

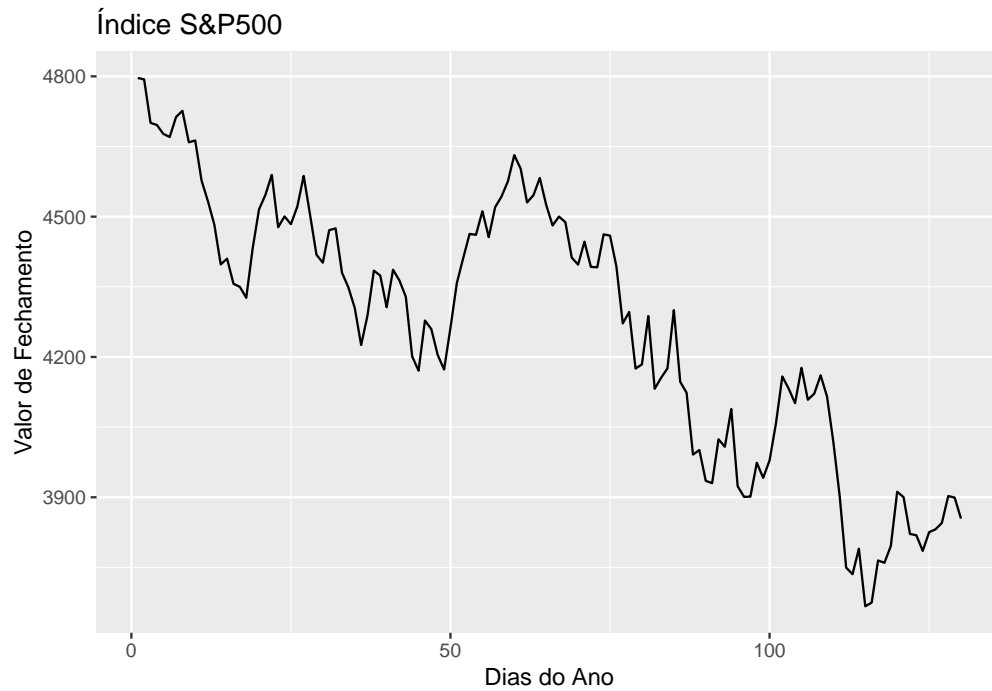
Prova GED-17

Arthur Stevenson

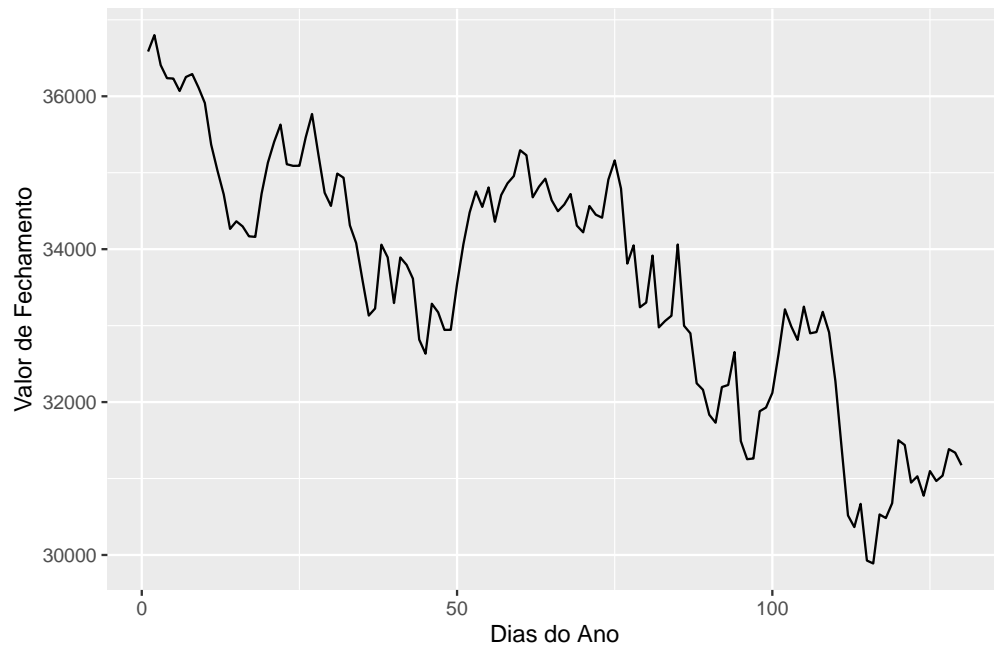
2022-07-05

Introdução

Inicialmente, são fornecidas várias séries temporais, representando os valores de diferentes índices, como o Bovespa, e a cotação de diferentes moedas, como o Dólar. Assim, tratando dos valores de fechamento para essas séries, podemos gerar os seus respectivos plots.

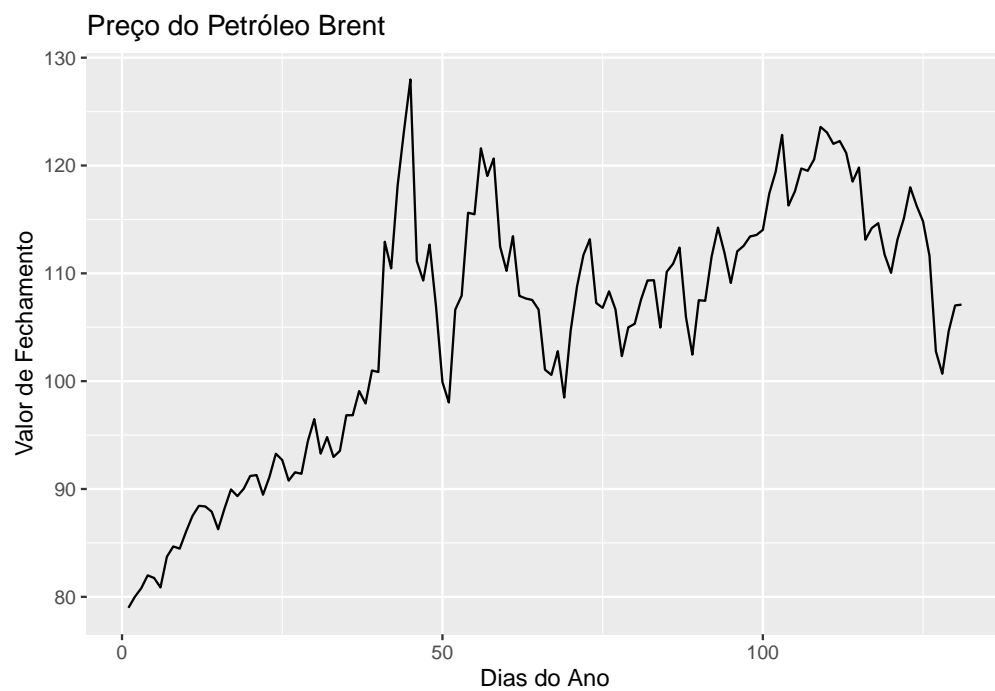
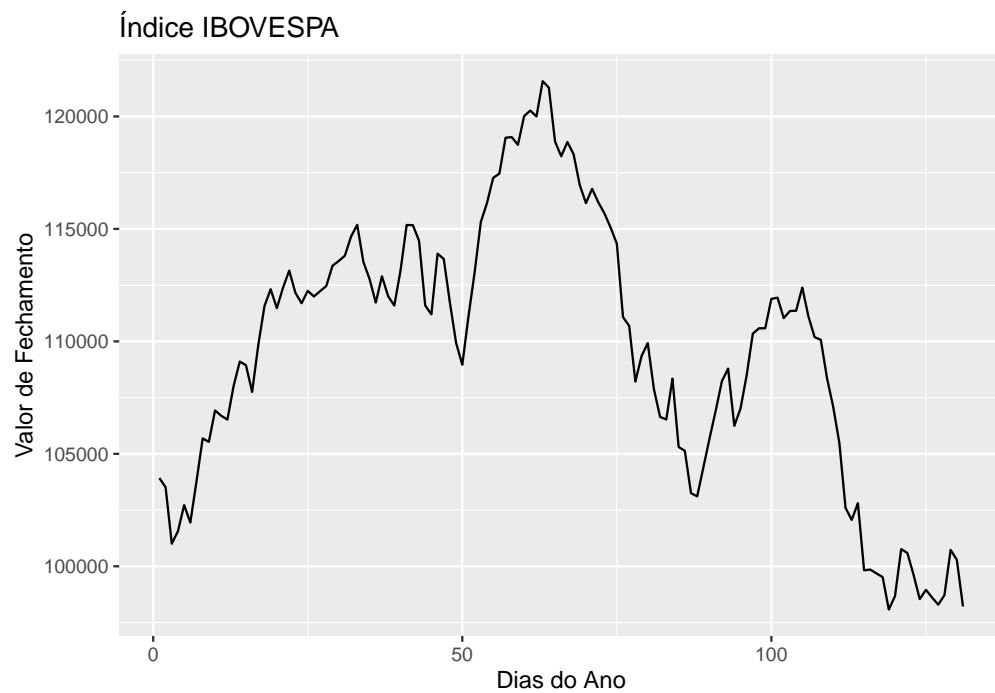


