p-value: 0.01157
```

From the results of the regression, the beta came out to be 1.31, which implies that if index portfolio excess returns increase by 1%, then the returns of RUBYMILLS increase by 1.31%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.2021, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of RUBYMILLS are 0.2021%.

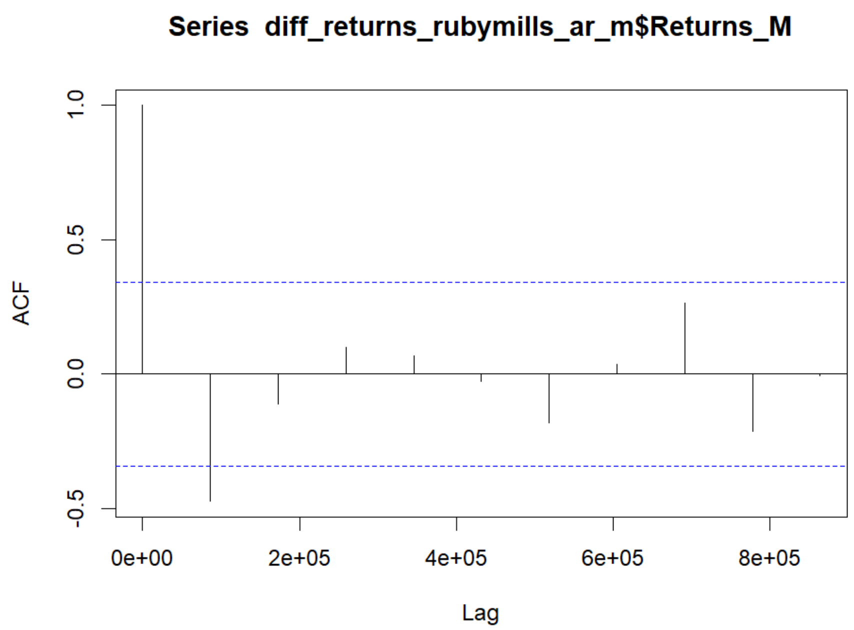
4.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_rubymills_ar_m,alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_rubymills_ar_m
Dickey-Fuller = -3.7125, Lag order = 3, p-value = 0.03918
alternative hypothesis: stationary
```

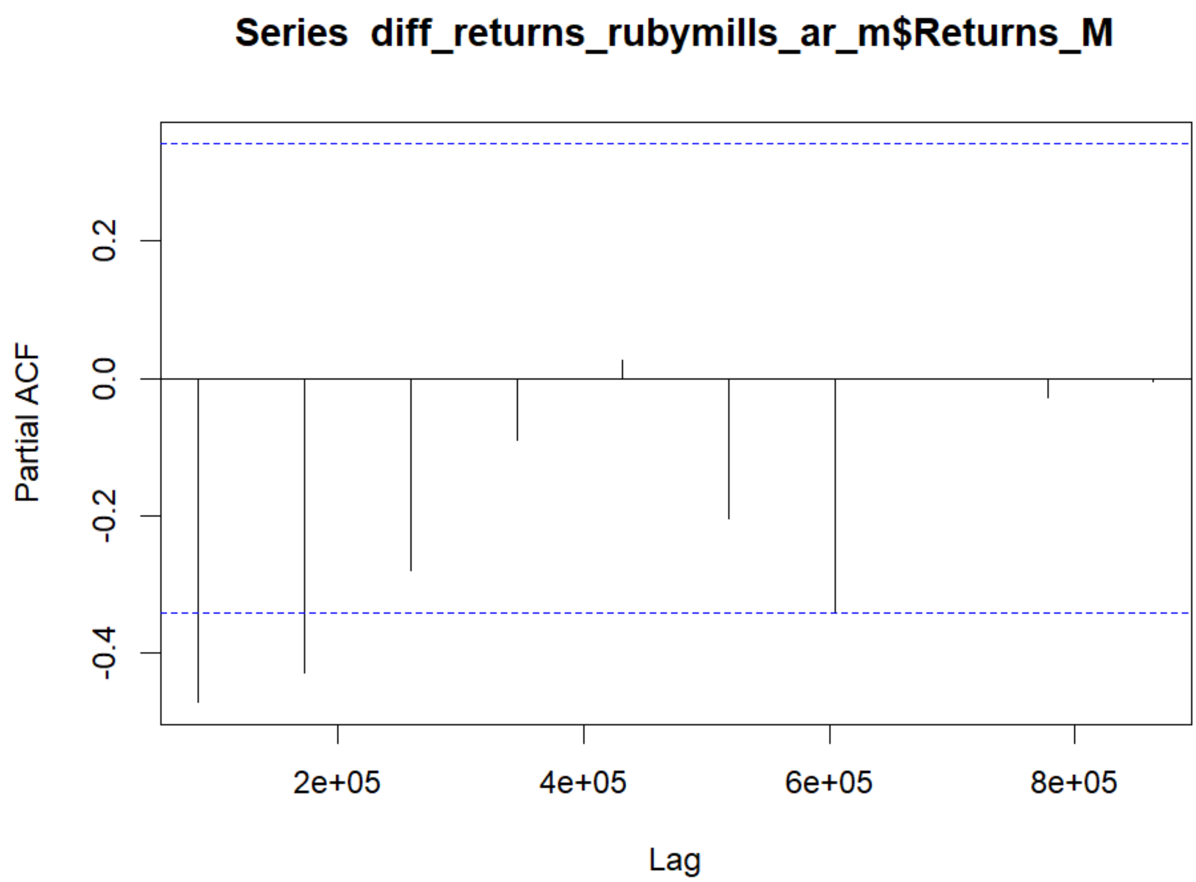
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.03918. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -3.7125.

4.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(1) model since the correlation is significant only at one lag; after that, values are not significant.

4.2.2 PACF plot



From the above plot it can be derived that the series is an AR(2) model since initial 2 lags are significant.

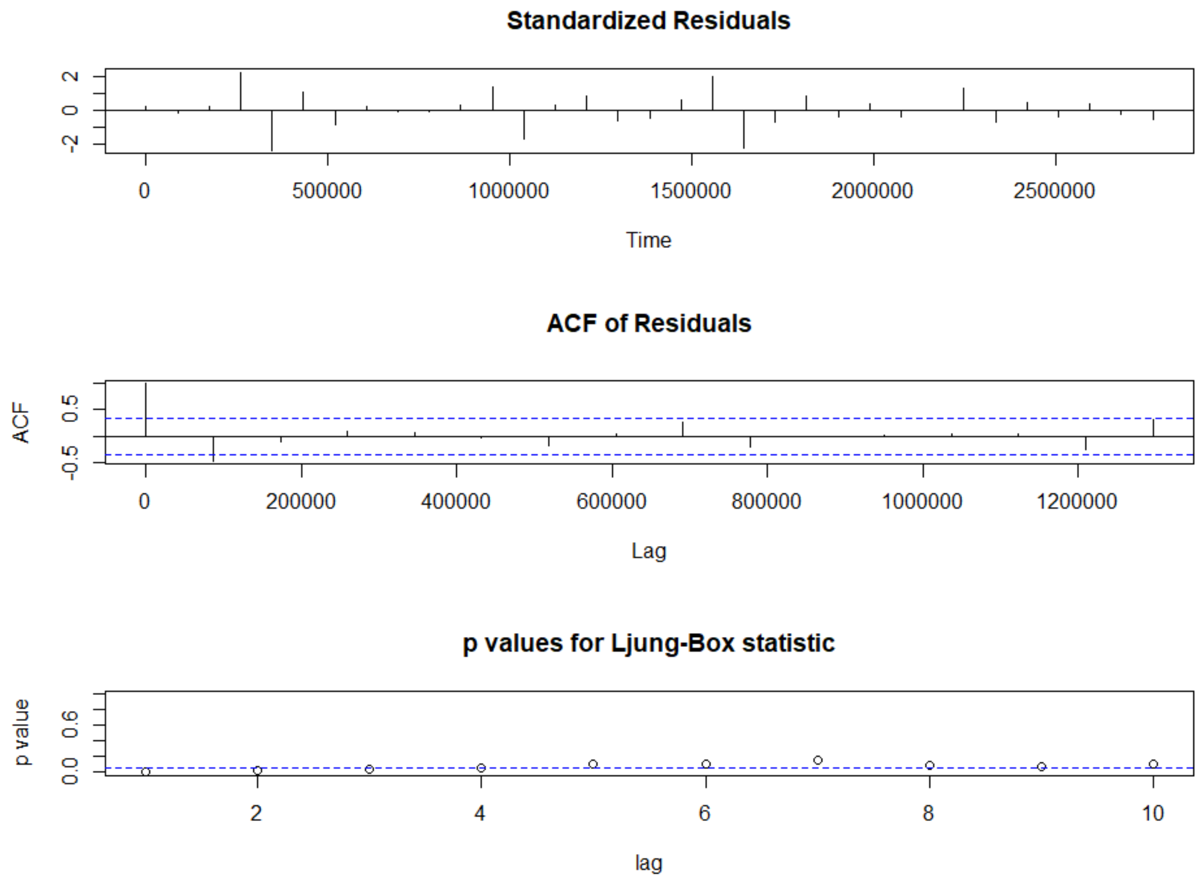
To finally interpret the correct model we use Auto.arima function as shown below-

4.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_rubymills_ar_m$Returns)
Series: returns_rubymills_ar_m$Returns
ARIMA(0,0,0) with zero mean

sigma^2 = 0.03414:  log likelihood = 9.17
AIC=-16.33   AICc=-16.21   BIC=-14.81
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



4.3 GARCH and EGARCH models

Running GARCH on monthly return of RUBYMILLS yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
-----------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
-----------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The monthly returns of RUBYMILLS were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
-----------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
-----------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.009305    0.005121  1.817219 0.069184
ar1     0.615324    0.301413  2.041463 0.041205
ma1    -0.494863    0.328707 -1.505486 0.132199
omega   0.000000    0.000004  0.000002 0.999999
alpha1  0.007736    0.009247  0.836528 0.402858
beta1   0.984282    0.010373 94.885086 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.009305    0.005661   1.6438 0.100211
ar1     0.615324    0.218645   2.8143 0.004889
ma1    -0.494863    0.284122  -1.7417 0.081556
omega   0.000000    0.000015   0.0000 1.000000
alpha1  0.007736    0.018538   0.4173 0.676462
beta1   0.984282    0.022446  43.8516 0.000000

LogLikelihood : 238.7793
```

```
Information Criteria
------------------------------------

Akaike       -2.9844
Bayes        -2.8670
Shibata      -2.9872
Hannan-Quinn -2.9367

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.02422  0.8763
Lag[2*(p+q)+(p+q)-1][5]   0.68418  1.0000
Lag[4*(p+q)+(p+q)-1][9]   1.70767  0.9936
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.407  0.2355
Lag[2*(p+q)+(p+q)-1][5]     3.167  0.3774
Lag[4*(p+q)+(p+q)-1][9]     3.920  0.6025
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.704 0.500 2.000  0.1918
ARCH Lag[5]     2.381 1.440 1.667  0.3930
ARCH Lag[7]     2.516 2.315 1.543  0.6092
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  8.7559
Individual Statistics:
mu     0.17169
ar1    0.09534
ma1    0.10386
omega  0.18353
alpha1 0.17545
beta1  0.19989

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value    prob sig
Sign Bias           0.6815 0.49661
Negative Sign Bias  0.8092 0.41968
Positive Sign Bias  1.8570 0.06526   *
Joint Effect        5.9068 0.11623


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     21.18       0.3270
2    30     28.62       0.4852
3    40     44.51       0.2509
4    50     50.41       0.4175
```

4.3.1 Interpretation

- The Log Likelihood obtained from the model is 238.77.

- GARCH(1,1) is the best-fit model for RUBYMILLS monthly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major discrepancy between the observed value and the predicted value.

4.3.2 Forecast using GARCH

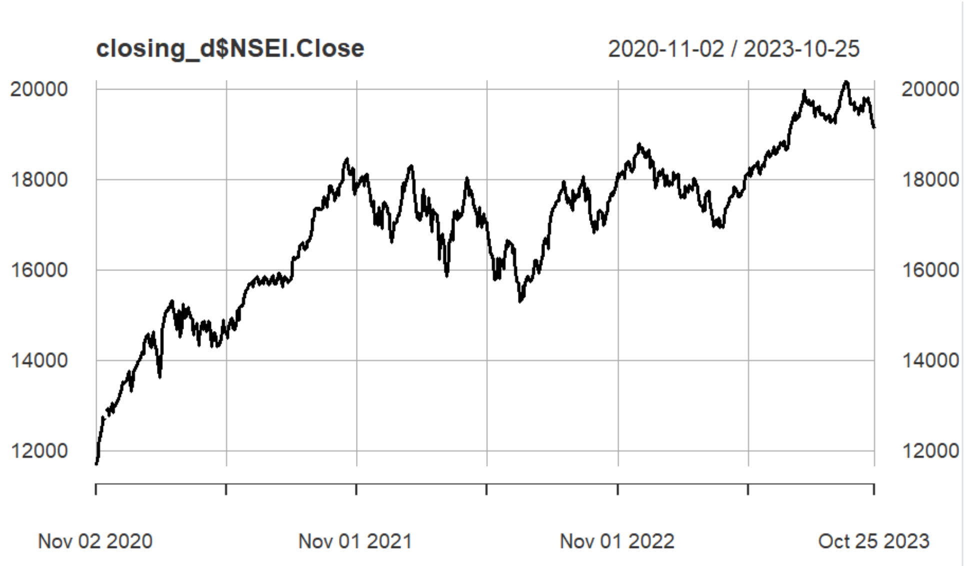
The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-month period are expected to be positive, with an approximate value of 4.4%, accompanied with a standard deviation in close proximity to 7.7%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of RUBYMILLS within the subsequent 10-month period, aligning with the forecast provided by the ARIMA model.

```
*---------------------------------*
*       GARCH Model Forecast      *
*---------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
      Series   Sigma
T+1  0.01983 0.08248
T+2  0.05902 0.08132
T+3  0.02694 0.08017
T+4  0.05320 0.07904
T+5  0.03170 0.07793
T+6  0.04930 0.07683
T+7  0.03490 0.07574
T+8  0.04669 0.07467
T+9  0.03704 0.07362
T+10 0.04494 0.07258
```

2. SHANTIGEAR

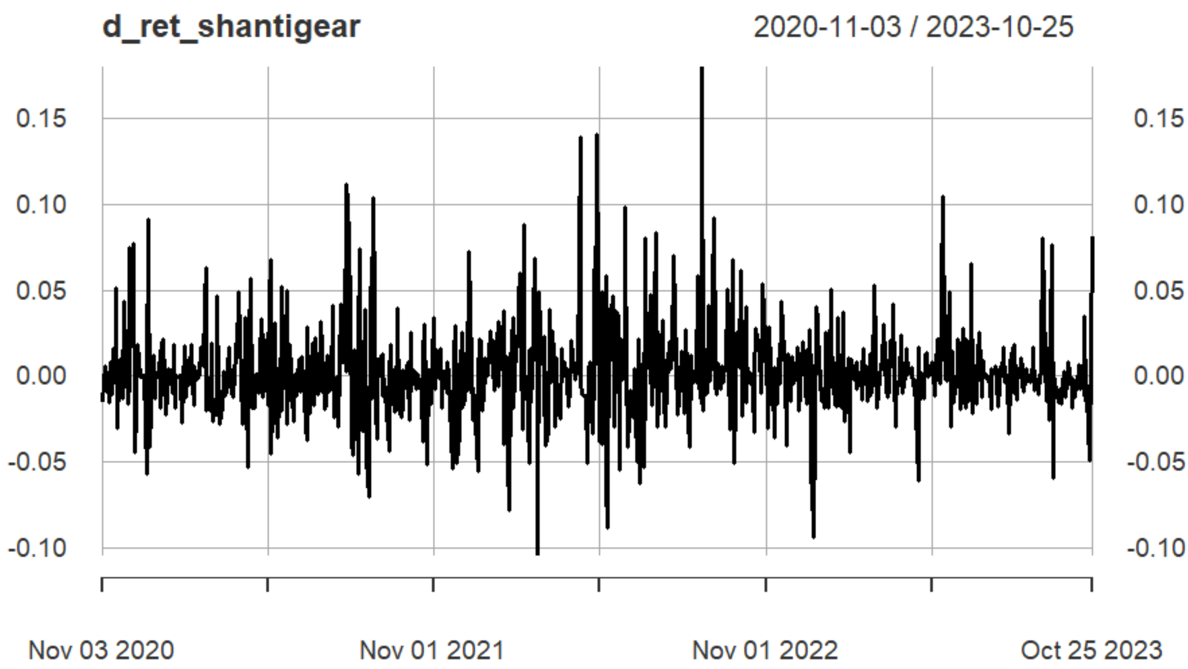
SECTION 2: DAILY RETURNS ANALYSIS

2.1 Estimating Beta Using CAPM Model



The provided figure illustrates the daily closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.

The provided figure illustrates the daily returns derived from SHANTIGEAR stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price. Over the course of a three-year period, there has been a more than fourfold increase.



The above graph illustrates the daily returns derived from SHANTIGEAR. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

2.1.1 Interpretation of the regression

```
Call:
lm(formula = exshantigear_d ~ exnifty_d)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.086487 -0.014436 -0.002764  0.010889  0.173719 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.001643   0.002170  -0.757    0.449    
exnifty_d    0.815047   0.106781   7.633 7.31e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02756 on 719 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.07496,	Adjusted R-squared:  0.07367 
F-statistic: 58.26 on 1 and 719 DF,  p-value: 7.314e-14
```

From the results of the regression, the beta came out to be 0.815, which implies that if index portfolio excess returns increase by 1%, then the returns of SHANTIGEAR increase by 0.815%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is -0.001643, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of SHANTIGEAR are -0.001643%.

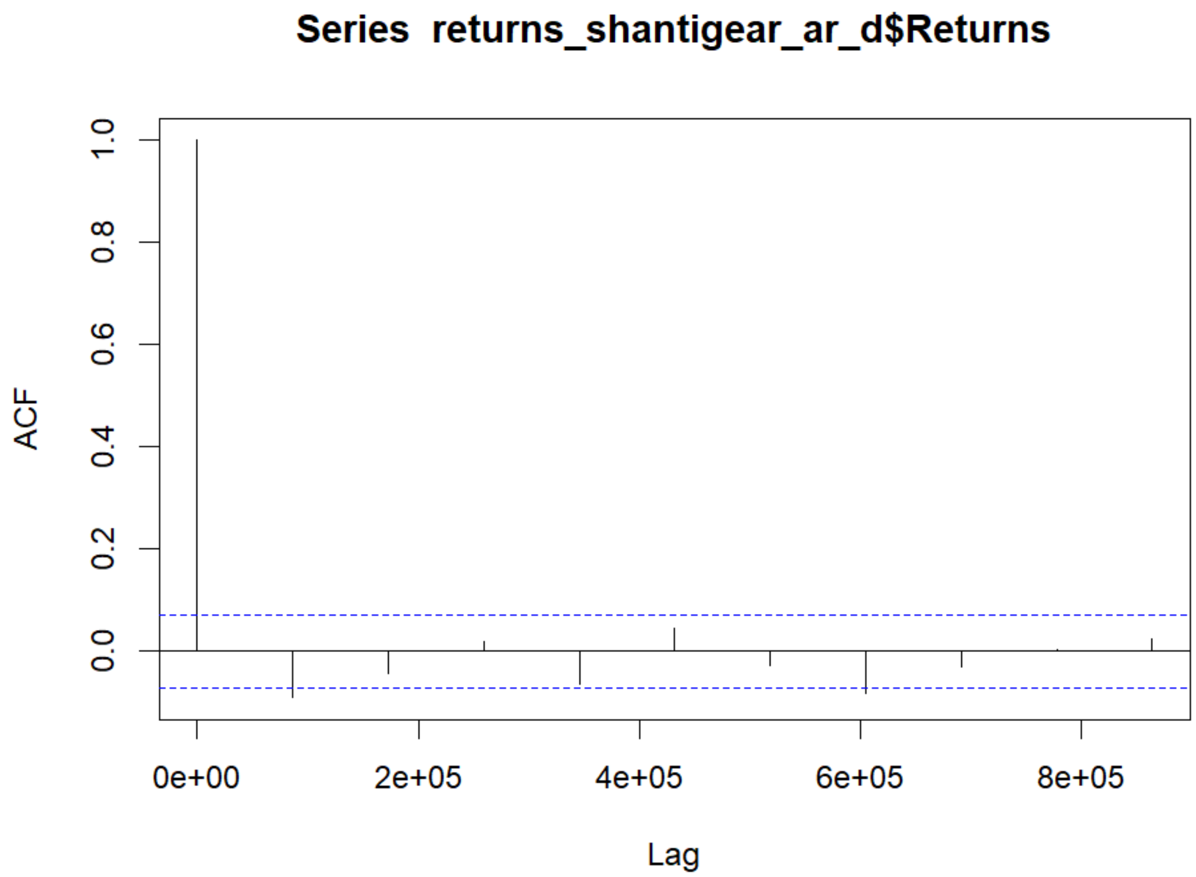
2.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_shantigear_ar_d$Returns, alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_shantigear_ar_d$Returns
Dickey-Fuller = -9.5594, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary
```

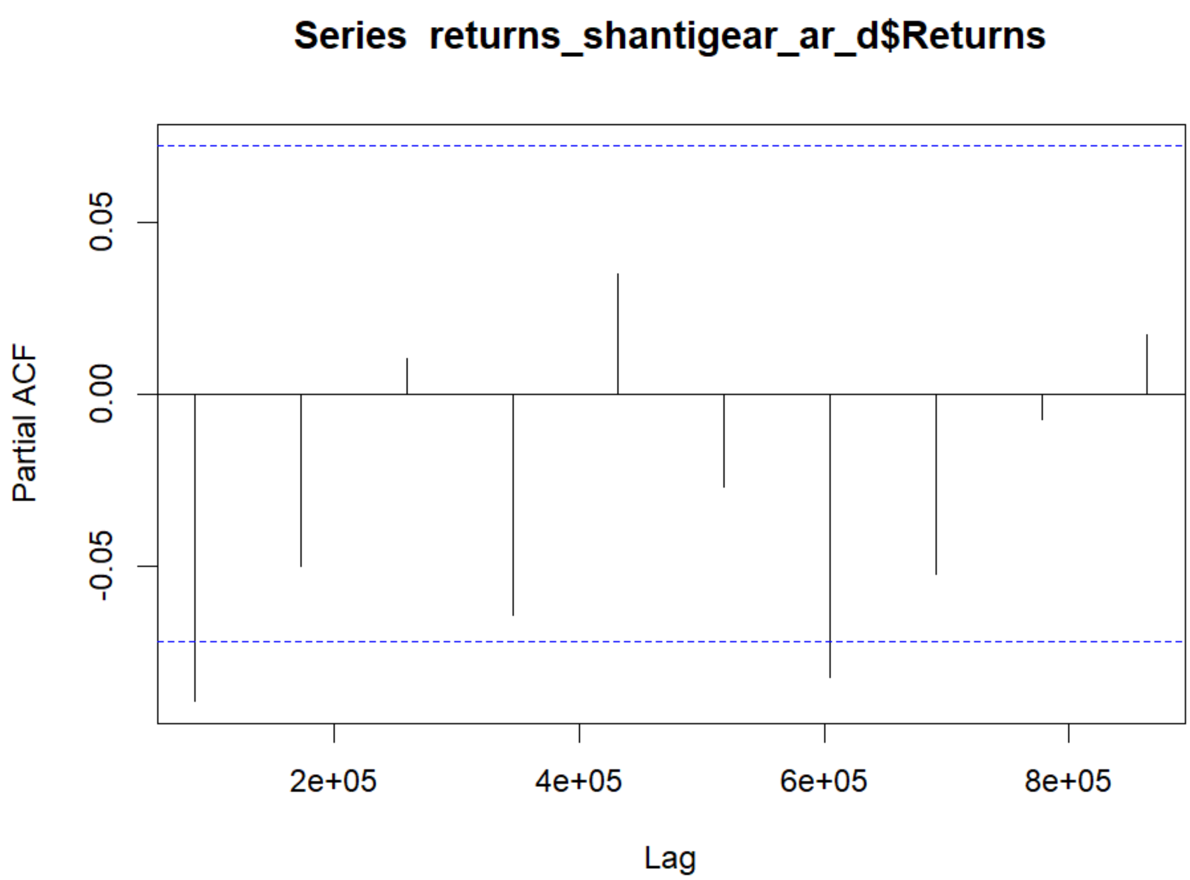
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series.   Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary.   The ADF test-statistic has a value of -9.5594.

2.2.1 ACF Plot.



From the above plot, it can be derived that the series is MA(1) model since the correlation is significant at one lag.

2.2.2 PACF plot



From the above plot it can be derived that the series is AR(1) model since only one lag is significant.

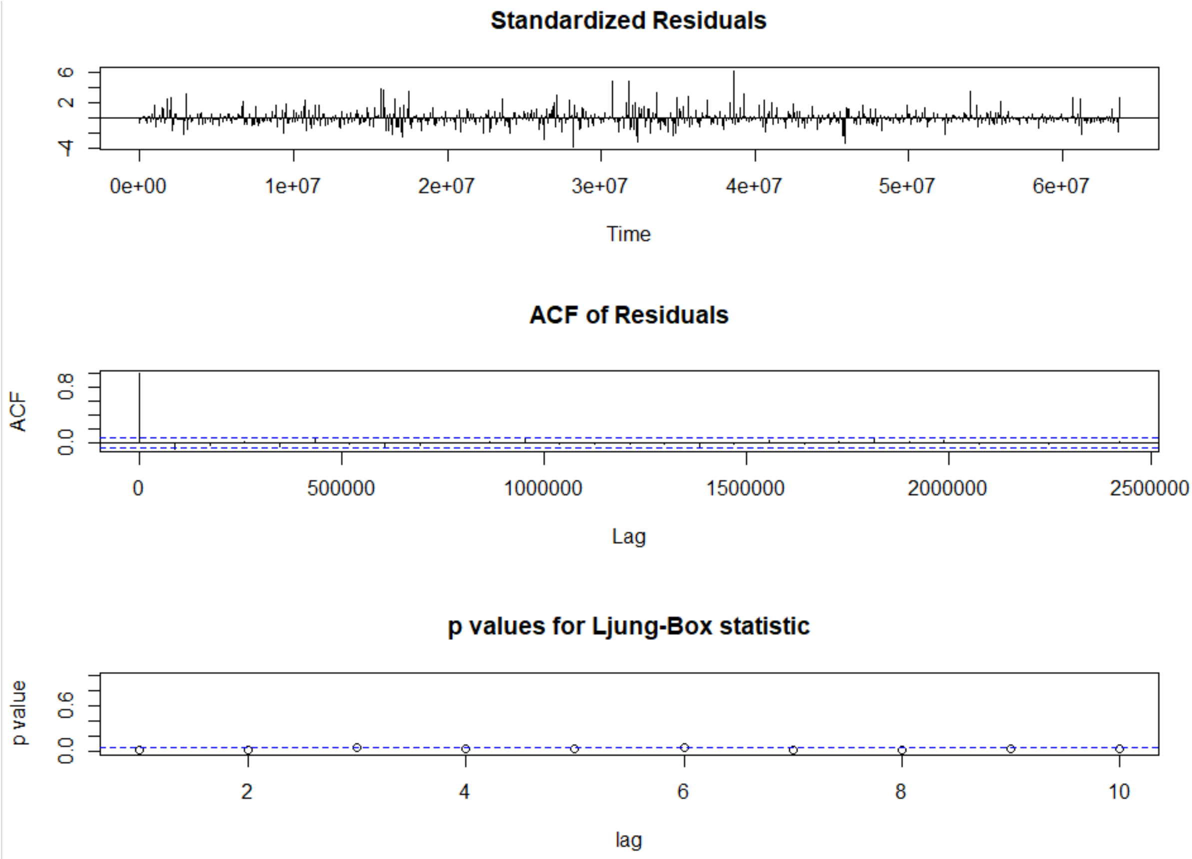
To finally interpret the correct model we use Auto.arima function as shown below-

2.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_shantigear_ar_d$Returns)
Series: returns_shantigear_ar_d$Returns
ARIMA(0,0,1) with non-zero mean

Coefficients:
          ma1    mean
      -0.0990  0.0024
s.e.   0.0383  0.0009

sigma^2 = 0.0008035:  log likelihood = 1583.49
AIC=-3160.99   AICc=-3160.95   BIC=-3147.17
```

The ARIMA function recommended a (0,0,1) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



2.3 GARCH and EGARCH models

Running GARCH on daily return of SHANTIGEAR yielded the result that are shown below-

```
> ug_spec_d

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
-----------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
-----------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The daily returns of SHANTIGEAR were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.002149    0.000870  2.46853 0.013567
ar1     0.219130    0.379482  0.57744 0.563639
ma1    -0.314642    0.368892 -0.85294 0.393693
omega   0.000074    0.000034  2.19866 0.027902
alpha1  0.067051    0.026231  2.55615 0.010584
beta1   0.843644    0.060732 13.89124 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.002149    0.000879  2.44505 0.014483
ar1     0.219130    0.398104  0.55043 0.582023
ma1    -0.314642    0.388551 -0.80978 0.418065
omega   0.000074    0.000061  1.21733 0.223478
alpha1  0.067051    0.052903  1.26744 0.204998
beta1   0.843644    0.115573  7.29966 0.000000

LogLikelihood : 1602.275
```

```
Information Criteria
------------------------------------

Akaike       -4.3201
Bayes        -4.2827
Shibata      -4.3202
Hannan-Quinn -4.3057

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.03893  0.8436
Lag[2*(p+q)+(p+q)-1][5]   0.62255  1.0000
Lag[4*(p+q)+(p+q)-1][9]   2.83248  0.9144
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1728  0.6777
Lag[2*(p+q)+(p+q)-1][5]    0.3240  0.9811
Lag[4*(p+q)+(p+q)-1][9]    1.0111  0.9858
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]   0.01295 0.500 2.000  0.9094
ARCH Lag[5]   0.22689 1.440 1.667  0.9590
ARCH Lag[7]   0.59405 2.315 1.543  0.9691
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  0.764
Individual Statistics:
mu      0.06372
ar1     0.06240
ma1     0.05472
omega   0.19762
alpha1  0.13734
beta1   0.22359

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.2397 0.8107
Negative Sign Bias  0.4057 0.6851
Positive Sign Bias  0.3831 0.7018
Joint Effect        0.3503 0.9503


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     157.0    9.722e-24
2    30     181.9    4.455e-24
3    40     190.0    9.603e-22
4    50     206.4    3.256e-21
```

2.3.1 Interpretation

- The Log Likelihood obtained from the model is 1602.275.

• GARCH(1,1) is the best-fit model for SHANTIGEAR daily returns.

• The optimal parameters beta, alpha and omega all have significant values .

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values less than 0.05, indicating that the null hypothesis should be rejected. This suggests a significant disparity between the observed and predicted values.

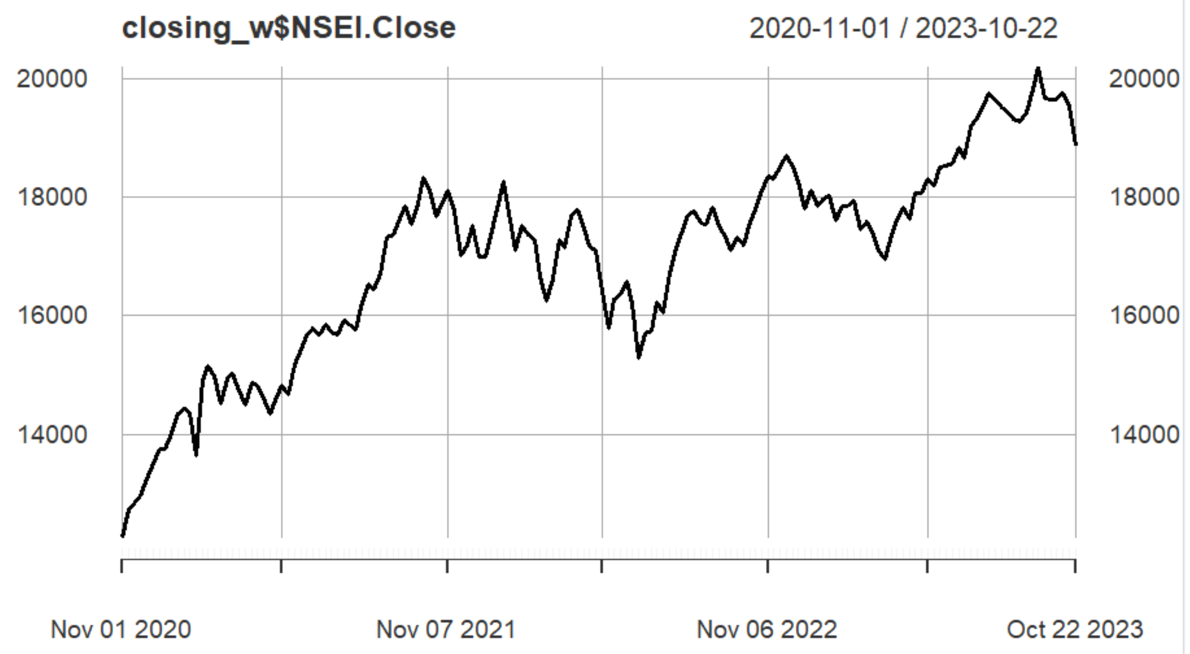
2.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-day period are expected to be positive, with an approximate value of 0.2%, accompanied with a standard deviation in close proximity to 3.2%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of SHANTIGEAR within the subsequent 10-day period, aligning with the forecast provided by the ARIMA model.

