Cipla stock time series analysis

Code

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Downloading and loading relevant packages

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```
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 4.3.2Registered S3 method overwritten by
'quantmod':
  method            from
  as.zoo.data.frame zoo

    ‘tseries’ version: 0.10-55

    ‘tseries’ is a package for time series analysis and computational finance.

    See ‘library(help="tseries")’ for details.

Loading required package: forecast
Warning: package ‘forecast’ was built under R version 4.3.2Loading required package: FinTS
Warning: package ‘FinTS’ was built under R version 4.3.2Loading 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 4.3.2Loading 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 4.3.2Loading required package: xts
Warning: package ‘xts’ was built under R version 4.3.2Loading 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
```

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Loading stock price data from Yahoo

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

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

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Removing NA values from data

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

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

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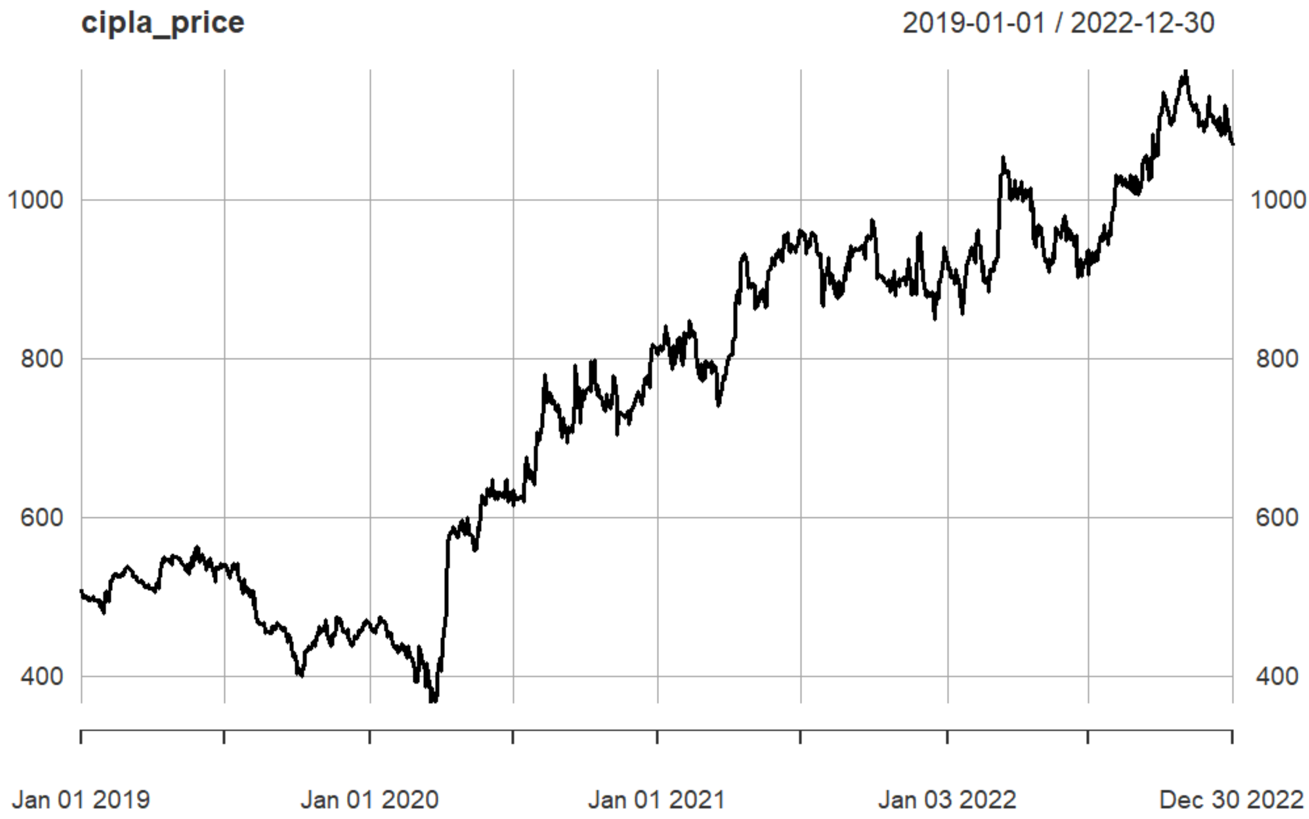
```
plot( cipla_price)
```



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ADF test for price to check stationarity

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

Analysis : Extracted stock price data and checked for stationarity; H0 : 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

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```
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
```

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Obtaining cipla stock return price

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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; H0 : 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.