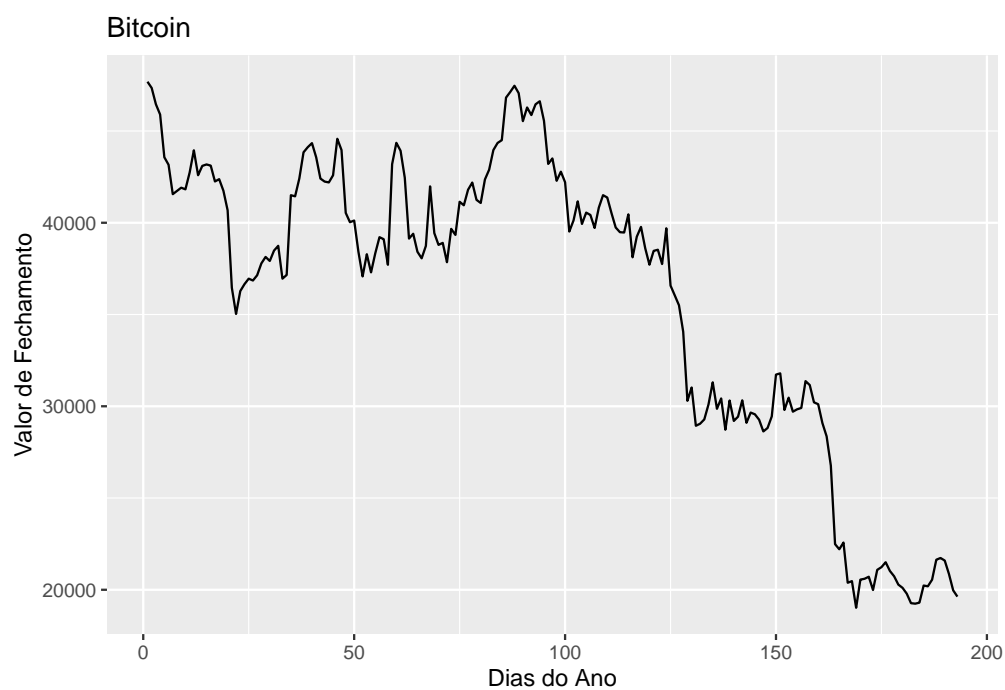
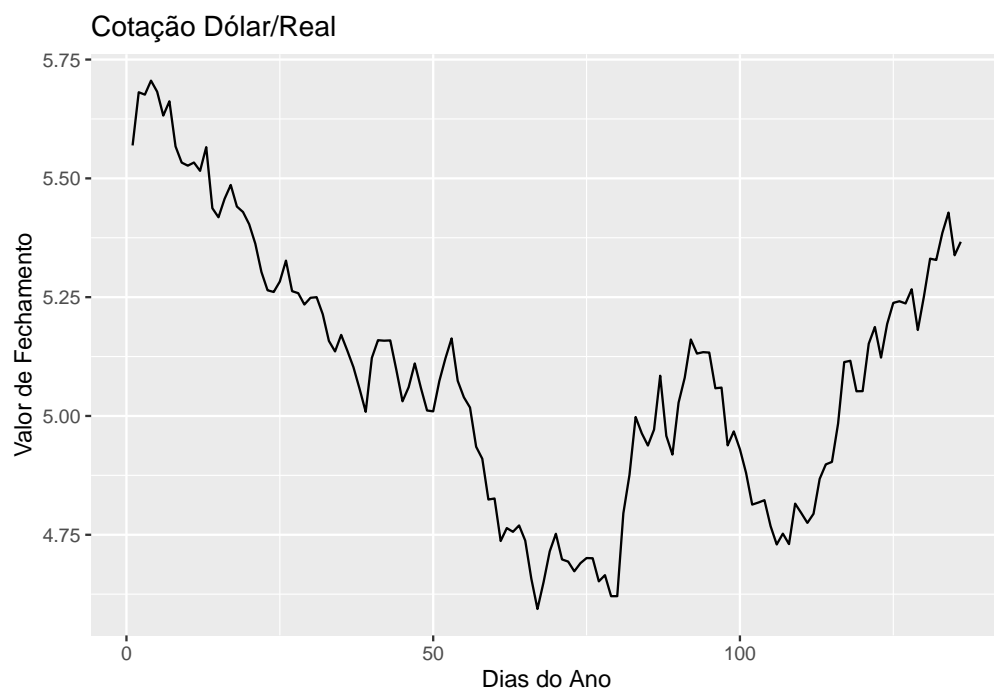
Índice Dow Jones



Índice Nasdaq







Em seguida, podemos fazer o teste ADF para as séries temporais originais obtidas.

```
## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag    ADF p.value
## [1,]  0 -1.37  0.188
## [2,]  1 -1.33  0.201
## [3,]  2 -1.25  0.229
## [4,]  3 -1.27  0.224
```

```

## [5,] 4 -1.17 0.261
## Type 2: with drift no trend
## lag ADF p.value
## [1,] 0 -1.61 0.481
## [2,] 1 -1.66 0.462
## [3,] 2 -1.40 0.557
## [4,] 3 -1.40 0.558
## [5,] 4 -1.42 0.548
## Type 3: with drift and trend
## lag ADF p.value
## [1,] 0 -2.66 0.298
## [2,] 1 -2.78 0.250
## [3,] 2 -2.60 0.325
## [4,] 3 -2.59 0.329
## [5,] 4 -2.77 0.256
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
## lag ADF p.value
## [1,] 0 -1.22 0.239
## [2,] 1 -1.22 0.240
## [3,] 2 -1.20 0.247
## [4,] 3 -1.17 0.257
## [5,] 4 -1.10 0.284
## Type 2: with drift no trend
## lag ADF p.value
## [1,] 0 -1.66 0.462
## [2,] 1 -1.84 0.392
## [3,] 2 -1.61 0.481
## [4,] 3 -1.58 0.491
## [5,] 4 -1.68 0.452
## Type 3: with drift and trend
## lag ADF p.value
## [1,] 0 -2.78 0.252
## [2,] 1 -3.02 0.150
## [3,] 2 -2.80 0.243
## [4,] 3 -2.83 0.229
## [5,] 4 -3.08 0.128
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
## lag ADF p.value
## [1,] 0 -1.60 0.103
## [2,] 1 -1.53 0.129
## [3,] 2 -1.38 0.182
## [4,] 3 -1.46 0.155
## [5,] 4 -1.35 0.194

```

```

## Type 2: with drift no trend
##      lag    ADF p.value
## [1,]  0 -1.91  0.362
## [2,]  1 -1.80  0.405
## [3,]  2 -1.48  0.528
## [4,]  3 -1.45  0.538
## [5,]  4 -1.39  0.560
## Type 3: with drift and trend
##      lag    ADF p.value
## [1,]  0 -2.96  0.177
## [2,]  1 -2.92  0.194
## [3,]  2 -2.71  0.277
## [4,]  3 -2.59  0.327
## [5,]  4 -2.68  0.293
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag    ADF p.value
## [1,]  0 -0.423  0.522
## [2,]  1 -0.371  0.537
## [3,]  2 -0.228  0.578
## [4,]  3 -0.278  0.563
## [5,]  4 -0.299  0.558
## Type 2: with drift no trend
##      lag    ADF p.value
## [1,]  0 -0.679  0.809
## [2,]  1 -1.018  0.690
## [3,]  2 -1.008  0.694
## [4,]  3 -1.064  0.674
## [5,]  4 -1.284  0.597
## Type 3: with drift and trend
##      lag    ADF p.value
## [1,]  0 -1.55  0.761
## [2,]  1 -1.84  0.639
## [3,]  2 -2.11  0.524
## [4,]  3 -2.11  0.525
## [5,]  4 -2.26  0.465
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag    ADF p.value
## [1,]  0 0.402  0.758
## [2,]  1 0.399  0.757
## [3,]  2 0.399  0.757
## [4,]  3 0.417  0.762
## [5,]  4 0.350  0.743
## Type 2: with drift no trend

```

```

##      lag    ADF p.value
## [1,]  0 -2.48  0.141
## [2,]  1 -2.45  0.153
## [3,]  2 -2.43  0.161
## [4,]  3 -2.35  0.192
## [5,]  4 -2.50  0.134
## Type 3: with drift and trend
##      lag    ADF p.value
## [1,]  0 -2.68  0.293
## [2,]  1 -2.66  0.299
## [3,]  2 -2.66  0.301
## [4,]  3 -2.50  0.367
## [5,]  4 -2.97  0.172
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag    ADF p.value
## [1,]  0 -0.398  0.529
## [2,]  1 -0.565  0.477
## [3,]  2 -0.542  0.485
## [4,]  3 -0.614  0.459
## [5,]  4 -0.536  0.487
## Type 2: with drift no trend
##      lag    ADF p.value
## [1,]  0 -1.61  0.480
## [2,]  1 -2.06  0.306
## [3,]  2 -1.96  0.345
## [4,]  3 -2.12  0.281
## [5,]  4 -2.15  0.272
## Type 3: with drift and trend
##      lag    ADF p.value
## [1,]  0 -0.713  0.967
## [2,]  1 -1.098  0.920
## [3,]  2 -0.868  0.953
## [4,]  3 -0.904  0.950
## [5,]  4 -1.037  0.929
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag    ADF p.value
## [1,]  0 -1.69  0.0885
## [2,]  1 -1.66  0.0938
## [3,]  2 -1.57  0.1150
## [4,]  3 -1.45  0.1582
## [5,]  4 -1.34  0.1993
## Type 2: with drift no trend
##      lag    ADF p.value

```

```
## [1,] 0 -0.652 0.819
## [2,] 1 -0.639 0.823
## [3,] 2 -0.597 0.838
## [4,] 3 -0.666 0.814
## [5,] 4 -0.456 0.888
## Type 3: with drift and trend
##      lag    ADF p.value
## [1,] 0 -1.71 0.697
## [2,] 1 -1.71 0.695
## [3,] 2 -1.74 0.685
## [4,] 3 -1.89 0.619
## [5,] 4 -1.86 0.634
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01
```

Diferença do Logaritmo

Analisando-se os resultados dos ADFs de cada uma das séries temporais, nota-se que todos os p-valores encontrados são superiores a 5%. Portanto, não podemos rejeitar a hipótese nula e, assim, é necessária uma transformação na série para que seja possível trabalhá-la.

Com os plots das séries temporais, podemos, então, obter as séries do log, e da diferença do log e, assim realizar o teste ADF novamente. Analisando-se os resultados, nota-se que há uma queda considerável nos p-valores de todas as séries analisadas.