```
*---------------------------------*
*       GARCH Model Forecast      *
*---------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
         Series   Sigma
T+1  -0.0037188 0.03258
T+2   0.0008628 0.03225
T+3   0.0018668 0.03195
T+4   0.0020868 0.03168
T+5   0.0021350 0.03143
T+6   0.0021456 0.03120
T+7   0.0021479 0.03099
T+8   0.0021484 0.03080
T+9   0.0021485 0.03062
T+10  0.0021485 0.03046
```

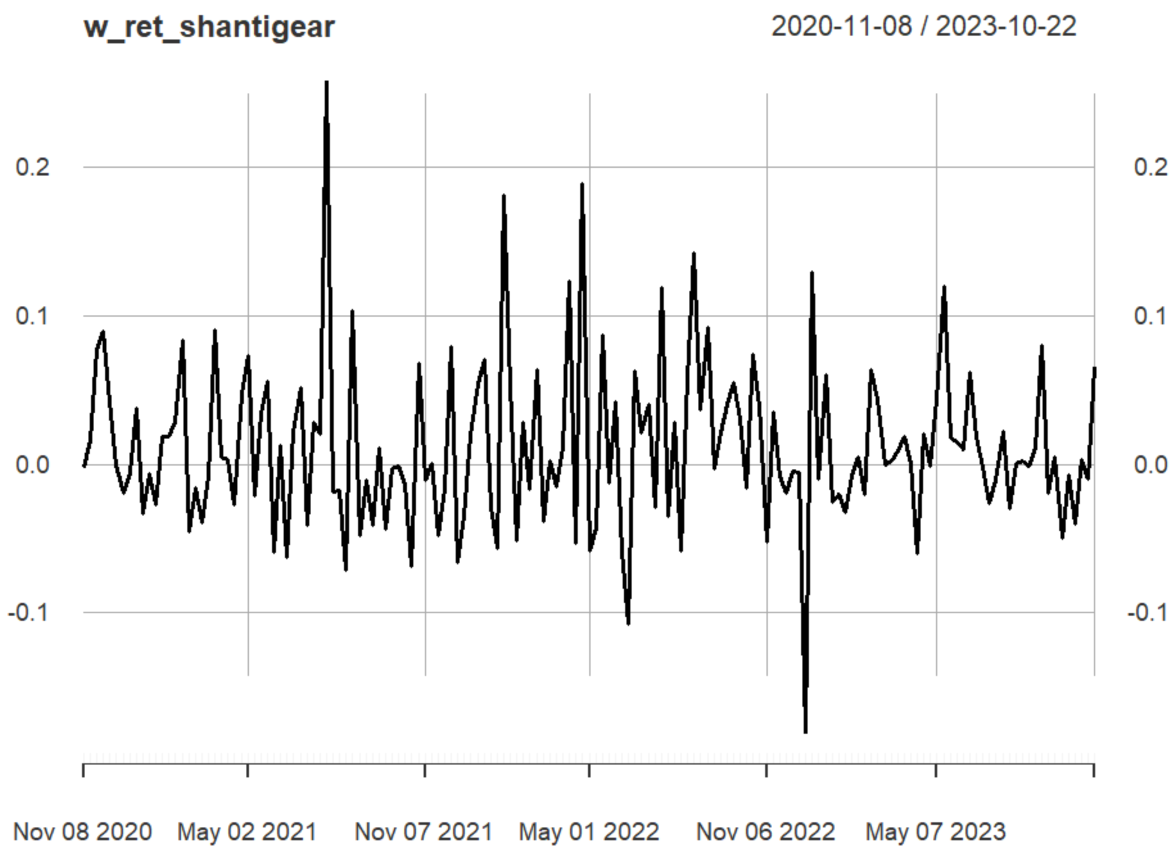
SECTION 3: WEEKLY RETURNS ANALYSIS

3.1 Estimating Beta Using CAPM Model



The provided figure illustrates the weekly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.

The provided figure illustrates the weekly returns derived from SHANTIGEAR stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price. Over the course of a three-year period, there has been a more than fourfold increase.



The above graph illustrates the weekly returns derived from SHANTIGEAR. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

3.1.1 Interpretation of the regression

```
> summary(regression_w)

Call:
lm(formula = exshantigear_w ~ exnifty_w)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.172904 -0.033317 -0.006656  0.025246  0.256382 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.02005    0.02288  -0.876    0.382    
exnifty_w    0.77681    0.17609   4.412 1.93e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05388 on 153 degrees of freedom
Multiple R-squared:  0.1128,	Adjusted R-squared:  0.107 
F-statistic: 19.46 on 1 and 153 DF,  p-value: 1.927e-05
```

From the results of the regression, the beta came out to be 0.77, which implies that if index portfolio excess returns increase by 1%, then the returns of SHANTIGEAR increase by 0.77%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is -0.02005, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of SHANTIGEAR are -0.02005%.

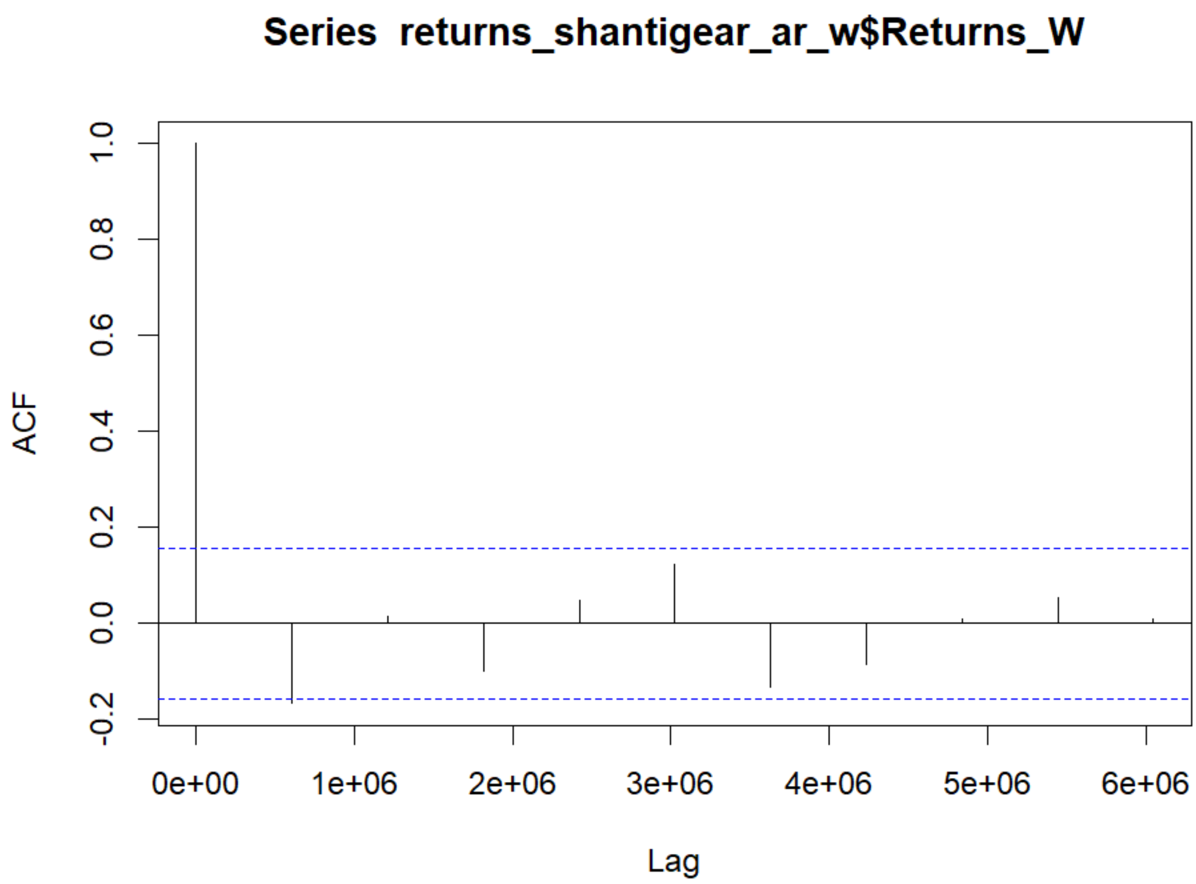
3.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_shantigear_ar_w,alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_shantigear_ar_w
Dickey-Fuller = -5.2182, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

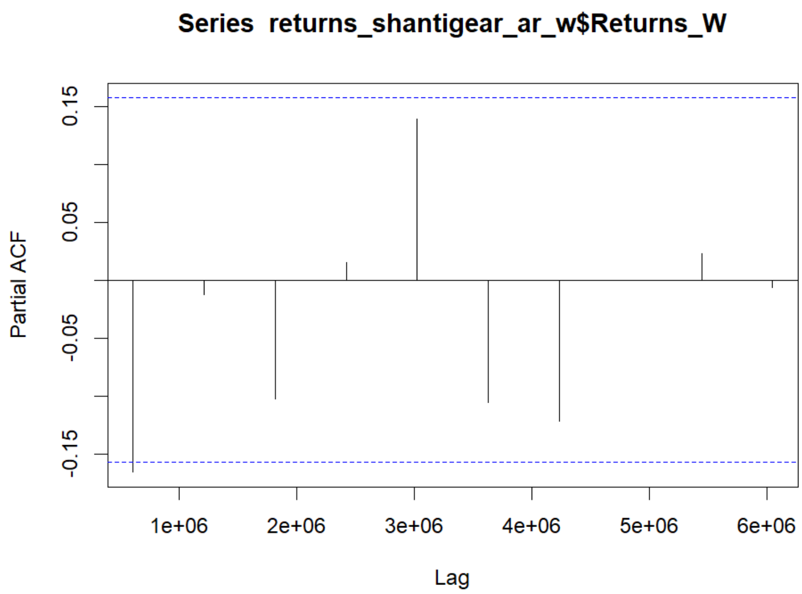
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -5.2182.

3.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(1) model since the correlation is significant only at one lag; after that, values are not significant.

3.2.2 PACF plot



From the above plot it can be derived that the series is AR(1) model since only one lag is significant

To finally interpret the correct model we use Auto.arima function as shown below-

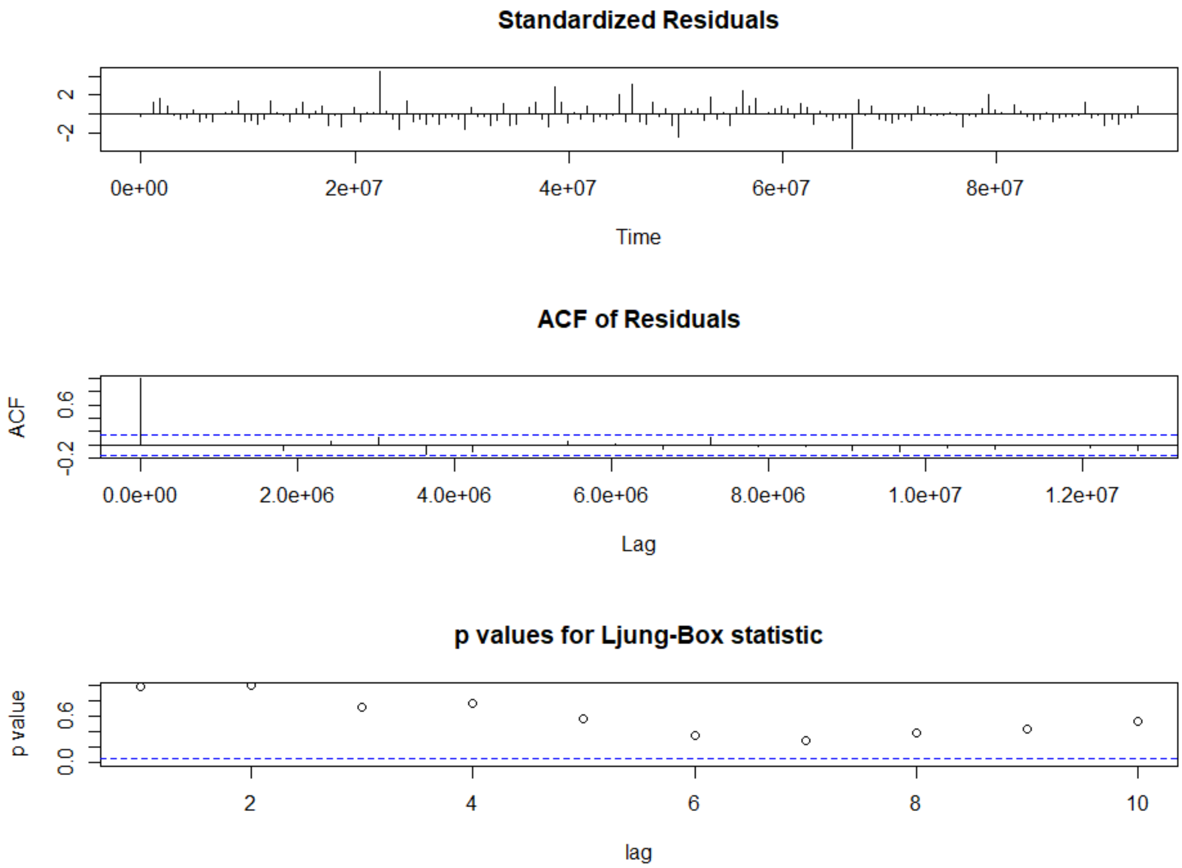
3.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_shantigear_ar_w$Returns)
Series: returns_shantigear_ar_w$Returns
ARIMA(0,0,1) with non-zero mean

Coefficients:
          ma1    mean
      -0.1724  0.0114
s.e.   0.0810  0.0037

sigma^2 = 0.003078:  log likelihood = 229.28
AIC=-452.56   AICc=-452.4   BIC=-443.43
```

The ARIMA function recommended a (0,0,1) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and

BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



3.3 GARCH and EGARCH models

Running GARCH on weekly return of SHANTIGEAR yielded the result that are shown below-

```
> #Implementing univariate GARCH
> ug_spec_w=ugarchspec()
> ug_spec_w

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
-----------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
-----------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The weekly returns of SHANTIGEAR were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
> #Implementing EGARCH
> eg_spec_w=ugarchspec(variance.model=list(model="eGARCH"))
> eg_spec_w

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error     t value Pr(>|t|)
mu      0.010804    0.003535    3.056707 0.002238
ar1     0.155516    0.576155    0.269921 0.787221
ma1    -0.321632    0.555493   -0.579003 0.562587
omega   0.000000    0.000007    0.060067 0.952103
alpha1  0.000000    0.000224    0.000006 0.999995
beta1   0.999000    0.000224 4463.180718 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.010804    0.003816  2.8315e+00 0.004633
ar1     0.155516    0.639915  2.4303e-01 0.807985
ma1    -0.321632    0.615970 -5.2216e-01 0.601562
omega   0.000000    0.000019  2.2891e-02 0.981737
alpha1  0.000000    0.000109  1.3000e-05 0.999989
beta1   0.999000    0.000065  1.5354e+04 0.000000

LogLikelihood : 231.2534
```

```
Information Criteria
------------------------------------

Akaike       -2.8879
Bayes        -2.7706
Shibata      -2.8907
Hannan-Quinn -2.8402

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.001257  0.9717
Lag[2*(p+q)+(p+q)-1][5]  1.296284  0.9997
Lag[4*(p+q)+(p+q)-1][9]  3.951081  0.7024
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.07487  0.7844
Lag[2*(p+q)+(p+q)-1][5]   0.22082  0.9910
Lag[4*(p+q)+(p+q)-1][9]   0.37891  0.9994
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]   0.00533 0.500 2.000  0.9418
ARCH Lag[5]   0.11791 1.440 1.667  0.9834
ARCH Lag[7]   0.15014 2.315 1.543  0.9984
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  15.7178
Individual Statistics:
mu      0.06423
ar1     0.11229
ma1     0.12126
omega   0.19508
alpha1  0.25682
beta1   0.35193

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           1.0625 0.2897
Negative Sign Bias  0.7291 0.4671
Positive Sign Bias  1.0845 0.2799
Joint Effect        1.7236 0.6317


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     29.13       0.0640
2    30     37.08       0.1443
3    40     57.33       0.0293
4    50     58.74       0.1606
```

3.3.1 Interpretation

- The Log Likelihood obtained from the model is 231.25.

• GARCH(1,1) is the best-fit model for SHANTIGEAR weekly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major discrepancy between the observed value and the predicted value.

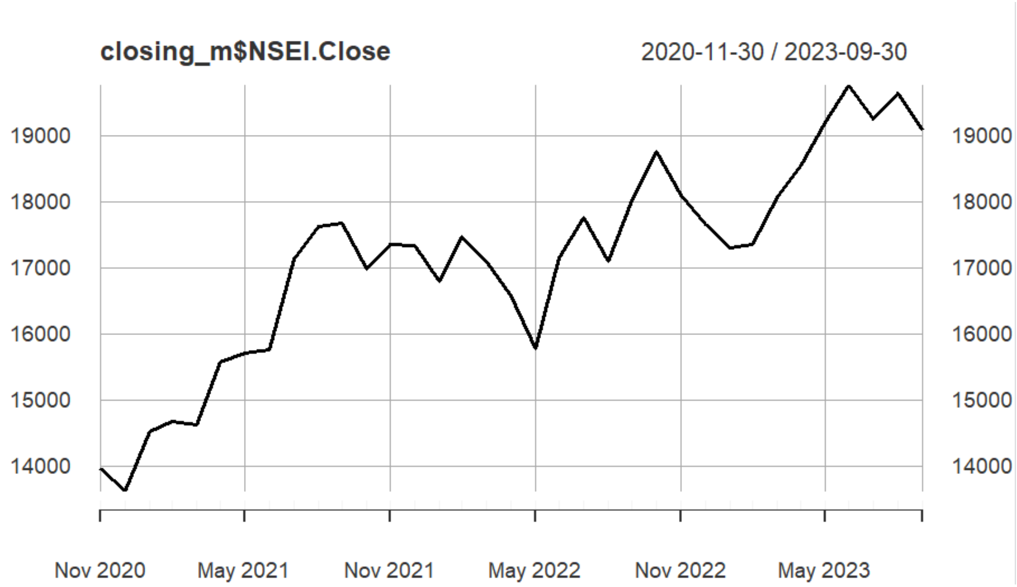
3.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-week period are expected to be positive, with an approximate value of 1%, accompanied with a standard deviation in close proximity to 5.1%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of SHANTIGEAR within the subsequent 10-week period, aligning with the forecast provided by the ARIMA model.

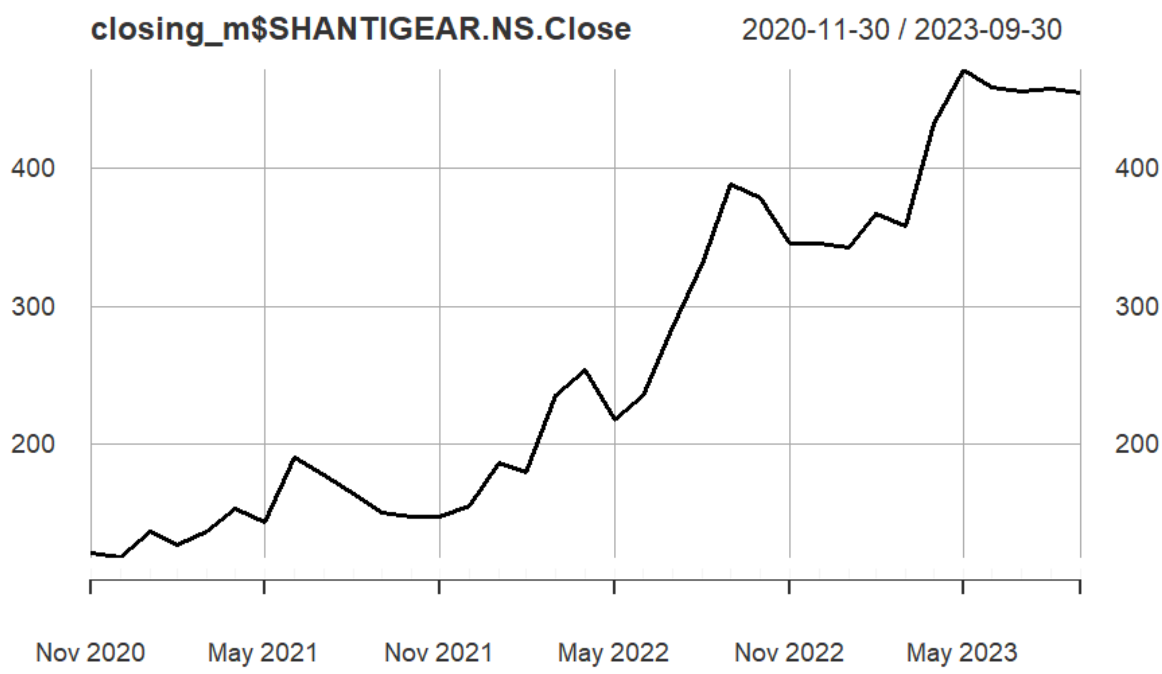
```
*---------------------------------*
*       GARCH Model Forecast      *
*---------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1   0.009437 0.05150
T+2   0.010592 0.05148
T+3   0.010771 0.05146
T+4   0.010799 0.05144
T+5   0.010804 0.05142
T+6   0.010804 0.05140
T+7   0.010804 0.05138
T+8   0.010804 0.05135
T+9   0.010804 0.05133
T+10  0.010804 0.05131
```

SECTION 4: MONTHLY RETURNS ANALYSIS

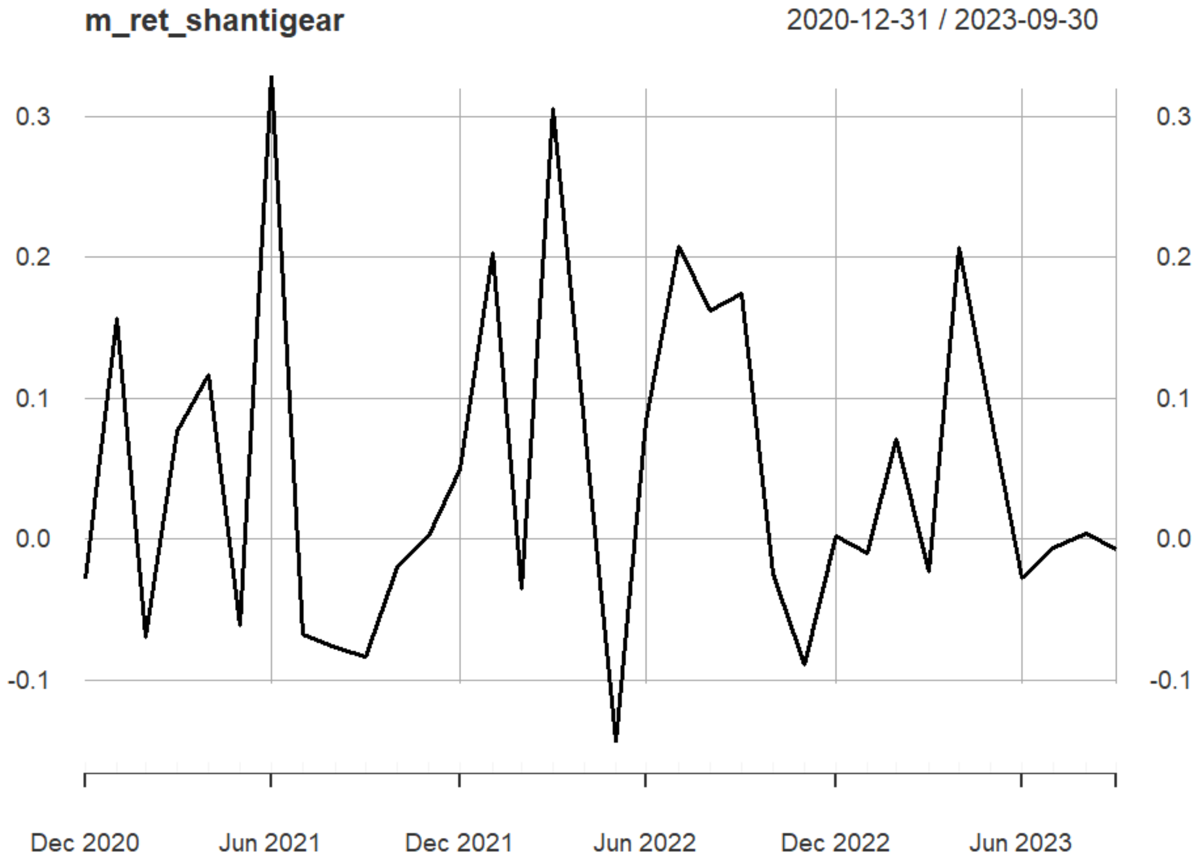
4.1 Estimating Beta Using CAPM Model



The provided figure illustrates the monthly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the monthly returns derived from SHANTIGEAR stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price. Over the course of a three-year period, there has been a more than fourfold increase.



The above graph illustrates the monthly returns derived from SHANTIGEAR. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

4.1.1 Interpretation of the regression

```
> summary(regression_m)

Call:
lm(formula = exshantigear_m ~ exnifty_m)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.17626 -0.09499 -0.02975  0.06749  0.30979 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)  -0.1970     0.1823  -1.081   0.2877  
exnifty_m     0.5848     0.3231   1.810   0.0797 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1179 on 32 degrees of freedom
Multiple R-squared:  0.09287,	Adjusted R-squared:  0.06452 
F-statistic: 3.276 on 1 and 32 DF,  p-value: 0.07969
```

From the results of the regression, the beta came out to be 0.58, which implies that if index portfolio excess returns increase by 1%, then the returns of SHANTIGEAR increase by 0.58%. Also, the beta value is significant at 95% since the p-value is less than 0.05 ($p < 0.05$). The intercept value obtained from the regression is -0.197, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of SHANTIGEAR are- 0.197%.

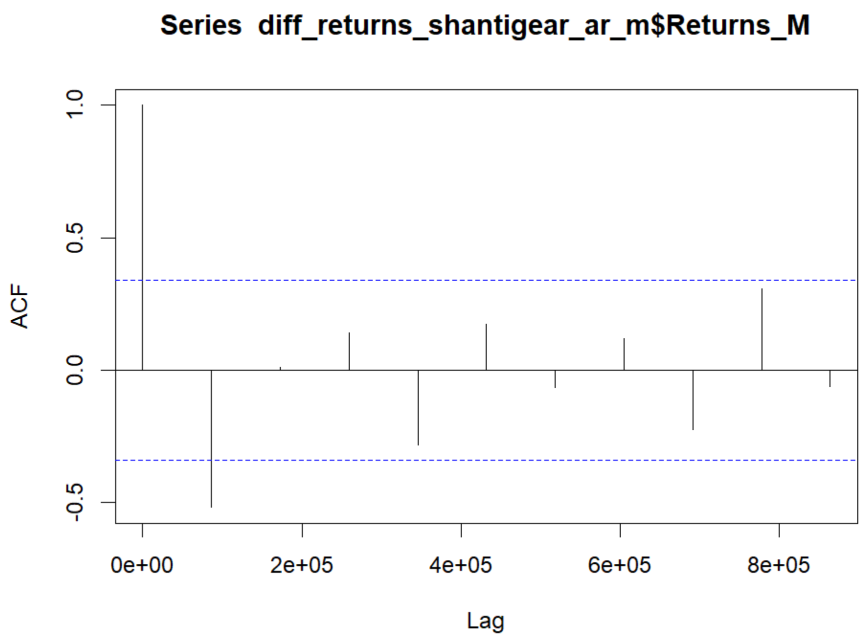
4.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

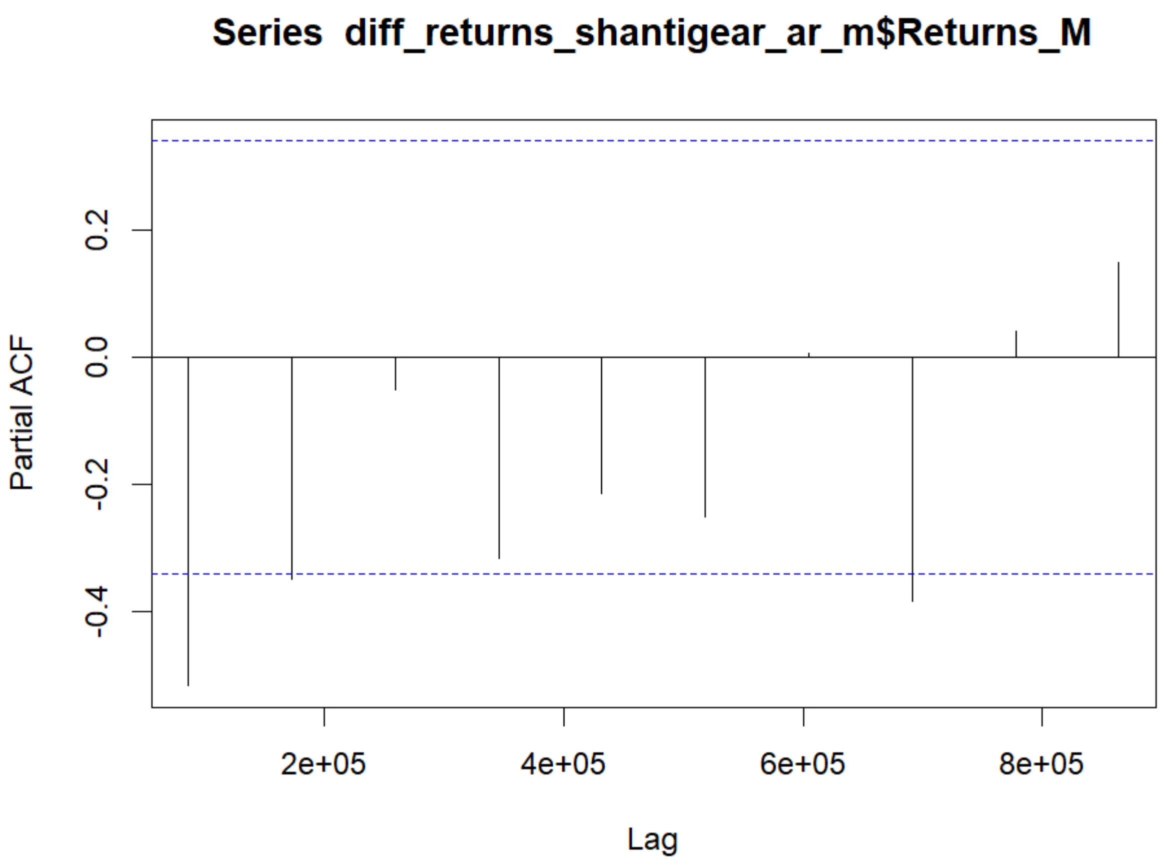
```
> adf.test(returns_shantigear_ar_m,alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_shantigear_ar_m
Dickey-Fuller = -3.8215, Lag order = 3, p-value = 0.03103
alternative hypothesis: stationary
```

The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.03103. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -3.8125.

4.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(1) model since the correlation is significant only at one lag; after that, values are not significant.



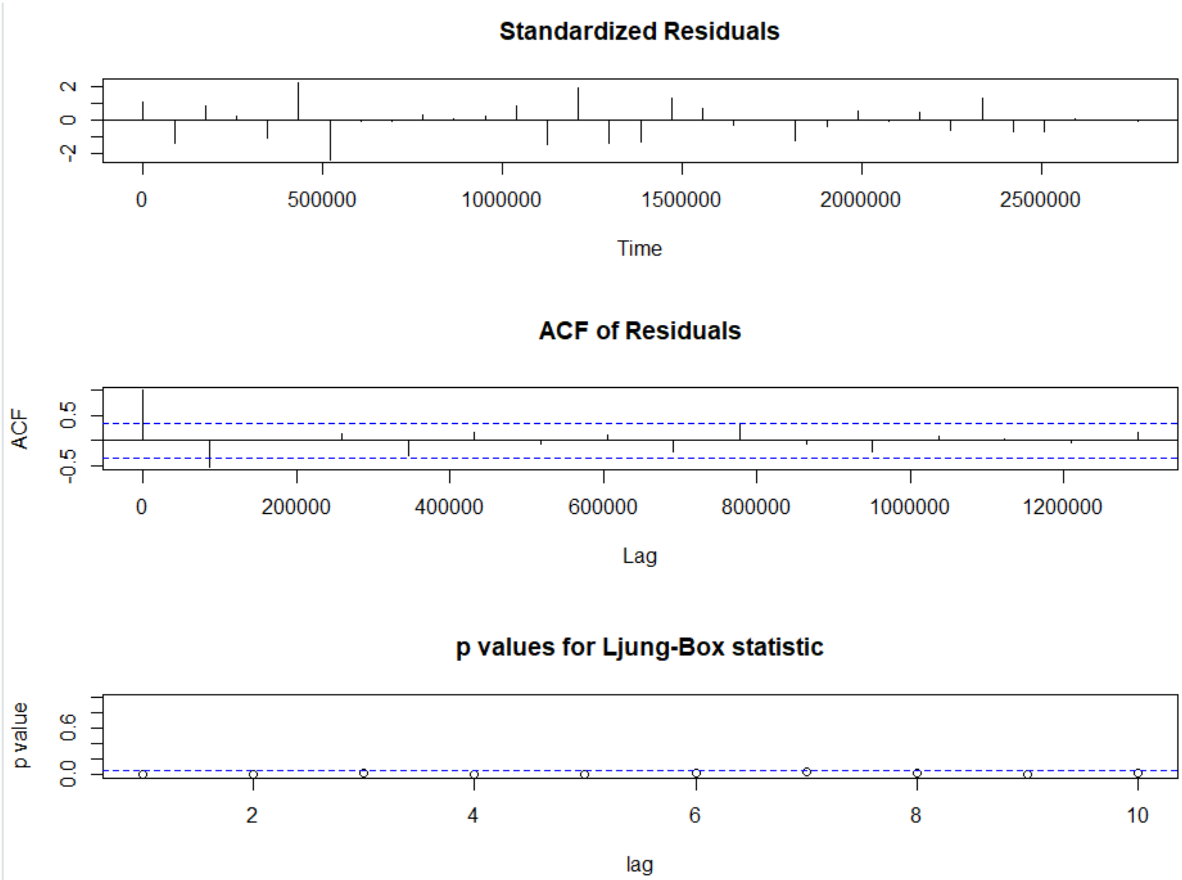
From the above plot it can be derived that the series is an AR(2) model since both initial lags are significant.