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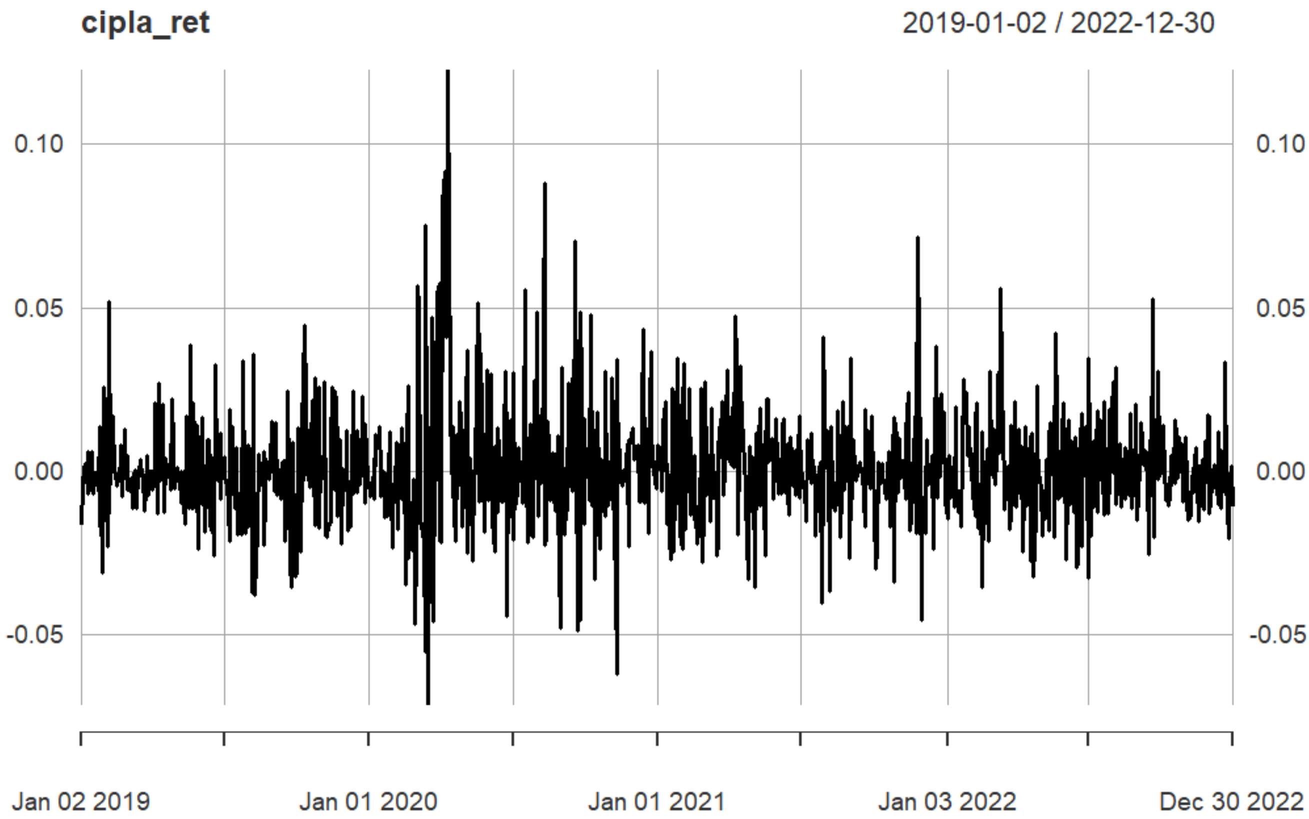
```
cipla_ret =na.omit(diff(log(cipla_price)))
plot(cipla_ret)
```



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

```
Warning: p-value smaller than printed p-value
```

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```
adf_test_cipla
```

```

	Augmented Dickey-Fuller Test

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

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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