Nesses novos casos, constata-se que os p-valores das séries são, novamente, significativamente menores e, mais importante que isso, que eles são inferiores à margem significativa de 5%. Dessa forma, podemos rejeitar a hipótese nula, e é seguro supor que a série é estacionária.

```
## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag    ADF p.value
## [1,] 0 -10.91 0.01
## [2,] 1 -8.18 0.01
## [3,] 2 -6.58 0.01
## [4,] 3 -5.32 0.01
## [5,] 4 -5.07 0.01
## Type 2: with drift no trend
##      lag    ADF p.value
## [1,] 0 -10.99 0.01
## [2,] 1 -8.27 0.01
## [3,] 2 -6.69 0.01
## [4,] 3 -5.43 0.01
## [5,] 4 -5.19 0.01
## Type 3: with drift and trend
##      lag    ADF p.value
## [1,] 0 -10.95 0.01
## [2,] 1 -8.23 0.01
## [3,] 2 -6.66 0.01
## [4,] 3 -5.40 0.01
## [5,] 4 -5.17 0.01
```



```

## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag      ADF p.value
## [1,]  0 -10.67    0.01
## [2,]  1  -8.27    0.01
## [3,]  2  -6.54    0.01
## [4,]  3  -5.25    0.01
## [5,]  4  -5.00    0.01
## Type 2: with drift no trend
##      lag      ADF p.value
## [1,]  0 -10.74    0.01
## [2,]  1  -8.35    0.01
## [3,]  2  -6.63    0.01
## [4,]  3  -5.34    0.01
## [5,]  4  -5.11    0.01
## Type 3: with drift and trend
##      lag      ADF p.value
## [1,]  0 -10.70    0.01
## [2,]  1  -8.32    0.01
## [3,]  2  -6.61    0.01
## [4,]  3  -5.32    0.01
## [5,]  4  -5.09    0.01
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag      ADF p.value
## [1,]  0 -11.35    0.01
## [2,]  1  -8.14    0.01
## [3,]  2  -6.85    0.01
## [4,]  3  -5.63    0.01
## [5,]  4  -5.26    0.01
## Type 2: with drift no trend
##      lag      ADF p.value
## [1,]  0 -11.46    0.01
## [2,]  1  -8.25    0.01
## [3,]  2  -6.99    0.01
## [4,]  3  -5.76    0.01
## [5,]  4  -5.43    0.01
## Type 3: with drift and trend
##      lag      ADF p.value
## [1,]  0 -11.43    0.01
## [2,]  1  -8.21    0.01
## [3,]  2  -6.96    0.01
## [4,]  3  -5.74    0.01
## [5,]  4  -5.41    0.01
## ----

```

```
## Note: in fact, p.value = 0.01 means p.value <= 0.01
```

```
## Augmented Dickey-Fuller Test
```

```
## alternative: stationary
```

```
##
```

```
## Type 1: no drift no trend
```

```
##      lag    ADF p.value
```

```
## [1,]  0 -9.28    0.01
```

```
## [2,]  1 -8.17    0.01
```

```
## [3,]  2 -6.01    0.01
```

```
## [4,]  3 -4.60    0.01
```

```
## [5,]  4 -4.01    0.01
```

```
## Type 2: with drift no trend
```

```
##      lag    ADF p.value
```

```
## [1,]  0 -9.26    0.01
```

```
## [2,]  1 -8.14    0.01
```

```
## [3,]  2 -5.99    0.01
```

```
## [4,]  3 -4.58    0.01
```

```
## [5,]  4 -4.00    0.01
```

```
## Type 3: with drift and trend
```

```
##      lag    ADF p.value
```

```
## [1,]  0 -9.51    0.01
```

```
## [2,]  1 -8.63    0.01
```

```
## [3,]  2 -6.46    0.01
```

```
## [4,]  3 -4.99    0.01
```

```
## [5,]  4 -4.48    0.01
```

```
## ----
```

```
## Note: in fact, p.value = 0.01 means p.value <= 0.01
```

```
## Augmented Dickey-Fuller Test
```

```
## alternative: stationary
```

```
##
```

```
## Type 1: no drift no trend
```

```
##      lag    ADF p.value
```

```
## [1,]  0 -11.48   0.01
```

```
## [2,]  1  -8.17   0.01
```

```
## [3,]  2  -6.96   0.01
```

```
## [4,]  3  -5.31   0.01
```

```
## [5,]  4  -5.79   0.01
```

```
## Type 2: with drift no trend
```

```
##      lag    ADF p.value
```

```
## [1,]  0 -11.49   0.01
```

```
## [2,]  1  -8.20   0.01
```

```
## [3,]  2  -6.99   0.01
```

```
## [4,]  3  -5.35   0.01
```

```
## [5,]  4  -5.86   0.01
```

```
## Type 3: with drift and trend
```

```
##      lag    ADF p.value
```

```
## [1,]  0 -11.57   0.01
```

```
## [2,]  1  -8.29   0.01
```

```
## [3,]  2  -7.11   0.01
```

```
## [4,]  3  -5.47   0.01
```

```
## [5,]  4  -6.06   0.01
```

```
## ----
```

```
## Note: in fact, p.value = 0.01 means p.value <= 0.01
```

```

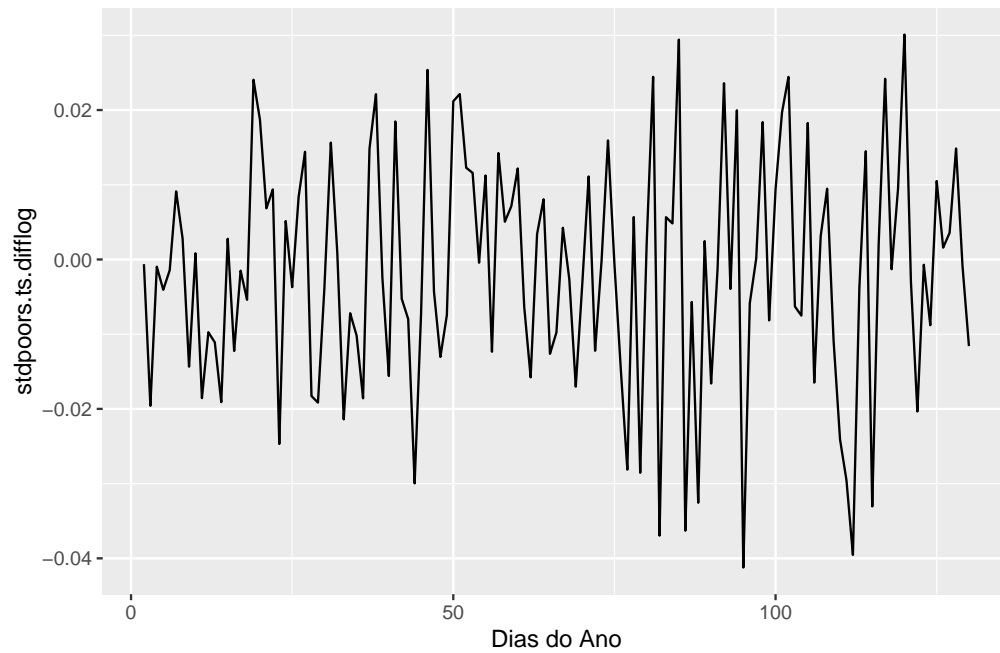
## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag      ADF p.value
## [1,]  0 -10.42    0.01
## [2,]  1  -8.24    0.01
## [3,]  2  -6.80    0.01
## [4,]  3  -5.20    0.01
## [5,]  4  -4.25    0.01
## Type 2: with drift no trend
##      lag      ADF p.value
## [1,]  0 -10.40    0.01
## [2,]  1  -8.22    0.01
## [3,]  2  -6.79    0.01
## [4,]  3  -5.20    0.01
## [5,]  4  -4.24    0.01
## Type 3: with drift and trend
##      lag      ADF p.value
## [1,]  0 -10.75    0.01
## [2,]  1  -8.68    0.01
## [3,]  2  -7.40    0.01
## [4,]  3  -5.80    0.01
## [5,]  4  -4.78    0.01
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##      lag      ADF p.value
## [1,]  0 -13.74    0.01
## [2,]  1  -9.00    0.01
## [3,]  2  -6.90    0.01
## [4,]  3  -6.10    0.01
## [5,]  4  -5.65    0.01
## Type 2: with drift no trend
##      lag      ADF p.value
## [1,]  0 -13.92    0.01
## [2,]  1  -9.17    0.01
## [3,]  2  -7.07    0.01
## [4,]  3  -6.26    0.01
## [5,]  4  -5.83    0.01
## Type 3: with drift and trend
##      lag      ADF p.value
## [1,]  0 -13.94    0.01
## [2,]  1  -9.21    0.01
## [3,]  2  -7.12    0.01
## [4,]  3  -6.34    0.01
## [5,]  4  -5.92    0.01
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

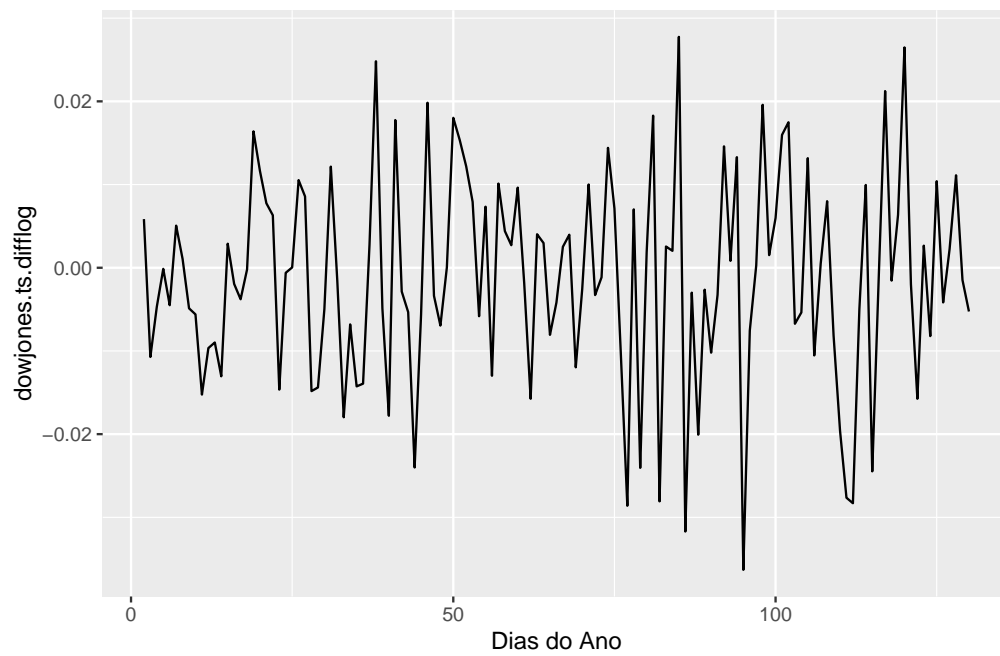
```

