

Cipla stock time series analysis

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=====

Downloading and loading relevant packages

```
packages = c('tseries', 'forecast', 'FinTS', 'rugarch', 'quantmod')
lapply(packages, require, character.only = TRUE)
```

```
## Loading required package: tseries
```

```
## Warning: package 'tseries' was built under R version 4.3.2
```

```
## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo
```

```
## Loading required package: forecast
```

```
## Warning: package 'forecast' was built under R version 4.3.2
```

```
## Loading required package: FinTS
```

```
## Warning: package 'FinTS' was built under R version 4.3.2
```

```
## Loading required package: zoo
```

```
## Warning: package 'zoo' was built under R version 4.3.2
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric
```

```
##
## Attaching package: 'FinTS'
```

```
## The following object is masked from 'package:forecast':
##
##   Acf
```

```
## Loading required package: rugarch
```

```
## Warning: package 'rugarch' was built under R version 4.3.2
```

```
## Loading required package: parallel
```

```
##  
## Attaching package: 'rugarch'
```

```
## The following object is masked from 'package:stats':  
##  
##      sigma
```

```
## Loading required package: quantmod
```

```
## Warning: package 'quantmod' was built under R version 4.3.2
```

```
## Loading required package: xts
```

```
## Warning: package 'xts' was built under R version 4.3.2
```

```
## Loading required package: TTR
```

```
## Warning: package 'TTR' was built under R version 4.3.2
```

```
## [[1]]  
## [1] TRUE  
##  
## [[2]]  
## [1] TRUE  
##  
## [[3]]  
## [1] TRUE  
##  
## [[4]]  
## [1] TRUE  
##  
## [[5]]  
## [1] TRUE
```

Loading stock price data from Yahoo

```
getSymbols(Symbols = 'CIPLA.NS',  
           src = 'yahoo',  
           from = as.Date('2019-01-01'),  
           to = as.Date('2022-12-31'),  
           periodicity = 'daily')
```

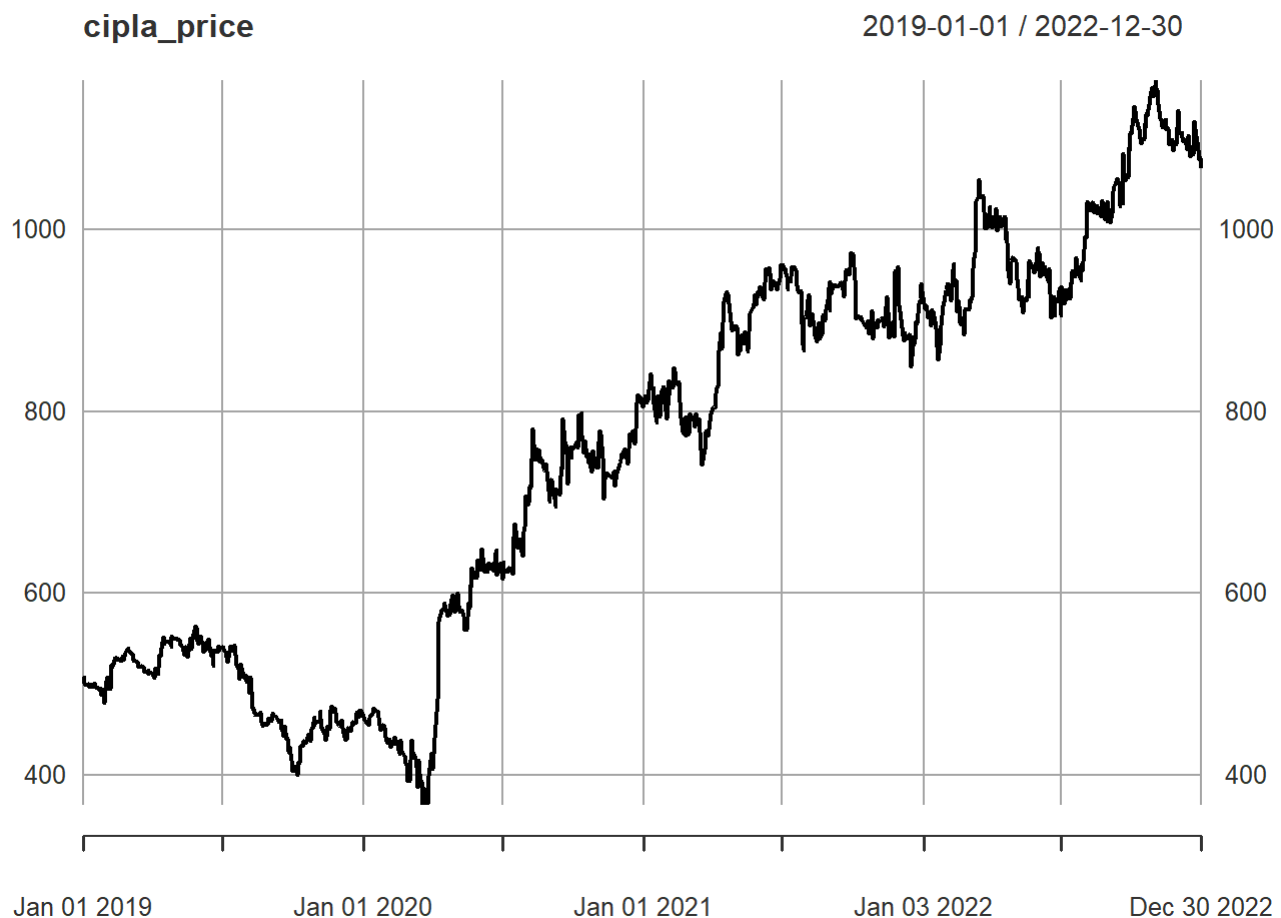
```
## [1] "CIPLA.NS"
```

Removing NA values from data

```
cipla_price = na.omit(CIPLA.NS$CIPLA.NS.Adjusted)  
class(cipla_price)
```

```
## [1] "xts" "zoo"
```

```
plot( cipla_price)
```