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```
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
```

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Modelling for ARIMA

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Plotting ACF and PACF plots to determine lag value

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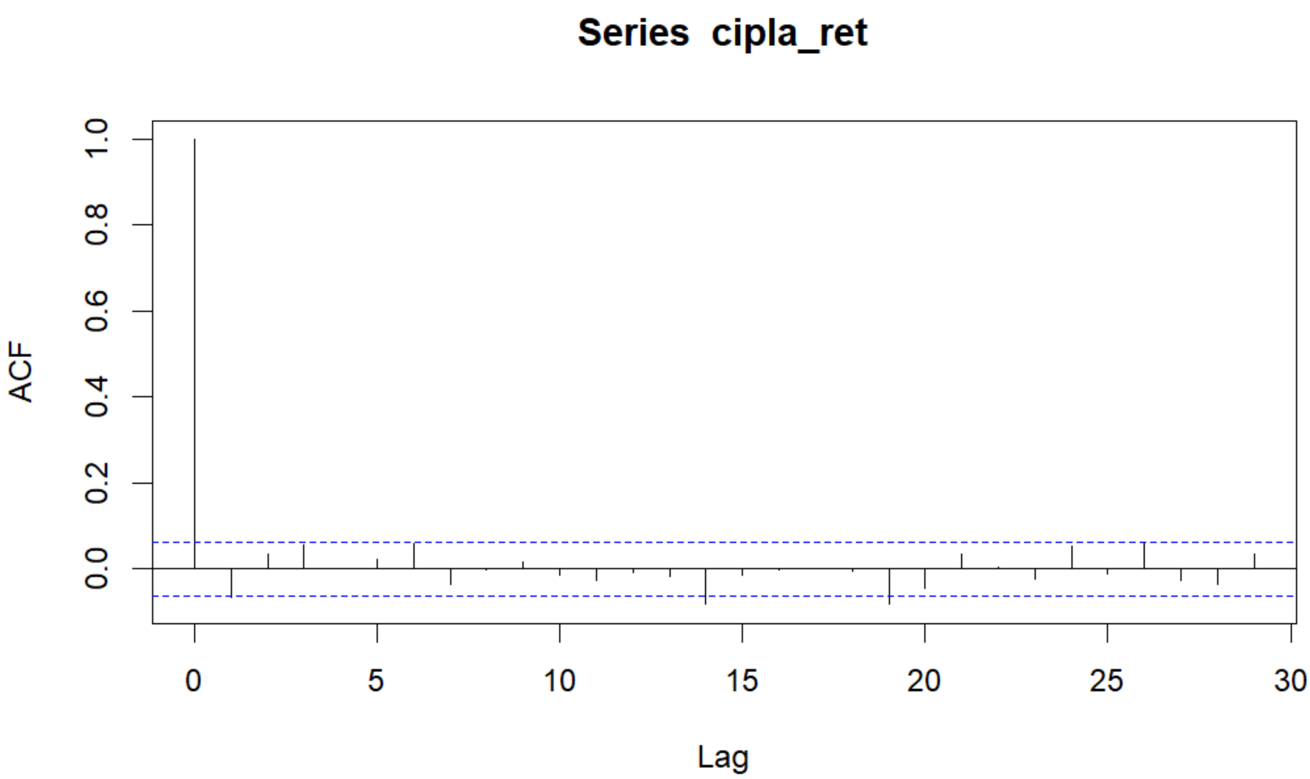
```
acf(cipla_ret)
```



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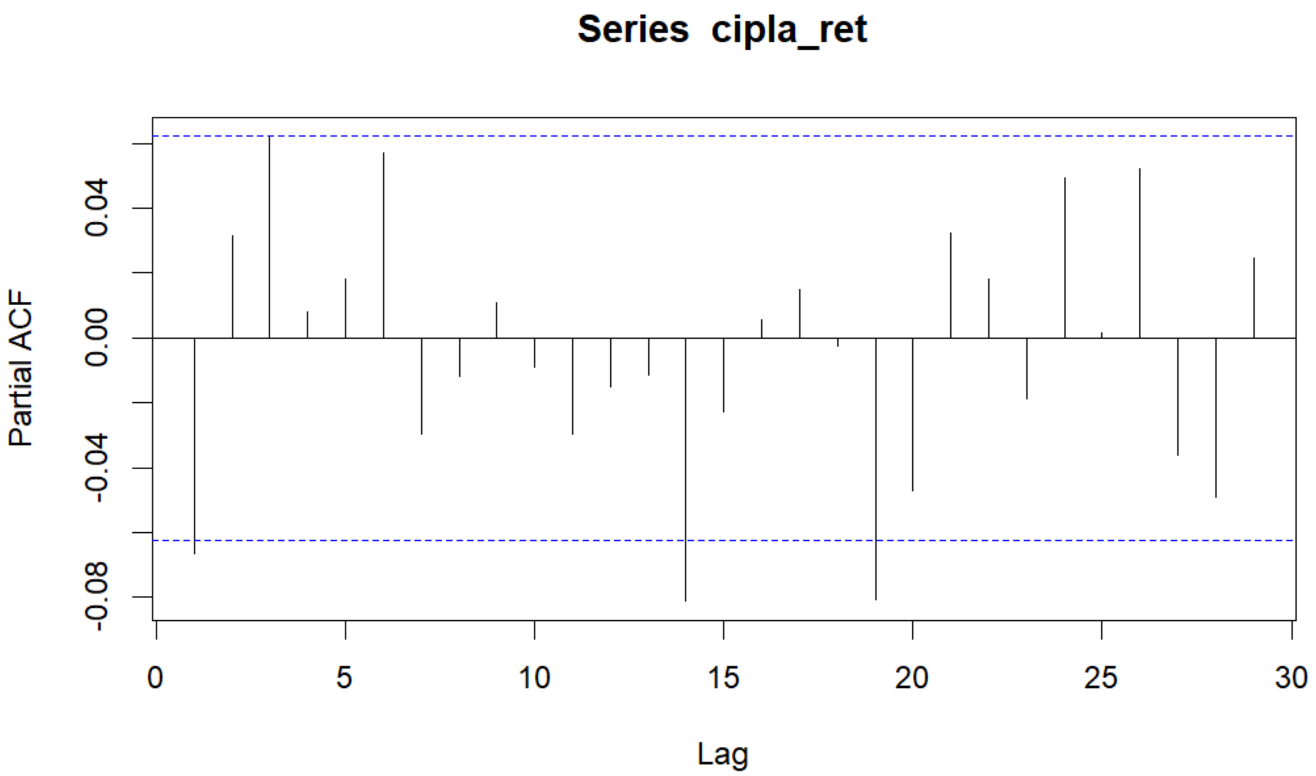
```
pacf(cipla_ret)
```



MA order: ACF cuts off after 0 lags

AR order : PACF slowly declines / tapers