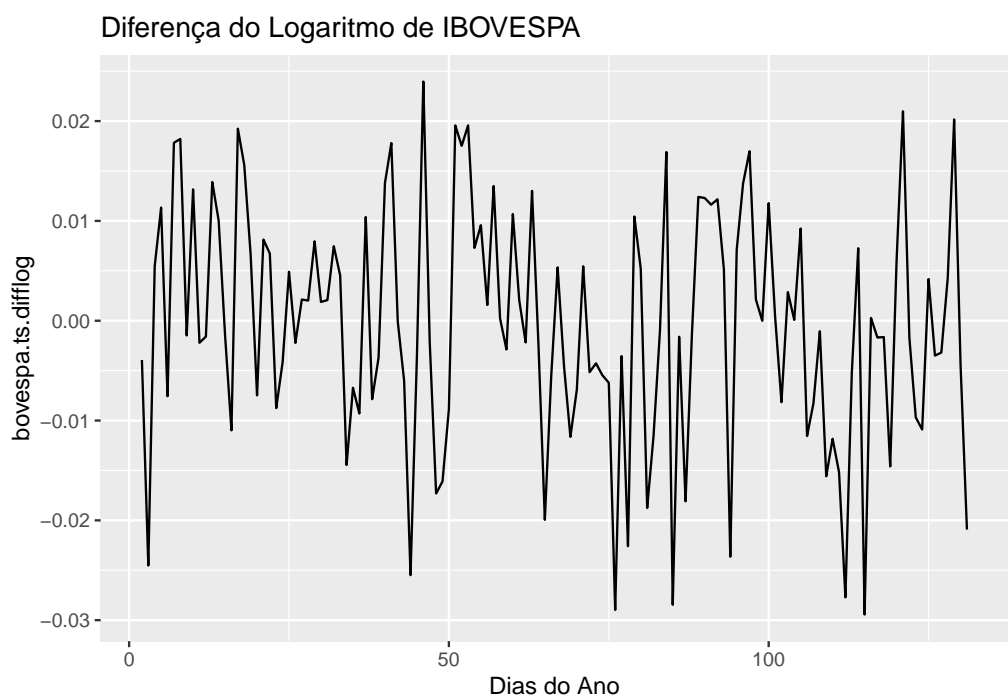
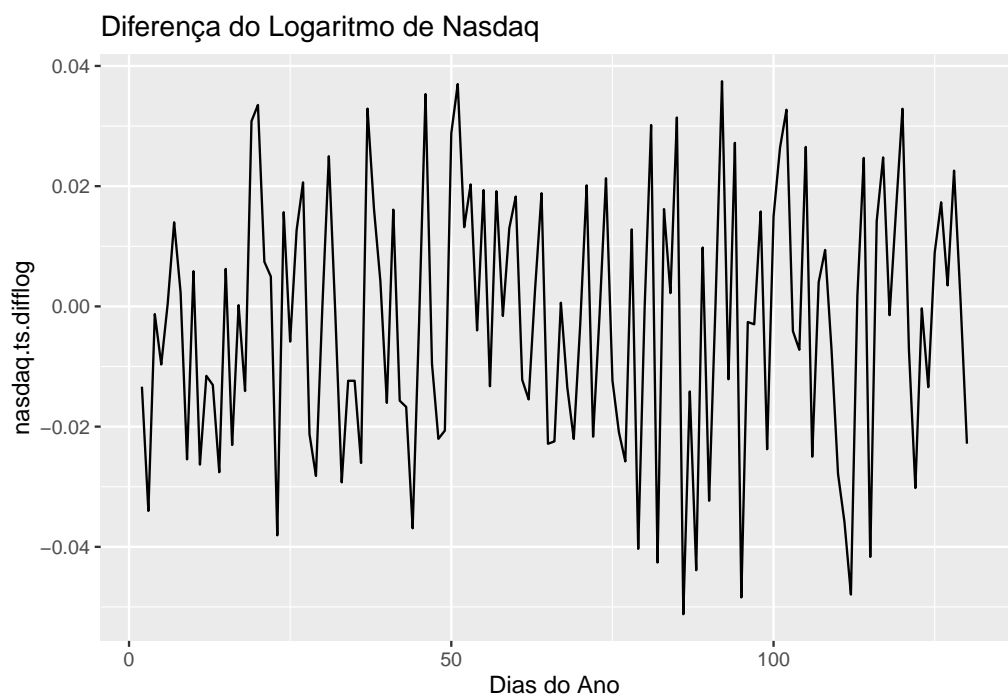
Assim, com os resultados do teste ADF, podemos então realizar o plot das séries da diferença do logaritmo.