ADF test for price to check stationarity

Objective : To load stock price dataset and check for its stationarity

Analysis : Extracted stock price data and checked for stationarity; H_0 : Price is not stationary

Results : Null hypothesis is accepted; p-value = 0.277

Managerial implication : Stock price of Cipla is not stationary in the given time period and thus returns needs to be calculated

```
adf_test_cipla_price = adf.test(cipla_price)  
adf_test_cipla_price
```

```
##  
## Augmented Dickey-Fuller Test  
##  
## data: cipla_price  
## Dickey-Fuller = -2.7118, Lag order = 9, p-value = 0.277  
## alternative hypothesis: stationary
```

Obtaining cipla stock return price

ADF test for price to check stationarity

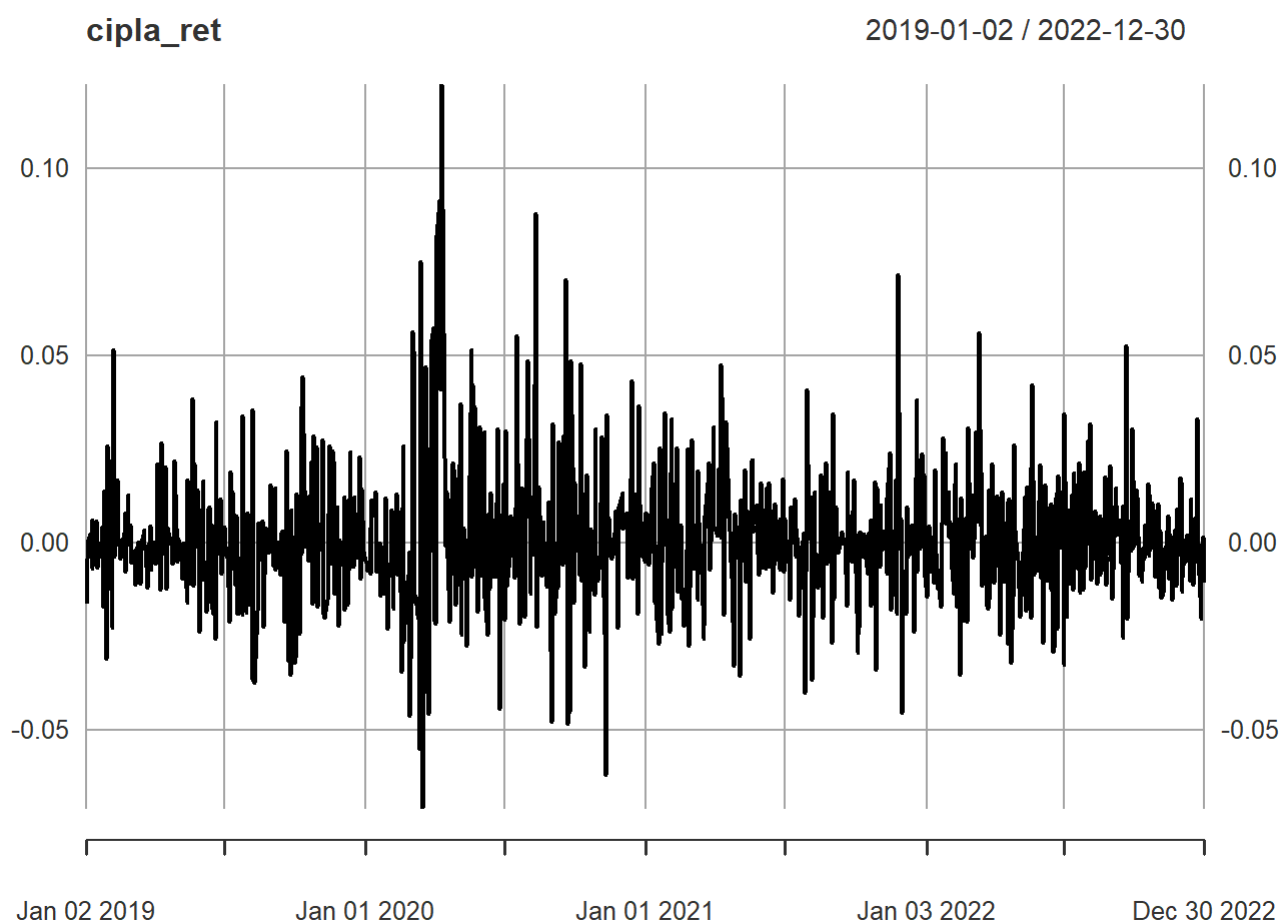
Objective : To obtain returns from stock price dataset and check for its stationarity

Analysis : Extracted return, visualised and checked for stationarity; H_0 : Price is not stationary

Results : Null hypothesis is rejected; p-value = 0.01

Managerial implication : Returns of Cipla is stationary in the given time period.

```
cipla_ret =na.omit(diff(log(cipla_price)))  
plot(cipla_ret)
```



```
adf_test_cipla = adf.test(cipla_ret)
```

```
## Warning in adf.test(cipla_ret): p-value smaller than printed p-value
```

```
adf_test_cipla
```

```
##  
## Augmented Dickey-Fuller Test  
##  
## data: cipla_ret  
## Dickey-Fuller = -9.4492, Lag order = 9, p-value = 0.01  
## alternative hypothesis: stationary
```

Checking for autocorrelation using Ljung-Box Test

Objective : To check for presence of autocorrelation in the returns dataset.