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Using auto - ARIMA

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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 - 04 -n0.0665*y(t-1) + e(t)

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```
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

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```
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

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Forcasting for 40 days

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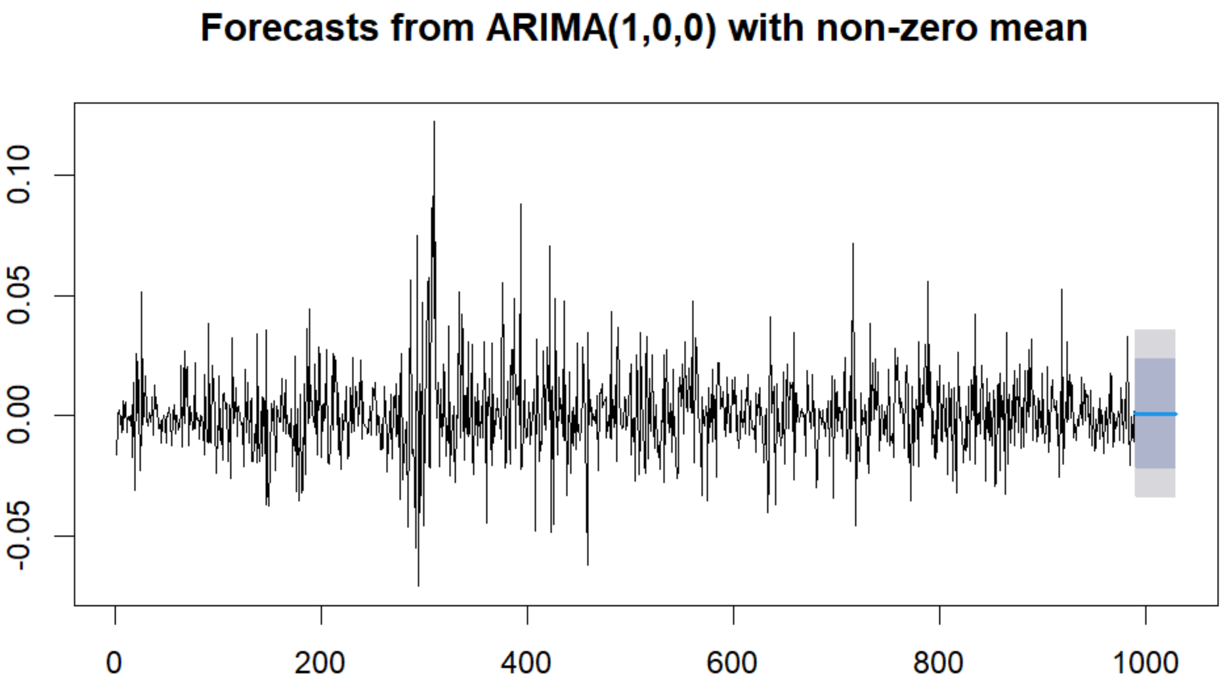