Diferença do Logaritmo de S&P500

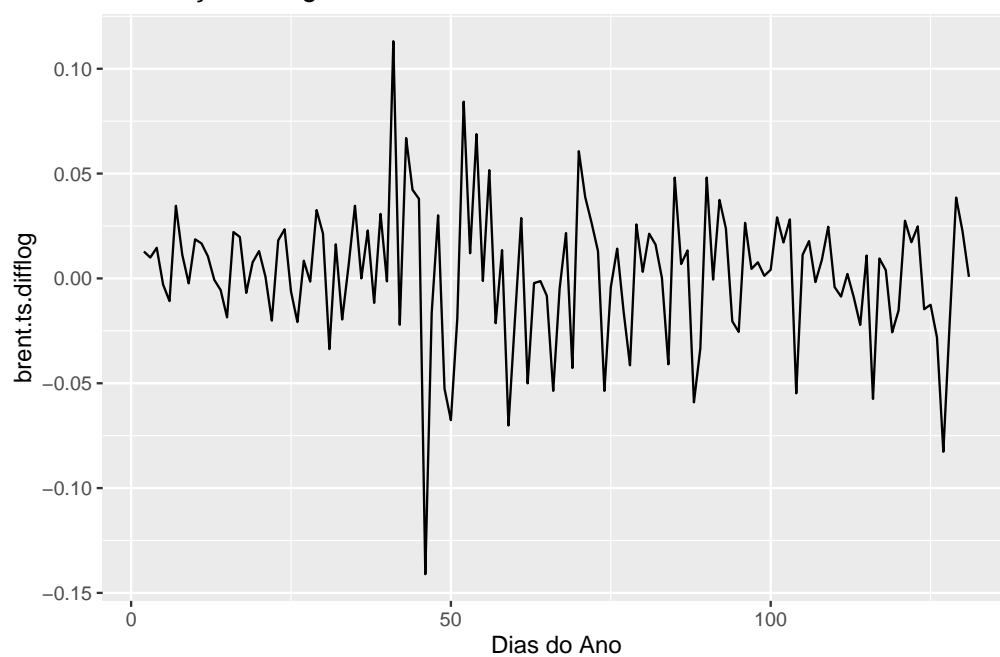


Diferença do Logaritmo de Dow Jones

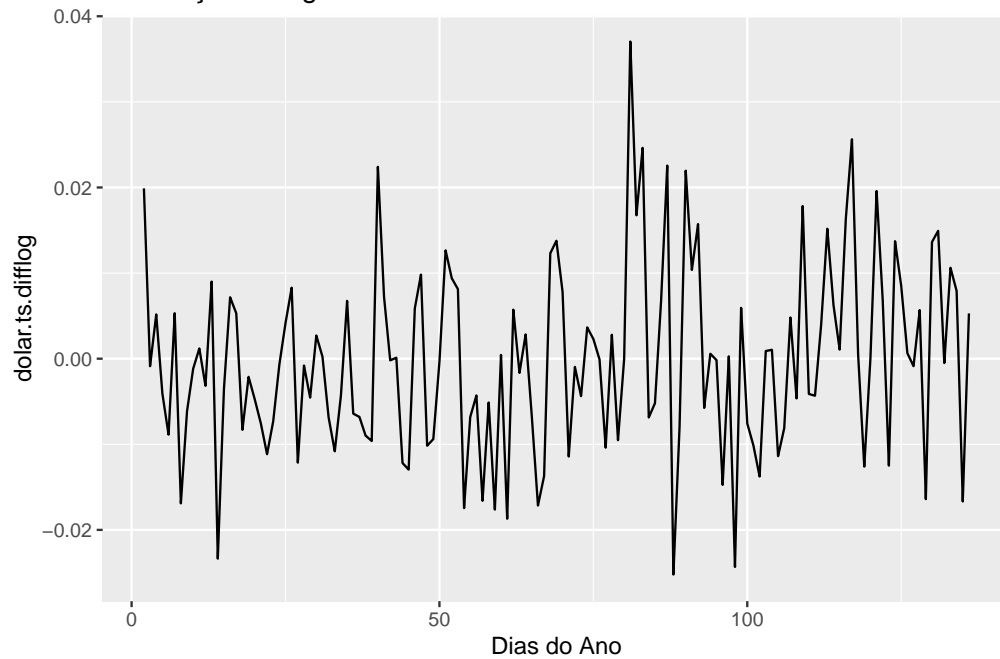


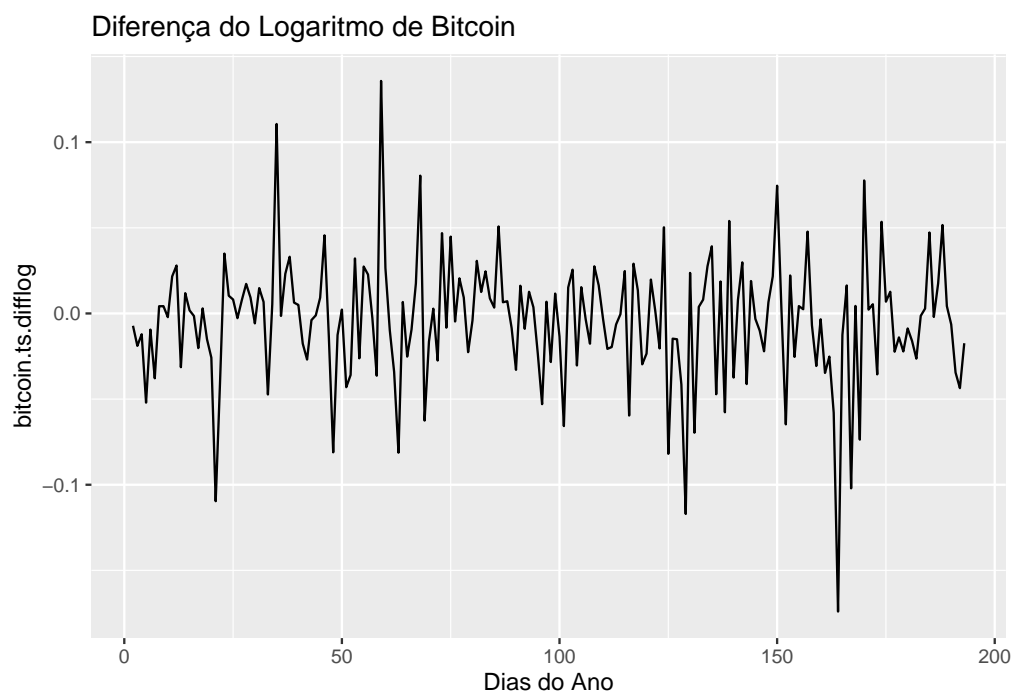


Diferença do Logaritmo de Petróleo Brent



Diferença do Logaritmo de Dólar

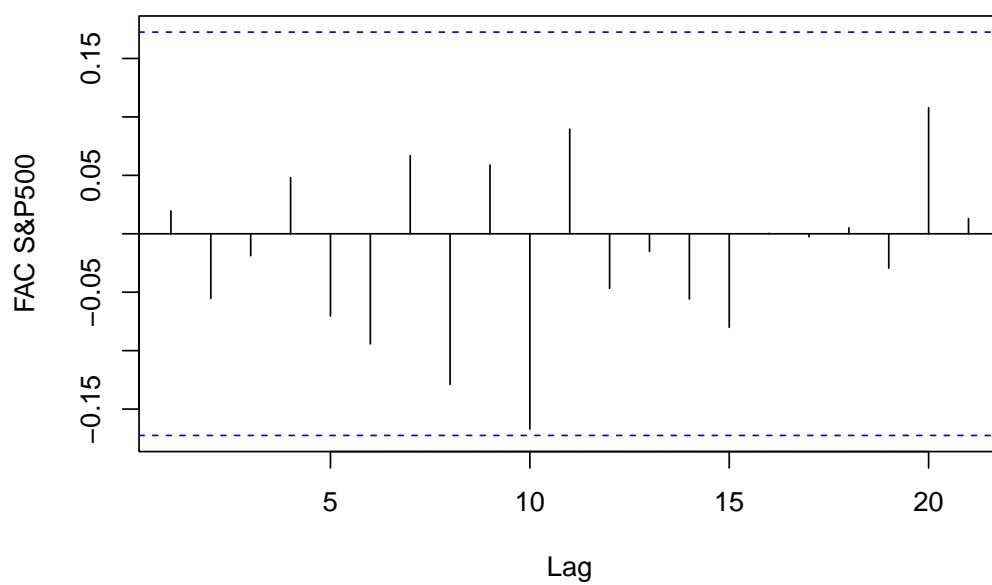




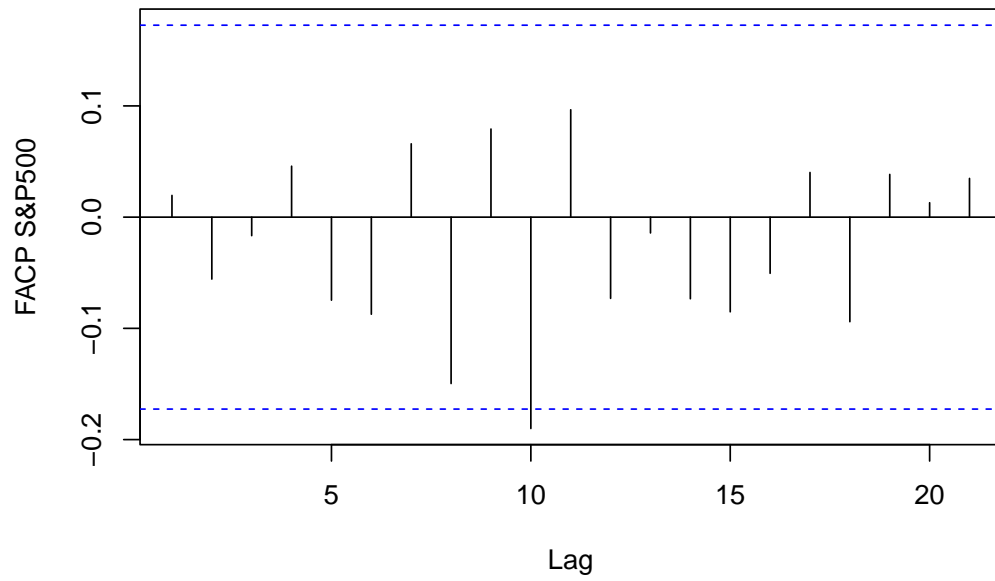
Correlogramas

Feitos os plots das diferenças dos logaritmos, podemos, então, construir o correlograma da série da diferença do logaritmo de cada uma das séries criadas.