To finally interpret the correct model we use Auto.arima function as shown below-

```
> auto.arima(returns_shantigear_ar_m$Returns)
Series: returns_shantigear_ar_m$Returns
ARIMA(0,0,0) with non-zero mean

Coefficients:
        mean
      0.0456
s.e.  0.0197

sigma^2 = 0.01356:  log likelihood = 25.37
AIC=-46.74   AICc=-46.35   BIC=-43.68
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



4.3 GARCH and EGARCH models

Running GARCH on monthly return of SHANTIGEAR yielded the result that are shown below-

```
> #Implementing univariate GARCH
> ug_spec_m=ugarchspec()
> ug_spec_m

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The monthly returns of SHANTIGEAR were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
> #Implementing EGARCH
> eg_spec_m=ugarchspec(variance.model=list(model="eGARCH"))
> eg_spec_m

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.049783    0.001938  25.6907        0
ar1     0.659178    0.128161   5.1434        0
ma1    -1.000000    0.104677  -9.5532        0
omega   0.000000    0.000137   0.0000        1
alpha1  0.000000    0.065747   0.0000        1
beta1   0.995319    0.066095  15.0590        0

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.049783    0.002531  19.6680  0.0e+00
ar1     0.659178    0.154183   4.2753  1.9e-05
ma1    -1.000000    0.090752 -11.0190  0.0e+00
omega   0.000000    0.000094   0.0000  1.0e+00
alpha1  0.000000    0.076908   0.0000  1.0e+00
beta1   0.995319    0.083893  11.8642  0.0e+00

LogLikelihood : 31.03183
```

```
Information Criteria
------------------------------------

Akaike       -1.3907
Bayes        -1.1267
Shibata      -1.4363
Hannan-Quinn -1.2985

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1396  0.7087
Lag[2*(p+q)+(p+q)-1][5]    1.5749  0.9964
Lag[4*(p+q)+(p+q)-1][9]    2.8542  0.9115
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.03648  0.8485
Lag[2*(p+q)+(p+q)-1][5]   0.38845  0.9735
Lag[4*(p+q)+(p+q)-1][9]   1.10997  0.9812
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.1645 0.500 2.000  0.6851
ARCH Lag[5]    0.5600 1.440 1.667  0.8658
ARCH Lag[7]    0.9071 2.315 1.543  0.9282
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  4.3985
Individual Statistics:
mu     0.09919
ar1    0.06449
ma1    0.48700
omega  0.36491
alpha1 0.25765
beta1  0.38882

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:          1.49 1.68 2.12
Individual Statistic:     0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.6400 0.5269
Negative Sign Bias  1.2694 0.2138
Positive Sign Bias  0.2161 0.8303
Joint Effect        1.8234 0.6099


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     12.89       0.8442
2    30     34.00       0.2393
3    40     39.56       0.4451
4    50     58.44       0.1672
```

4.3.1 Interpretation

• The Log Likelihood obtained from the model is 31.031.

• GARCH(1,1) is the best-fit model for SHANTIGEAR monthly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

•The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major discrepancy between the observed value and the predicted value.

4.3.2 Forecast using GARCH

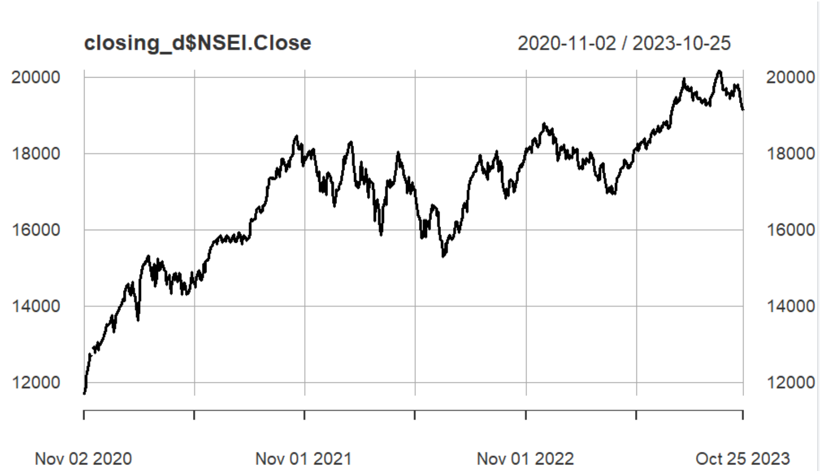
The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-month period are expected to be positive, with an approximate value of 6%, accompanied with a standard deviation in close proximity to 9.3%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of SHANTIGEAR within the subsequent 10-month period, aligning with the forecast provided by the ARIMA model.

```
> #Forecasting
> ugforecast_m=ugarchforecast(ugfit_m,n.ahead = 10)
> ugforecast_m

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
      Series   Sigma
T+1   0.08758 0.09409
T+2   0.07470 0.09387
T+3   0.06620 0.09365
T+4   0.06061 0.09343
T+5   0.05692 0.09321
T+6   0.05449 0.09299
T+7   0.05288 0.09277
T+8   0.05183 0.09256
T+9   0.05113 0.09234
T+10  0.05067 0.09212
```

3. <u>SPLIL</u>

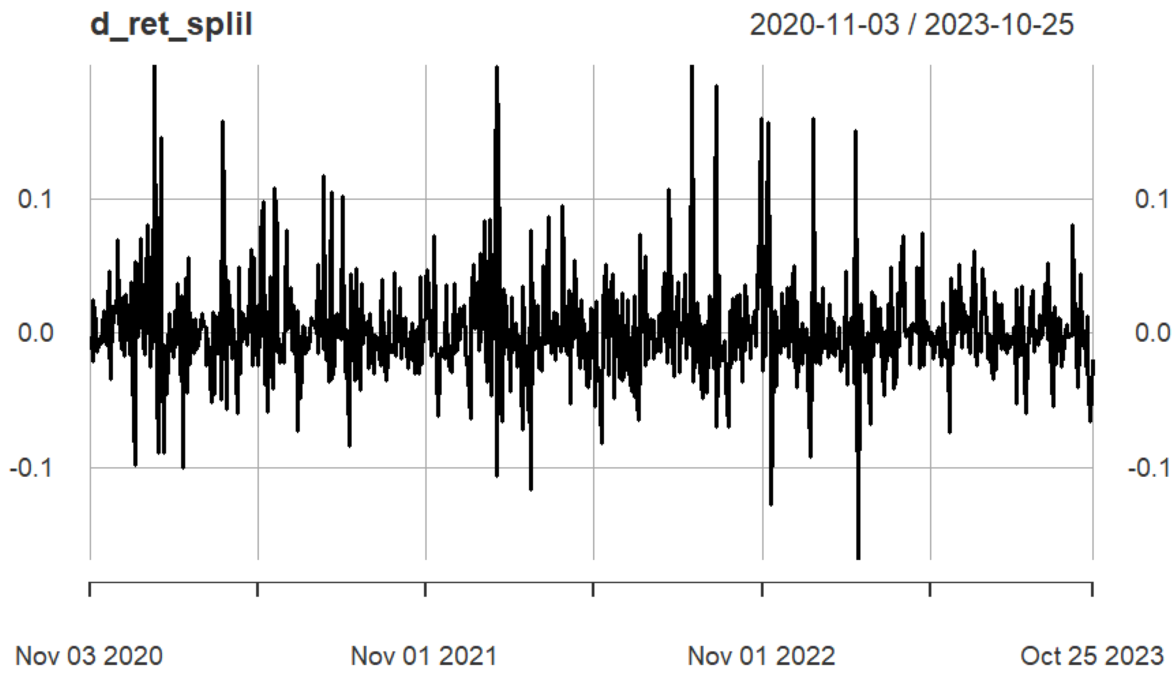
SECTION 2: DAILY RETURNS ANALYSIS

2.1 Estimating Beta Using CAPM Model



The provided figure illustrates the daily closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.

The provided figure illustrates the daily returns derived from SPLIL stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the conclusion of 2022, followed by a subsequent correction. Over the course of a three-year period, there has been a more than twofold increase.



The above graph illustrates the daily returns derived from SPLIL. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

2.1.1 Interpretation of the regression

```
> #Running the regression model
> regression_d<-lm(exsplil_d~exnifty_d)
> #slope parameter is the beta in CAPM model
> summary(regression_d)

Call:
lm(formula = exsplil_d ~ exnifty_d)

Residuals:
      Min        1Q    Median        3Q       Max
-0.163518 -0.019748 -0.003502  0.014761  0.194948

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.005085   0.002908   1.749   0.0808 .
exnifty_d   1.225086   0.142949   8.570   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03686 on 717 degrees of freedom
  (3 observations deleted due to missingness)
Multiple R-squared:  0.09292,   Adjusted R-squared:  0.09165
F-statistic: 73.45 on 1 and 717 DF,  p-value: < 2.2e-16
```

From the results of the regression, the beta came out to be 1.22, which implies that if index portfolio excess returns increase by 1%, then the returns of SPLIL increase by 1.22%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.005, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of SPLIL are 0.005%.

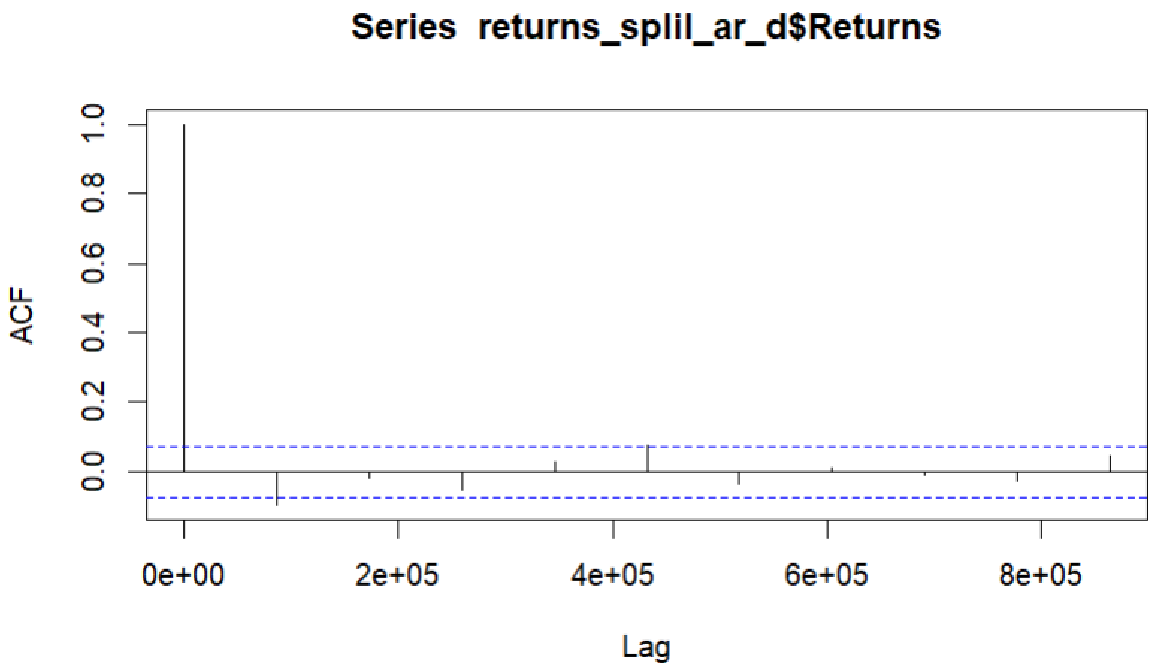
2.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
        Augmented Dickey-Fuller Test

data:  returns_splil_ar_d$Returns
Dickey-Fuller = -8.302, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary
```

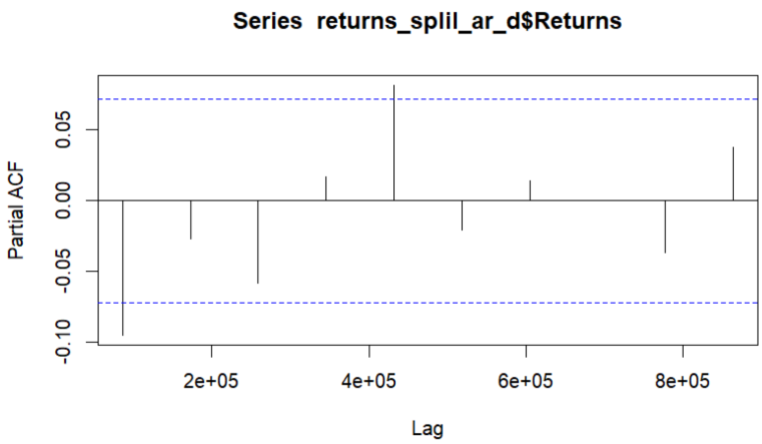
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series.   Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary.   The ADF test-statistic has a value of -8.302.

2.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(1) model since the correlation is significant only at one lag; after that, values are not significant.

2.2.2 PACF plot



From the above plot it can be derived that the series is AR(0) model since only one lag is significant.

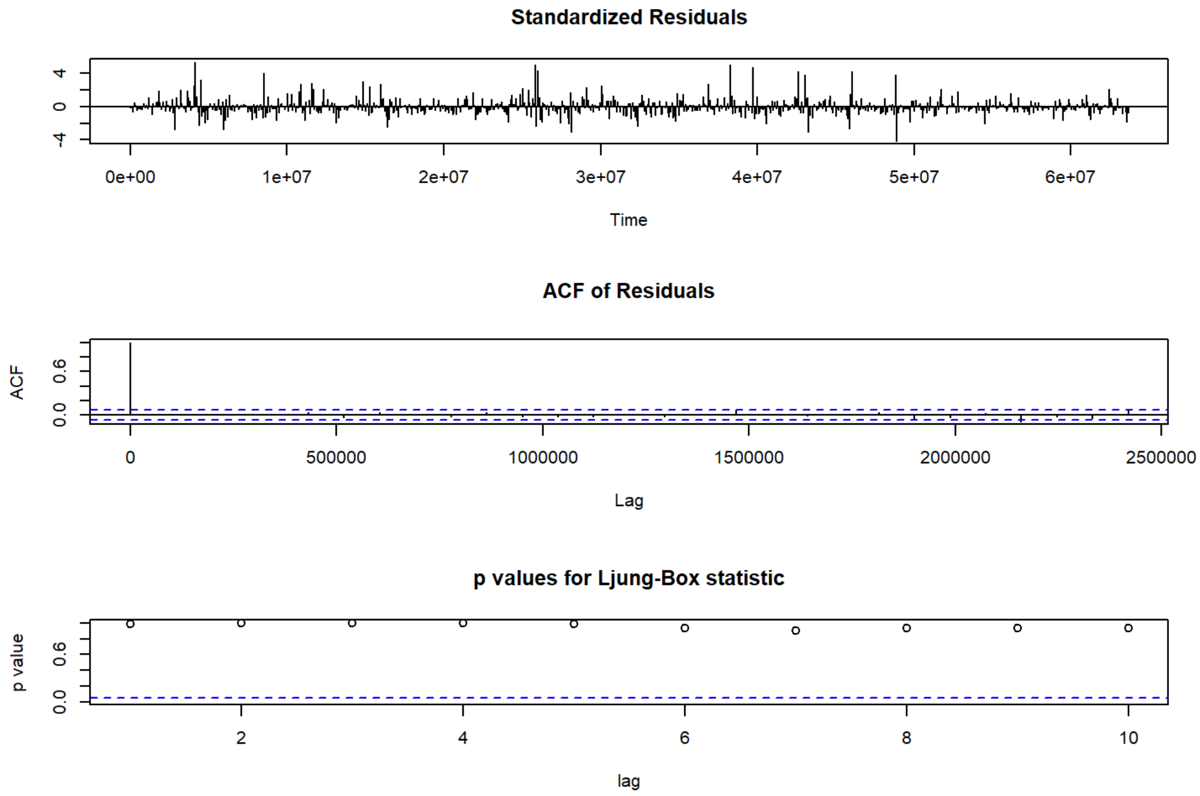
To finally interpret the correct model we use Auto.arima function as shown below-

2.2.3 Identification and interpretation of the ARIMA model

```
Series: returns_splil_ar_d
ARIMA(0,0,1) with non-zero mean

Coefficients:
          ma1    mean
      -0.1013  0.0018
s.e.   0.0378  0.0013

sigma^2 = 0.001454:  log likelihood = 1364.56
AIC=-2723.12   AICc=-2723.09   BIC=-2709.31
```

The ARIMA function recommended a (0,0,1) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



2.3 GARCH and EGARCH models

Running GARCH on daily return of SPLIL yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The daily returns of RUBYMILLS were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
> #Estimating the models
> ugfit_d=ugarchfit(spec=ug_spec_d,data=r_split_ge_d)
> ugfit_d #lower aic value models are better

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error     t value Pr(>|t|)
mu      0.001904    0.000360      5.2969    0e+00
ar1     0.962977    0.009247    104.1374    0e+00
ma1    -0.990051    0.000016 -61216.8687    0e+00
omega   0.000991    0.000073     13.6591    0e+00
alpha1  0.383586    0.085769      4.4723    8e-06
beta1   0.000000    0.016153      0.0000    1e+00

Robust Standard Errors:
        Estimate  Std. Error     t value Pr(>|t|)
mu      0.001904    0.000412      4.6209 0.000004
ar1     0.962977    0.009503    101.3328 0.000000
ma1    -0.990051    0.000047 -20924.7209 0.000000
omega   0.000991    0.000143      6.9495 0.000000
alpha1  0.383586    0.128086      2.9947 0.002747
beta1   0.000000    0.021123      0.0000 1.000000

LogLikelihood : 1400.641
```

```
Information Criteria
------------------------------------

Akaike       -3.7795
Bayes        -3.7421
Shibata      -3.7796
Hannan-Quinn -3.7651

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.388  0.2387
Lag[2*(p+q)+(p+q)-1][5]     3.500  0.2061
Lag[4*(p+q)+(p+q)-1][9]     7.016  0.1265
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.2589  0.6109
Lag[2*(p+q)+(p+q)-1][5]    2.2832  0.5532
Lag[4*(p+q)+(p+q)-1][9]    6.0610  0.2912
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.4436 0.500 2.000 0.50539
ARCH Lag[5]    5.6029 1.440 1.667 0.07443
ARCH Lag[7]    7.1659 2.315 1.543 0.07997
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  1.7841
Individual Statistics:
mu     0.29025
ar1    0.05544
ma1    0.17435
omega  0.22980
alpha1 0.09088
beta1  0.10693

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:        1.49 1.68 2.12
Individual Statistic:   0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.8559 0.3923
Negative Sign Bias  0.1023 0.9186
Positive Sign Bias  0.1806 0.8567
Joint Effect        1.9160 0.5900


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     103.6    1.175e-13
2    30     117.9    1.134e-12
3    40     138.3    4.918e-13
4    50     162.4    4.508e-14


Elapsed time : 0.203017
```

2.3.1 Interpretation

• The Log Likelihood obtained from the model is 1400.641.

• GARCH(1,1) is the best-fit model for SPLIL daily returns.

• The optimal parameter beta has insignificant value while alpha and omega are significant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both only beta is insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values less than 0.05, indicating that the null hypothesis should be rejected. This suggests a significant disparity between the observed and predicted values.

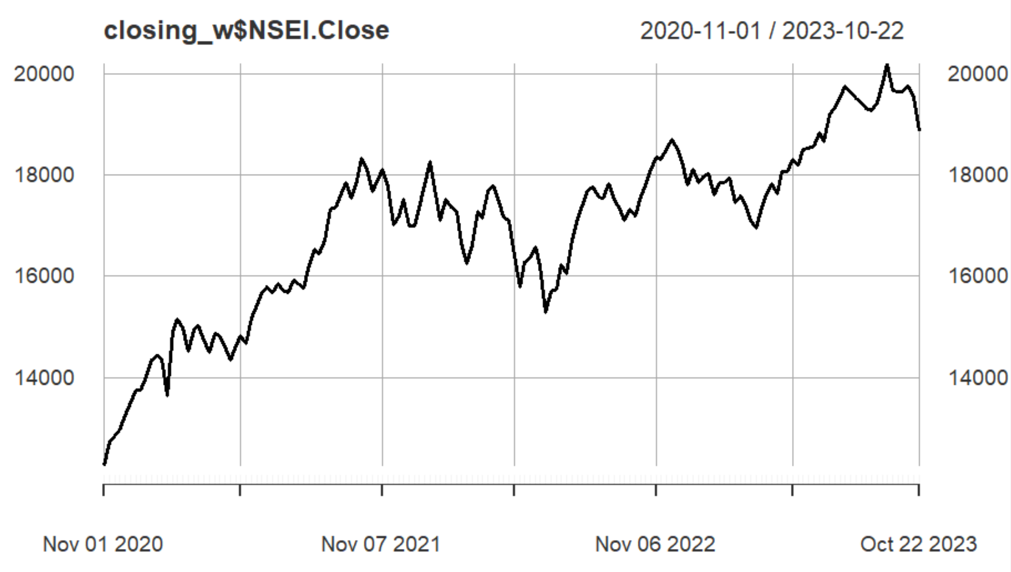
2.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-day period are expected to be positive, with an approximate value of 0.6%, accompanied with a standard deviation in close proximity to 4%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of SPLIL within the subsequent 10-day period, aligning with the forecast provided by the ARIMA model.

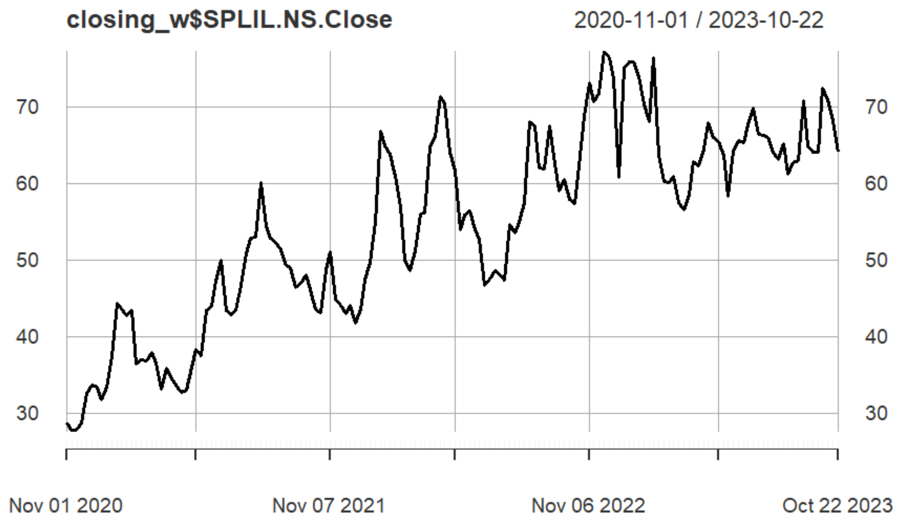
```
> #Forecasting
> ugforecast_d=ugarchforecast(ugfit_d,n.ahead=10)
> ugforecast_d

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1  0.006886 0.03557
T+2  0.006701 0.03842
T+3  0.006524 0.03946
T+4  0.006353 0.03985
T+5  0.006188 0.04000
T+6  0.006029 0.04006
T+7  0.005877 0.04008
T+8  0.005730 0.04009
T+9  0.005588 0.04009
T+10 0.005452 0.04009
```

SECTION 3: WEEKLY RETURNS ANALYSIS

3.1 Estimating Beta Using CAPM Model

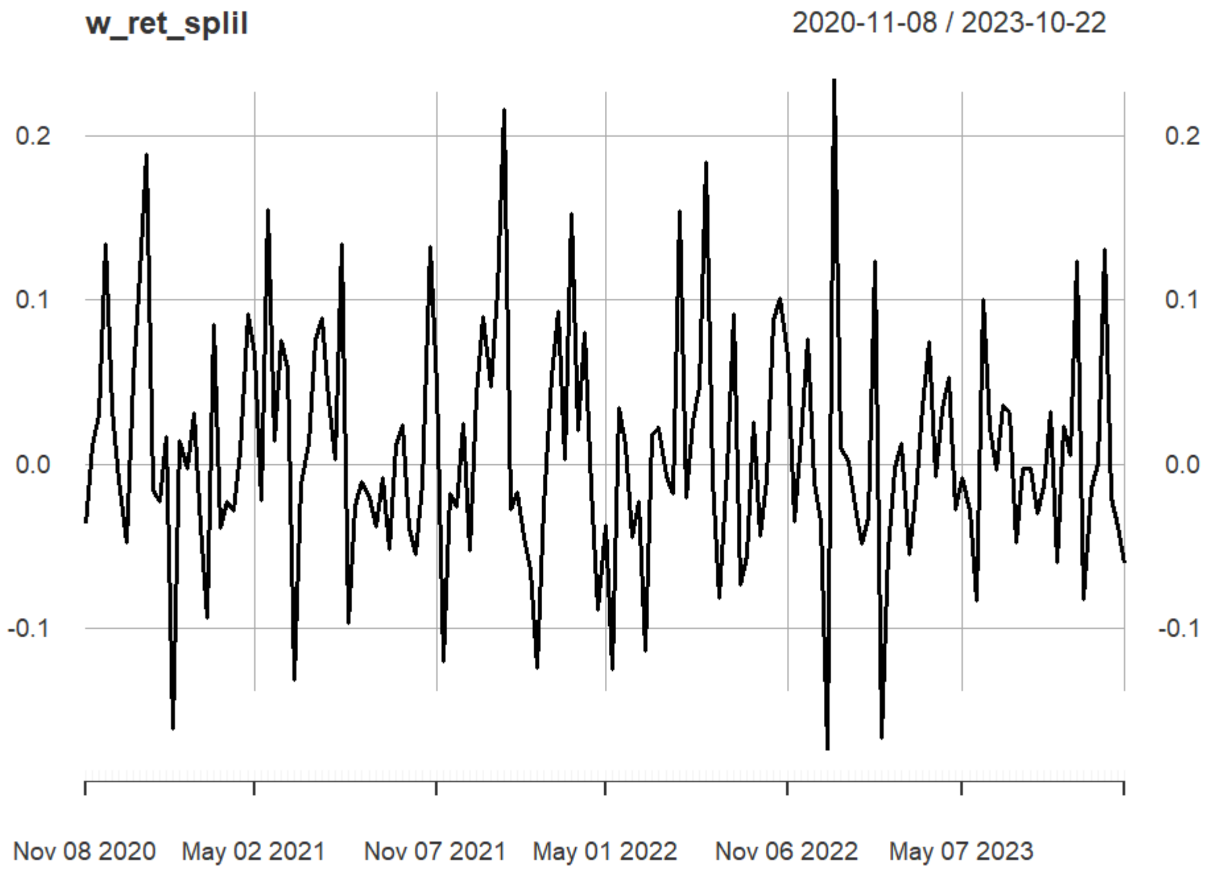


Provided figure illustrates the weekly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the weekly returns derived from SPLIL stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the conclusion of 2022, followed by a subsequent correction.

Over the course of a three-year period, there has been a more than twofold increase.



The above graph illustrates the weekly returns derived from SPLIL. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

3.1.1 Interpretation of the regression

```
> #Running the regression model
> regression_w<-lm(exsplil_w~exnifty_w)
> #slope parameter is beta in CAPM model
> summary(regression_w)

Call:
lm(formula = exsplil_w ~ exnifty_w)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.188298 -0.035716 -0.005891  0.028196  0.253819 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.03296    0.02846   1.158    0.249    
exnifty_w    1.22154    0.21907   5.576 1.09e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.06703 on 153 degrees of freedom
Multiple R-squared:  0.1689,	Adjusted R-squared:  0.1635 
F-statistic: 31.09 on 1 and 153 DF,  p-value: 1.086e-07
```

From the results of the regression, the beta came out to be 1.22, which implies that if index portfolio excess returns increase by 1%, then the returns of SPLIL increase by 1.22%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.003296, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of SPLIL are 0.003296%.

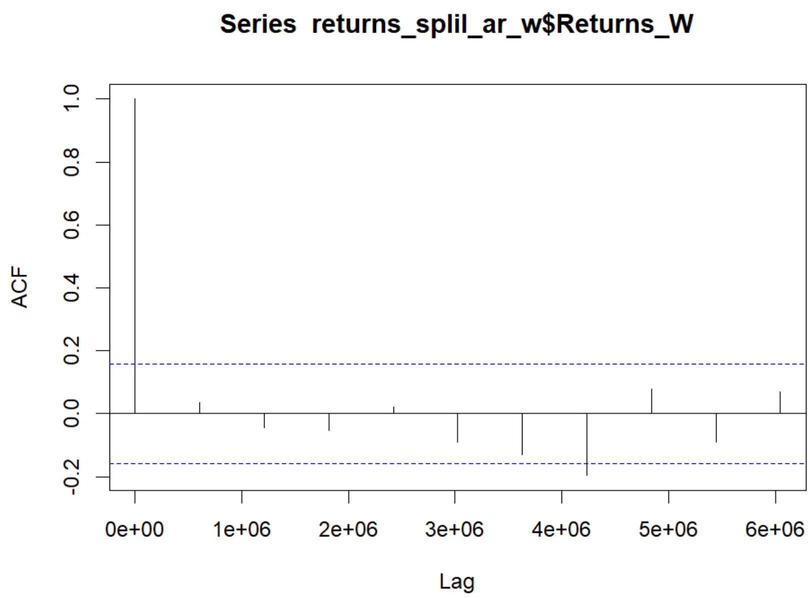
3.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_splil_ar_w,alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_splil_ar_w
Dickey-Fuller = -6.1794, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

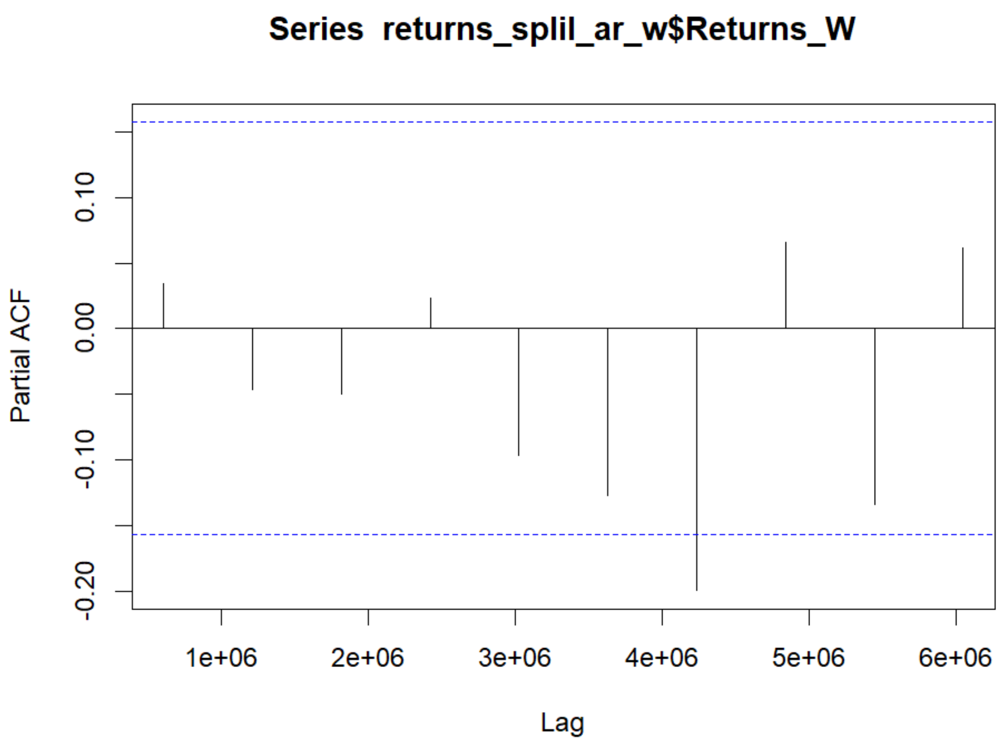
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -6.1794.

3.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(0) model since the initial lags are insignificant.

3.2.2 PACF plot



From the above plot it can be derived that the series is an AR(0) model since initial lags are insignificant.

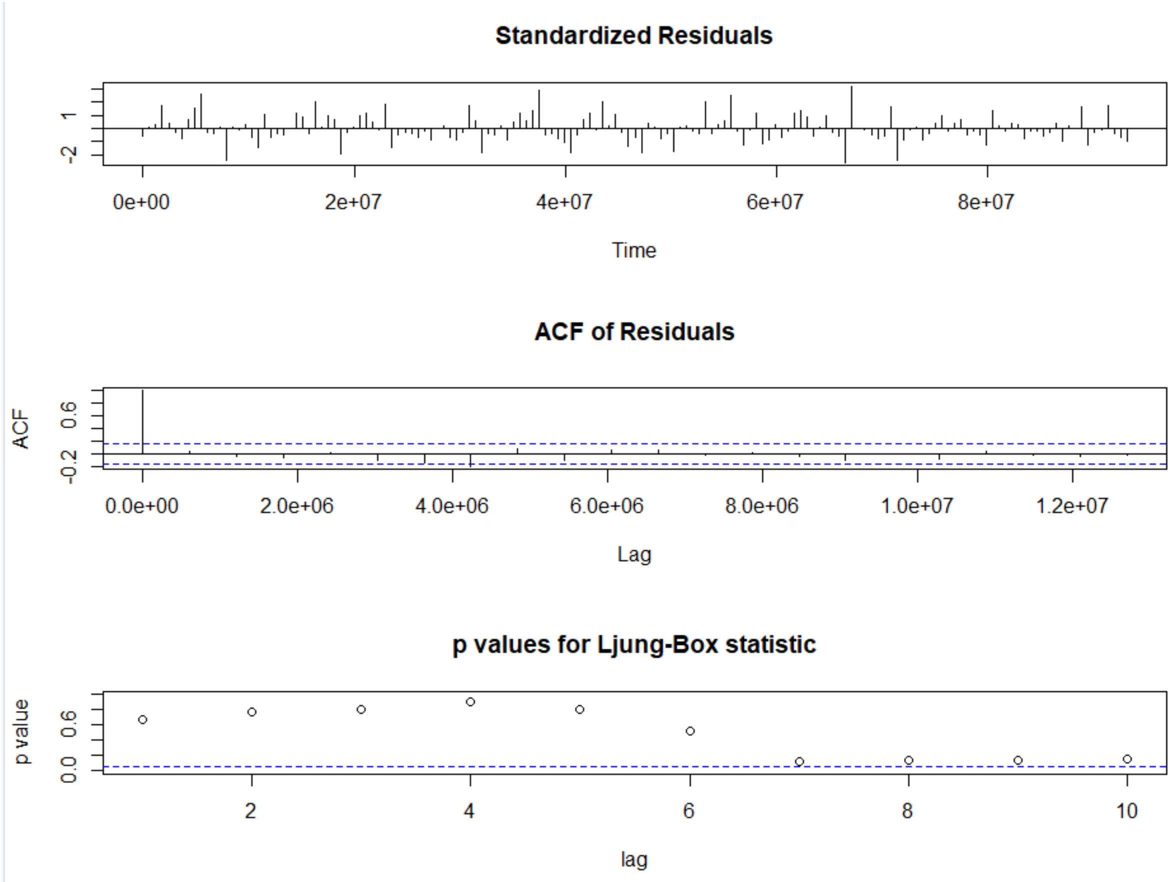
To finally interpret the correct model we use Auto.arima function as shown below-

3.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_splil_ar_w$Returns)
Series: returns_splil_ar_w$Returns
ARIMA(0,0,0) with zero mean

sigma^2 = 0.005154:  log likelihood = 188.33
AIC=-374.66   AICc=-374.63   BIC=-371.61
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



3.3 GARCH and EGARCH models

Running GARCH on weekly return of SPLIL yielded the result that are shown below-