```
cipla_ds_fpq = forecast(arma_pq_cipla, h = 40)
plot(cipla_ds_fpq)
```



Squaring ARIMA residuals and checking for autocorrelation

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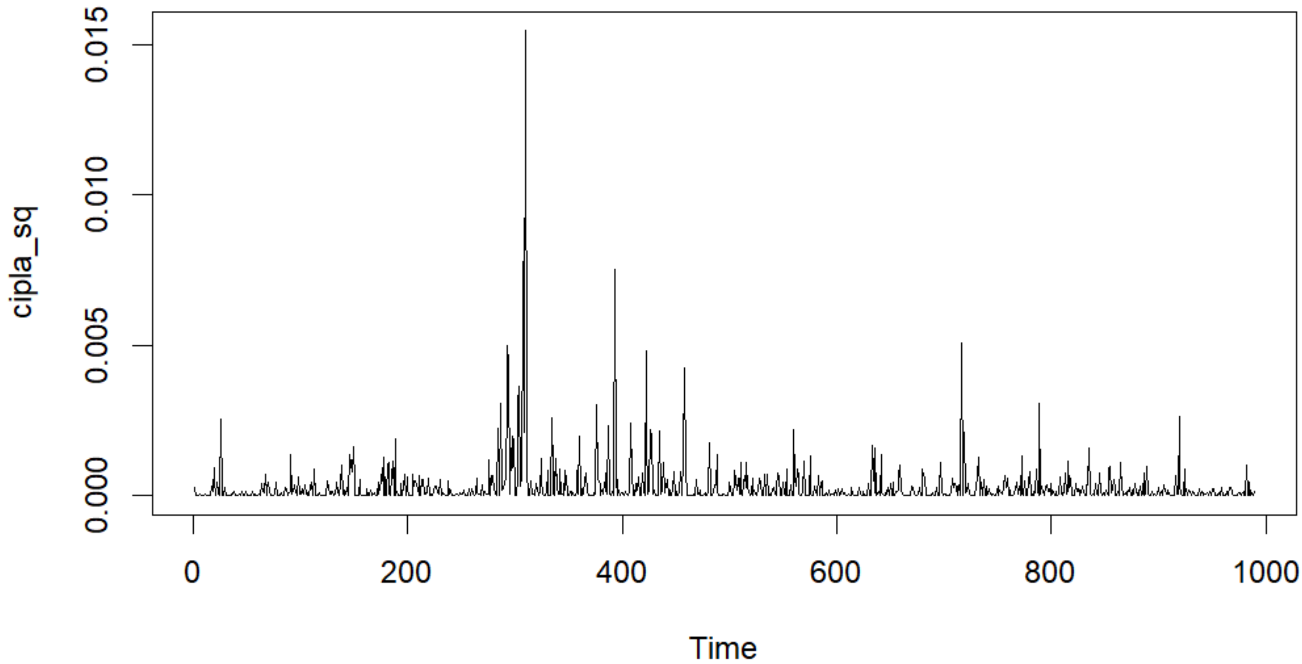
```
cipla_sq = arma_pq_cipla$residuals^2
plot(cipla_sq)
```



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

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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.

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```
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
```