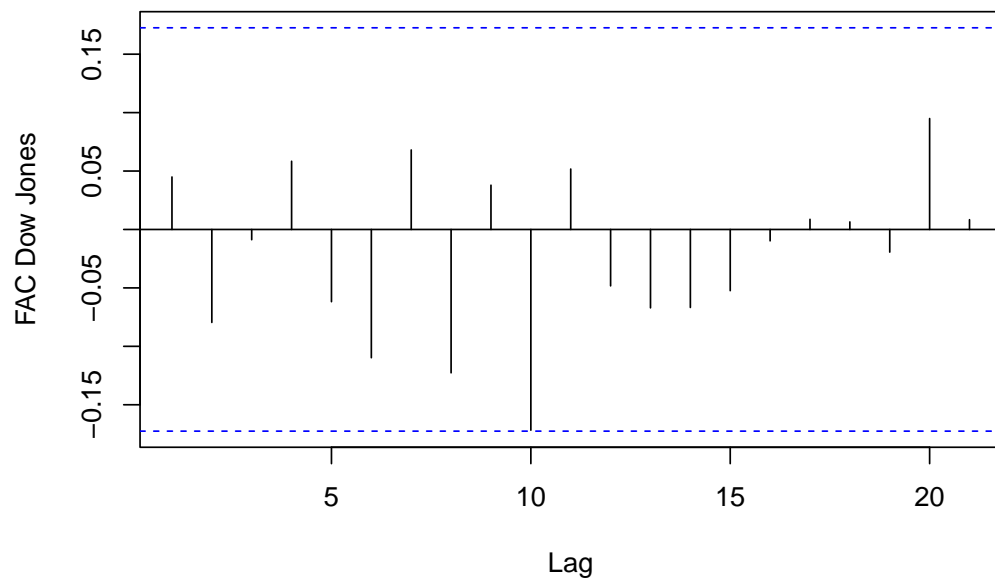
stdpoors.ts.difflog



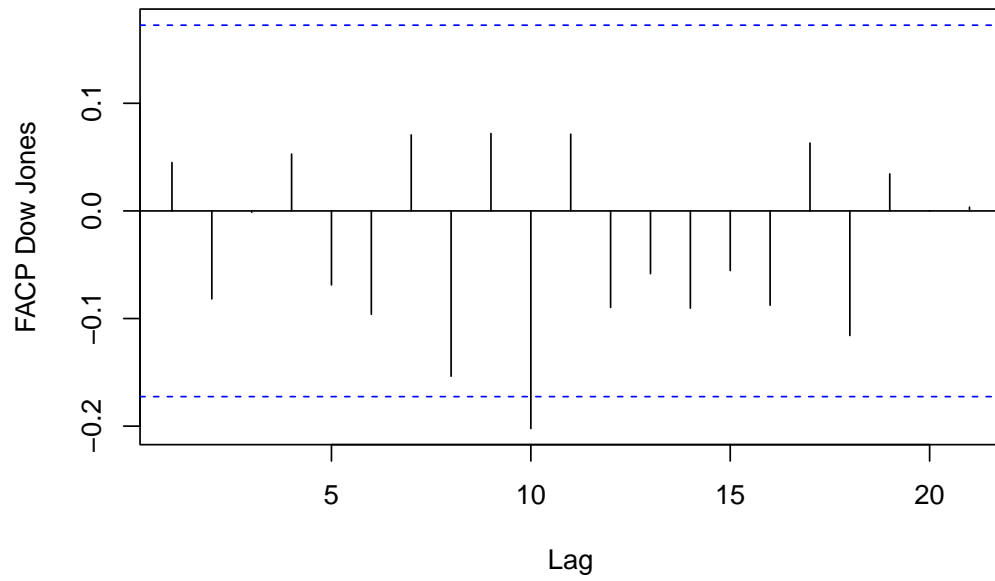
Series stdpoors.ts.difflog



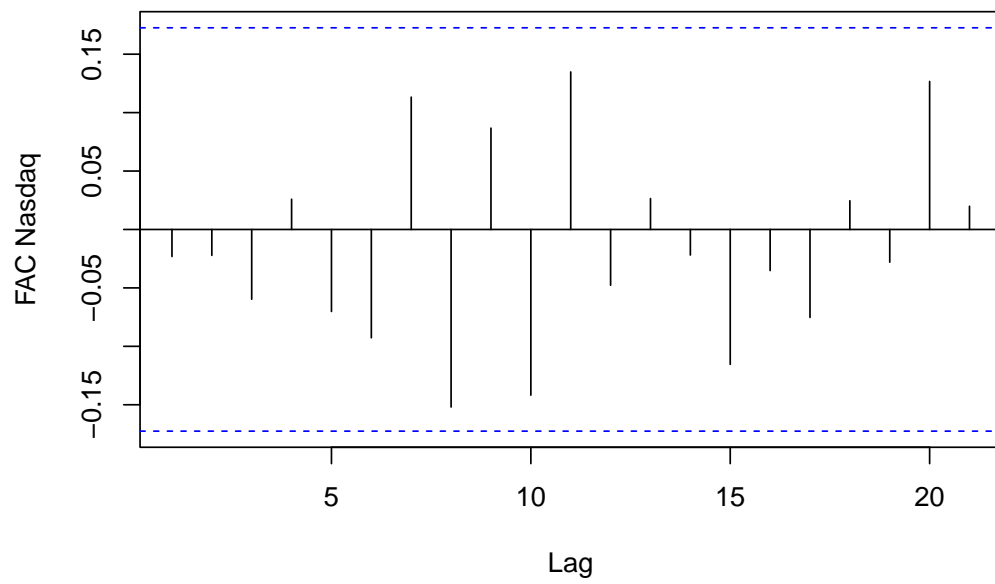
dowjones.ts.difflog



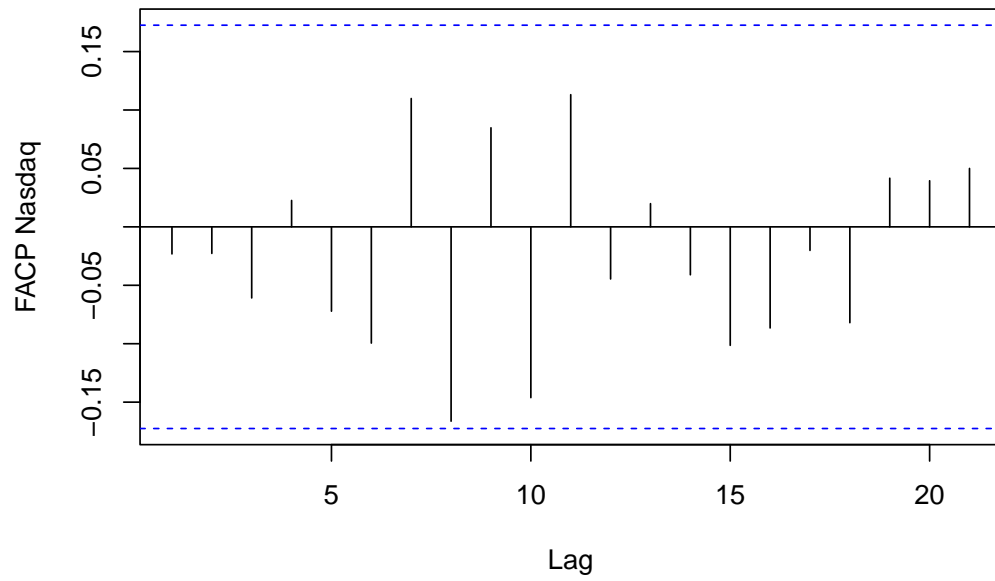
Series dowjones.ts.difflog



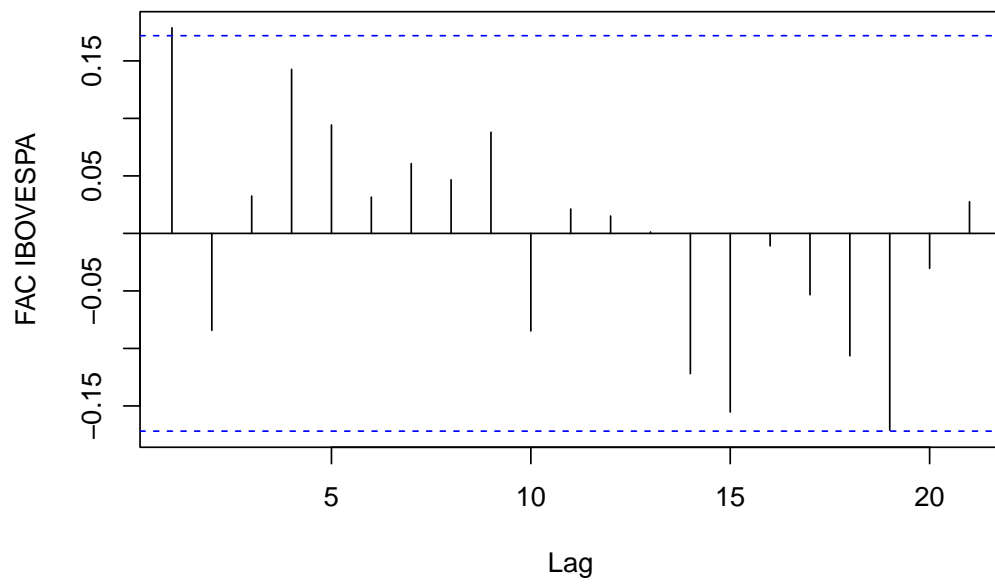
nasdaq.ts.difflog



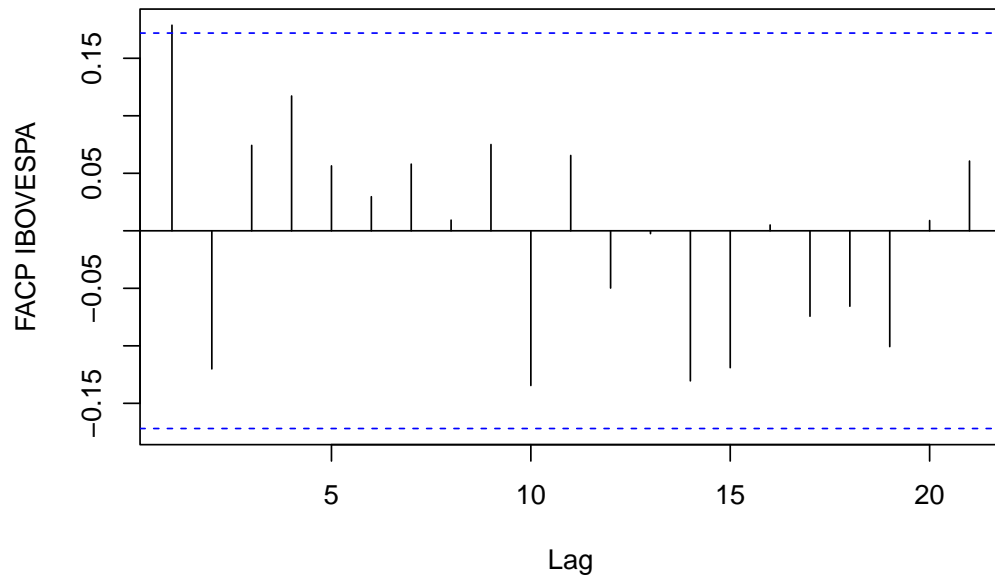
Series nasdaq.ts.difflog



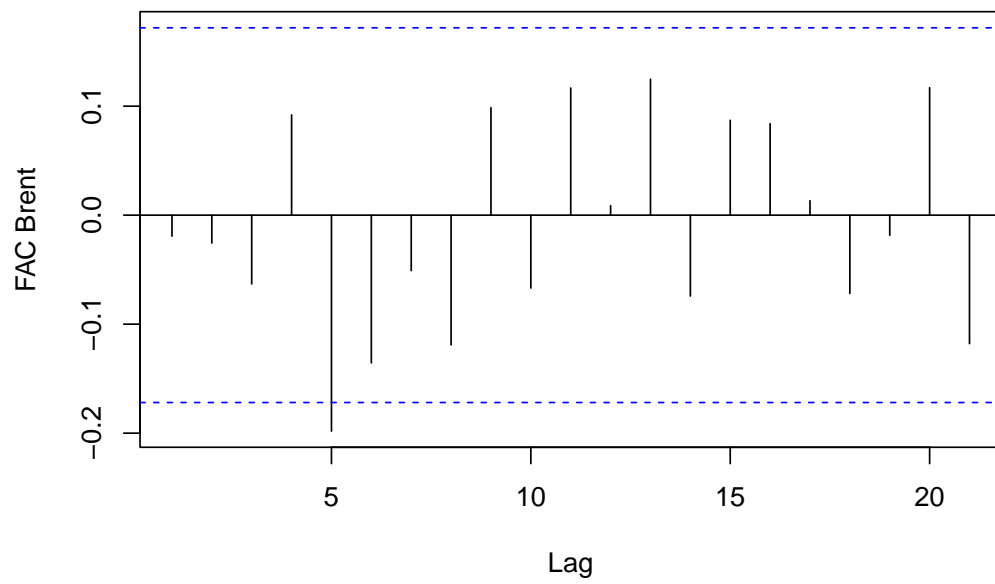
bovespa.ts.difflog



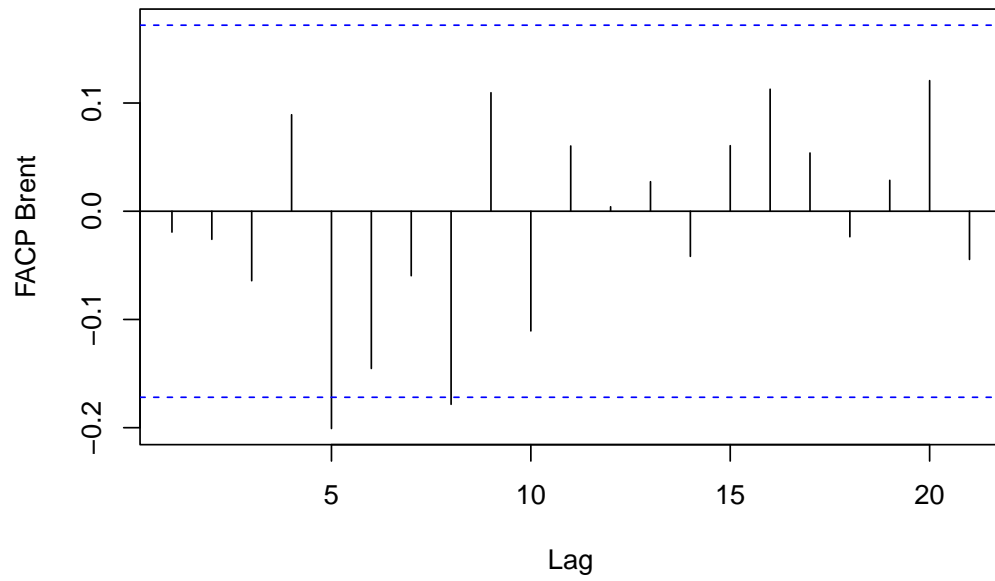
Series bovespa.ts.difflog



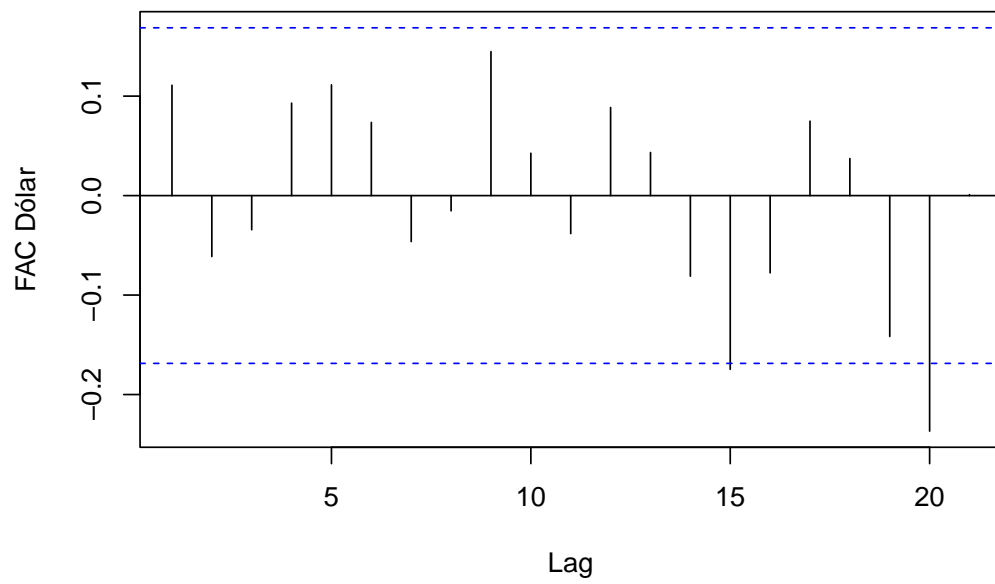
brent.ts.difflog



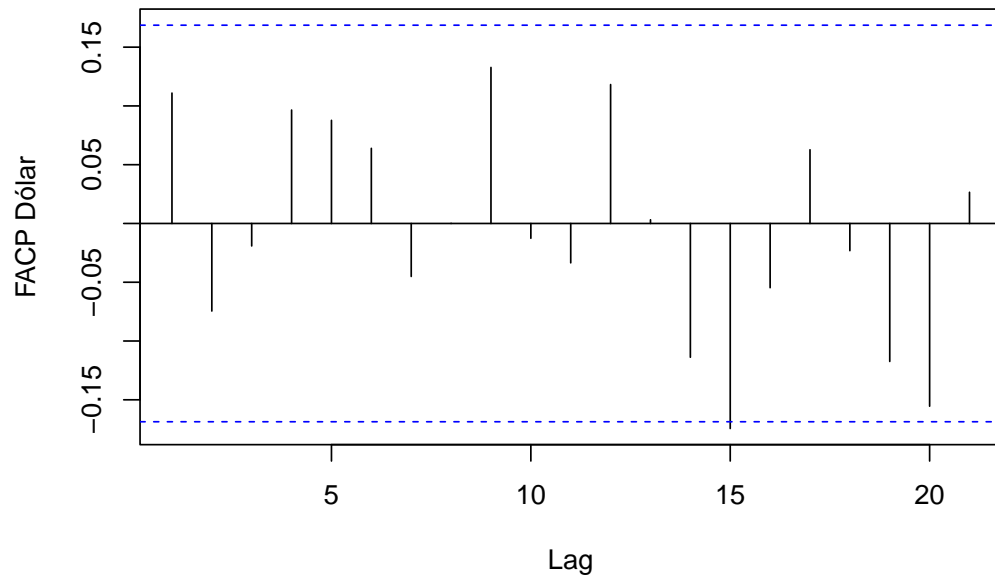
Series brent.ts.difflog



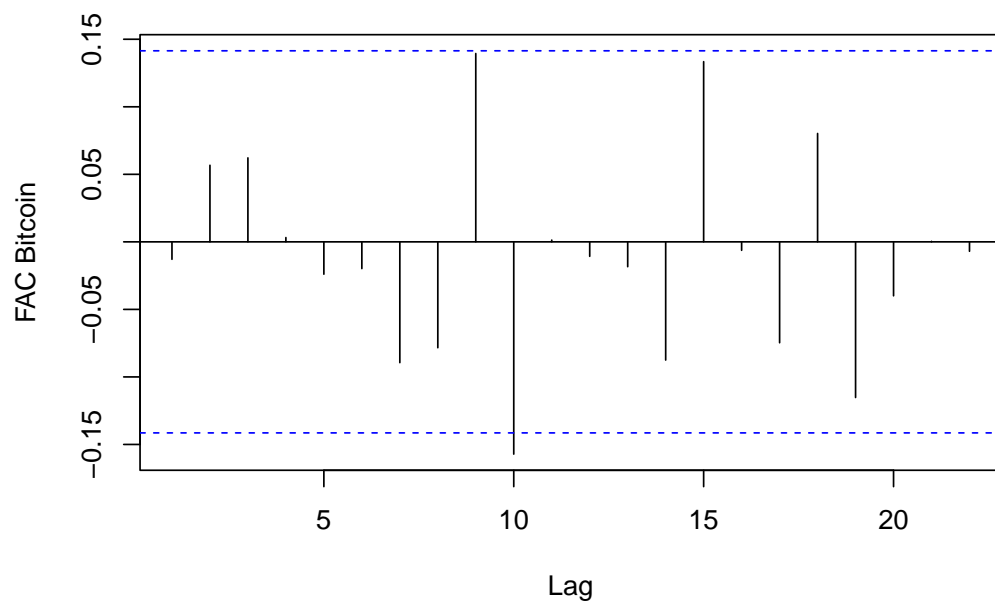
dolar.ts.difflog



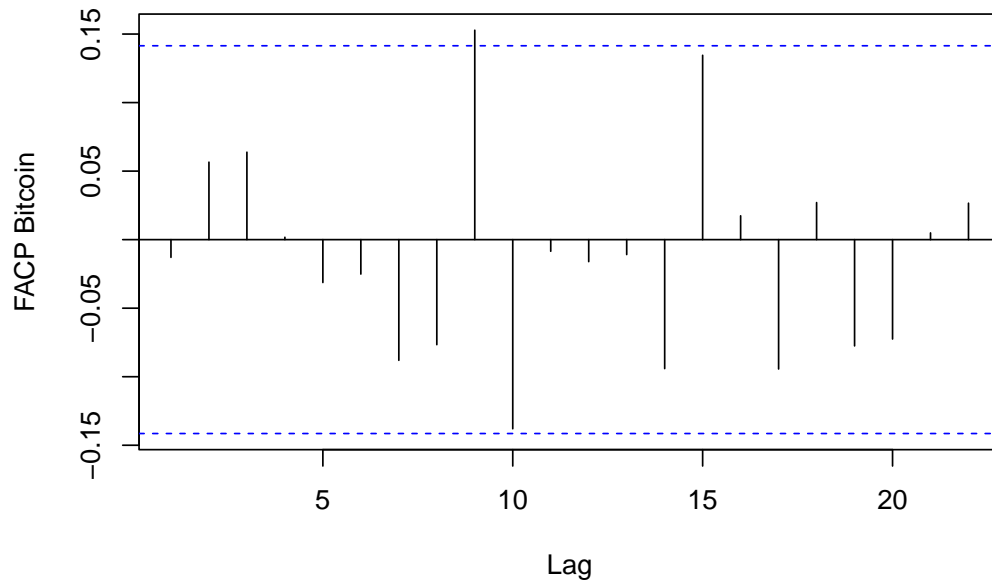
Series dolar.ts.difflog



bitcoin.ts.difflog



Series bitcoin.ts.difflog



Assim, observando-se os correlogramas gerados, pode ser extrapolado o melhor modelo para cada uma das séries analisadas. Dessa forma, temos que:

- S&P500: FAC e FACP ambas declinantes. Consideramos ARMA(1,1).
- Dow Jones: FAC e FACP declinantes. Consideramos ARMA(1,1) a ARMA(2,2), com as combinações intermediárias.