```
> #Implementing univariate GARCH
> ug_spec_w=ugarchspec()
> ug_spec_w

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The weekly returns of SPLIL were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
> #Implementing EGARCH
> eg_spec_w=ugarchspec(variance.model=list(model="eGARCH"))
> eg_spec_w

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.007139    0.005924  1.204960  0.22822
ar1    -0.202978    0.792406 -0.256154  0.79783
ma1     0.245261    0.781306  0.313912  0.75359
omega   0.000004    0.000021  0.172670  0.86291
alpha1  0.000000    0.002472  0.000001  1.00000
beta1   0.999000    0.001624 615.251046  0.00000

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.007139    0.005513   1.294927  0.19535
ar1    -0.202978    0.249245  -0.814373  0.41543
ma1     0.245261    0.216300   1.133894  0.25684
omega   0.000004    0.000022   0.160976  0.87211
alpha1  0.000000    0.000853   0.000001  1.00000
beta1   0.999000    0.000411 2430.088313  0.00000

LogLikelihood : 190.5158
```

```
Information Criteria
------------------------------------

Akaike       -2.3656
Bayes        -2.2483
Shibata      -2.3684
Hannan-Quinn -2.3179

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.002521  0.9600
Lag[2*(p+q)+(p+q)-1][5]  0.776691  1.0000
Lag[4*(p+q)+(p+q)-1][9]  4.887835  0.4793
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.4716  0.4922
Lag[2*(p+q)+(p+q)-1][5]    5.1615  0.1407
Lag[4*(p+q)+(p+q)-1][9]    6.6718  0.2282
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     3.084 0.500 2.000 0.07905
ARCH Lag[5]     3.647 1.440 1.667 0.20871
ARCH Lag[7]     4.206 2.315 1.543 0.31782
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  14.8409
Individual Statistics:
mu     0.07470
ar1    0.23393
ma1    0.23414
omega  0.07540
alpha1 0.08481
beta1  0.10784

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias          0.79292 0.4291
Negative Sign Bias 0.86388 0.3890
Positive Sign Bias 0.05254 0.9582
Joint Effect       1.09481 0.7783


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     28.62      0.07228
2    30     32.08      0.31651
3    40     46.56      0.18914
4    50     54.26      0.28098
```

3.3.1 Interpretation

- The Log Likelihood obtained from the model is 190.515.
- GARCH(1,1) is the best-fit model for SPLIL weekly returns.

•The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

•The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major discrepancy between the observed value and the predicted value.

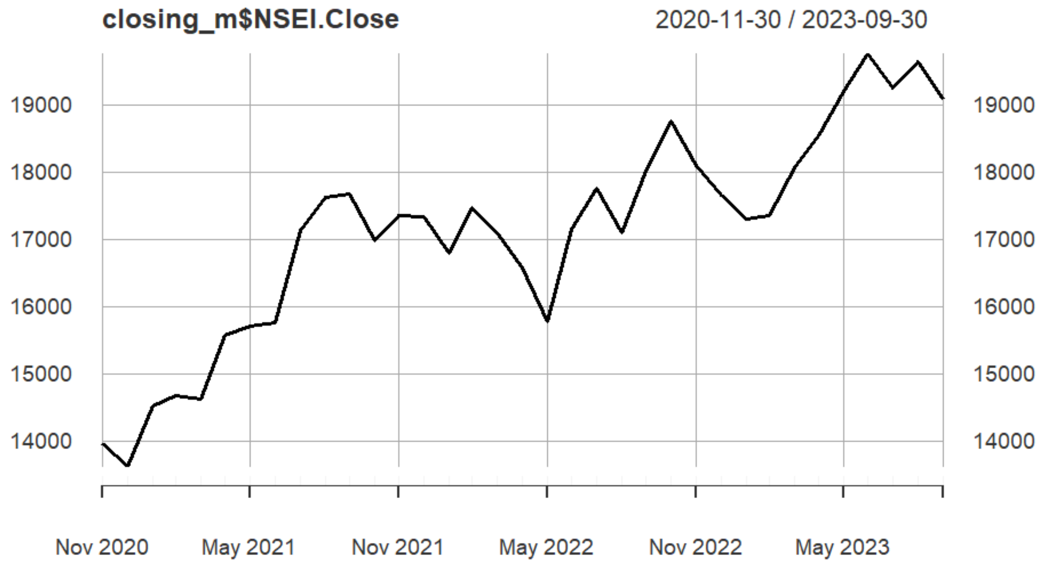
3.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-week period are expected to be positive, with an approximate value of 0.7%, accompanied with a standard deviation in close proximity to 6.97%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of SPLIL within the subsequent 10-week period, aligning with the forecast provided by the ARIMA model.

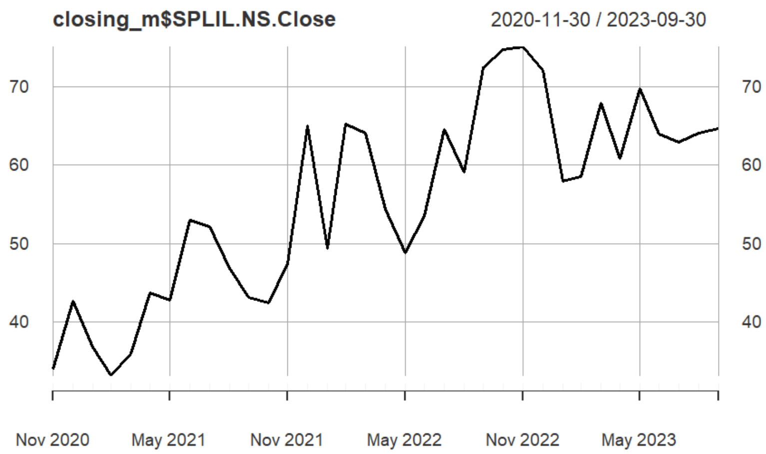
```
> #Forecasting
> ugforecast_w=ugarchforecast(ugfit_w,n.ahead = 10)
> ugforecast_w

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
        Series   Sigma
T+1   0.003561 0.06981
T+2   0.007865 0.06980
T+3   0.006991 0.06979
T+4   0.007169 0.06978
T+5   0.007133 0.06977
T+6   0.007140 0.06976
T+7   0.007138 0.06975
T+8   0.007139 0.06974
T+9   0.007139 0.06973
T+10  0.007139 0.06973
```

SECTION 4: MONTHLY RETURNS ANALYSIS

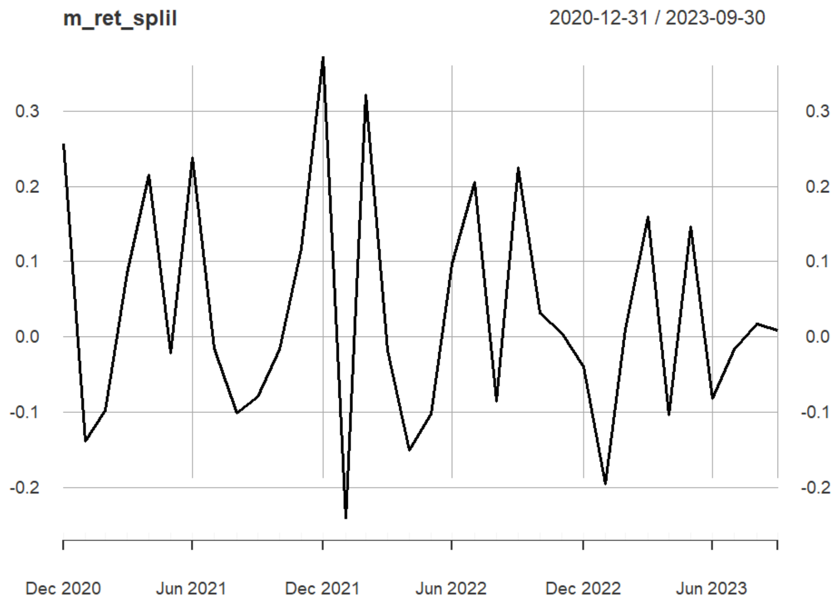
4.1 CAPM Model – Estimating Beta of the company



Provided figure illustrates the monthly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the monthly returns derived from SPLIL stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the conclusion of 2022, followed by a subsequent correction. Over the course of a three-year period, there has been a more than twofold increase.



The above graph illustrates the monthly returns derived from SPLIL. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

4.1.1 Interpretation of the regression

```
Call:
lm(formula = exsplil_m ~ exnifty_m)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.25646 -0.11296 -0.00578  0.08329  0.35261 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept)   0.1922     0.2234   0.860  0.39603   
exnifty_m     1.3077     0.3961   3.302  0.00237 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1445 on 32 degrees of freedom
Multiple R-squared:  0.2541,	Adjusted R-squared:  0.2308 
F-statistic:  10.9 on 1 and 32 DF,  p-value: 0.002369
```

From the results of the regression, the beta came out to be 1.31, which implies that if index portfolio excess returns increase by 1%, then the returns of SPLIL increase by 1.31%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.1922, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of SPLIL are 0.1922%.

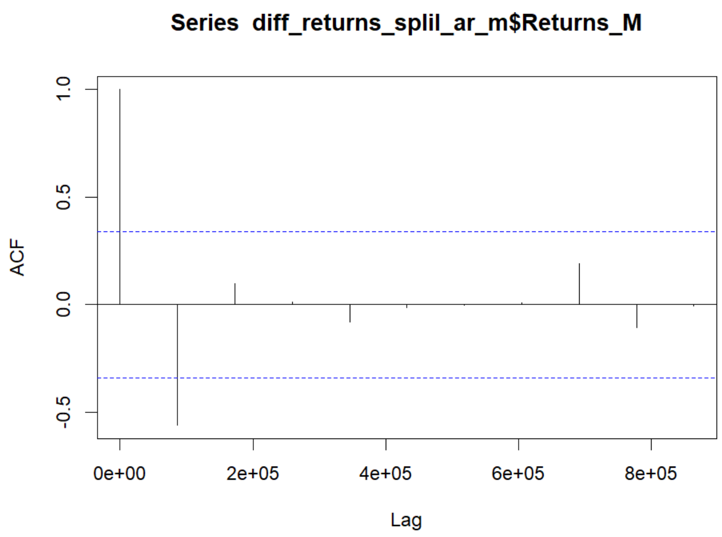
4.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_splil_ar_m,alternative=c("stationary"))

	Augmented Dickey-Fuller Test

data:  returns_splil_ar_m
Dickey-Fuller = -4.2785, Lag order = 3, p-value = 0.01104
alternative hypothesis: stationary
```

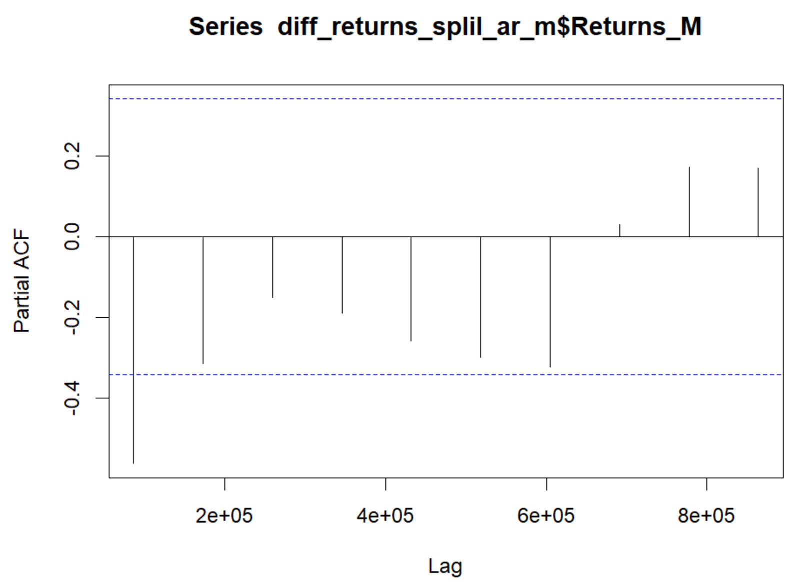
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01104. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -4.2785.

4.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(1) model since the correlation is significant only at one lag; after that, values are not significant.

4.2.2 PACF plot



From the above plot it can be derived that the series is an AR(1) model since initial 1 lag is significant.

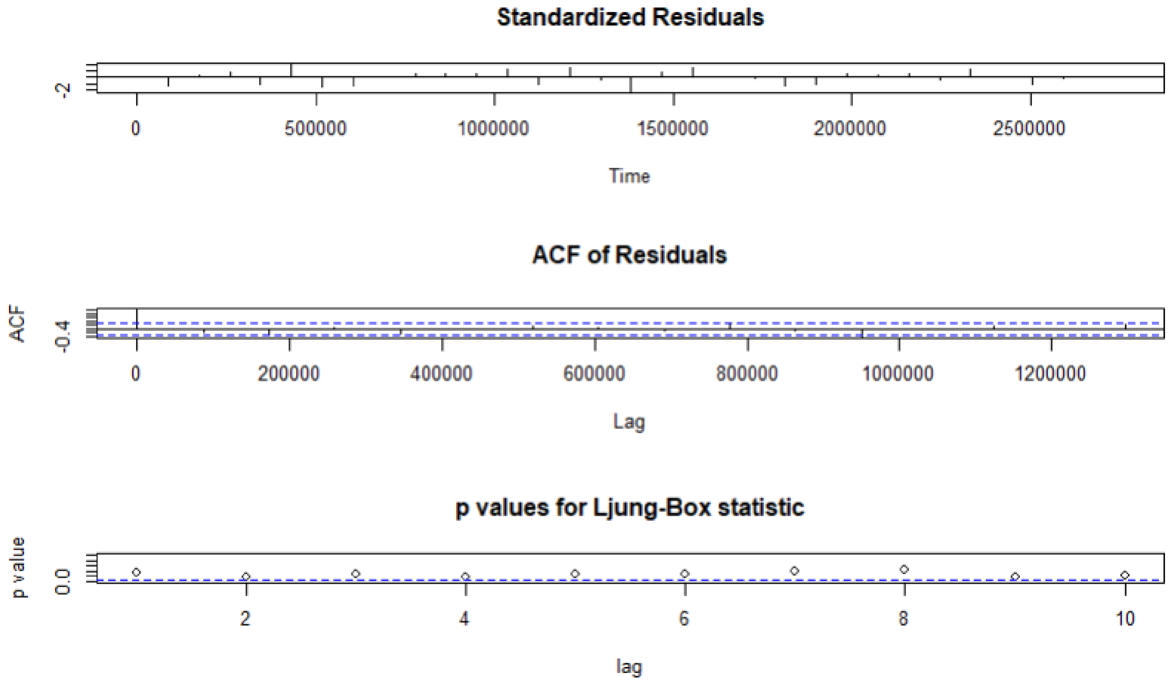
To finally interpret the correct model we use Auto.arima function as shown below-

4.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_splil_ar_m$Returns)
Series: returns_splil_ar_m$Returns
ARIMA(0,0,1) with non-zero mean

Coefficients:
          ma1    mean
      -0.4696  0.0282
s.e.   0.2804  0.0131

sigma^2 = 0.02094:  log likelihood = 18.38
AIC=-30.77   AICc=-29.97   BIC=-26.19
```

The ARIMA function recommended a (0,0,1) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



4.3 GARCH and EGARCH models

Running GARCH on monthly return of SPLIL yielded the result that are shown below-

```
> #Implementing univariate GARCH
> ug_spec_m=ugarchspec()
> ug_spec_m

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model            : sGARCH(1,1)
Variance Targeting     : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model             : ARFIMA(1,0,1)
Include Mean           : TRUE
GARCH-in-Mean          : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The monthly returns of SPLIL were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
> #Implementing EGARCH
> eg_spec_m=ugarchspec(variance.model=list(model="eGARCH"))
> eg_spec_m

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.031369    0.009396  3.338700 0.000842
ar1     0.405444    0.249021  1.628152 0.103493
ma1    -0.777238    0.168180 -4.621456 0.000004
omega   0.000000    0.000181  0.000000 1.000000
alpha1  0.000000    0.081323  0.000001 0.999999
beta1   0.994311    0.082688 12.024832 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.031369    0.012139  2.584183 0.009761
ar1     0.405444    0.201683  2.010306 0.044399
ma1    -0.777238    0.137874 -5.637314 0.000000
omega   0.000000    0.000090  0.000000 1.000000
alpha1  0.000000    0.040957  0.000003 0.999998
beta1   0.994311    0.046837 21.229102 0.000000

LogLikelihood : 20.59667
```

```
Information Criteria
------------------------------------

Akaike       -0.81093
Bayes        -0.54701
Shibata      -0.85658
Hannan-Quinn -0.71881

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.007299  0.9319
Lag[2*(p+q)+(p+q)-1][5]  0.496175  1.0000
Lag[4*(p+q)+(p+q)-1][9]  2.881017  0.9078
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.488  0.2226
Lag[2*(p+q)+(p+q)-1][5]     3.460  0.3295
Lag[4*(p+q)+(p+q)-1][9]     4.283  0.5416
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     0.999 0.500 2.000  0.3176
ARCH Lag[5]     1.271 1.440 1.667  0.6544
ARCH Lag[7]     1.561 2.315 1.543  0.8090
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  2.3902
Individual Statistics:
mu     0.3959
ar1    0.1510
ma1    0.1914
omega  0.1814
alpha1 0.1148
beta1  0.1925

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.6531 0.5185
Negative Sign Bias  0.2313 0.8186
Positive Sign Bias  1.5922 0.1215
Joint Effect        2.8381 0.4173


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     26.22      0.12412
2    30     34.00      0.23926
3    40     52.89      0.06802
4    50     47.33      0.54090
```

4.3.1 Interpretation

- The Log Likelihood obtained from the model is 20.59.

• GARCH(1,1) is the best-fit model for SPLIL monthly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major disparity between the observed value and the predicted value.

4.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-month period are expected to be positive, with an approximate value of 3%, accompanied with a standard deviation in close proximity to 12.2%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of SPLIL within the subsequent 10-month period, aligning with the forecast provided by the ARIMA model.

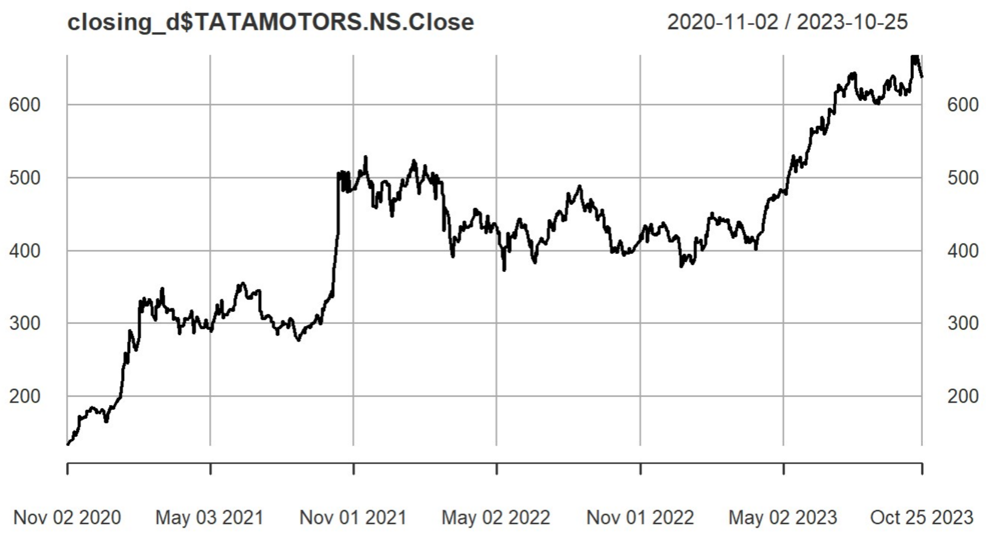
```
> #Forecasting
> ugforecast_m=ugarchforecast(ugfit_m,n.ahead = 10)
> ugforecast_m

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
      Series  Sigma
T+1  0.08828 0.1236
T+2  0.05444 0.1232
T+3  0.04073 0.1229
T+4  0.03516 0.1225
T+5  0.03291 0.1222
T+6  0.03199 0.1218
T+7  0.03162 0.1215
T+8  0.03147 0.1211
T+9  0.03141 0.1208
T+10 0.03139 0.1204
```

4. TATAMOTORS

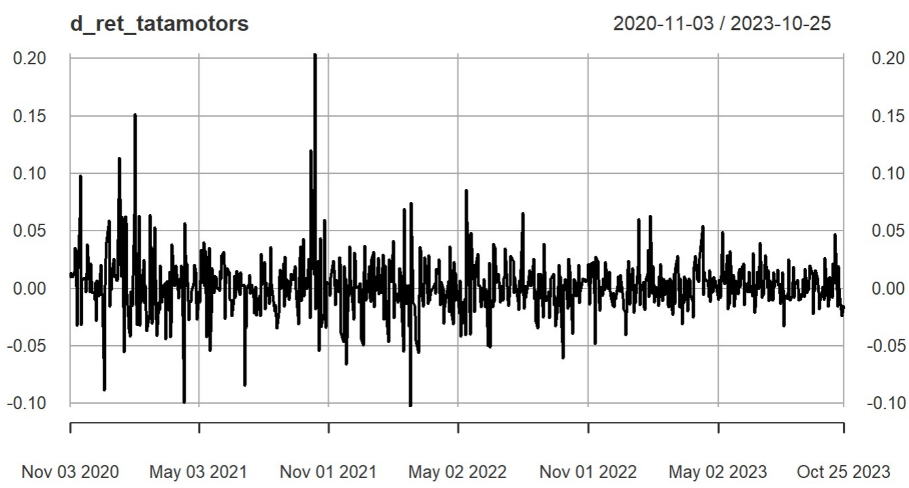
SECTION 2: DAILY RETURNS ANALYSIS

2.1 Estimating Beta Using CAPM Model

The provided figure illustrates the daily closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the daily returns derived from TATAMOTORS stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price. Over the course of a three-year period, there has been a more than threefold increase.



The above graph illustrates the daily returns derived from TATAMOTORS. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

2.1.1 Interpretation of the regression

```
> #Running the regression model
> regression_d<-lm(extatamotors_d~exnifty_d)
> #slope parameter is the beta in CAPM model
> summary(regression_d)

Call:
lm(formula = extatamotors_d ~ exnifty_d)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.084990 -0.010865 -0.001905  0.008498  0.187881 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.011448   0.001604   7.135 2.36e-12 ***
exnifty_d   1.547026   0.078966  19.591  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02038 on 719 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.348,	Adjusted R-squared:  0.3471 
F-statistic: 383.8 on 1 and 719 DF,  p-value: < 2.2e-16
```

From the results of the regression, the beta came out to be 1.54, which implies that if index portfolio excess returns increase by 1%, then the returns of TATAMOTORS increase by 1.54%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.011448, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of TATAMOTORS are 0.011448%.

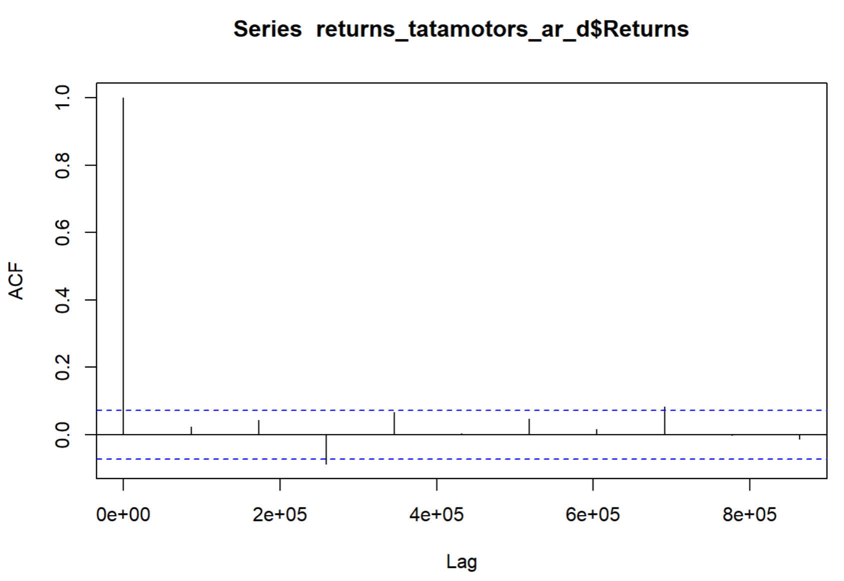
2.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_tatamotors_ar_d$Returns, alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_tatamotors_ar_d$Returns
Dickey-Fuller = -7.8248, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary
```

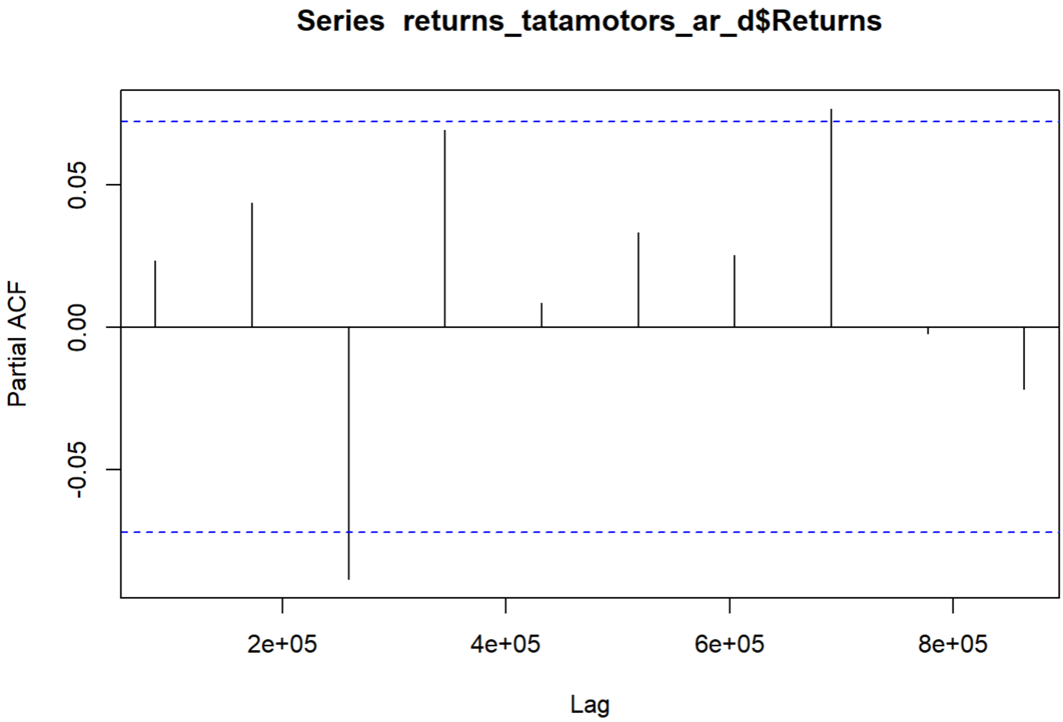
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series.   Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary.   The ADF test-statistic has a value of -7.8248.

2.2.1 ACF Plot



From the above plot it can be derived that the series is MA(0) model since none of the initial lags are significant.

2.2.2 PACF plot



From the above plot it can be derived that the series is AR(2) model since only lag 2 is significant.