Analysis : Performed Box-Pierce test, to assess the presence of autocorrelation in cipla returns dataset

Results : Null hypothesis is rejected; p-value = 0.03651; H0: Autocorrelation is absent

Managerial implication : Statistically significant autocorrelation present in the returns of the Cipla stock, there is a pattern or relationship between the returns at different time periods, which could be important for further analysis or modeling of the data

```
lb_test_cipla_ds = Box.test(cipla_ret)  
lb_test_cipla_ds
```

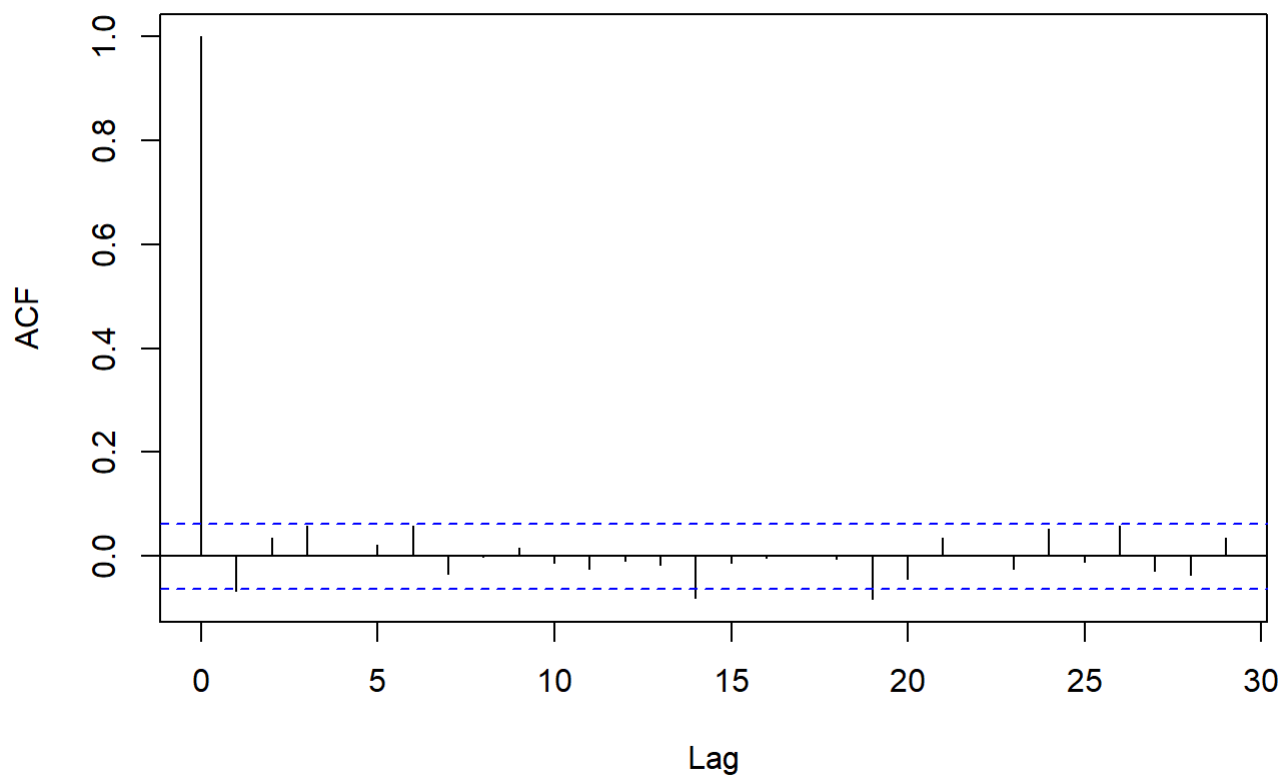
```
##  
## Box-Pierce test  
##  
## data: cipla_ret  
## X-squared = 4.3731, df = 1, p-value = 0.03651
```