- Nasdaq: FAC e FACP declinantes. Consideramos ARMA(3,3).
- IBOVESPA: FAC e FACP declinantes. Consideramos de ARMA(1,1) a ARMA(2,2), com as combinações intermediárias.
- Brent: FAC e FACP declinantes. Consideramos de ARMA(1, 1) a ARMA(3,3), com as combinações intermediárias.
- Dólar: FAC e FACP declinantes. Consideramos ARMA(1,1).
- Bitcoin: FAC e FACP declinantes. Consideramos ARMA(1,1).

Portanto, podemos então estimar os diferentes modelos ARMA para cada uma das séries analisadas, e verificar a significância dos coeficientes de cada um. Ademais, podem ser feitos os testes e plotados o gráfico do teste de Ljung-Box, para analisar os resíduos de cada modelo.

p-valores

S&P500

```
##               ar1               ma1       intercept
## ar1          0.0003214643 -0.0004325517    0.1405391
## ma1          -0.0004325517  0.0086887481   -0.3388139
## intercept    0.1405391064 -0.3388138600 51763.4659118

## intercept
##           0

## ar1
##    0
```

```
##          ma1
## 0.3062257
```

Analisando os p-valores, nota-se que o referente ao índice 1 do modelo MA é superior a 5%. Assim, consideramos um modelo AR(1) para a série S&P500.