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Modelling for GARCH

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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

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```
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   8.2524    0.000
alpha1  0.098120    0.012051   8.1423    0.000
beta1   0.855640    0.016434  52.0643    0.000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000511    0.000436   1.1729 0.240846
omega   0.000015    0.000003   4.8304 0.000001
alpha1  0.098120    0.018379   5.3386 0.000000
beta1   0.855640    0.023568  36.3048 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:  8.8493
Individual Statistics:
mu     0.07977
omega  1.52908
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 <dbl>	prob <dbl>	sig <chr>
Sign Bias	1.1266169	0.26017917	
Negative Sign Bias	1.7490147	0.08060027	*
Positive Sign Bias	0.6297225	0.52902234	
Joint Effect	3.4646201	0.32537985	

4 rows

```
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    118.53    1.081e-07


Elapsed time : 0.1536529
```

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```
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    -0.091546    0.206337 -0.44367  0.65728
ma1    -0.021904    0.205731 -0.10647  0.91521
omega   0.000015    0.000003  5.88300  0.00000
alpha1  0.101914    0.012912  7.89291  0.00000
beta1   0.848754    0.016678 50.88964  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ar1    -0.091546    0.138681 -0.66012 0.509178
ma1    -0.021904    0.133830 -0.16367 0.869991
omega   0.000015    0.000005  2.95170 0.003160
alpha1  0.101914    0.022620  4.50553 0.000007
beta1   0.848754    0.028786 29.48535 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]                   0.004357  0.9474
Lag[2*(p+q)+(p+q)-1][5]  0.638922  1.0000
Lag[4*(p+q)+(p+q)-1][9]  2.044809  0.9826
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.000577  0.9808
Lag[2*(p+q)+(p+q)-1][5]  2.313787  0.5464
Lag[4*(p+q)+(p+q)-1][9]  3.859287  0.6128
d.o.f=2
```

```
Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     2.530 0.500 2.000  0.1117
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:  6.9216
Individual Statistics:
ar1    0.09642
ma1    0.08780
omega  1.16389
alpha1 0.21268
beta1  0.19358

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 <dbl>	prob <dbl>	sig <chr>
Sign Bias	1.1404967	0.25435696	
Negative Sign Bias	1.6522804	0.09879643	*
Positive Sign Bias	0.6526022	0.51416520	
Joint Effect	3.1596445	0.36766002	

4 rows

```
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 : 0.13729
```

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```
arima_model <- arima(cipla_ret, order = c(1,0,0))
arima_residuals <- residuals(arima_model)
garch_spec <- ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)),
                         mean.model = list(armaOrder = c(0,0), include.mean = 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:"
```

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```
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
```

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```
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
```

Hide

```
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   1.017e-05 0.01420
T+4  -9.307e-07 0.01439
T+5   8.520e-08 0.01457
T+6  -7.800e-09 0.01474
T+7   7.141e-10 0.01490
T+8  -6.537e-11 0.01505
T+9   5.984e-12 0.01519
T+10 -5.478e-13 0.01532
T+11  5.015e-14 0.01545
T+12 -4.591e-15 0.01556
T+13  4.203e-16 0.01567
T+14 -3.848e-17 0.01578
T+15  3.522e-18 0.01588
T+16 -3.225e-19 0.01597
T+17  2.952e-20 0.01606
T+18 -2.703e-21 0.01614
T+19  2.474e-22 0.01622
T+20 -2.265e-23 0.01630
T+21  2.073e-24 0.01637
T+22 -1.898e-25 0.01643
T+23  1.738e-26 0.01650
T+24 -1.591e-27 0.01656
T+25  1.456e-28 0.01661
T+26 -1.333e-29 0.01667
T+27  1.220e-30 0.01672
T+28 -1.117e-31 0.01677
T+29  1.023e-32 0.01681
T+30 -9.364e-34 0.01686
T+31  8.572e-35 0.01690
T+32 -7.847e-36 0.01694
T+33  7.184e-37 0.01697
T+34 -6.577e-38 0.01701
T+35  6.021e-39 0.01704
T+36 -5.512e-40 0.01707
T+37  5.046e-41 0.01710
T+38 -4.619e-42 0.01713
T+39  4.229e-43 0.01716
T+40 -3.871e-44 0.01719
T+41  3.544e-45 0.01721
T+42 -3.244e-46 0.01723
T+43  2.970e-47 0.01726
T+44 -2.719e-48 0.01728
```

```
T+45  2.489e-49 0.01730
T+46 -2.279e-50 0.01731
T+47  2.086e-51 0.01733
T+48 -1.910e-52 0.01735
T+49  1.748e-53 0.01737
T+50 -1.600e-54 0.01738
```