Modelling for ARIMA

Plotting ACF and PACF plots to determine lag value

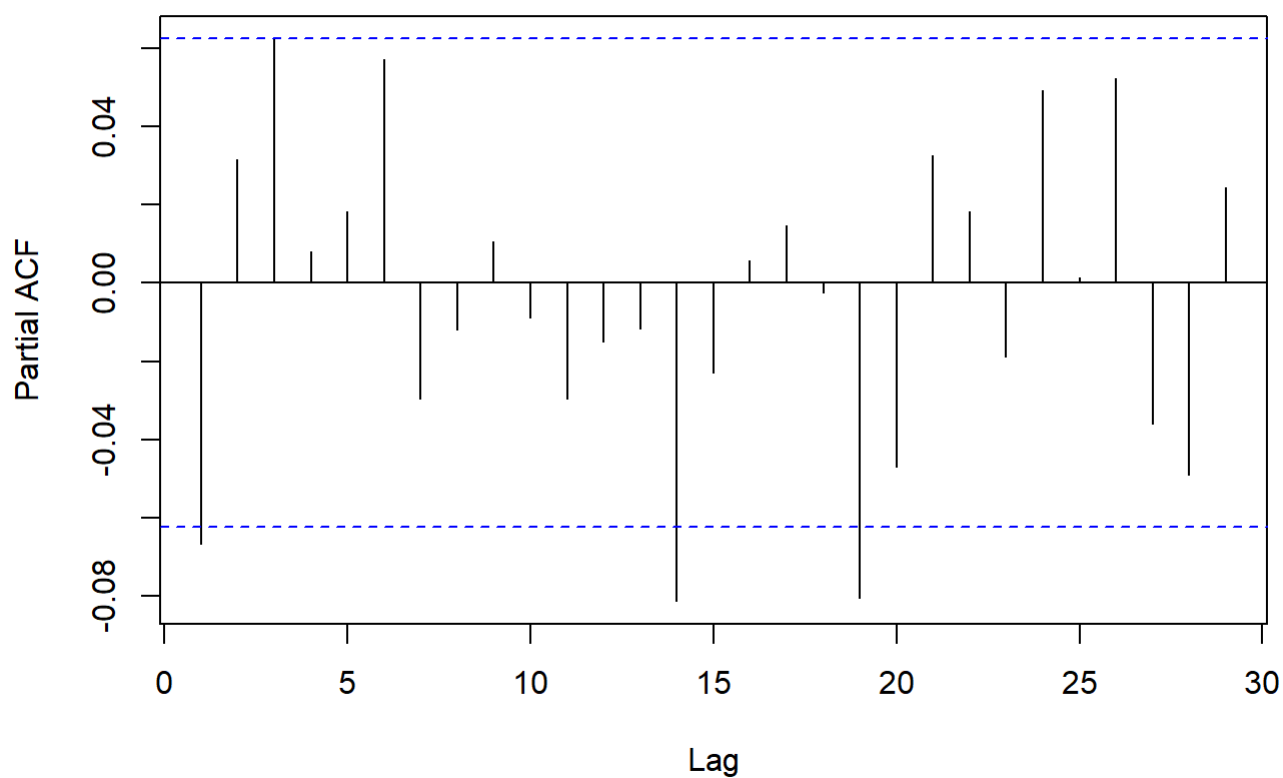
```
acf(cipla_ret)
```

Series cipla_ret



```
pacf(cipla_ret)
```

Series cipla_ret



MA order: ACF cuts off after 0 lags

AR order : PACF slowly declines / tapers

Using auto - ARIMA

Objective : To perform autoARIMA modeling on the daily returns of Cipla stock

Analysis : Used the 'auto.arima' function to automatically select the ARIMA model for returns

Results : The ARIMA model is specified as (1,0,0), indicating that it includes an autoregressive (AR) term of order 1 and no differencing (I) or moving average (MA) terms i.e.

AR Order (p-Lags) : p lags = 1;

d-Degree of Differencing = 0 (returns price);

MA Order (q-Lags): q lags = 0

The autoregressive coefficient (ar1) is approximately -0.0665.

The mean coefficient (mean) is approximately 8e-04.

Managerial implication : The negative AR coefficient suggests a negative autocorrelation, indicating that past returns have a negative impact on current returns. The estimated parameters can be used to make predictions about future returns and assess the model's performance.

Model : $y(t) = 8e + (-0.0665)y(t-1) + e(t)$

```
arma_pq_cipla = auto.arima(cipla_ret)
arma_pq_cipla
```

```
## Series: cipla_ret
## ARIMA(1,0,0) with non-zero mean
##
## Coefficients:
##          ar1    mean
##      -0.0665  8e-04
## s.e.    0.0317  5e-04
##
## sigma^2 = 0.0003125: log likelihood = 2588.81
## AIC=-5171.62   AICc=-5171.59   BIC=-5156.93
```

Checking ARIMA residuals for autocorrelation using Ljung box test

```
lb_test_arma_pq_cipla_ds = Box.test(arma_pq_cipla$residuals)
lb_test_arma_pq_cipla_ds
```

```
##
## Box-Pierce test
##
## data:  arma_pq_cipla$residuals
## X-squared = 0.0043052, df = 1, p-value = 0.9477
```

Result: p-value = 0.9477, null hypothesis is accepted, ARIMA model is appropriate, no autocorrelation in residuals