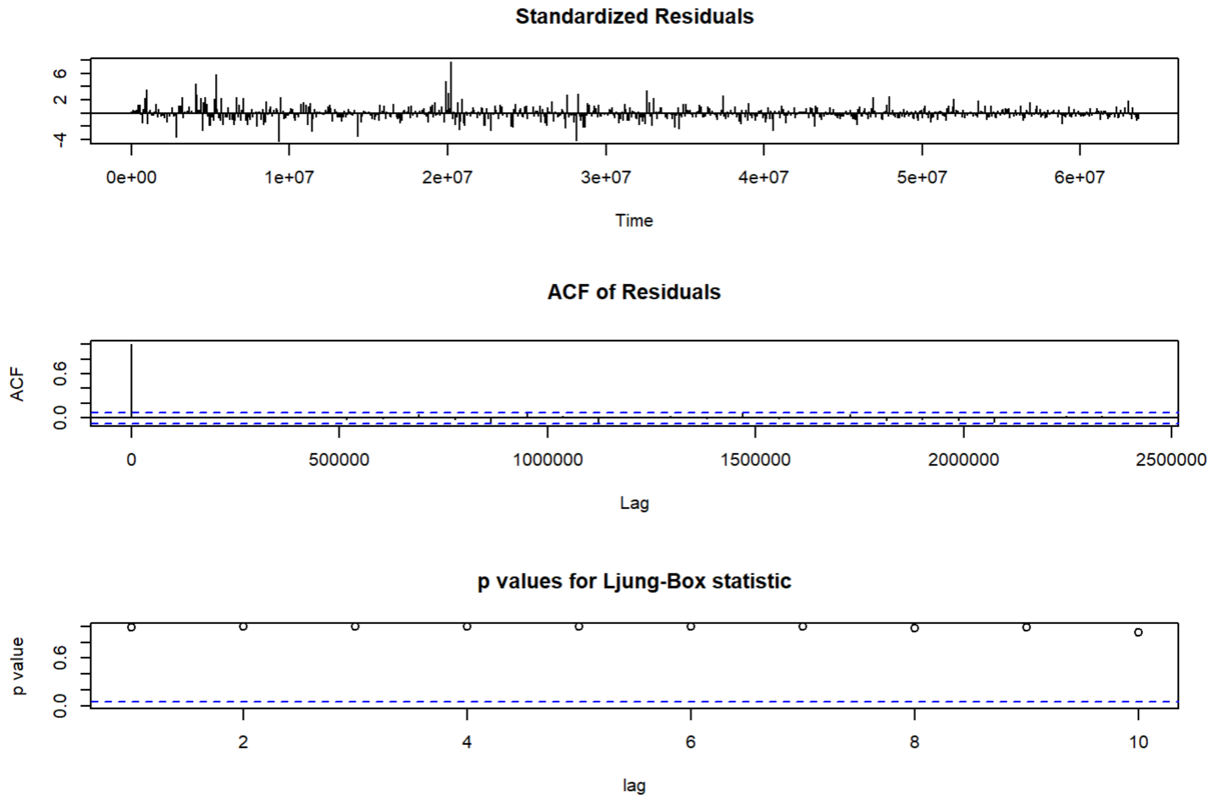
To finally interpret the correct model we use Auto.arima function as shown below-

2.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_tatamotors_ar_d$Returns)
Series: returns_tatamotors_ar_d$Returns
ARIMA(0,0,0) with non-zero mean

Coefficients:
        mean
      0.0024
s.e.  0.0009

sigma^2 = 0.000631:  log likelihood = 1672.19
AIC=-3340.37   AICc=-3340.36   BIC=-3331.16
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



2.3 GARCH and EGARCH models

Running GARCH on daily return of TATAMOTORS yielded the result that are shown below-

```
> #Implementing univariate GARCH
> ug_spec_d=ugarchspec()
> ug_spec_d

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The daily returns of TATAMOTORS were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
> #Implementing EGARCH
> eg_spec_d=ugarchspec(variance.model=list(model="eGARCH"))
> eg_spec_d

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model              : eGARCH(1,1)
Variance Targeting       : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model               : ARFIMA(1,0,1)
Include Mean             : TRUE
GARCH-in-Mean            : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
> #Estimating the models
> ugfit_d=ugarchfit(spec=ug_spec_d,data=r_tatamotors_ge_d)
> ugfit_d #lower aic value models are better

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.001396    0.000818  1.706760 0.087867
ar1    -0.038357    0.681177 -0.056310 0.955095
ma1     0.060850    0.680103  0.089472 0.928707
omega   0.000018    0.000014  1.271934 0.203397
alpha1  0.071020    0.023755  2.989736 0.002792
beta1   0.901586    0.043127 20.905402 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.001396    0.000796  1.75330 0.079551
ar1    -0.038357    0.270670 -0.14171 0.887308
ma1     0.060850    0.289104  0.21048 0.833294
omega   0.000018    0.000056  0.32259 0.747010
alpha1  0.071020    0.095841  0.74102 0.458681
beta1   0.901586    0.177889  5.06826 0.000000

LogLikelihood : 1730.911
```

```
Information Criteria
------------------------------------

Akaike       -4.6682
Bayes        -4.6308
Shibata      -4.6684
Hannan-Quinn -4.6538

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.05118  0.8210
Lag[2*(p+q)+(p+q)-1][5]   2.24294  0.8932
Lag[4*(p+q)+(p+q)-1][9]   3.84208  0.7275
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.4198 0.51702
Lag[2*(p+q)+(p+q)-1][5]    5.7915 0.10067
Lag[4*(p+q)+(p+q)-1][9]    9.8876 0.05302
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale  P-Value
ARCH Lag[3]     0.495 0.500 2.000 0.481697
ARCH Lag[5]    10.155 1.440 1.667 0.006024
ARCH Lag[7]    11.608 2.315 1.543 0.007700
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  1.7566
Individual Statistics:
mu     0.08838
ar1    0.11804
ma1    0.11914
omega  0.85181
alpha1 0.45947
beta1  0.59051

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:        1.49 1.68 2.12
Individual Statistic:   0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.3874 0.6986
Negative Sign Bias  1.1994 0.2308
Positive Sign Bias  0.2234 0.8233
Joint Effect        1.5452 0.6719


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     62.76    1.405e-06
2    30     73.19    1.096e-05
3    40     81.41    8.079e-05
4    50     85.29    1.015e-03
```

2.3.1 Interpretation

• The Log Likelihood obtained from the model is 1730.911.

• GARCH(1,1) is the best-fit model for TATAMOTORS daily returns.

- The optimal parameter beta has significant value while alpha and omega are insignificant.

- The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

- The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

- The Adjusted Pearson Goodness of Fit Test gave p-values less than 0.05, indicating that the null hypothesis should be rejected. This suggests a significant disparity between the observed and predicted values.

2.3.2 Forecast using GARCH

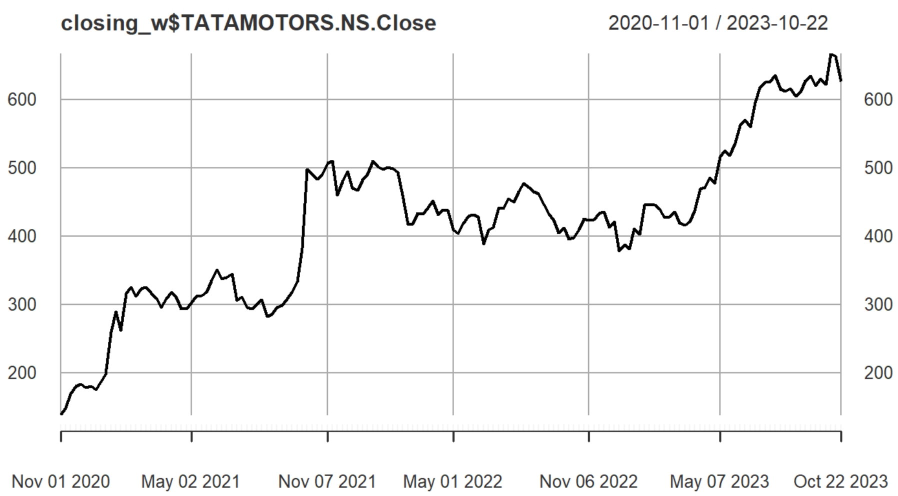
The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-day period are expected to be positive, with an approximate value of 0.14%, accompanied with a standard deviation in close proximity to 2.0%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of TATAMOTORS within the subsequent 10-day period, aligning with the forecast provided by the ARIMA model.

```
> #Forecasting
> ugforecast_d=ugarchforecast(ugfit_d,n.ahead=10)
> ugforecast_d

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1  0.001069 0.01974
T+2  0.001409 0.01993
T+3  0.001396 0.02010
T+4  0.001396 0.02027
T+5  0.001396 0.02044
T+6  0.001396 0.02059
T+7  0.001396 0.02075
T+8  0.001396 0.02089
T+9  0.001396 0.02104
T+10 0.001396 0.02117
```

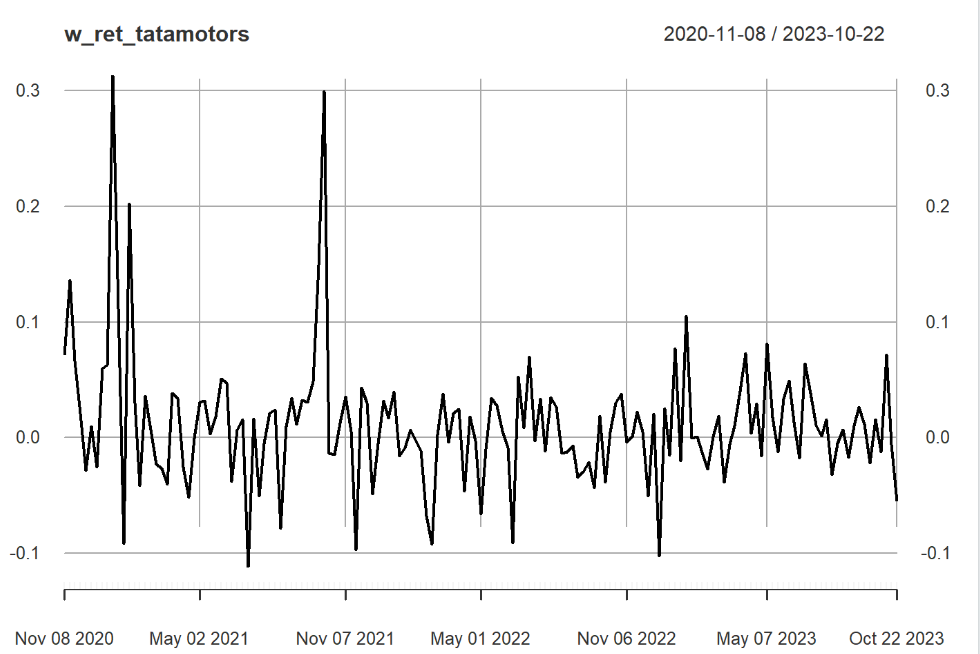
SECTION 3: WEEKLY RETURNS ANALYSIS

3.1 Estimating Beta Using CAPM Model

Provided figure illustrates the weekly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the weekly returns derived from TATAMOTORS stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price over the chosen period. Over the course of a three-year period, there has been a more than threefold increase.



The above graph illustrates the weekly returns derived from TATAMOTORS. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

3.1.1 Interpretation of the regression

```
> #Running the regression model
> regression_w<-lm(extatamotors_w~exnifty_w)
> #slope parameter is beta in CAPM model
> summary(regression_w)

Call:
lm(formula = extatamotors_w ~ exnifty_w)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.121040 -0.024538 -0.006515  0.015040  0.291069 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.06584    0.02001   3.291  0.00124 ** 
exnifty_w    1.45164    0.15401   9.426  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.04712 on 153 degrees of freedom
Multiple R-squared:  0.3674,	Adjusted R-squared:  0.3632 
F-statistic: 88.84 on 1 and 153 DF,  p-value: < 2.2e-16
```

From the results of the regression, the beta came out to be 1.45, which implies that if index portfolio excess returns increase by 1%, then the returns of TATAMOTORS increase by 1.45%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.06584, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of TATAMOTORS are 0.06584%.

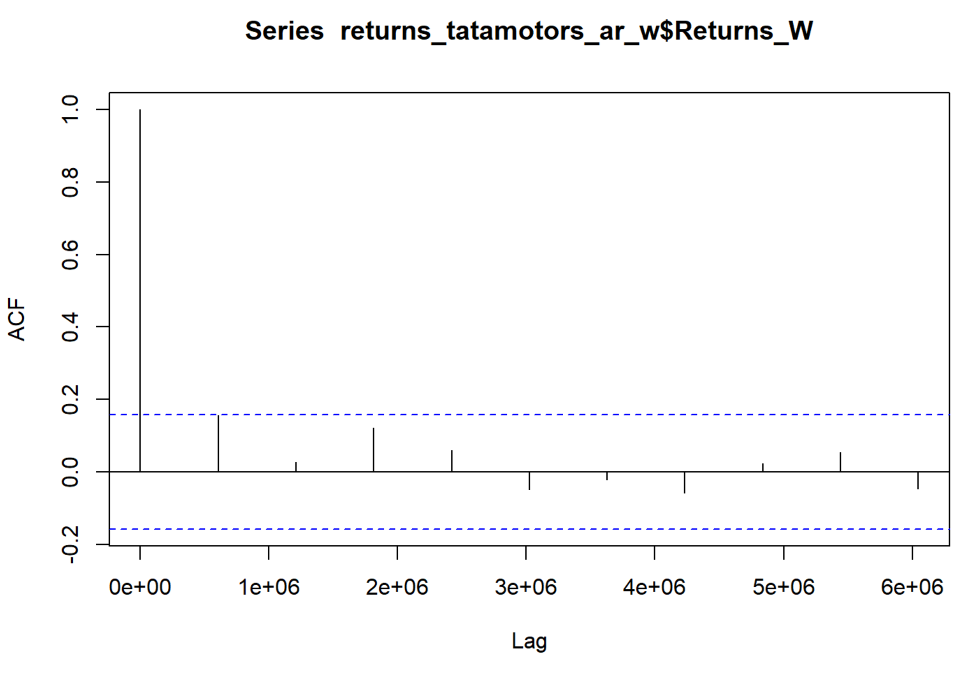
3.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
        Augmented Dickey-Fuller Test

data:  returns_tatamotors_ar_w
Dickey-Fuller = -4.7994, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

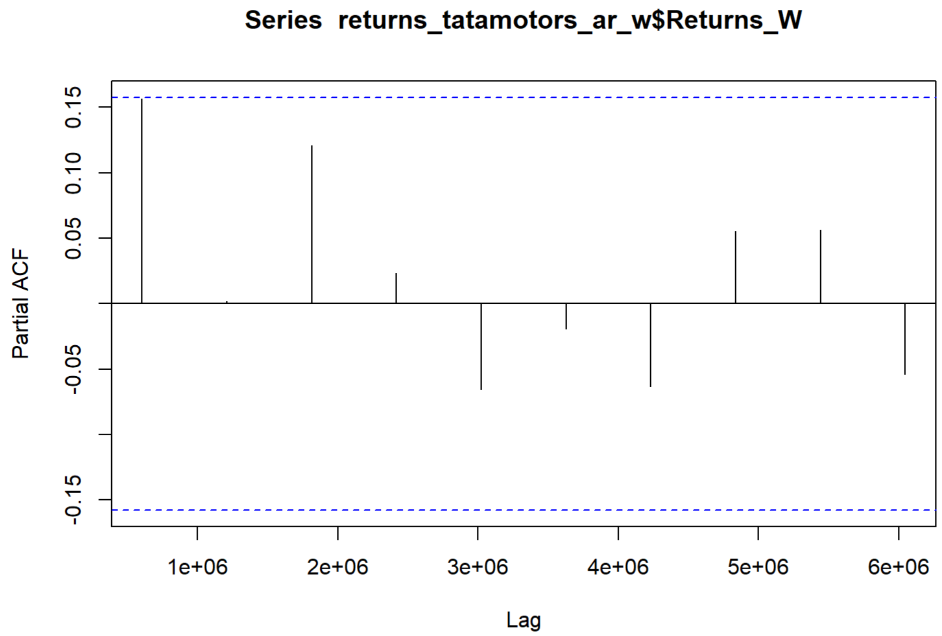
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -4.7994.

3.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(0) model since the initial lags are insignificant.

3.2.2 PACF plot



From the above plot it can be derived that the series is an AR(0) model since initial lags are insignificant.

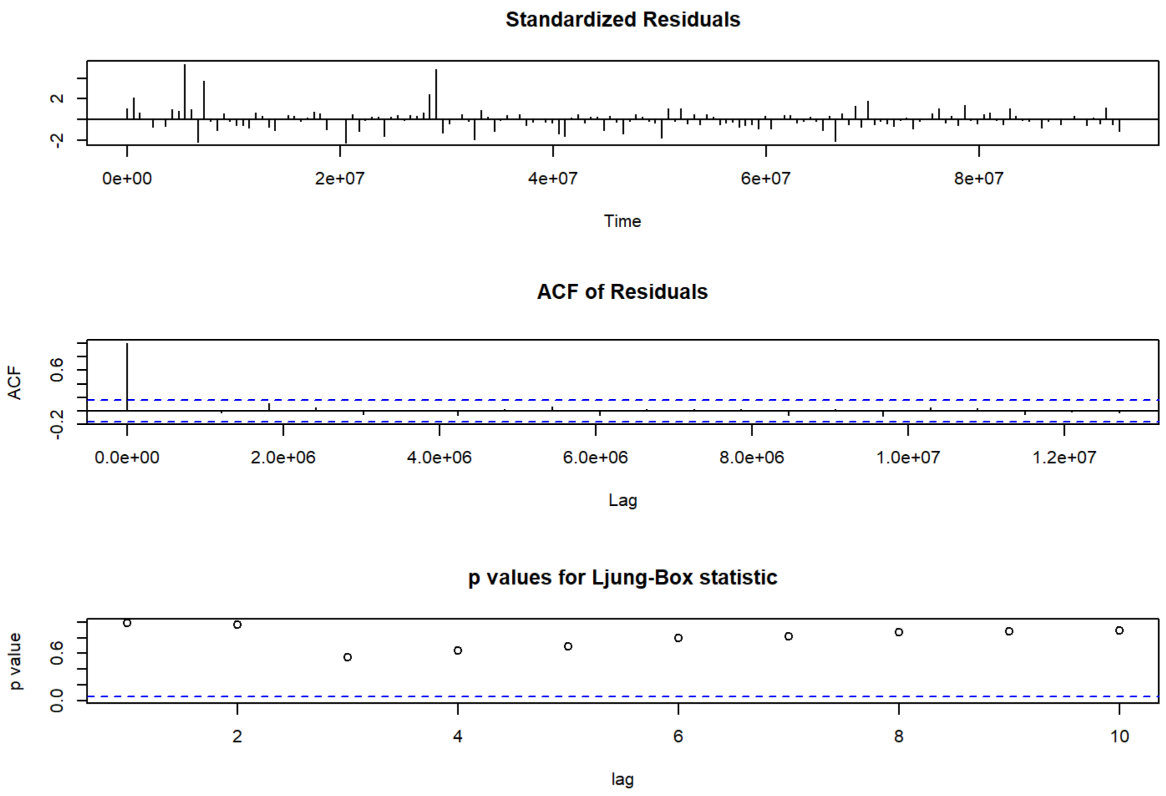
To finally interpret the correct model we use Auto.arima function as shown below-

```
> auto.arima(returns_tatamotors_ar_w$Returns)
Series: returns_tatamotors_ar_w$Returns
ARIMA(2,0,0) with non-zero mean

Coefficients:
         ar1     ar2    mean
      0.1576  0.0044  0.0112
s.e.  0.0805  0.0816  0.0053

sigma^2 = 0.003108:  log likelihood = 229.04
AIC=-450.09   AICc=-449.82   BIC=-437.92
```

The ARIMA function recommended a (2,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and

BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



3.3 GARCH and EGARCH models

Running GARCH on weekly return of TATAMOTORS yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The weekly returns of TATAMOTORS were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model                : eGARCH(1,1)
Variance Targeting         : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model                 : ARFIMA(1,0,1)
Include Mean               : TRUE
GARCH-in-Mean              : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.009305    0.005121  1.817219 0.069184
ar1     0.615324    0.301413  2.041463 0.041205
ma1    -0.494863    0.328707 -1.505486 0.132199
omega   0.000000    0.000004  0.000002 0.999999
alpha1  0.007736    0.009247  0.836528 0.402858
beta1   0.984282    0.010373 94.885086 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.009305    0.005661   1.6438 0.100211
ar1     0.615324    0.218645   2.8143 0.004889
ma1    -0.494863    0.284122  -1.7417 0.081556
omega   0.000000    0.000015   0.0000 1.000000
alpha1  0.007736    0.018538   0.4173 0.676462
beta1   0.984282    0.022446  43.8516 0.000000

LogLikelihood : 238.7793
```

```
Information Criteria
------------------------------------

Akaike       -2.9844
Bayes        -2.8670
Shibata      -2.9872
Hannan-Quinn -2.9367

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.02422  0.8763
Lag[2*(p+q)+(p+q)-1][5]   0.68418  1.0000
Lag[4*(p+q)+(p+q)-1][9]   1.70767  0.9936
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.407  0.2355
Lag[2*(p+q)+(p+q)-1][5]     3.167  0.3774
Lag[4*(p+q)+(p+q)-1][9]     3.920  0.6025
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.704 0.500 2.000  0.1918
ARCH Lag[5]     2.381 1.440 1.667  0.3930
ARCH Lag[7]     2.516 2.315 1.543  0.6092
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  8.7559
Individual Statistics:
mu     0.17169
ar1    0.09534
ma1    0.10386
omega  0.18353
alpha1 0.17545
beta1  0.19989

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value    prob sig
Sign Bias           0.6815 0.49661    
Negative Sign Bias  0.8092 0.41968    
Positive Sign Bias  1.8570 0.06526   *
Joint Effect        5.9068 0.11623    


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     21.18       0.3270
2    30     28.62       0.4852
3    40     44.51       0.2509
4    50     50.41       0.4175


Elapsed time : 0.09428883
```

3.3.1 Interpretation

• The Log Likelihood obtained from the model is 238.77.

• GARCH(1,1) is the best-fit model for TATAMOTORS weekly returns.

- The optimal parameter beta has significant value while alpha and omega are insignificant.

- The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

- The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

- The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major disparity between the observed value and the predicted value.

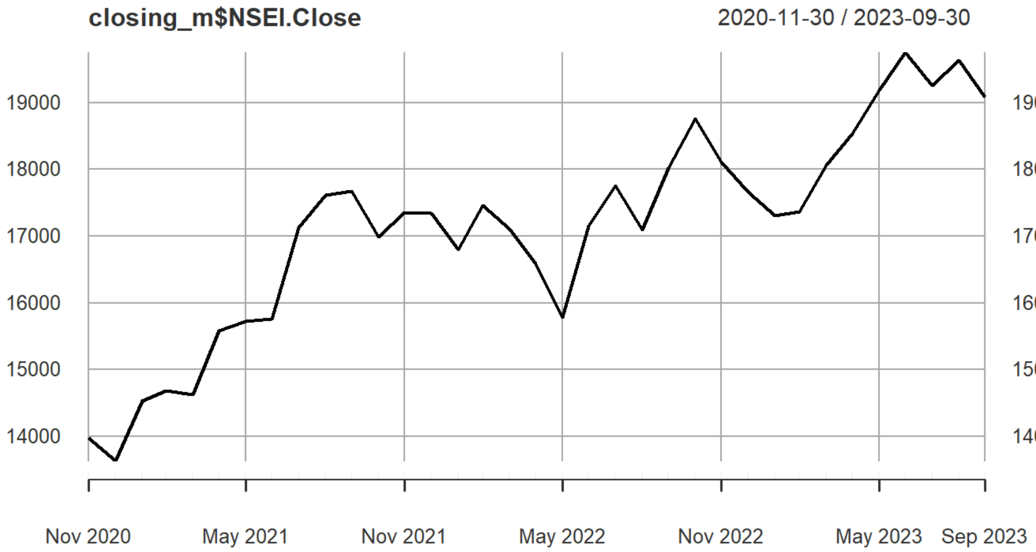
3.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-week period are expected to be positive, with an approximate value of 0.8%, accompanied with a standard deviation in close proximity to 3.2%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of TATAMOTORS within the subsequent 10-week period, aligning with the forecast provided by the ARIMA model.

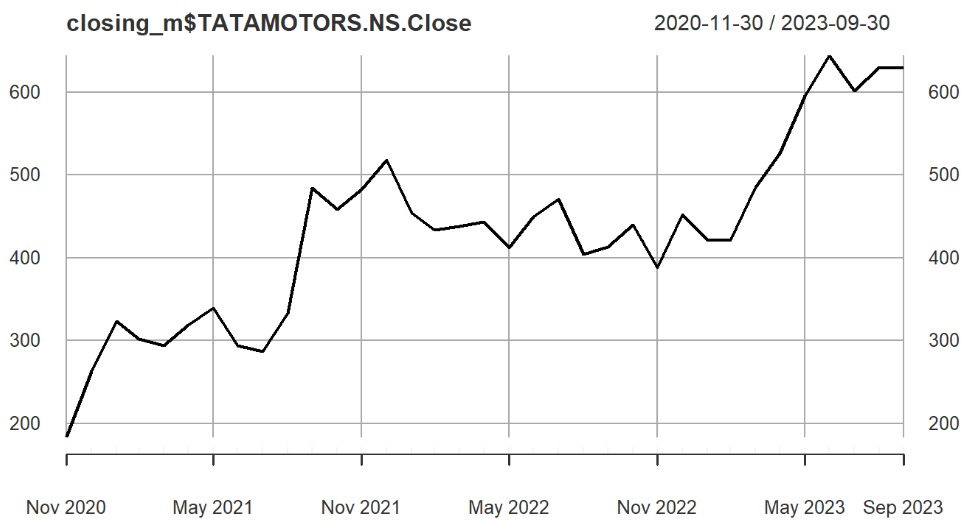
```
> #Forecasting
> ugforecast_w=ugarchforecast(ugfit_w,n.ahead = 10)
> ugforecast_w

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1   0.004149 0.03321
T+2   0.006132 0.03308
T+3   0.007353 0.03294
T+4   0.008104 0.03281
T+5   0.008566 0.03268
T+6   0.008850 0.03255
T+7   0.009025 0.03242
T+8   0.009133 0.03229
T+9   0.009199 0.03216
T+10 0.009240 0.03203
```

SECTION 4: MONTHLY RETURNS ANALYSIS

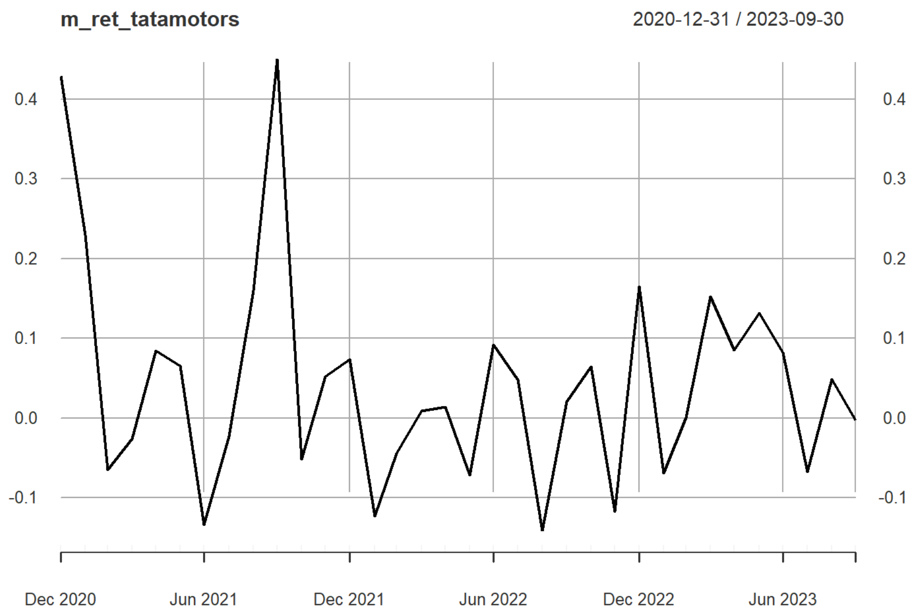
4.1 CAPM Model – Estimating Beta of the company



Provided figure illustrates the monthly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the monthly returns derived from TATAMOTORS stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price over the chosen period. Over the course of a three-year period, there has been a more than threefold increase.



The above graph illustrates the monthly returns derived from TATAMOTORS. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

4.1.1 Interpretation of the regression

```
> summary(regression_m)

Call:
lm(formula = extatamotors_m ~ exnifty_m)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.18912 -0.06421 -0.02028  0.03446  0.40502 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   0.2287     0.2025   1.129 0.267218    
exnifty_m     1.3458     0.3590   3.749 0.000706 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.131 on 32 degrees of freedom
Multiple R-squared:  0.3051,	Adjusted R-squared:  0.2834 
F-statistic: 14.05 on 1 and 32 DF,  p-value: 0.0007059
```

From the results of the regression, the beta came out to be 1.34, which implies that if index portfolio excess returns increase by 1%, then the returns of TATAMOTORS increase by 1.34%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.2287, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of TATAMOTORS are 0.2287%.

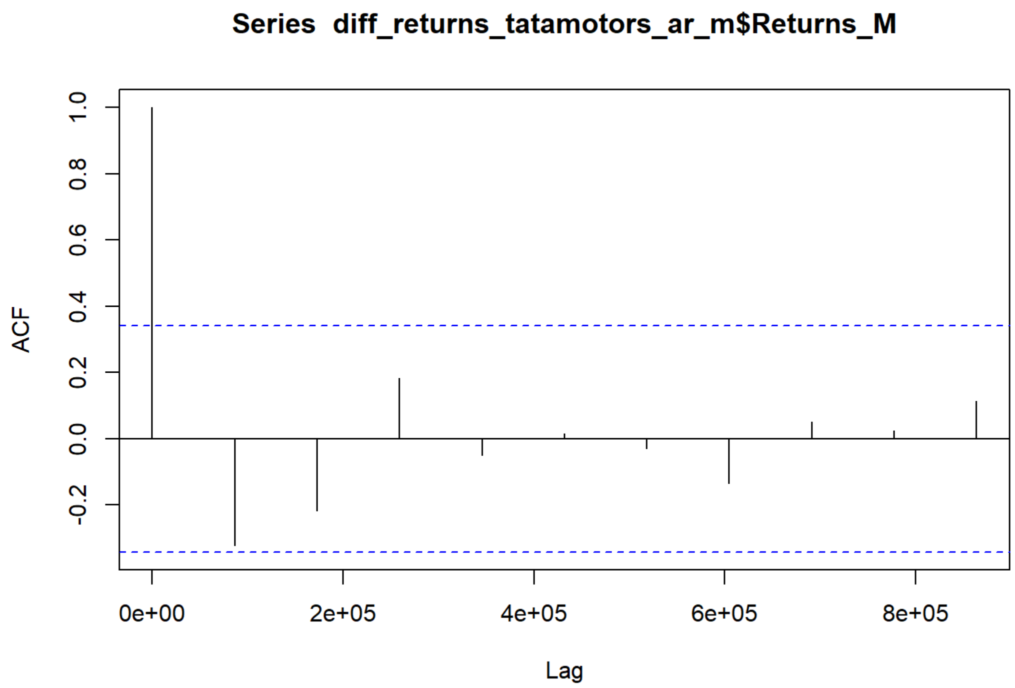
4.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary of integrated or order 1, which means the first difference is stationary. To test this, we perform ADF Test shown below-

```
> adf.test(diff_returns_tatamotors_ar_m,alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  diff_returns_tatamotors_ar_m
Dickey-Fuller = -4.0971, Lag order = 3, p-value = 0.01804
alternative hypothesis: stationary
```

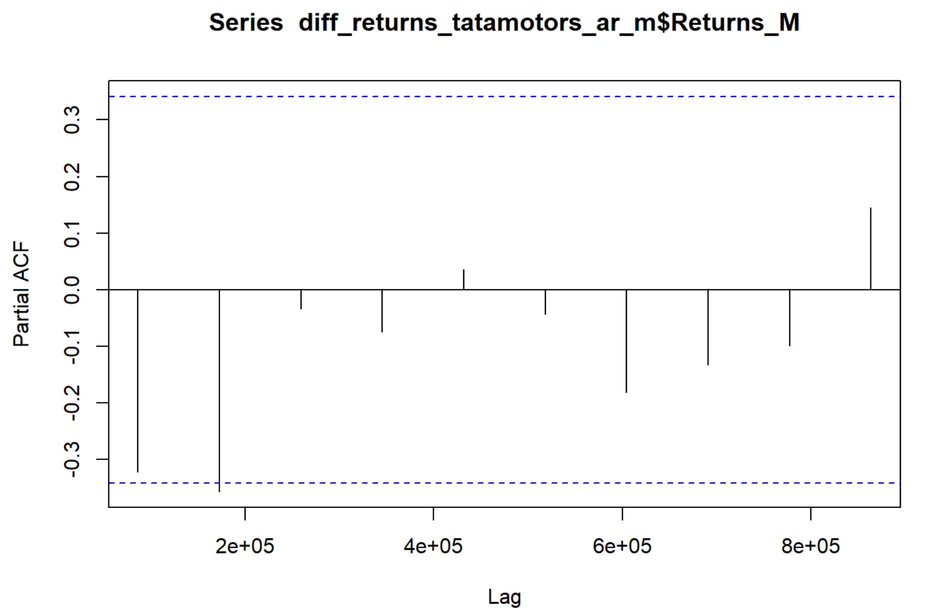
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01804. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -4.0971.

4.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(0) model since the correlation is significant in none of the lags.

4.2.2 PACF plot



From the above plot it can be derived that the series is an AR(1) model since initial lags are significant.

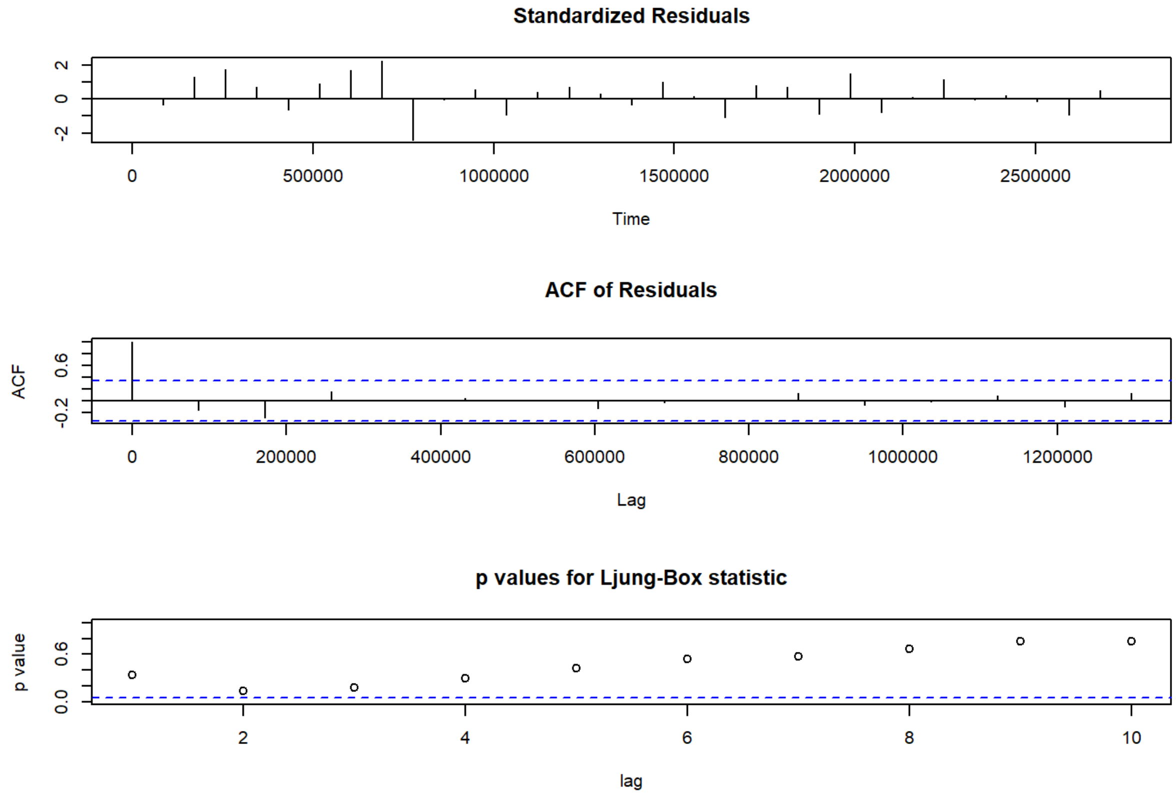
To finally interpret the correct model we use Auto.arima function as shown below-

4.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_rubymills_ar_m$Returns)
Series: returns_rubymills_ar_m$Returns
ARIMA(0,0,0) with zero mean

sigma^2 = 0.03414:  log likelihood = 9.17
AIC=-16.33   AICc=-16.21   BIC=-14.81
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



4.3 GARCH and EGARCH models

Running GARCH on monthly return of TATAMOTORS yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The monthly returns of TATAMOTORS were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu       0.041380    0.021854  1.893529 0.058287
ar1     -0.818576    0.150626 -5.434495 0.000000
ma1      0.925061    0.090708 10.198254 0.000000
omega    0.000000    0.000128  0.000000 1.000000
alpha1   0.000002    0.107028  0.000017 0.999987
beta1    0.971979    0.159841  6.080921 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu       0.041380    0.032567  1.270611 0.203867
ar1     -0.818576    0.113173 -7.232970 0.000000
ma1      0.925061    0.079056 11.701396 0.000000
omega    0.000000    0.000176  0.000000 1.000000
alpha1   0.000002    0.246376  0.000007 0.999994
beta1    0.971979    0.357191  2.721173 0.006505

LogLikelihood : 22.49661
```

```
Information Criteria
------------------------------------

Akaike       -0.91648
Bayes        -0.65256
Shibata      -0.96213
Hannan-Quinn -0.82436

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1187  0.7305
Lag[2*(p+q)+(p+q)-1][5]    0.5407  1.0000
Lag[4*(p+q)+(p+q)-1][9]    1.1687  0.9994
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.2216  0.6378
Lag[2*(p+q)+(p+q)-1][5]    0.4443  0.9659
Lag[4*(p+q)+(p+q)-1][9]    1.6033  0.9467
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.0466 0.500 2.000  0.8291
ARCH Lag[5]    0.3687 1.440 1.667  0.9215
ARCH Lag[7]    0.7515 2.315 1.543  0.9503
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  4.2807
Individual Statistics:
mu     0.18609
ar1    0.06520
ma1    0.09569
omega  0.09618
alpha1 0.09772
beta1  0.13184

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:        1.49 1.68 2.12
Individual Statistic:   0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.3421 0.7346
Negative Sign Bias  0.8688 0.3916
Positive Sign Bias  0.0640 0.9494
Joint Effect        0.8430 0.8391


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     14.00       0.7837
2    30     17.33       0.9567
3    40     35.11       0.6479
4    50     44.56       0.6537
```

4.3.1 Interpretation

• The Log Likelihood obtained from the model is 22.49.

• GARCH(1,1) is the best-fit model for TATAMOTORS monthly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major disparity between the observed value and the predicted value.

4.3.2 Forecast using GARCH

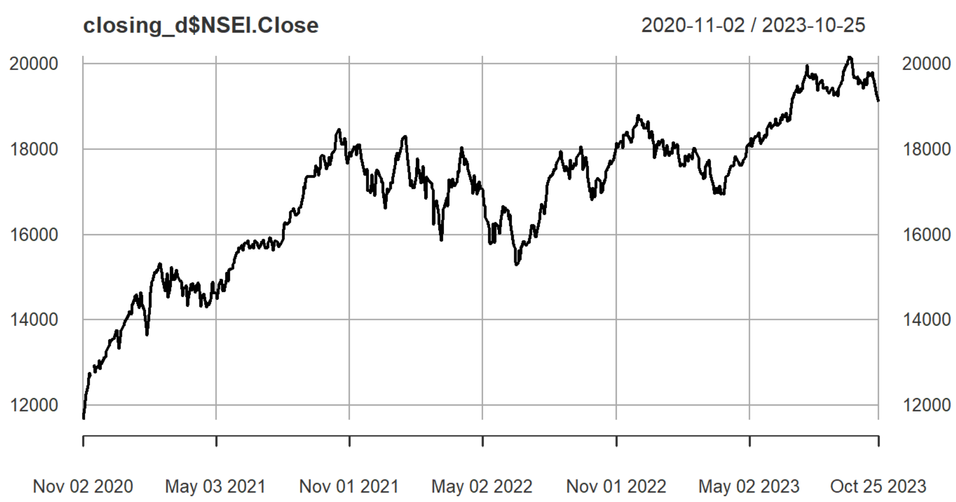
The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-month period are expected to be positive, with an approximate value of 4%, accompanied with a standard deviation in close proximity to 7.5%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of TATAMOTORS within the subsequent 10-month period, aligning with the forecast provided by the ARIMA model.

```
> #Forecasting
> ugforecast_m=ugarchforecast(ugfit_m,n.ahead = 10)
> ugforecast_m

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1   0.01983 0.08248
T+2   0.05902 0.08132
T+3   0.02694 0.08017
T+4   0.05320 0.07904
T+5   0.03170 0.07793
T+6   0.04930 0.07683
T+7   0.03490 0.07574
T+8   0.04669 0.07467
T+9   0.03704 0.07362
T+10 0.04494 0.07258
```

5. TRIL

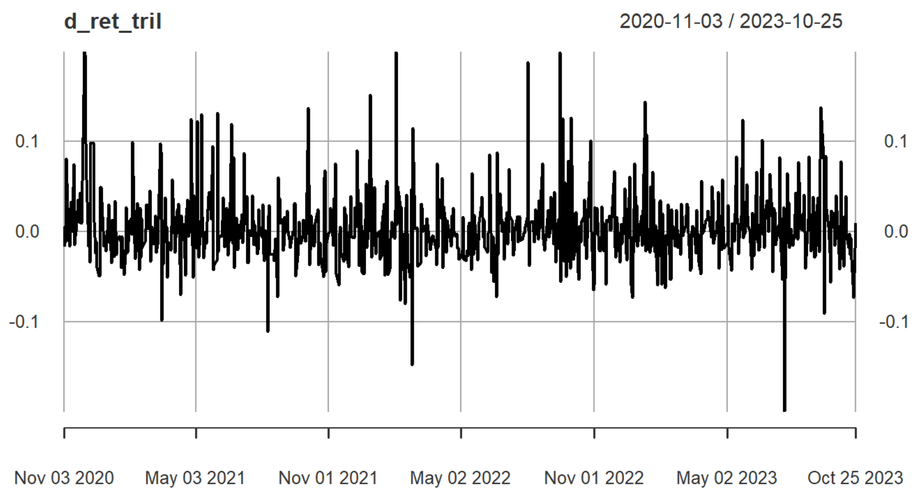
SECTION 2: DAILY RETURNS ANALYSIS

2.1 Estimating Beta Using CAPM Model



The provided figure illustrates the daily closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.

The provided figure illustrates the daily returns derived from TRIL stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price. Over the course of a three-year period, there has been a more than sevenfold increase.



The above graph illustrates the daily returns derived from TRIL. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

2.1.1 Interpretation of the regression

```
> #Running the regression model
> regression_d<-lm(extril_d~exnifty_d)
> #slope parameter is the beta in CAPM model
> summary(regression_d)

Call:
lm(formula = extril_d ~ exnifty_d)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.211492 -0.022936 -0.005939  0.015746  0.203100 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.005457   0.003158   1.728   0.0844 .  
exnifty_d   1.094633   0.155409   7.044 4.39e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.04011 on 719 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.06455,	Adjusted R-squared:  0.06325 
F-statistic: 49.61 on 1 and 719 DF,  p-value: 4.391e-12
```

From the results of the regression, the beta came out to be 1.09, which implies that if index portfolio excess returns increase by 1%, then the returns of TRIL increase by 1.09%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.005457, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of TRIL are 0.005457%.

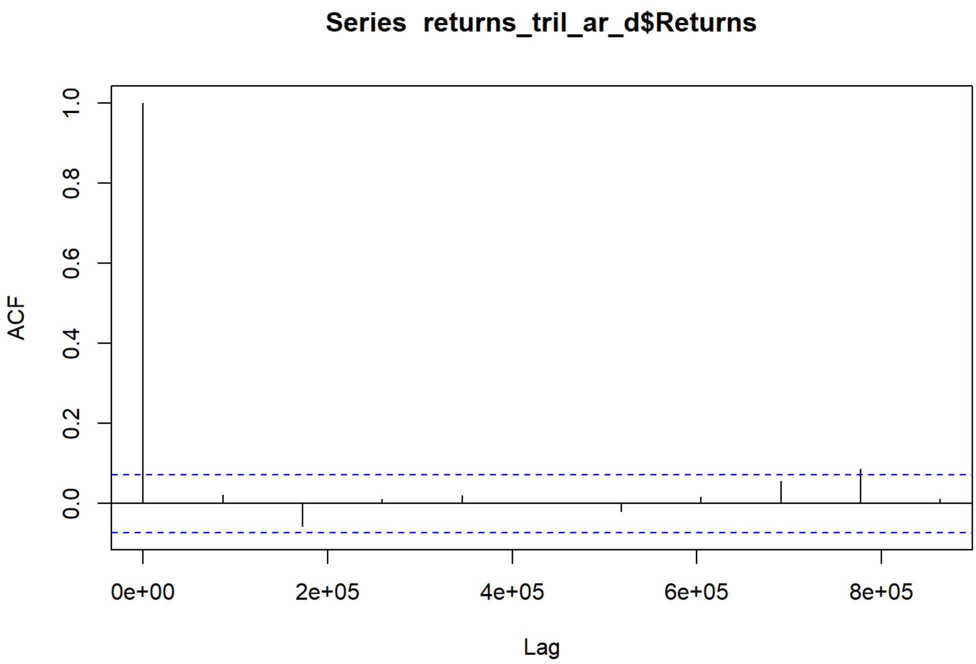
2.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_tril_ar_d$Returns, alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_tril_ar_d$Returns
Dickey-Fuller = -7.2748, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary
```

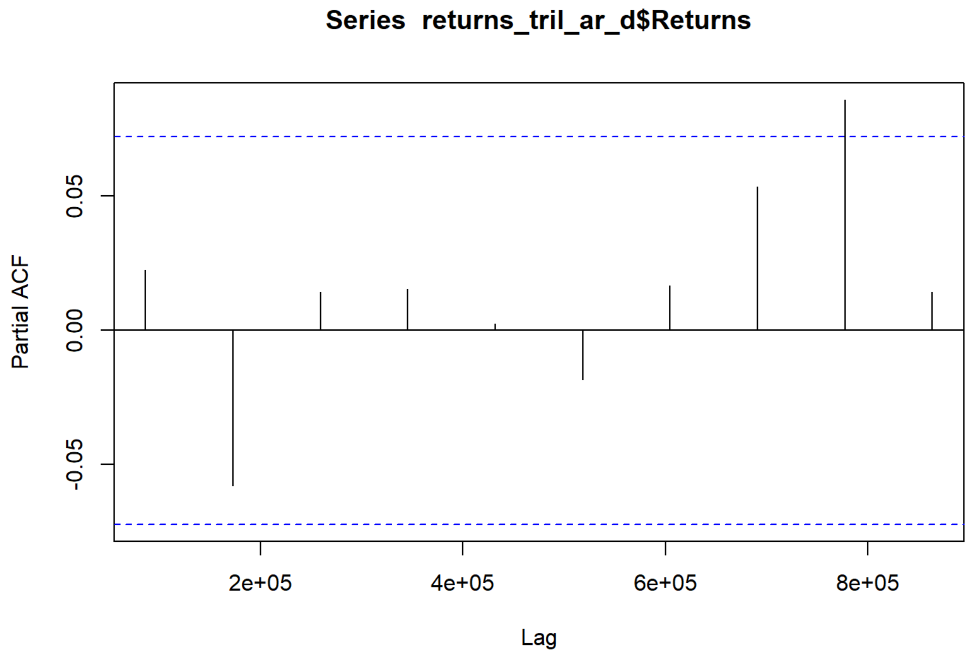
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -7.2748.

2.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(0) model since the correlation is significant at none of the lags.

2.2.2 PACF plot



From the above plot it can be derived that the series is an AR(0) model since none of the initial lags are significant.

To finally interpret the correct model we use Auto.arima function as shown below-

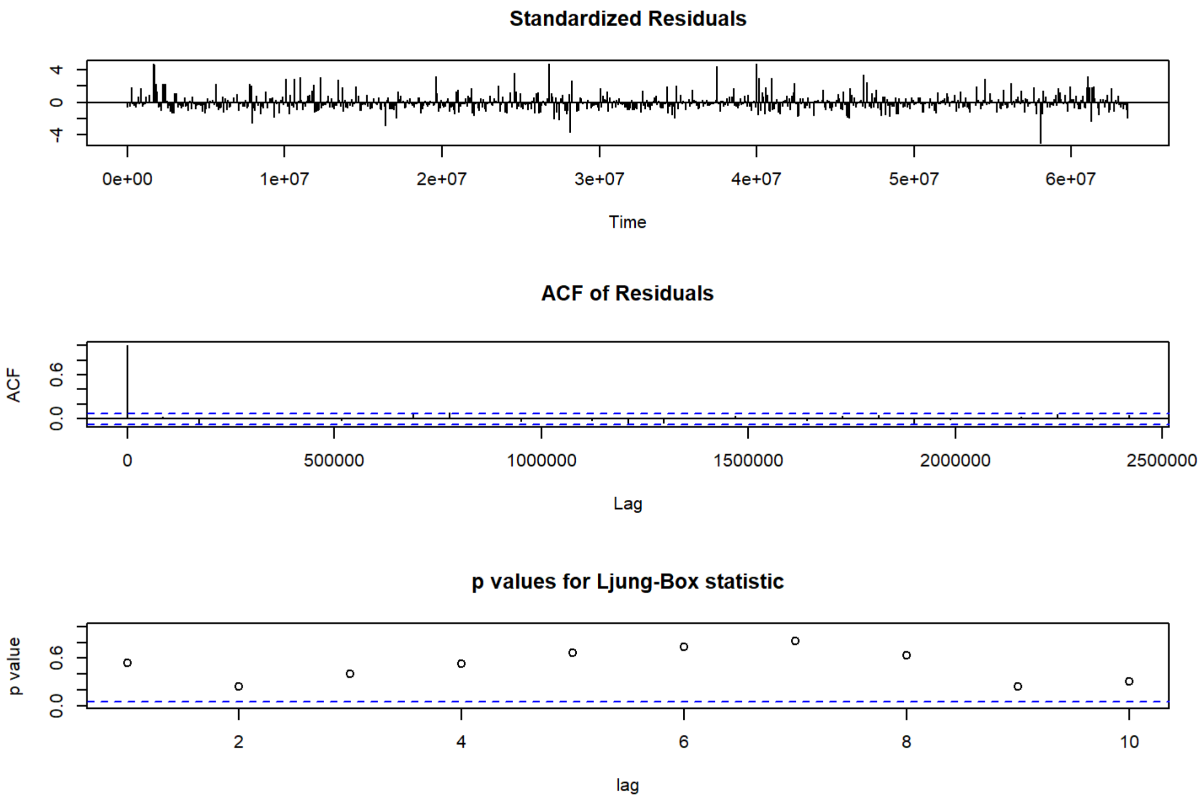
2.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_tril_ar_d$Returns)
Series: returns_tril_ar_d$Returns
ARIMA(0,0,0) with non-zero mean

Coefficients:
        mean
      0.0047
s.e.  0.0015

sigma^2 = 0.00171:  log likelihood = 1304.25
AIC=-2604.5   AICc=-2604.48   BIC=-2595.29
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and

BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



2.3 GARCH and EGARCH models

Running GARCH on daily return of TRIL yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model            : sGARCH(1,1)
Variance Targeting     : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model             : ARFIMA(1,0,1)
Include Mean           : TRUE
GARCH-in-Mean          : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The daily returns of TRIL were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.004659    0.001551  3.0038e+00 0.002666
ar1    -0.633503    0.375111 -1.6888e+00 0.091250
ma1     0.670747    0.361202  1.8570e+00 0.063313
omega   0.000004    0.000000  2.1088e+02 0.000000
alpha1  0.000026    0.000295  8.7612e-02 0.930185
beta1   0.997397    0.000071  1.4065e+04 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.004659    0.001618  2.8801e+00 0.003975
ar1    -0.633503    0.366882 -1.7267e+00 0.084218
ma1     0.670747    0.333772  2.0096e+00 0.044474
omega   0.000004    0.000000  6.4401e+02 0.000000
alpha1  0.000026    0.000531  4.8675e-02 0.961178
beta1   0.997397    0.000099  1.0080e+04 0.000000

LogLikelihood : 1307.354
```

```
Information Criteria
------------------------------------

Akaike       -3.5219
Bayes        -3.4845
Shibata      -3.5221
Hannan-Quinn -3.5075

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1367  0.7116
Lag[2*(p+q)+(p+q)-1][5]    1.0670  1.0000
Lag[4*(p+q)+(p+q)-1][9]    2.4706  0.9543
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic   p-value
Lag[1]                      15.06 1.039e-04
Lag[2*(p+q)+(p+q)-1][5]     18.73 4.318e-05
Lag[4*(p+q)+(p+q)-1][9]     19.44 2.796e-04
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.4429 0.500 2.000  0.5057
ARCH Lag[5]    0.6598 1.440 1.667  0.8357
ARCH Lag[7]    0.8344 2.315 1.543  0.9389
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  7.8393
Individual Statistics:
mu     0.08574
ar1    0.34031
ma1    0.32657
omega  0.51352
alpha1 0.05196
beta1  0.03960

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value    prob sig
Sign Bias            1.436 0.15131
Negative Sign Bias   2.324 0.02042  **
Positive Sign Bias   2.110 0.03523  **
Joint Effect        13.088 0.00445 ***


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     113.7    1.656e-15
2    30     124.2    9.574e-14
3    40     152.4    2.484e-15
4    50     178.4    1.338e-16
```

2.3.1 Interpretation

• The Log Likelihood obtained from the model is 1307.35.

• GARCH(1,1) is the best-fit model for TRIL daily returns.

• The optimal parameter beta and omega have significant values while alpha is insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that only alpha is insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

The Adjusted Pearson Goodness of Fit Test gave p-values less than 0.05, indicating that the null hypothesis should be rejected. This suggests a significant disparity between the observed and predicted values.

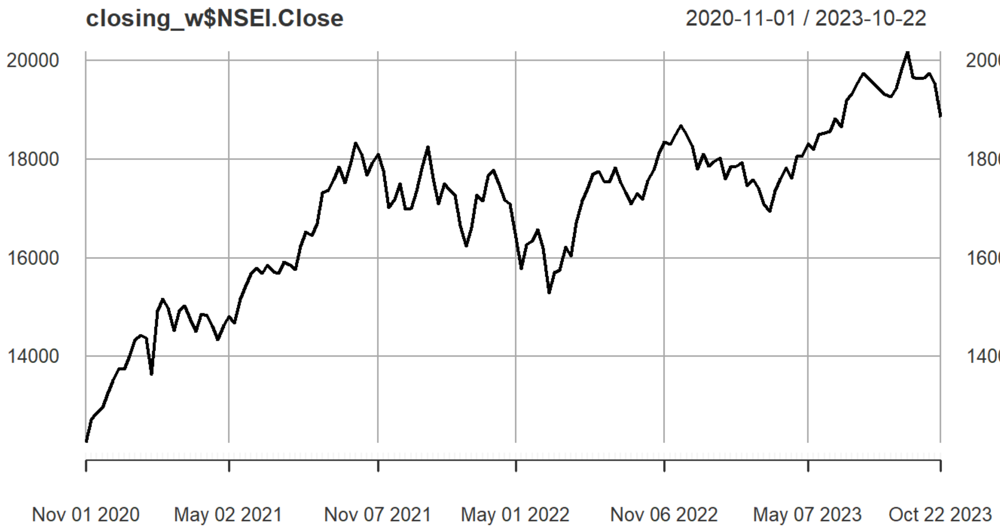
2.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-day period are expected to be positive, with an approximate value of 0.48%, accompanied with a standard deviation in close proximity to 4%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of TRIL within the subsequent 10-day period, aligning with the forecast provided by the ARIMA model.

```
> #Forecasting
> ugforecast_d=ugarchforecast(ugfit_d,n.ahead=10)
> ugforecast_d

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1  0.006144 0.04022
T+2  0.003719 0.04022
T+3  0.005255 0.04022
T+4  0.004282 0.04022
T+5  0.004898 0.04022
T+6  0.004508 0.04022
T+7  0.004755 0.04022
T+8  0.004599 0.04022
T+9  0.004698 0.04022
T+10 0.004635 0.04022
```

SECTION 3: WEEKLY RETURNS ANALYSIS

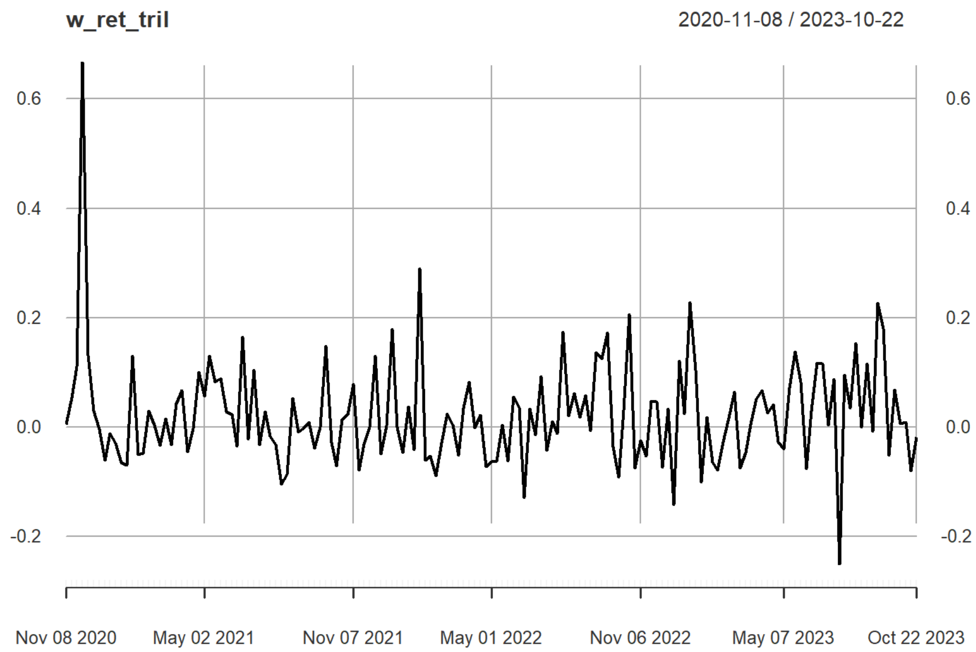
3.1 Estimating Beta Using CAPM Model



Provided figure illustrates the weekly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.

The provided figure illustrates the weekly returns derived from TRIL stock price throughout the time period spanning from November 2, 2020, to October

25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price. Over the course of a three-year period, there has been a more than sevenfold increase.



The above graph illustrates the weekly returns derived from TRIL. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

3.1.1 Interpretation of the regression

```
> #Running the regression model
> regression_w<-lm(extril_w~exnifty_w)
> #slope parameter is beta in CAPM model
> summary(regression_w)

Call:
lm(formula = extril_w ~ exnifty_w)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.28016 -0.06028 -0.01757  0.04184  0.61205 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.06957    0.03875   1.795   0.0746 .  
exnifty_w    1.39274    0.29827   4.669 6.56e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.09126 on 153 degrees of freedom
Multiple R-squared:  0.1247,	Adjusted R-squared:  0.119 
F-statistic:  21.8 on 1 and 153 DF,  p-value: 6.558e-06
```

From the results of the regression, the beta came out to be 1.39, which implies that if index portfolio excess returns increase by 1%, then the returns of TRIL increase by 1.39%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.06957, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of TRIL are 0.06957%.

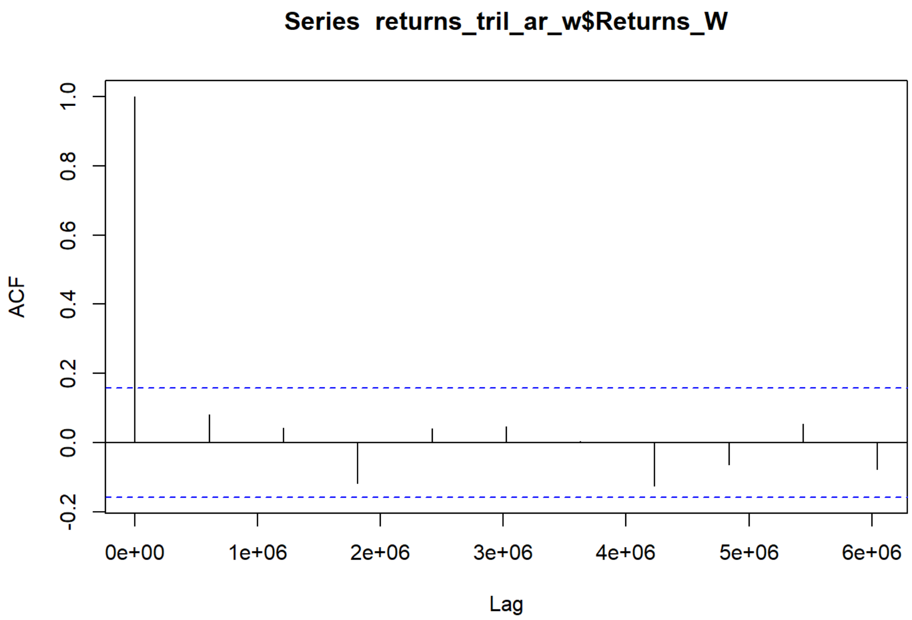
3.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_tril_ar_w,alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_tril_ar_w
Dickey-Fuller = -5.839, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

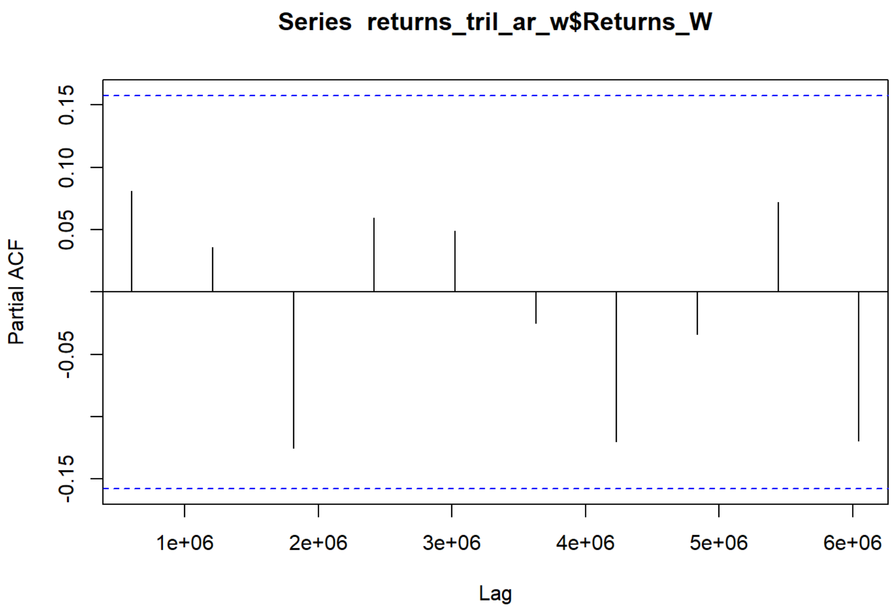
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -5.839.

3.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(0) model since the initial lags are insignificant.

3.2.2 PACF plot



From the above plot it can be derived that the series is an AR(0) model since initial lags are insignificant.

To finally interpret the correct model we use Auto.arima function as shown below-

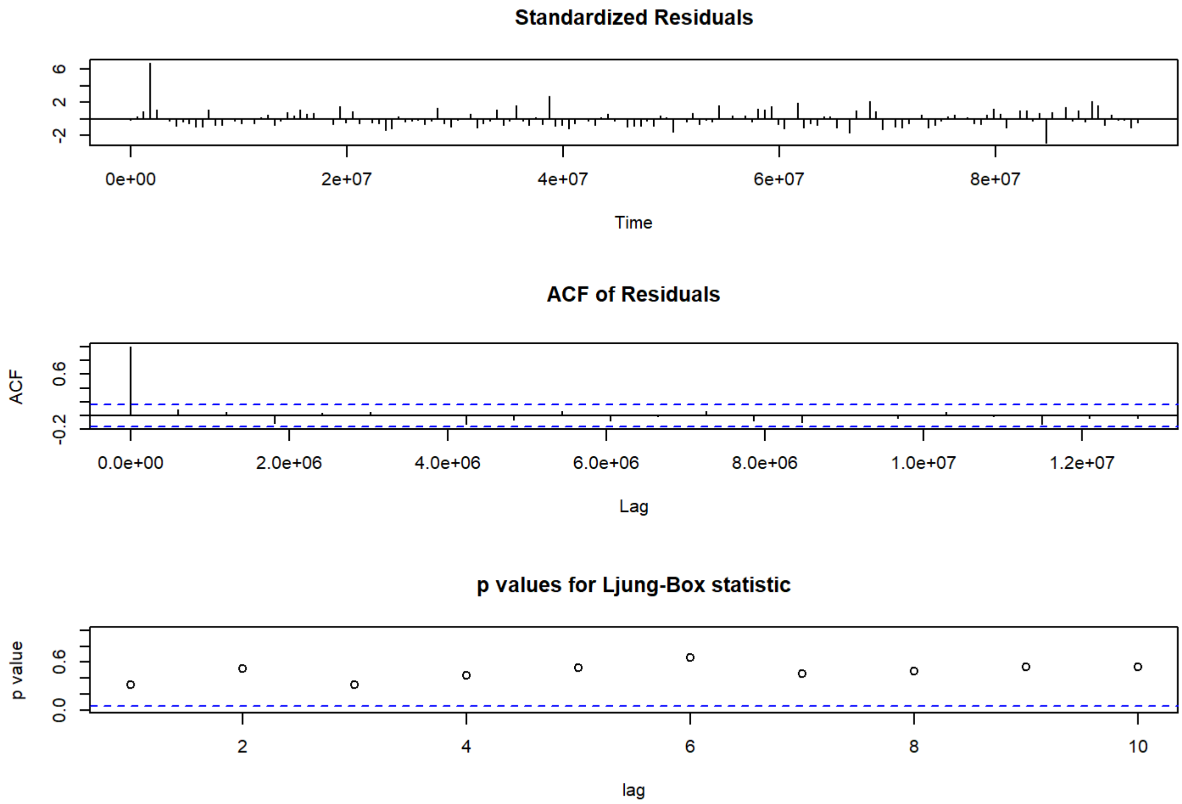
3.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_tril_ar_w$Returns)
Series: returns_tril_ar_w$Returns
ARIMA(0,0,0) with non-zero mean

Coefficients:
        mean
      0.0225
s.e.  0.0077

sigma^2 = 0.00922:  log likelihood = 143.76
AIC=-283.52   AICc=-283.44   BIC=-277.43
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and

BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



3.3 GARCH and EGARCH models

Running GARCH on weekly return of TRIL yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The weekly returns of TRIL were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
> #Estimating the models
> ugfit_w=ugarchfit(spec=ug_spec_w, data=r_tril_ge_w)
> ugfit_w#lower aic value models are better

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.021434    0.008127   2.63738 0.008355
ar1     0.188110    0.562648   0.33433 0.738131
ma1    -0.117232    0.564417  -0.20770 0.835460
omega   0.000357    0.000184   1.93706 0.052738
alpha1  0.000000    0.006443   0.00000 1.000000
beta1   0.950554    0.005980 158.95332 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.021434    0.009595  2.23395 0.025486
ar1     0.188110    0.226450  0.83069 0.406150
ma1    -0.117232    0.215339 -0.54441 0.586162
omega   0.000357    0.000237  1.51022 0.130986
alpha1  0.000000    0.008223  0.00000 1.000000
beta1   0.950554    0.036601 25.97066 0.000000

LogLikelihood : 146.8773
```

```
Information Criteria
------------------------------------

Akaike       -1.8061
Bayes        -1.6888
Shibata      -1.8089
Hannan-Quinn -1.7585

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                  7.609e-05  0.9930
Lag[2*(p+q)+(p+q)-1][5] 2.133e+00  0.9276
Lag[4*(p+q)+(p+q)-1][9] 4.080e+00  0.6721
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.0274  0.8685
Lag[2*(p+q)+(p+q)-1][5]    0.3505  0.9781
Lag[4*(p+q)+(p+q)-1][9]    0.4914  0.9985
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.1267 0.500 2.000  0.7219
ARCH Lag[5]    0.2544 1.440 1.667  0.9521
ARCH Lag[7]    0.3129 2.315 1.543  0.9921
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  14.8127
Individual Statistics:
mu     0.07448
ar1    0.33785
ma1    0.33304
omega  0.13129
alpha1 2.49221
beta1  0.12455

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.5733 0.5673
Negative Sign Bias  0.2731 0.7851
Positive Sign Bias  0.1250 0.9007
Joint Effect        1.4684 0.6896