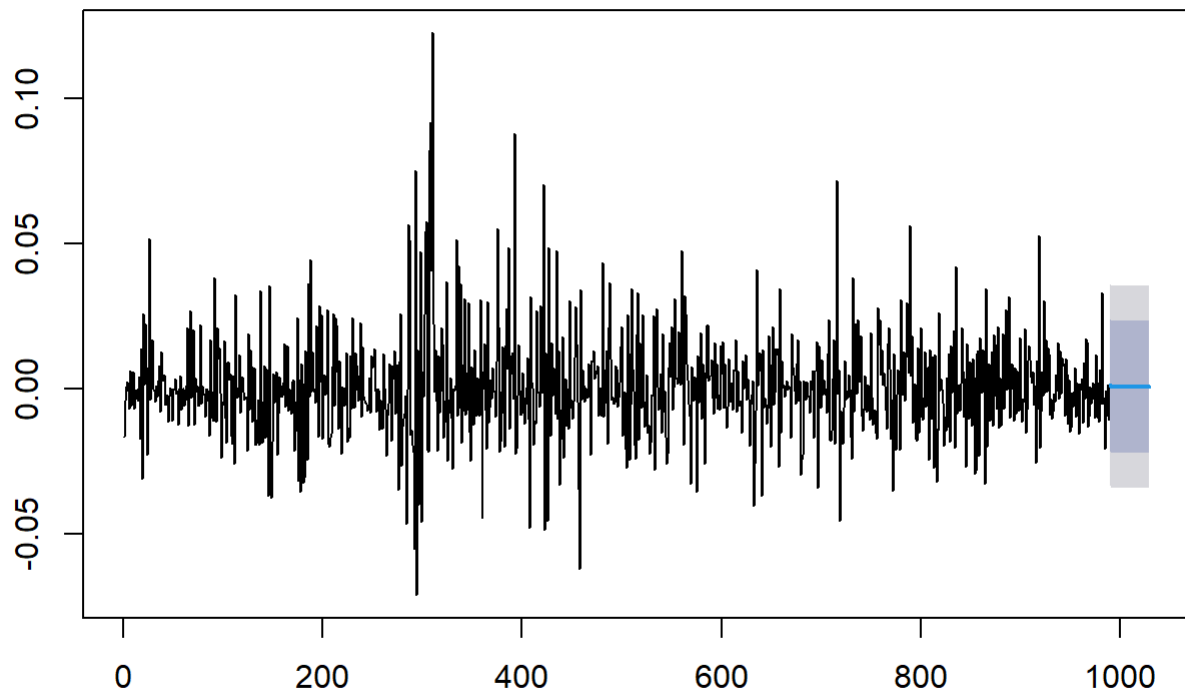
Forecasting for 40 days

Objective : To fit ARIMA (1,0,0) model to the stock returns and generate a forecast for 40 days

Analysis and result: Visual plot for a forecast upto 40 days was created using the historical data

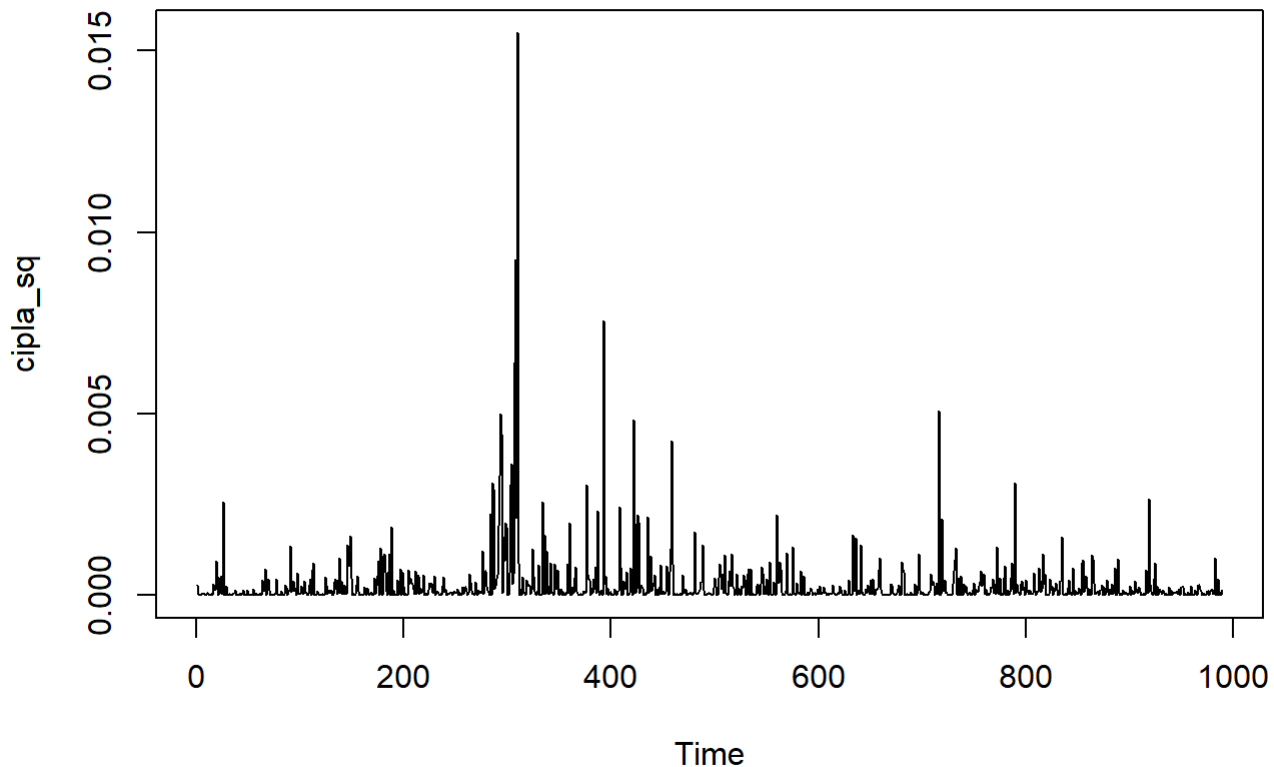
```
cipla_ds_fpq = forecast(arma_pq_cipla, h = 40)
plot(cipla_ds_fpq)
```

Forecasts from ARIMA(1,0,0) with non-zero mean



Squaring ARIMA residuals and checking for autocorrelation

```
cipla_sq = arma_pq_cipla$residuals^2  
plot(cipla_sq)
```

```
cipla_ret_sq_box_test = Box.test(cipla_sq, lag = 10)
cipla_ret_sq_box_test
```

```
##
## Box-Pierce test
##
## data:  cipla_sq
## X-squared = 234.11, df = 10, p-value < 2.2e-16
```

Null is accepted, p-value < 2.2e-16; H0: Return Variance Series is Not Serially Correlated

Checking for Heteroskedasticity using ARCH LM test

Objective : To test for volatility clustering or heteroskedasticity in the residuals of the ARIMA(1, 0, 0) model

Analysis : Conducted Box test and ARCH test on the squared residuals to assess the presence of volatility clustering

Results : Null hypothesis is rejected; p-value = 0.01419; H0: No heteroskedasticity present

Managerial implication : There are significant ARCH effects present in the returns of the Cipla stock. In other words, the variance of the returns is not constant over time, indicating that the volatility of the stock's returns varies over time.

```
cipla_arch_test = ArchTest(cipla_sq, lags = 1)
cipla_arch_test
```

```
##
## ARCH LM-test; Null hypothesis: no ARCH effects
##
## data:  cipla_sq
## Chi-squared = 6.0147, df = 1, p-value = 0.01419
```

Modelling for GARCH

Objective : To fit GARCH models to the residuals of the ARIMA(1, 0, 0) model and test for volatility clustering.

Analysis : Fitted two GARCH models and conducted ARCH test on residuals

Results : Since the p-value (0.102) is greater than the typical significance level of 0.05, we fail to reject the null hypothesis. This means that there is not enough evidence to conclude that there are ARCH effects present in the squared residuals at a significance level of 0.05

Managerial implication : The result suggests that the squared residuals from the GARCH model do not exhibit significant conditional heteroskedasticity. Therefore, the volatility clustering or conditional heteroskedasticity patterns in the data might be adequately captured by the current GARCH model

```
garch_model1 = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.  
model = list(armaOrder = c(0,0), include.mean = TRUE))  
cipla_ret_garch1 = ugarchfit(garch_model1, data = cipla_ret);  
cipla_ret_garch1
```

```

##
## *-----*
## *          GARCH Model Fit          *
## *-----*
##
## Conditional Variance Dynamics
## -----
## GARCH Model   : sGARCH(1,1)
## Mean Model    : ARFIMA(0,0,0)
## Distribution   : norm
##
## Optimal Parameters
## -----
##      Estimate  Std. Error  t value Pr(>|t|)
## mu      0.000511   0.000479   1.0669   0.286
## omega    0.000015   0.000002   8.2529   0.000
## alpha1   0.098120   0.012051   8.1424   0.000
## beta1    0.855641   0.016434  52.0648   0.000
##
## Robust Standard Errors:
##      Estimate  Std. Error  t value Pr(>|t|)
## mu      0.000511   0.000436   1.1729 0.240847
## omega    0.000015   0.000003   4.8308 0.000001
## alpha1   0.098120   0.018379   5.3388 0.000000
## beta1    0.855641   0.023568  36.3058 0.000000
##
## LogLikelihood : 2664.151
##
## Information Criteria
## -----
##
## Akaike      -5.3795
## Bayes       -5.3597
## Shibata     -5.3795
## Hannan-Quinn -5.3719
##
## Weighted Ljung-Box Test on Standardized Residuals
## -----
##              statistic  p-value
## Lag[1]              8.726 0.003137
## Lag[2*(p+q)+(p+q)-1][2] 8.742 0.004113
## Lag[4*(p+q)+(p+q)-1][5] 9.297 0.013915
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## -----
##              statistic  p-value
## Lag[1]              0.1478 0.7006
## Lag[2*(p+q)+(p+q)-1][5] 2.3295 0.5429
## Lag[4*(p+q)+(p+q)-1][9] 3.7577 0.6301
## d.o.f=2
##
## Weighted ARCH LM Tests
## -----

```

```

##           Statistic Shape Scale P-Value
## ARCH Lag[3]      1.976 0.500 2.000  0.1598
## ARCH Lag[5]      4.059 1.440 1.667  0.1687
## ARCH Lag[7]      4.351 2.315 1.543  0.2988
##
## Nyblom stability test
## -----
## Joint Statistic:  8.8497
## Individual Statistics:
## mu      0.07977
## omega   1.52915
## alpha1  0.20561
## beta1   0.18353
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:      1.07 1.24 1.6
## Individual Statistic:  0.35 0.47 0.75
##
## Sign Bias Test
## -----
##           t-value   prob sig
## Sign Bias      1.1266 0.2602
## Negative Sign Bias 1.7490 0.0806  *
## Positive Sign Bias 0.6297 0.5290
## Joint Effect      3.4646 0.3254
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## -----
##   group statistic p-value(g-1)
## 1    20      85.20   2.327e-10
## 2    30     98.01   2.034e-09
## 3    40    103.13   1.064e-07
## 4    50    118.13   1.223e-07
##
##
## Elapsed time : 0.1441472

```

```

garch_model2 = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.
model = list(armaOrder = c(1,1), include.mean = FALSE))
cipla_ret_garch2 = ugarchfit(garch_model2, data = cipla_ret);
cipla_ret_garch2