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     20.67       0.3555
2    30     23.23       0.7659
3    40     32.21       0.7711
4    50     38.23       0.8667
```

3.3.1 Interpretation

• The Log Likelihood obtained from the model is 192.0216.

• GARCH(1,1) is the best-fit model for TRIL weekly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major disparity between the observed value and the predicted value.

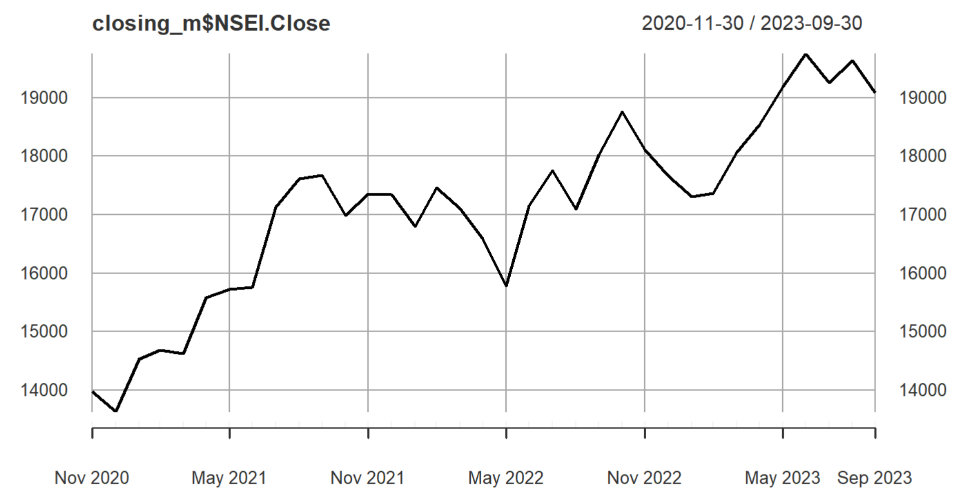
3.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-week period are expected to be positive, with an approximate value of 2.1%, accompanied with a standard deviation in close proximity to 8.5%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of TRIL within the subsequent 10-week period, aligning with the forecast provided by the ARIMA model.

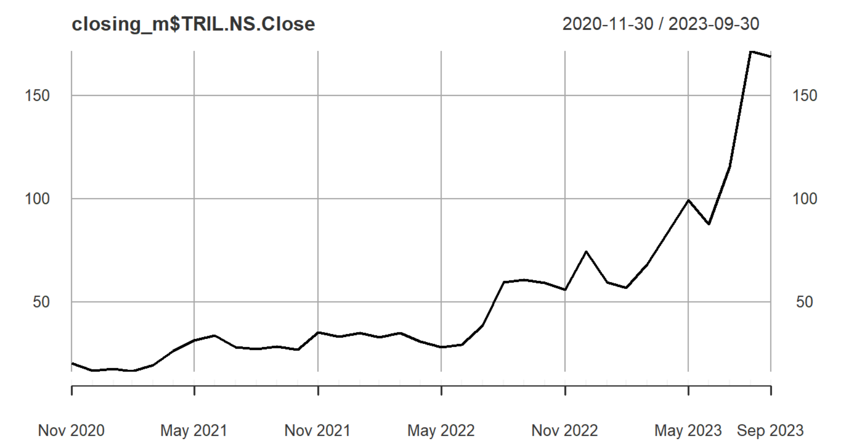
```
> #Forecasting
> ugforecast_w=ugarchforecast(ugfit_w,n.ahead = 10)
> ugforecast_w

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
      Series Sigma
T+1  0.01446 0.085
T+2  0.02012 0.085
T+3  0.02119 0.085
T+4  0.02139 0.085
T+5  0.02143 0.085
T+6  0.02143 0.085
T+7  0.02143 0.085
T+8  0.02143 0.085
T+9  0.02143 0.085
T+10 0.02143 0.085
```

SECTION 4: MONTHLY RETURNS ANALYSIS

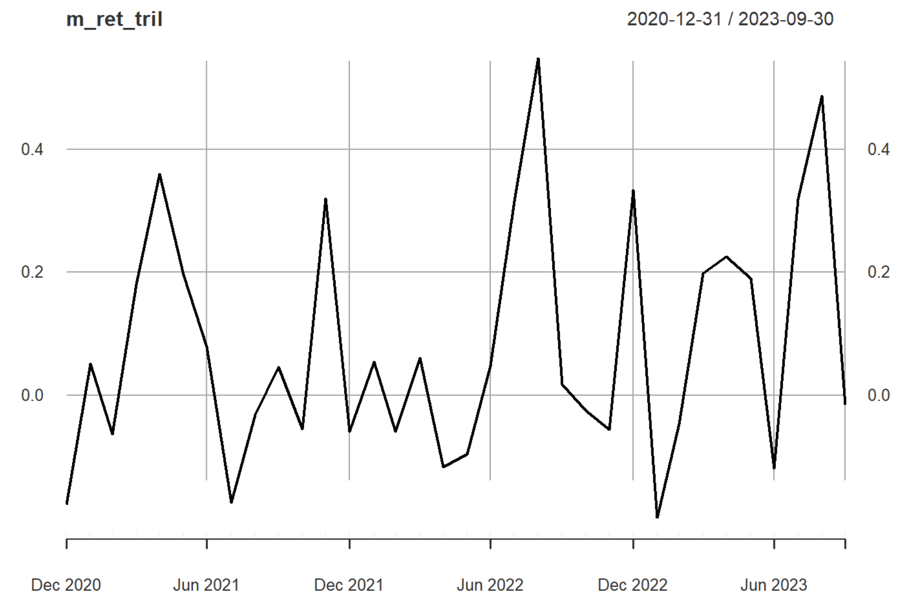
4.1 CAPM Model – Estimating Beta of the company



Provided figure illustrates the monthly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the monthly returns derived from TRIL stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price over the chosen period. Over the course of a three-year period, there has been a more than sevenfold increase.



The above graph illustrates the monthly returns derived from TRIL. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

4.1.1 Interpretation of the regression

```
> summary(regression_m)

Call:
lm(formula = extril_m ~ exnifty_m)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.28873 -0.13796 -0.06123  0.13779  0.47121 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.1995     0.3034  -0.658    0.515
exnifty_m     0.5181     0.5378   0.963    0.343

Residual standard error: 0.1962 on 32 degrees of freedom
Multiple R-squared:  0.02819,	Adjusted R-squared:  -0.002182 
F-statistic: 0.9282 on 1 and 32 DF,  p-value: 0.3426
```

From the results of the regression, the beta came out to be 0.51, which implies that if index portfolio excess returns increase by 1%, then the returns of TRIL increase by 0.51%. Also, the beta value is insignificant at both 95% and 99% since the p-value is greater than 0.01 ($p < 0.01$). The intercept value obtained from the regression is -0.1995, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of TRIL are -0.1995%.

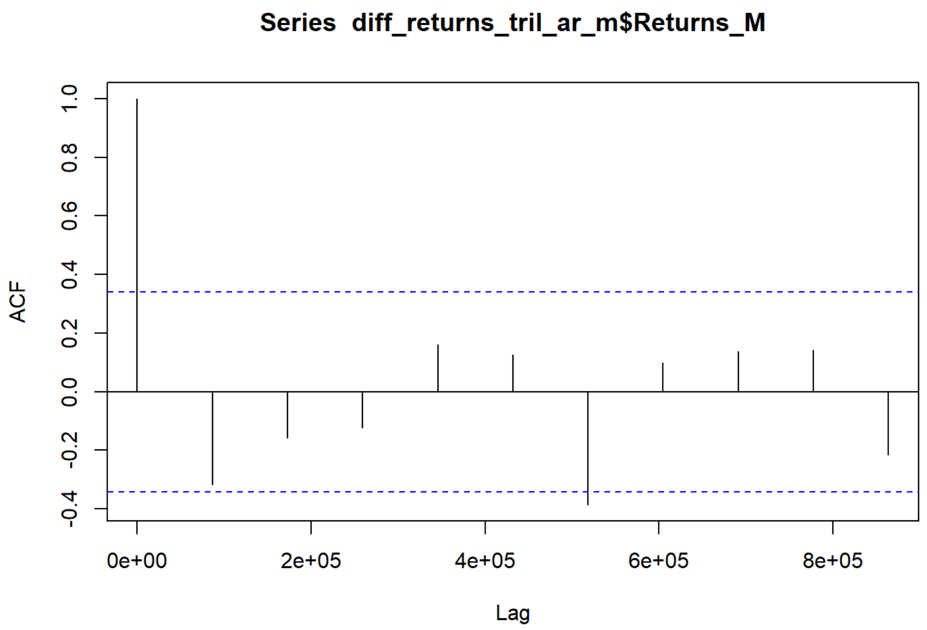
4.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary of integrated or order 1, which means the first difference is stationary. To test this, we perform ADF Test shown below-

```
	Augmented Dickey-Fuller Test

data:  diff_returns_tril_ar_m
Dickey-Fuller = -4.5833, Lag order = 3, p-value = 0.01
alternative hypothesis: stationary
```

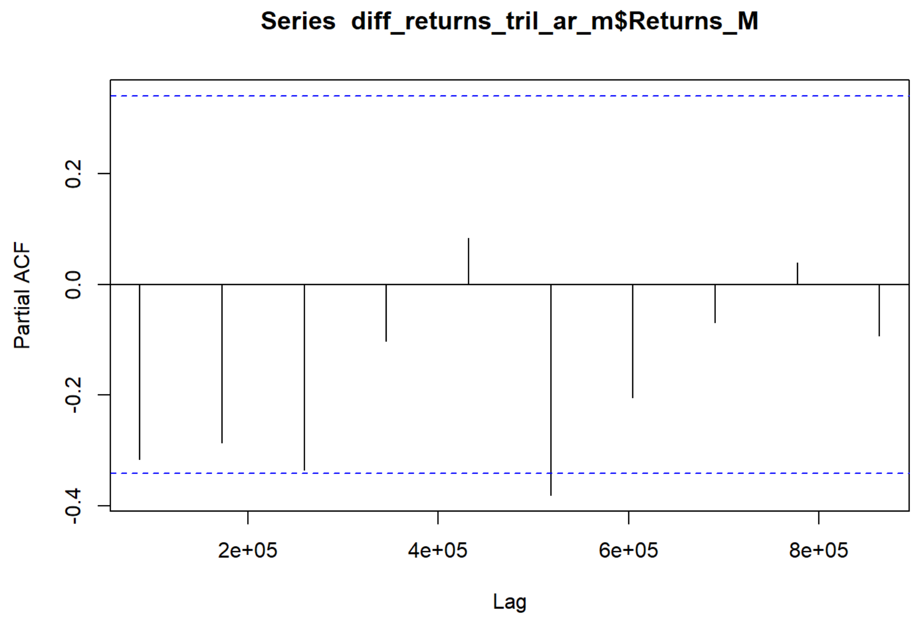
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -4.5833.

4.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(0) model since none of the initial lags are significant.

4.2.2 PACF plot



From the above plot it can be derived that the series is an AR(0) model since none of the initial lags are significant.

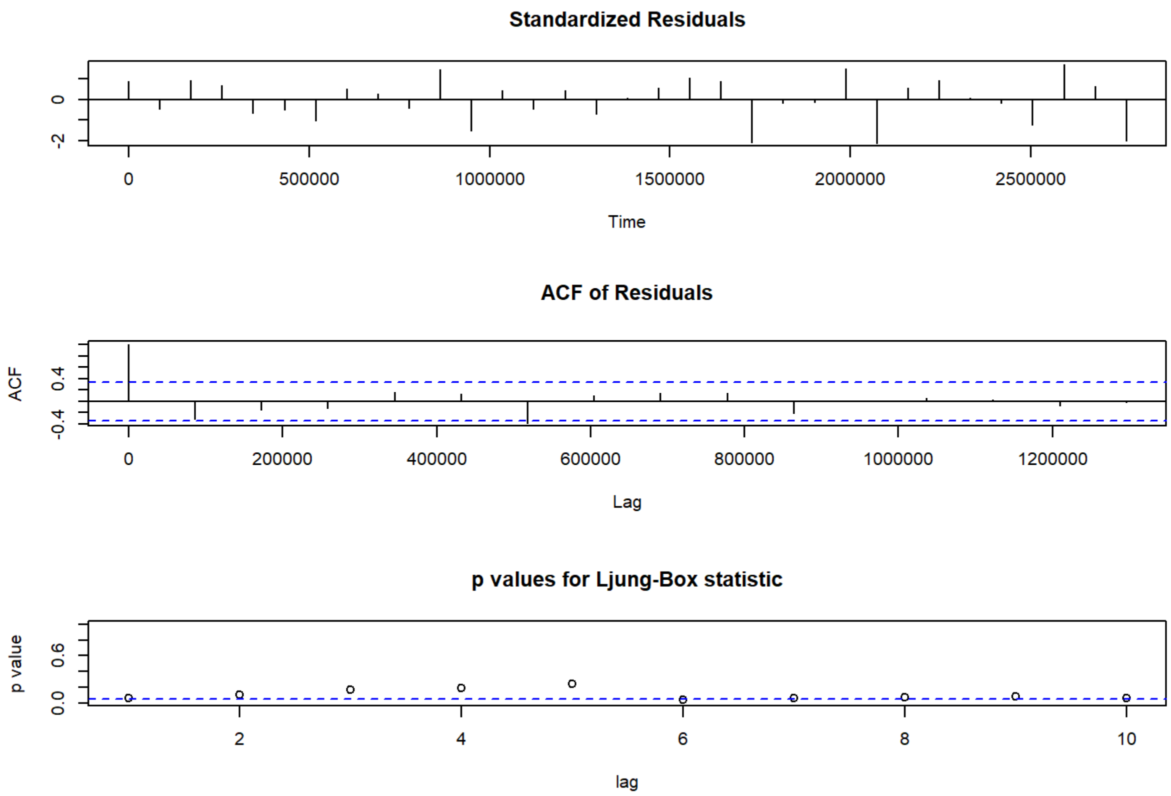
To finally interpret the correct model we use Auto.arima function as shown below-

4.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_tril_ar_m$Returns)
Series: returns_tril_ar_m$Returns
ARIMA(0,0,0) with non-zero mean

Coefficients:
        mean
      0.0805
s.e.  0.0328

sigma^2 = 0.03762:  log likelihood = 8.03
AIC=-12.06   AICc=-11.67   BIC=-9.01
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



4.3 GARCH and EGARCH models

Running GARCH on monthly return of TRIL yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model               : sGARCH(1,1)
Variance Targeting        : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model                : ARFIMA(1,0,1)
Include Mean              : TRUE
GARCH-in-Mean             : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The monthly returns of TRIL were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.021434    0.008127   2.63738 0.008355
ar1     0.188110    0.562648   0.33433 0.738131
ma1    -0.117232    0.564417  -0.20770 0.835460
omega   0.000357    0.000184   1.93706 0.052738
alpha1  0.000000    0.006443   0.00000 1.000000
beta1   0.950554    0.005980 158.95332 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.021434    0.009595  2.23395 0.025486
ar1     0.188110    0.226450  0.83069 0.406150
ma1    -0.117232    0.215339 -0.54441 0.586162
omega   0.000357    0.000237  1.51022 0.130986
alpha1  0.000000    0.008223  0.00000 1.000000
beta1   0.950554    0.036601 25.97066 0.000000

LogLikelihood : 146.8773
```

```
Information Criteria
------------------------------------

Akaike       -1.8061
Bayes        -1.6888
Shibata      -1.8089
Hannan-Quinn -1.7585

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                  7.609e-05  0.9930
Lag[2*(p+q)+(p+q)-1][5] 2.133e+00  0.9276
Lag[4*(p+q)+(p+q)-1][9] 4.080e+00  0.6721
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.0274  0.8685
Lag[2*(p+q)+(p+q)-1][5]    0.3505  0.9781
Lag[4*(p+q)+(p+q)-1][9]    0.4914  0.9985
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.1267 0.500 2.000  0.7219
ARCH Lag[5]    0.2544 1.440 1.667  0.9521
ARCH Lag[7]    0.3129 2.315 1.543  0.9921
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  14.8127
Individual Statistics:
mu     0.07448
ar1    0.33785
ma1    0.33304
omega  0.13129
alpha1 2.49221
beta1  0.12455

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.5733 0.5673
Negative Sign Bias  0.2731 0.7851
Positive Sign Bias  0.1250 0.9007
Joint Effect        1.4684 0.6896


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     20.67       0.3555
2    30     23.23       0.7659
3    40     32.21       0.7711
4    50     38.23       0.8667
```

4.3.1 Interpretation

• The Log Likelihood obtained from the model is 146.86.

• GARCH(1,1) is the best-fit model for TRIL monthly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major disparity between the observed value and the predicted value.

4.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-month period are expected to be positive, with an approximate value of 4%, accompanied with a standard deviation in close proximity to 7.7%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of TRIL within the subsequent 10-month period, aligning with the forecast provided by the ARIMA model.

```
> ugforecast_m

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
      Series   Sigma
T+1  0.01983 0.08248
T+2  0.05902 0.08132
T+3  0.02694 0.08017
T+4  0.05320 0.07904
T+5  0.03170 0.07793
T+6  0.04930 0.07683
T+7  0.03490 0.07574
T+8  0.04669 0.07467
T+9  0.03704 0.07362
T+10 0.04494 0.07258
```

6. VETO

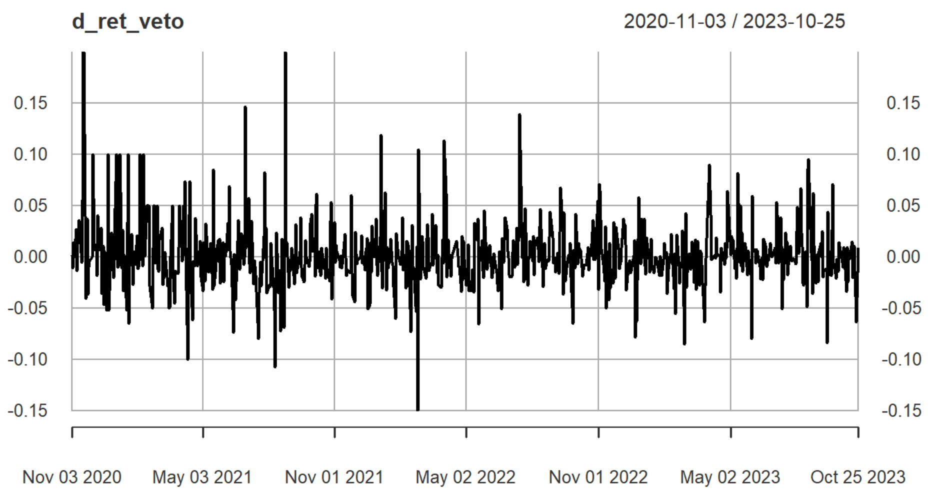
SECTION 2: DAILY RETURNS ANALYSIS

2.1 Estimating Beta Using CAPM Model

The provided figure illustrates the daily closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.

The provided figure illustrates the daily returns derived from VETO stock price throughout the time period spanning from November 2, 2020, to October 25,

2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the mid of 2021, followed by a subsequent correction. Over the course of a three-year period, there has been a more than twofold increase.



The above graph illustrates the daily returns derived from VETO. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

2.1.1 Interpretation of the regression

From the results of the regression, the beta came out to be 1.008, which implies that if index portfolio excess returns increase by 1%, then the returns of VETO increase by 1.008%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.001216, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of VETO are 0.001216%.

```
> #Running the regression model
> regression_d<-lm(exveto_d~exnifty_d)
> #slope parameter is the beta in CAPM model
> summary(regression_d)

Call:
lm(formula = exveto_d ~ exnifty_d)

Residuals:
      Min        1Q    Median        3Q       Max
-0.108973 -0.017794 -0.003338  0.012202  0.211502

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.001216   0.002534   0.480    0.631
exnifty_d   1.008523   0.124708   8.087  2.6e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03219 on 719 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.08338,	Adjusted R-squared:  0.0821
F-statistic:  65.4 on 1 and 719 DF,  p-value: 2.596e-15
```

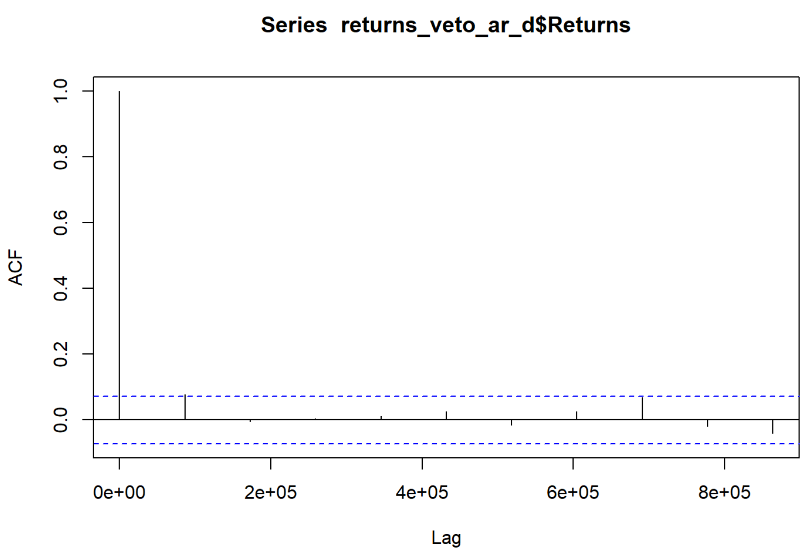
2.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_veto_ar_d$Returns, alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_veto_ar_d$Returns
Dickey-Fuller = -8.4376, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary
```

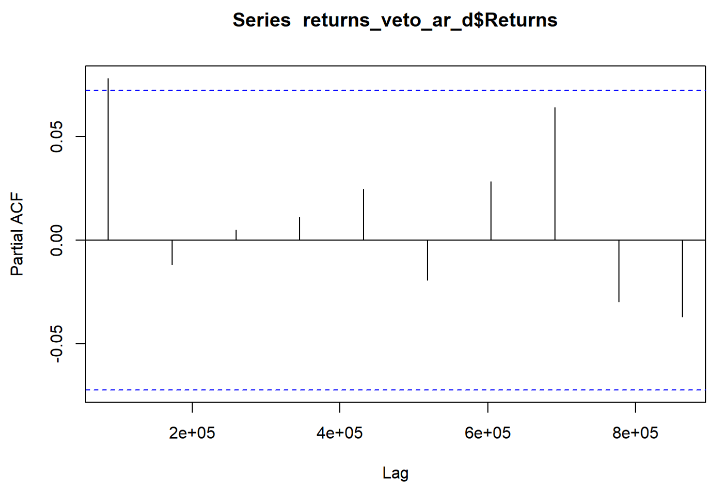
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -8.4376.

2.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(1) model since the correlation is significant only at one lag; after that, values are not significant.

2.2.2 PACF plot



From the above plot it can be derived that the series is AR(1) model since only one lag is significant

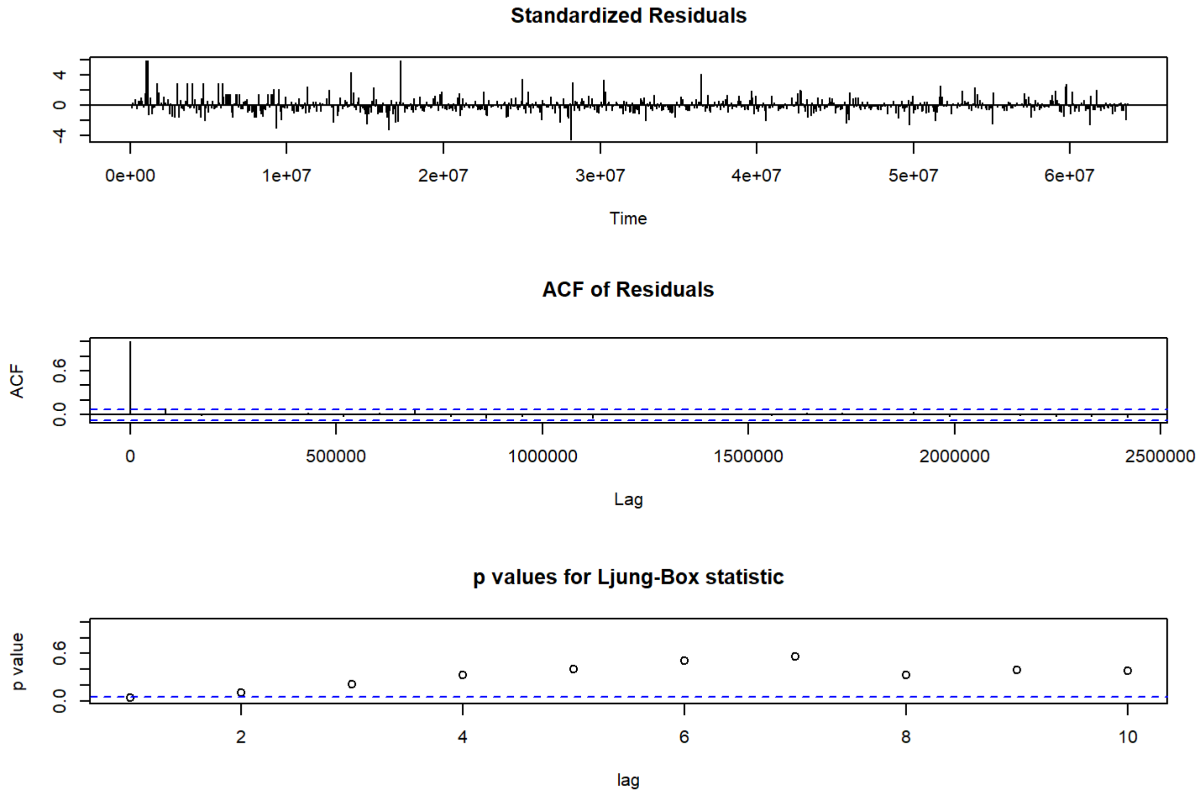
To finally interpret the correct model we use Auto.arima function as shown below-

2.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_veto_ar_d$Returns)
Series: returns_veto_ar_d$Returns
ARIMA(0,0,1) with zero mean

Coefficients:
         ma1
      0.0817
s.e.  0.0368

sigma^2 = 0.00112:  log likelihood = 1460.31
AIC=-2916.61   AICc=-2916.6   BIC=-2907.41
```

The ARIMA function recommended a (0,0,1) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



2.3 GARCH and EGARCH models

Running GARCH on daily return of VETO yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model              : sGARCH(1,1)
Variance Targeting       : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model               : ARFIMA(1,0,1)
Include Mean             : TRUE
GARCH-in-Mean            : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The daily returns of VETO were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model      : sGARCH(1,1)
Mean Model       : ARFIMA(1,0,1)
Distribution     : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.001490    0.001257 1.1851e+00  0.23597
ar1     0.008802    0.588366 1.4960e-02  0.98806
ma1     0.052895    0.587494 9.0035e-02  0.92826
omega   0.000002    0.000002 1.5632e+00  0.11801
alpha1  0.005675    0.000921 6.1620e+00  0.00000
beta1   0.990993    0.000669 1.4811e+03  0.00000

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.001490    0.001349 1.1047e+00 0.269275
ar1     0.008802    0.638825 1.3778e-02 0.989007
ma1     0.052895    0.639903 8.2661e-02 0.934121
omega   0.000002    0.000006 3.8682e-01 0.698890
alpha1  0.005675    0.001623 3.4960e+00 0.000472
beta1   0.990993    0.000319 3.1094e+03 0.000000

LogLikelihood : 1476.575
```

```
Information Criteria
------------------------------------

Akaike       -3.9799
Bayes        -3.9425
Shibata      -3.9800
Hannan-Quinn -3.9655

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1055  0.7453
Lag[2*(p+q)+(p+q)-1][5]    0.1739  1.0000
Lag[4*(p+q)+(p+q)-1][9]    1.1444  0.9995
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic   p-value
Lag[1]                      32.56 1.155e-08
Lag[2*(p+q)+(p+q)-1][5]     33.31 3.676e-09
Lag[4*(p+q)+(p+q)-1][9]     34.38 2.714e-08
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.2169 0.500 2.000  0.6414
ARCH Lag[5]    0.6289 1.440 1.667  0.8450
ARCH Lag[7]    1.4729 2.315 1.543  0.8268
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  36.2025
Individual Statistics:
mu     0.22972
ar1    0.24206
ma1    0.25333
omega  0.88449
alpha1 0.09777
beta1  0.06770

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value      prob sig
Sign Bias           0.8245 0.4099026
Negative Sign Bias  1.7719 0.0768328   *
Positive Sign Bias  3.4620 0.0005672 ***
Joint Effect       19.9198 0.0001764 ***


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     111.3    4.674e-15
2    30     126.7    3.548e-14
3    40     137.5    6.683e-13
4    50     156.6    3.542e-13
```

2.3.1 Interpretation

• The Log Likelihood obtained from the model is 1476.575.

• GARCH(1,1) is the best-fit model for VETO daily returns.

• The optimal parameter beta and alpha have significant values while omega is insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that only omega is insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major disparity between the observed value and the predicted value.

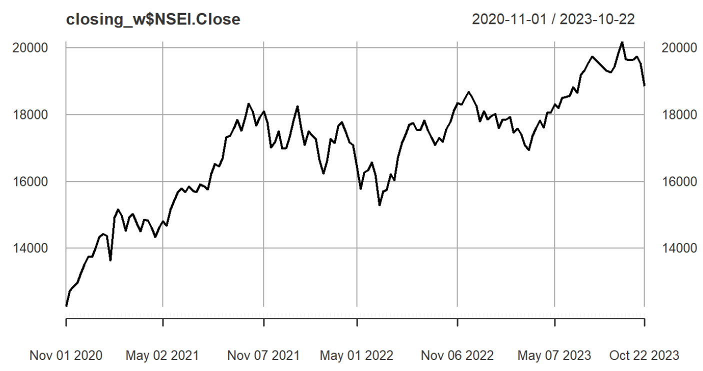
2.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-day period are expected to be positive, with an approximate value of 0.15%, accompanied with a standard deviation in close proximity to 2.7%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of VETO within the subsequent 10-day period, aligning with the forecast provided by the ARIMA model.

```
*---------------------------------*
*       GARCH Model Forecast      *
*---------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
       Series   Sigma
T+1  0.002136 0.02768
T+2  0.001495 0.02768
T+3  0.001490 0.02768
T+4  0.001490 0.02768
T+5  0.001490 0.02768
T+6  0.001490 0.02767
T+7  0.001490 0.02767
T+8  0.001490 0.02767
T+9  0.001490 0.02767
T+10 0.001490 0.02767
```

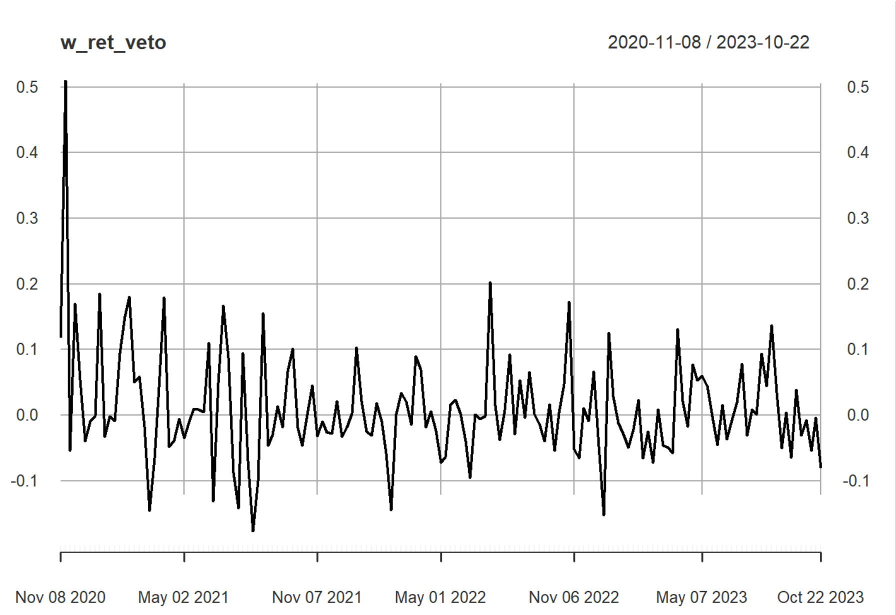
SECTION 3: WEEKLY RETURNS ANALYSIS

3.1 Estimating Beta Using CAPM Model



The provided figure illustrates the weekly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.

The provided figure illustrates the weekly returns derived from VETO stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the mid of 2021, followed by a subsequent correction. Over the course of a three-year period, there has been a more than twofold increase.



The above graph illustrates the weekly returns derived from VETO. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

3.1.1 Interpretation of the regression

```
> #Running the regression model
> regression_w<-lm(exveto_w~exnifty_w)
> #slope parameter is beta in CAPM model
> summary(regression_w)

Call:
lm(formula = exveto_w ~ exnifty_w)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.20674 -0.03991 -0.01251  0.02818  0.48793 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.03369    0.03311   1.017    0.311    
exnifty_w    1.21575    0.25486   4.770 4.26e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07798 on 153 degrees of freedom
Multiple R-squared:  0.1295,	Adjusted R-squared:  0.1238 
F-statistic: 22.75 on 1 and 153 DF,  p-value: 4.258e-06
```

From the results of the regression, the beta came out to be 1.21, which implies that if index portfolio excess returns increase by 1%, then the returns of VETO increase by 1.21%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.0033, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of VETO are 0.0033%.

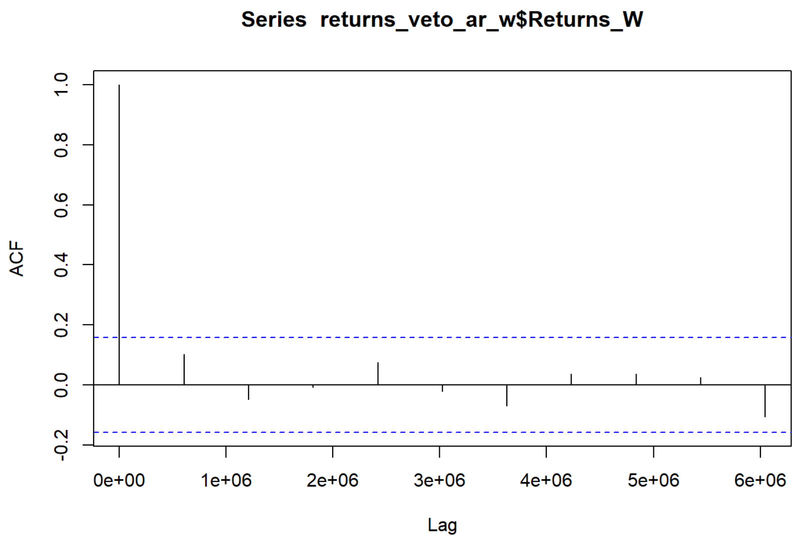
3.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary. To test this, we perform ADF Test shown below-

```
> adf.test(returns_veto_ar_w,alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  returns_veto_ar_w
Dickey-Fuller = -5.4778, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

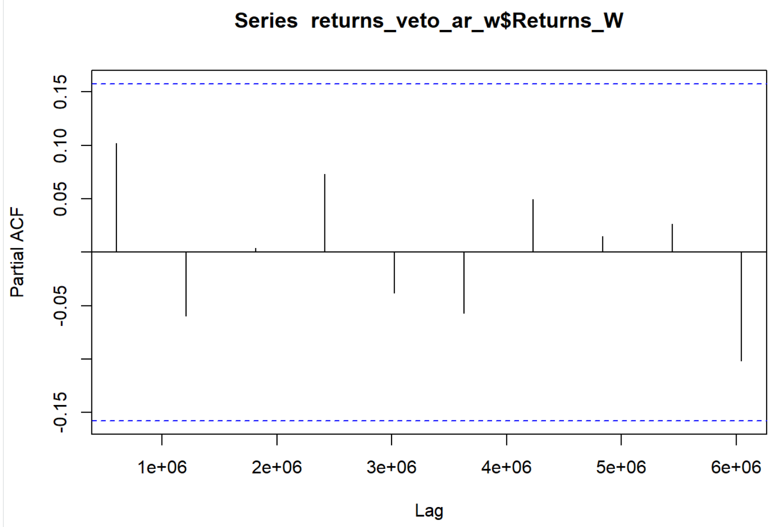
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.01. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -5.4778.