```

```

##
## *-----*
## *          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|)
## ar1    -0.091580    0.206320  -0.44388  0.65713
## ma1    -0.021881    0.205716  -0.10637  0.91529
## omega   0.000015    0.000003   5.88859  0.00000
## alpha1  0.101910    0.012911   7.89324  0.00000
## beta1   0.848766    0.016680  50.88593  0.00000
##
## Robust Standard Errors:
##      Estimate  Std. Error  t value Pr(>|t|)
## ar1    -0.091580    0.138672  -0.66041  0.508990
## ma1    -0.021881    0.133825  -0.16351  0.870118
## omega   0.000015    0.000005   2.95577  0.003119
## alpha1  0.101910    0.022607   4.50788  0.000007
## beta1   0.848766    0.028768  29.50403  0.000000
##
## LogLikelihood : 2668.856
##
## Information Criteria
## -----
##
## Akaike          -5.3870
## Bayes           -5.3622
## Shibata         -5.3870
## Hannan-Quinn   -5.3776
##
## Weighted Ljung-Box Test on Standardized Residuals
## -----
##
##              statistic p-value
## Lag[1]              0.004401  0.9471
## Lag[2*(p+q)+(p+q)-1][5] 0.639012  1.0000
## Lag[4*(p+q)+(p+q)-1][9] 2.044888  0.9826
## d.o.f=2
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## -----
##
##              statistic p-value
## Lag[1]              0.0005797  0.9808
## Lag[2*(p+q)+(p+q)-1][5] 2.3140042  0.5463
## Lag[4*(p+q)+(p+q)-1][9] 3.8595636  0.6127
## d.o.f=2
##

```

```
## Weighted ARCH LM Tests
## -----
##           Statistic Shape Scale P-Value
## ARCH Lag[3]      2.531 0.500 2.000  0.1116
## ARCH Lag[5]      4.226 1.440 1.667  0.1546
## ARCH Lag[7]      4.568 2.315 1.543  0.2720
##
## Nyblom stability test
## -----
## Joint Statistic:  6.9261
## Individual Statistics:
## ar1      0.09649
## ma1      0.08786
## omega    1.16462
## alpha1   0.21261
## beta1    0.19354
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:      1.28 1.47 1.88
## Individual Statistic:  0.35 0.47 0.75
##
## Sign Bias Test
## -----
##           t-value      prob sig
## Sign Bias      1.1405 0.25435
## Negative Sign Bias 1.6523 0.09879  *
## Positive Sign Bias 0.6526 0.51419
## Joint Effect      3.1597 0.36765
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## -----
##   group statistic p-value(g-1)
## 1    20      76.86  6.414e-09
## 2    30      95.64  4.815e-09
## 3    40      95.37  1.267e-06
## 4    50     111.05  1.025e-06
##
##
## Elapsed time : 0.107903
```

```
arma_model <- arima(cipla_ret, order = c(1,0,0))
arma_residuals <- residuals(arma_model)
garch_spec <- ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)),
                        mean.model = list(armaOrder = c(0,0), include.mean = FALSE))
garch_spec
```

```
##
## *-----*
## *      GARCH Model Spec      *
## *-----*
##
## Conditional Variance Dynamics
## -----
## GARCH Model      : sGARCH(1,1)
## Variance Targeting : FALSE
##
## Conditional Mean Dynamics
## -----
## Mean Model       : ARFIMA(0,0,0)
## Include Mean      : FALSE
## GARCH-in-Mean     : FALSE
##
## Conditional Distribution
## -----
## Distribution : norm
## Includes Skew   : FALSE
## Includes Shape   : FALSE
## Includes Lambda : FALSE
```

```
garch_fit <- ugarchfit(garch_spec, data = arima_residuals^2)
arch_lm_test <- ArchTest(residuals(garch_fit)^2, lags = 10)
print("ARCH LM-test for squared residuals of GARCH model:")
```

```
## [1] "ARCH LM-test for squared residuals of GARCH model:"
```

```
print(arch_lm_test)
```

```
##
## ARCH LM-test; Null hypothesis: no ARCH effects
##
## data: residuals(garch_fit)^2
## Chi-squared = 15.917, df = 10, p-value = 0.102
```

Result: The GARCH model used is specified as sGARCH(1,1), indicating a symmetric GARCH model with one lag each for the ARCH and GARCH terms.

- Variance Targeting: FALSE indicates that the model does not employ variance targeting, where the long-run variance is explicitly modeled.
- Mean Model: The mean model is specified as ARFIMA(0,0,0), indicating no autoregressive, differencing, or moving average components.
- Include Mean: FALSE indicates that the mean is not explicitly modeled in the GARCH process.
- GARCH-in-Mean: FALSE indicates that the GARCH model is not included in the mean equation.
- Distribution: The distribution is assumed to be normal. Includes Skew, Shape, Lambda: FALSE indicates that the model does not incorporate skewness, shape, or lambda parameters in the distribution.

- ARCH LM-test: The null hypothesis of the ARCH LM-test is that there are no ARCH effects present in the squared residuals of the GARCH model.
- Chi-squared: The test statistic is 15.917 with degrees of freedom (df) equal to 10.
- P-value: The p-value associated with the test is 0.102

Analysis : With a p-value of 0.102, the result of the ARCH LM-test does not provide significant evidence to reject the null hypothesis at conventional significance levels (e.g., $\alpha = 0.05$). This suggests that there may not be significant autocorrelation in the squared residuals of the GARCH model.

Managerial Implication: Since the p-value is relatively high, there is no strong evidence to suggest the presence of ARCH effects in the squared residuals. Therefore, the GARCH model may adequately capture the volatility dynamics of the data.

```
cipla_ret_garch_forecast1 = ugarchforecast(cipla_ret_garch1, n.ahead = 50);  
cipla_ret_garch_forecast1
```



```

##
## *-----*
## *          GARCH Model Forecast          *
## *-----*
## Model: sGARCH
## Horizon: 50
## Roll Steps: 0
## Out of Sample: 0
##
## 0-roll forecast [T0=2022-12-30]:
##      Series   Sigma
## T+1  0.0005113 0.01391
## T+2  0.0005113 0.01411
## T+3  0.0005113 0.01430
## T+4  0.0005113 0.01447
## T+5  0.0005113 0.01464
## T+6  0.0005113 0.01480
## T+7  0.0005113 0.01495
## T+8  0.0005113 0.01509
## T+9  0.0005113 0.01522
## T+10 0.0005113 0.01534
## T+11 0.0005113 0.01546
## T+12 0.0005113 0.01557
## T+13 0.0005113 0.01568
## T+14 0.0005113 0.01578
## T+15 0.0005113 0.01588
## T+16 0.0005113 0.01597
## T+17 0.0005113 0.01605
## T+18 0.0005113 0.01613
## T+19 0.0005113 0.01621
## T+20 0.0005113 0.01628
## T+21 0.0005113 0.01635
## T+22 0.0005113 0.01642
## T+23 0.0005113 0.01648
## T+24 0.0005113 0.01654
## T+25 0.0005113 0.01660
## T+26 0.0005113 0.01665
## T+27 0.0005113 0.01670
## T+28 0.0005113 0.01675
## T+29 0.0005113 0.01680
## T+30 0.0005113 0.01684
## T+31 0.0005113 0.01688
## T+32 0.0005113 0.01692
## T+33 0.0005113 0.01696
## T+34 0.0005113 0.01700
## T+35 0.0005113 0.01703
## T+36 0.0005113 0.01706
## T+37 0.0005113 0.01710
## T+38 0.0005113 0.01713
## T+39 0.0005113 0.01715
## T+40 0.0005113 0.01718
## T+41 0.0005113 0.01721
## T+42 0.0005113 0.01723
## T+43 0.0005113 0.01725
## T+44 0.0005113 0.01728

```

```
## T+45 0.0005113 0.01730
## T+46 0.0005113 0.01732
## T+47 0.0005113 0.01734
## T+48 0.0005113 0.01735
## T+49 0.0005113 0.01737
## T+50 0.0005113 0.01739
```

```
cipla_ret_garch_forecast2 = ugarchforecast(cipla_ret_garch2, n.ahead = 50); cipla_ret_garch_f
orecast2
```

```

##
## *-----*
## *          GARCH Model Forecast          *
## *-----*
## Model: sGARCH
## Horizon: 50
## Roll Steps: 0
## Out of Sample: 0
##
## 0-roll forecast [T0=2022-12-30]:
##      Series   Sigma
## T+1   1.213e-03 0.01378
## T+2  -1.111e-04 0.01400
## T+3   1.018e-05 0.01420
## T+4  -9.319e-07 0.01439
## T+5   8.534e-08 0.01457
## T+6  -7.815e-09 0.01474
## T+7   7.157e-10 0.01490
## T+8  -6.555e-11 0.01505
## T+9   6.003e-12 0.01519
## T+10 -5.498e-13 0.01532
## T+11  5.035e-14 0.01545
## T+12 -4.611e-15 0.01556
## T+13  4.223e-16 0.01567
## T+14 -3.867e-17 0.01578
## T+15  3.541e-18 0.01588
## T+16 -3.243e-19 0.01597
## T+17  2.970e-20 0.01606
## T+18 -2.720e-21 0.01614
## T+19  2.491e-22 0.01622
## T+20 -2.281e-23 0.01630
## T+21  2.089e-24 0.01637
## T+22 -1.913e-25 0.01643
## T+23  1.752e-26 0.01650
## T+24 -1.605e-27 0.01656
## T+25  1.470e-28 0.01661
## T+26 -1.346e-29 0.01667
## T+27  1.233e-30 0.01672
## T+28 -1.129e-31 0.01677
## T+29  1.034e-32 0.01681
## T+30 -9.467e-34 0.01686
## T+31  8.670e-35 0.01690
## T+32 -7.940e-36 0.01694
## T+33  7.272e-37 0.01697
## T+34 -6.659e-38 0.01701
## T+35  6.099e-39 0.01704
## T+36 -5.585e-40 0.01707
## T+37  5.115e-41 0.01710
## T+38 -4.684e-42 0.01713
## T+39  4.290e-43 0.01716
## T+40 -3.929e-44 0.01719
## T+41  3.598e-45 0.01721
## T+42 -3.295e-46 0.01723
## T+43  3.018e-47 0.01726
## T+44 -2.764e-48 0.01728

```

```
## T+45 2.531e-49 0.01730
## T+46 -2.318e-50 0.01731
## T+47 2.123e-51 0.01733
## T+48 -1.944e-52 0.01735
## T+49 1.780e-53 0.01737
## T+50 -1.630e-54 0.01738
```