3.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(0) model since the initial lags are insignificant.

3.2.2 PACF plot



From the above plot it can be derived that the series is an AR(0) model since initial lags are insignificant.

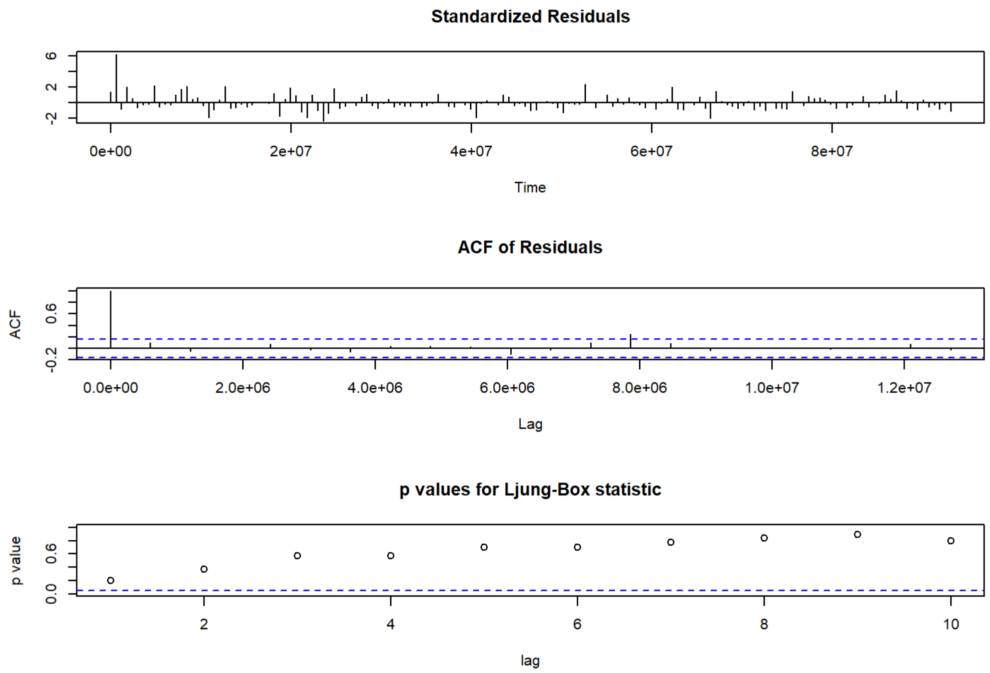
To finally interpret the correct model we use Auto.arima function as shown below-

3.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_veto_ar_w$Returns)
Series: returns_veto_ar_w$Returns
ARIMA(2,0,1) with zero mean

Coefficients:
         ar1      ar2     ma1
      0.0555  -0.0566  0.0625
s.e.  0.7028   0.1232  0.7000

sigma^2 = 0.006618:  log likelihood = 170.46
AIC=-332.91   AICc=-332.65   BIC=-320.74
```

The ARIMA function recommended a (2,0,1) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



3.3 GARCH and EGARCH models

Running GARCH on weekly return of VETO yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The weekly returns of VETO were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
> #Estimating the models
> ugfit_w=ugarchfit(spec=ug_spec_w, data=r_veto_ge_w)
> ugfit_w#lower aic value models are better

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.006262    0.006346  0.98688  0.32370
ar1    -0.189424    0.402964 -0.47008  0.63830
ma1     0.307760    0.386370  0.79654  0.42572
omega   0.000030    0.000061  0.48485  0.62778
alpha1  0.006441    0.007537  0.85458  0.39278
beta1   0.980154    0.018374 53.34481  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.006262    0.007222  0.86713  0.38587
ar1    -0.189424    0.292377 -0.64788  0.51706
ma1     0.307760    0.278017  1.10698  0.26830
omega   0.000030    0.000043  0.68778  0.49159
alpha1  0.006441    0.007010  0.91890  0.35815
beta1   0.980154    0.012247 80.03397  0.00000

LogLikelihood : 180.2377
```

```
Information Criteria
------------------------------------

Akaike       -2.2338
Bayes        -2.1165
Shibata      -2.2366
Hannan-Quinn -2.1862

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.01662  0.8974
Lag[2*(p+q)+(p+q)-1][5]   0.64217  1.0000
Lag[4*(p+q)+(p+q)-1][9]   1.26535  0.9990
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1771  0.6739
Lag[2*(p+q)+(p+q)-1][5]    0.6037  0.9406
Lag[4*(p+q)+(p+q)-1][9]    1.0354  0.9847
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.2256 0.500 2.000  0.6348
ARCH Lag[5]    0.2647 1.440 1.667  0.9495
ARCH Lag[7]    0.6315 2.315 1.543  0.9650
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  0.7695
Individual Statistics:
mu     0.16453
ar1    0.03964
ma1    0.04648
omega  0.04084
alpha1 0.07650
beta1  0.04958

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.3815 0.7034
Negative Sign Bias  0.6109 0.5422
Positive Sign Bias  0.9787 0.3293
Joint Effect        1.8000 0.6149


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     25.54      0.14357
2    30     40.54      0.07551
3    40     45.03      0.23433
4    50     65.15      0.06101
```

3.3.1 Interpretation

• The Log Likelihood obtained from the model is 180.24.

• GARCH(1,1) is the best-fit model for VETO weekly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major disparity between the observed value and the predicted value.

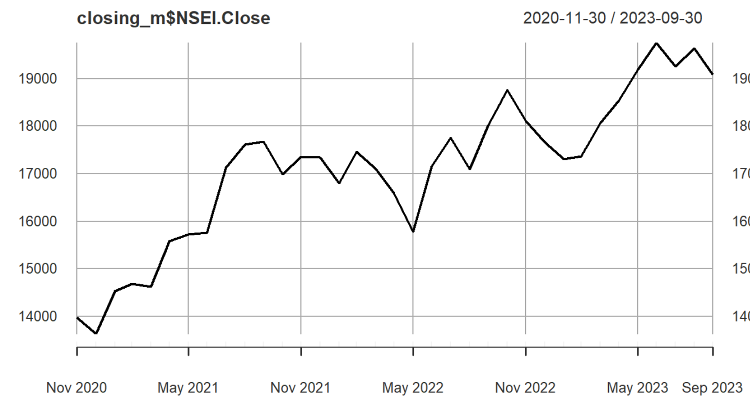
3.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-week period are expected to be positive, with an approximate value of 0.6%, accompanied with a standard deviation in close proximity to 5.3%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of VETO within the subsequent 10-week period, aligning with the forecast provided by the ARIMA model.

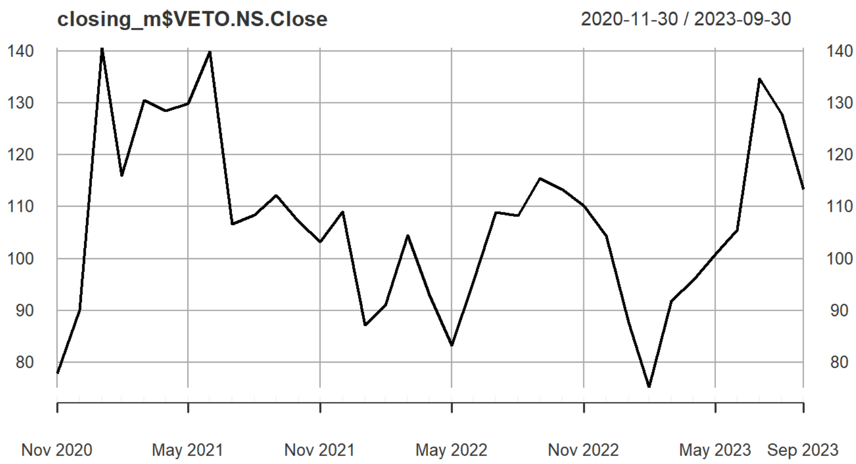
```
*---------------------------------*
*       GARCH Model Forecast      *
*---------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
        Series   Sigma
T+1  -0.001383 0.05384
T+2   0.007711 0.05376
T+3   0.005988 0.05367
T+4   0.006314 0.05359
T+5   0.006253 0.05351
T+6   0.006264 0.05342
T+7   0.006262 0.05334
T+8   0.006262 0.05326
T+9   0.006262 0.05318
T+10  0.006262 0.05310
```

SECTION 4: MONTHLY RETURNS ANALYSIS

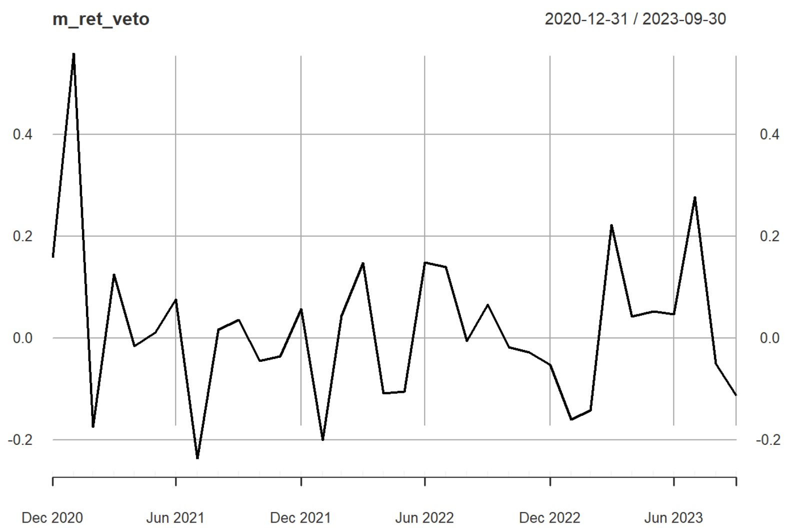
4.1 CAPM Model – Estimating Beta of the company



Provided figure illustrates the monthly closing prices of NSEI shares from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns.



The provided figure illustrates the monthly returns derived from VETO stock price throughout the time period spanning from November 2, 2020, to October 25, 2023. The closing price, rather than the modified closing price, is utilised for the computation of returns. The chart illustrates a consistent upward trend in the stock price until the mid of 2021, followed by a subsequent correction. Over the course of a three-year period, there has been a more than twofold increase.



The above graph illustrates the monthly returns derived from VETO. A significant rise has been seen on many occasions throughout the years.

The excess returns, represented by the difference between the expected return (E(R)) and the risk-free rate (Rf), were subjected to a regression analysis with the market risk premium (Rm - Rf) as the independent variable. The subsequent findings are presented in the next section.

4.1.1 Interpretation of the regression

```
> summary(regression_m)

Call:
lm(formula = exveto_m ~ exnifty_m)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.36009 -0.07716 -0.00619  0.04459  0.46242 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept)   0.1194     0.2301   0.519  0.60750   
exnifty_m     1.1923     0.4079   2.923  0.00631 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1488 on 32 degrees of freedom
Multiple R-squared:  0.2108,	Adjusted R-squared:  0.1861 
F-statistic: 8.545 on 1 and 32 DF,  p-value: 0.006313
```

From the results of the regression, the beta came out to be 1.19, which implies that if index portfolio excess returns increase by 1%, then the returns of VETO increase by 1.19%. Also, the beta value is significant at both 95% and 99% since the p-value is less than 0.01 ($p < 0.01$). The intercept value obtained from the regression is 0.1194, which implies that if all the independent variables are equal to zero (for our case, it is only Rm - Rf), then the returns of VETO are 0.1194%.

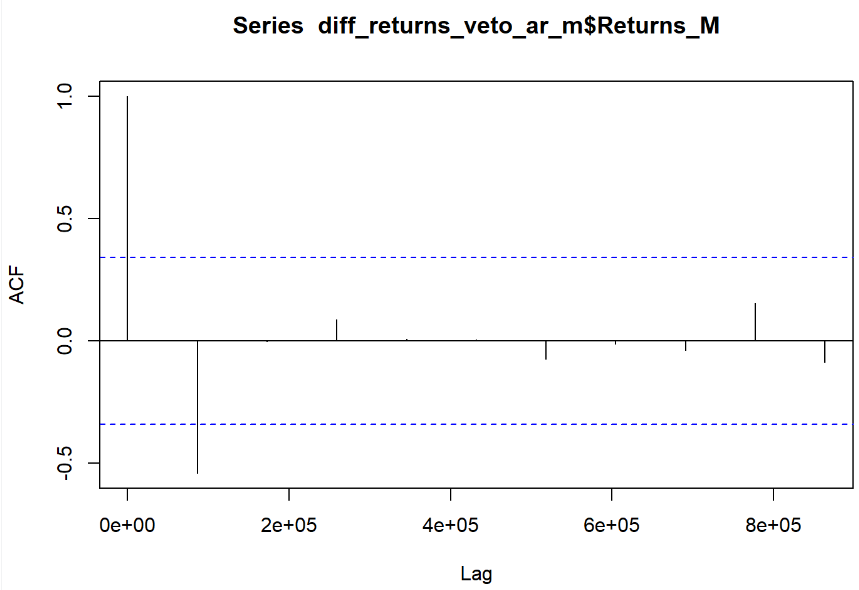
4.2 Estimating AR and MA coefficients using ARIMA

We can see that stock price data is non-stationary, and also we can interpret that the returns of the stock seem to be stationary of integrated or order 1, which means the first difference is stationary. To test this, we perform ADF Test shown below-

```
> adf.test(diff_returns_veto_ar_m,alternative=c("stationary"))

        Augmented Dickey-Fuller Test

data:  diff_returns_veto_ar_m
Dickey-Fuller = -4.2898, Lag order = 3, p-value = 0.01095
alternative hypothesis: stationary
```

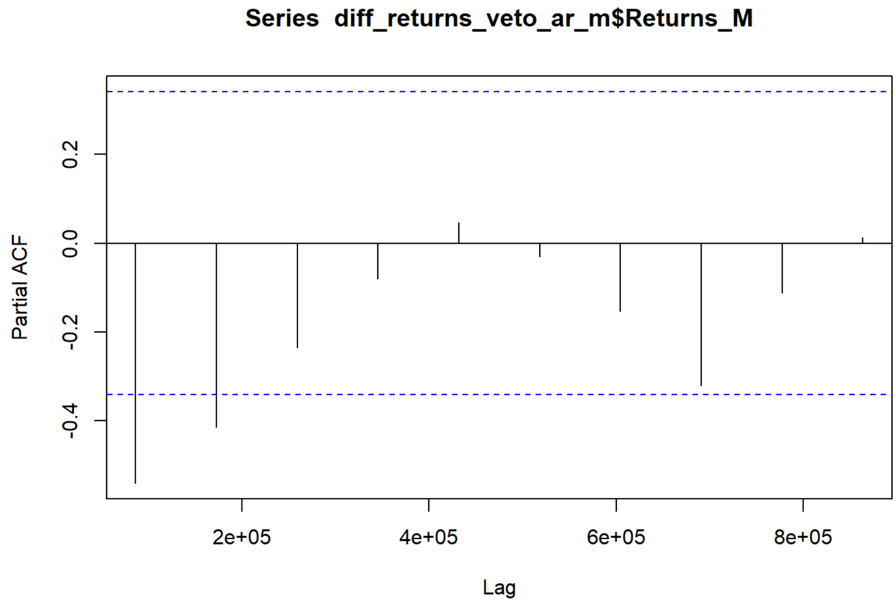
The null hypothesis of the ADF test posits the presence of a unit root in the coefficients, indicating non-stationarity of the series. Conversely, the alternative hypothesis suggests stationarity of the series. Based on the obtained data, it is evident that the p-value is 0.010905. This indicates that we have sufficient evidence to reject the null hypothesis and conclude that the series is stationary. The ADF test-statistic has a value of -4.2898.

4.2.1 ACF Plot



From the above plot, it can be derived that the series is MA(1) model since the correlation is significant only at one lag; after that, values are not significant.

4.2.2 PACF plot



From the above plot it can be derived that the series is an AR(2) model since initial 2 lags are significant.

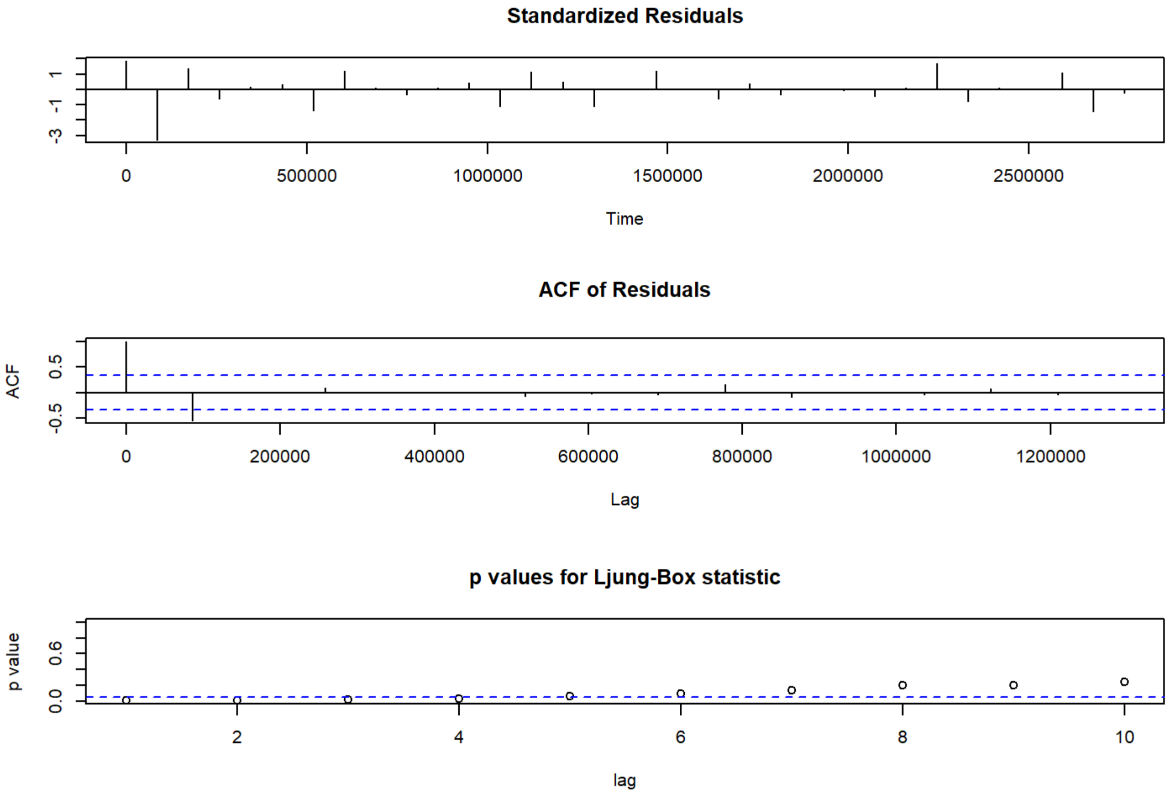
To finally interpret the correct model we use Auto.arima function as shown below-

4.2.3 Identification and interpretation of the ARIMA model

```
> auto.arima(returns_veto_ar_m$Returns)
Series: returns_veto_ar_m$Returns
ARIMA(0,0,0) with zero mean

sigma^2 = 0.0231:  log likelihood = 15.81
AIC=-29.63   AICc=-29.5   BIC=-28.1
```

The ARIMA function recommended a (0,0,0) model as the optimal choice among several (p, d, q) values due to its ability to provide the lowest AIC and BIC values. Consequently, this model facilitates more accurate estimations of the coefficients.

The diagnostic test of the model is shown below-



4.3 GARCH and EGARCH models

Running GARCH on monthly return of VETO yielded the result that are shown below-

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the visual representation provided in the aforementioned figure, it is evident that the GARCH (1,1) model is the most suitable choice. Additionally, it is worth noting that the default mean model employed in this context is ARFIMA(1,0,1).

The monthly returns of VETO were subjected to analysis using the EGRACH model, yielding the subsequent outcomes:

```
*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
-----------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
-----------------------------------
Distribution     :  norm
Includes Skew    :  FALSE
Includes Shape   :  FALSE
Includes Lambda  :  FALSE
```

Based on the information shown in the provided figure, it is observed that the EGARCH (1,1) model is derived, and subsequently, the default ARFIMA (1,0,1) model is employed. The findings exhibit resemblance to those obtained from the GARCH model.

After constructing GARCH and EGARCH models, we proceeded to estimate the model using the ugarchfit function, which produced the above results. The analysis and explanation of the findings are provided subsequent to the illustration presented.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,1)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.006262    0.006346  0.98688  0.32370
ar1    -0.189424    0.402964 -0.47008  0.63830
ma1     0.307760    0.386370  0.79654  0.42572
omega   0.000030    0.000061  0.48485  0.62778
alpha1  0.006441    0.007537  0.85458  0.39278
beta1   0.980154    0.018374 53.34481  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.006262    0.007222  0.86713  0.38587
ar1    -0.189424    0.292377 -0.64788  0.51706
ma1     0.307760    0.278017  1.10698  0.26830
omega   0.000030    0.000043  0.68778  0.49159
alpha1  0.006441    0.007010  0.91890  0.35815
beta1   0.980154    0.012247 80.03397  0.00000

LogLikelihood : 180.2377
```

```
Information Criteria
------------------------------------

Akaike       -2.2338
Bayes        -2.1165
Shibata      -2.2366
Hannan-Quinn -2.1862

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.01662  0.8974
Lag[2*(p+q)+(p+q)-1][5]   0.64217  1.0000
Lag[4*(p+q)+(p+q)-1][9]   1.26535  0.9990
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1771  0.6739
Lag[2*(p+q)+(p+q)-1][5]    0.6037  0.9406
Lag[4*(p+q)+(p+q)-1][9]    1.0354  0.9847
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.2256 0.500 2.000  0.6348
ARCH Lag[5]    0.2647 1.440 1.667  0.9495
ARCH Lag[7]    0.6315 2.315 1.543  0.9650
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  0.7695
Individual Statistics:
mu     0.16453
ar1    0.03964
ma1    0.04648
omega  0.04084
alpha1 0.07650
beta1  0.04958

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.3815 0.7034
Negative Sign Bias  0.6109 0.5422
Positive Sign Bias  0.9787 0.3293
Joint Effect        1.8000 0.6149


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     25.54      0.14357
2    30     40.54      0.07551
3    40     45.03      0.23433
4    50     65.15      0.06101
```

4.3.1 Interpretation

• The Log Likelihood obtained from the model is 180.23.

• GARCH(1,1) is the best-fit model for VETO monthly returns.

• The optimal parameter beta has significant value while alpha and omega are insignificant.

• The Alpha, Omega and Beta obtained from estimated robust standard error shows that both omega and alpha are insignificant because p-value is greater than 0.05.

• The p-values for both the Ljung-Box test and the ARCH LM test are more than 0.05. This indicates that the null hypothesis will be accepted, suggesting the absence of serial correlation. This is advantageous for the model.

• The Adjusted Pearson Goodness of Fit Test gave p-values more than 0.05, indicating that the null hypothesis cannot be denied. This implies that there is no major disparity between the observed value and the predicted value.

4.3.2 Forecast using GARCH

The projected outcomes utilising the GARCH model are depicted in the figure presented under. The findings indicate that the projected returns for the subsequent 10-month period are expected to be positive, with an approximate value of 4%, accompanied with a standard deviation in close proximity to 7.5%. The occurrence of a positive return implies that there is an expectation for an increase in the stock price of VETO within the subsequent 10-month period, aligning with the forecast provided by the ARIMA model.

```
> ugforecast_m

*---------------------------------*
*       GARCH Model Forecast      *
*---------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2023-10-25]:
      Series   Sigma
T+1  0.01983 0.08248
T+2  0.05902 0.08132
T+3  0.02694 0.08017
T+4  0.05320 0.07904
T+5  0.03170 0.07793
T+6  0.04930 0.07683
T+7  0.03490 0.07574
T+8  0.04669 0.07467
T+9  0.03704 0.07362
T+10 0.04494 0.07258
```

3. PART-2) VAR INTRODUCTION

VAR, short for Value at Risk, is a statistical method employed to assess the possible financial loss of an investment within a specific time frame and with a defined level of certainty. It provides information on the highest possible loss that a portfolio may incur within a given time period and with a certain level of confidence. It is a commonly employed risk mitigation instrument in the field of finance. The VAR model incorporates various elements, including asset correlation, past performance, and market volatility, in order to calculate risk. When calculating VAR, we often assume that future returns will be similar to and match the historical returns of the portfolio. Various techniques exist for calculating the Value at Risk (VAR), but the most often employed approaches are:

1. The Variance Covariance Method
2. The Monte Carlo Simulation
3. Analysis of Sensitivity

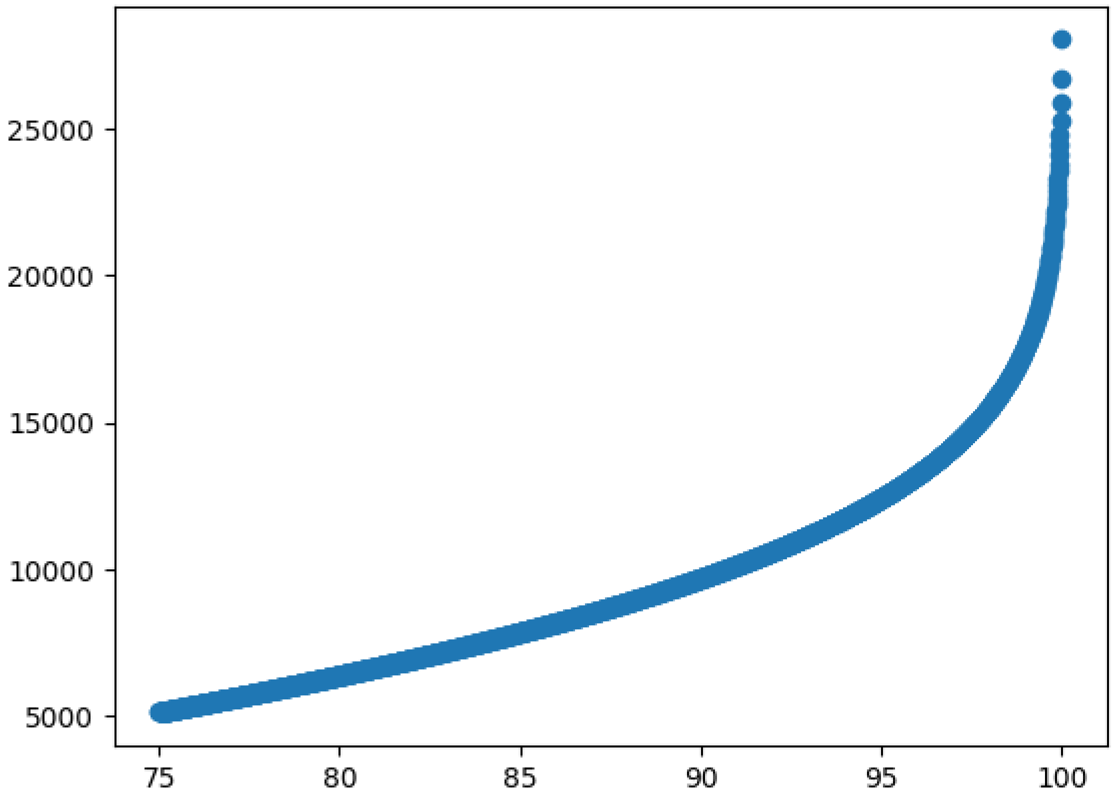
In this paper, the Variance Covariance Method was employed to compute the Value at Risk (VAR) for the portfolio comprising TATAMOTORS ,SPLIL, SHANTIGEAR, RUBYMILLS, TRIL, and VETO.

VAR Calculation for portfolio-

We constructed a portfolio of stocks that consists of TATAMOTORS ,SPLIL, SHANTIGEAR, RUBYMILLS, TRIL, and VETO.

The Composition of portfolio is as follows:

1. TATAMOTORS : 300 Shares
2. SPLIL: 250 Shares
3. SHANTIGEAR: 100 Shares
4. RUBYMILLS: 250 Shares
5. TRIL: 150 Shares
6. VETO: 200 Shares



Here is an analysis of the findings:

1. Portfolio Creation: - We have assembled a portfolio of stocks with the following tickers: TATAMOTORS.NS ,SPLIL.NS, SHANTIGEAR.NS, RUBYMILLS.NS, TRIL.NS, and VETO.NS.

- Additionally, we have explicitly indicated the quantity of shares purchased for each individual stock.

2. Data Download:

- The code downloads historical closing prices for these stocks starting from "2020-11-06" up to the current date using Yahoo Finance.

3. Initial Investment: -

The initial amount of money you invested was determined by multiplying the number of shares you purchased for each stock by their current pricing.

4. Calculation of Returns: -

We have computed the daily returns for each stock using the closing prices that were downloaded.

5. Correlation Matrix: -

The code calculates the correlation matrix for the stock returns. This matrix illustrates the correlation between the returns of several equities.

6. Standard Deviation: -
It computes the standard deviation of the returns for each stock, which serves as a metric for their level of volatility.

7. Calculation of Value-at-Risk (VaR):
The primary component of the algorithm entails a simulation that computes VaR (Value at Risk) over various confidence intervals.The programme executes a loop consisting of 2500 iterations, gradually increasing the confidence level from 75% to 100% in increments of 0.01.
- The minimum value of the variable is 5091.13. - The maximum value of the variable is 28071.34.
- During each iteration, the algorithm computes the Value at Risk (VaR) for the entire portfolio by employing the following formula:

The Value at Risk (VaR) is calculated by multiplying the standard deviation (σ) of an investment's returns by a constant (z) and the probability (P) of a loss exceeding a certain threshold.

- The Total VaR is computed by taking into consideration the correlations between stocks, using the following formula:

The formula for calculating the Total VaR is the square root of the product of the transpose of the vector P, the covariance matrix Σ, and the vector P.

8. Plotting:
Ultimately, the code generates a scatter plot to visually represent the fluctuations in Total VaR across various confidence levels. The x-axis corresponds to the confidence levels, while the y-axis corresponds to the Total VaR.

Interpreting the Plot-

- As we increase the confidence levels, such as from 75% to 100%, the Total VaR experiences an upward trend. This is logical since when confidence levels are higher, we are taking into account more severe situations when the portfolio is more prone to experiencing losses, resulting in a larger Value at Risk (VaR).

The graphic illustrates the level of risk associated with the portfolio at various confidence intervals. A higher Total VaR indicates a larger potential loss in the portfolio in the event of extreme market conditions.

Risk managers and investors frequently employ Value at Risk (VaR) as a means to evaluate and control the possible negative risk associated with a portfolio. It enables individuals to comprehend the potential losses they may incur at various confidence levels, a critical factor in making well-informed investing choices and establishing risk management tactics.