Dow Jones

```
##          ar1          ar2          ma1          ma2          intercept
## ar1      0.006816261 -0.005682737 -0.006886562 -0.004745388 -2.157770e-02
## ar2     -0.005682737  0.005966680  0.005548731  0.003539411 -2.967382e-01
## ma1     -0.006886562  0.005548731  0.014552679  0.012031417 -1.312437e+00
## ma2     -0.004745388  0.003539411  0.012031417  0.010793724 -1.261882e+00
## intercept -0.021577705 -0.296738185 -1.312437365 -1.261882091  1.424433e+06

## intercept
##          0

##          ma1
## 4.731771e-13

##          ma2
## 0.4875158

##          ar1
## 0.06735131

## ar2
##          0
```

Analisando os p-valores, nota-se que os referentes aos índice 2 do modelo MA e ao índice 1 do modelo AR são os únicos superiores a 5%. Portanto, consideramos um modelo MA(1) para a série Dow Jones.

Nasdaq

```
## intercept
##          0

## ma1
##          0

##          ma2
## 2.228117e-06

##          ma3
## 0.5036498

## ar1
##          1

## ar2
##          0

## ar3
##          0
```

Analisando os p-valores, nota-se que os referentes ao índice 3 do modelo MA e ao índice 1 do modelo AR são superiores a 5%. Logo, o modelo considerado para a série Nasdaq é um MA(2).

IBOVESPA

```
## intercept
##      0

##      ma1
## 0.3784477

##      ma2
## 0.6562594

##      ar1
## 0.06152252

##      ar2
## 0.5167551
```

Analisando os p-valores, temos que o modelo para a série referente a IBOVESPA é um ARMA(2,2).

Petróleo Brent

```
## intercept
##      0

##      ma1
## 2.054157e-11

##      ma2
## 0.000851899

##      ma3
## 0.8553896

##      ar1
## 0.9154927

##      ar2
## 0.0001005846

##      ar3
## 2.775853e-05
```

Analisando os p-valores, temos que o modelo para a série referente ao petróleo Brent é um MA(2).

Dólar

```
##              ar1              ma1      intercept
## ar1      0.0002650200 -0.0003571131  0.001098815
## ma1      -0.0003571131  0.0084961123 -0.001586646
## intercept 0.0010988148 -0.0015866461  0.040712878

## intercept
##      0

## ar1
##      0

##      ma1
## 0.07977517
```

Analisando os p-valores, temos que o modelo para a série referente ao Dólar é um AR(1).

Bitcoin

```
##               ar1               ma1      intercept
## ar1          5.652753e-05 -9.027666e-05 -7.924534e+00
## ma1          -9.027666e-05  5.067298e-03  9.694560e+00
## intercept    -7.924534e+00  9.694560e+00  7.718165e+07

##      intercept
## 6.809819e-05

##      ar1
##      0

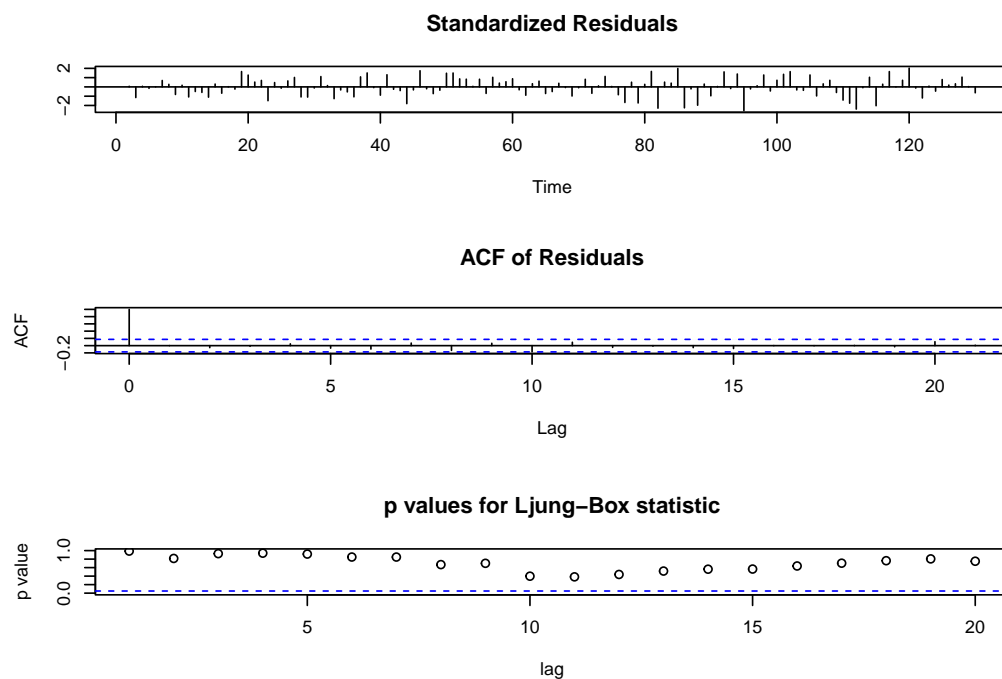
##      ma1
## 0.4097981
```

Analisando os p-valores, temos que o modelo para a série referente ao Bitcoin é um AR(1).

Teste de Ljung-Box

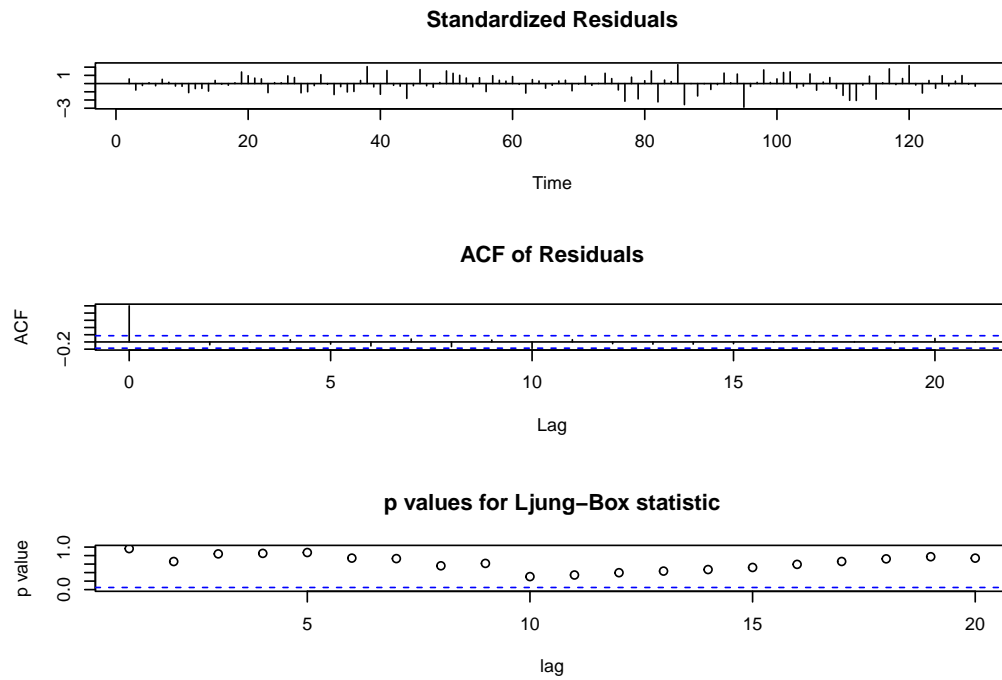
Assim, podemos então plotar os gráficos referentes ao teste de Ljung-Box.

S&P 500



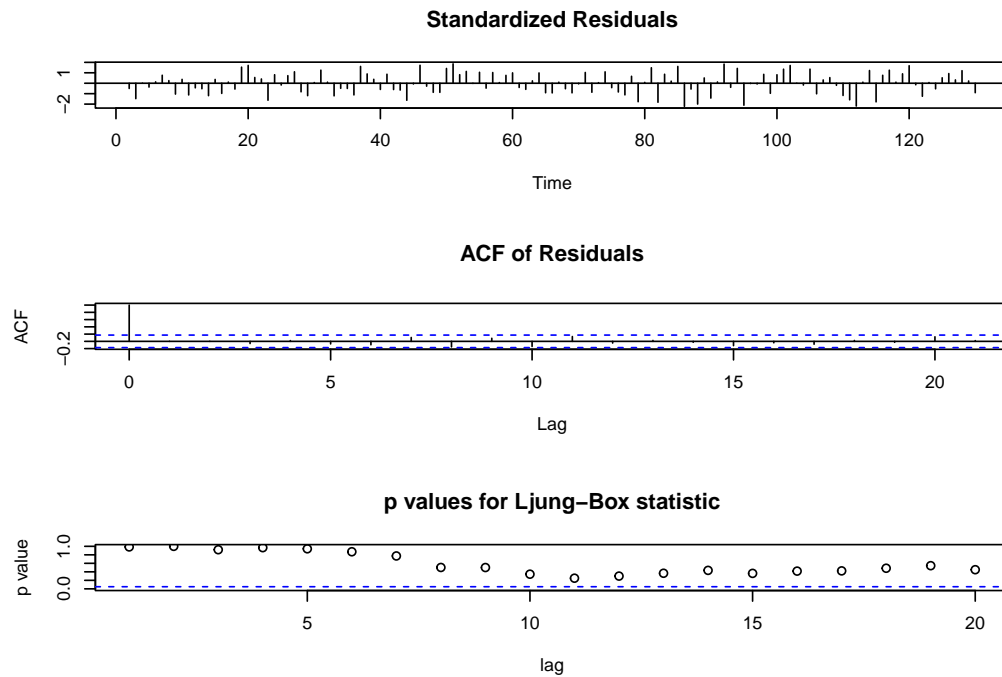
```
##
## Box-Ljung test
##
## data:  rstandard(modelo.arma)
## X-squared = 15.45, df = 20, p-value = 0.7501
```

Dow Jones



```
##  
## Box-Ljung test  
##  
## data: rstandard(modelo.arma)  
## X-squared = 15.62, df = 20, p-value = 0.7399
```

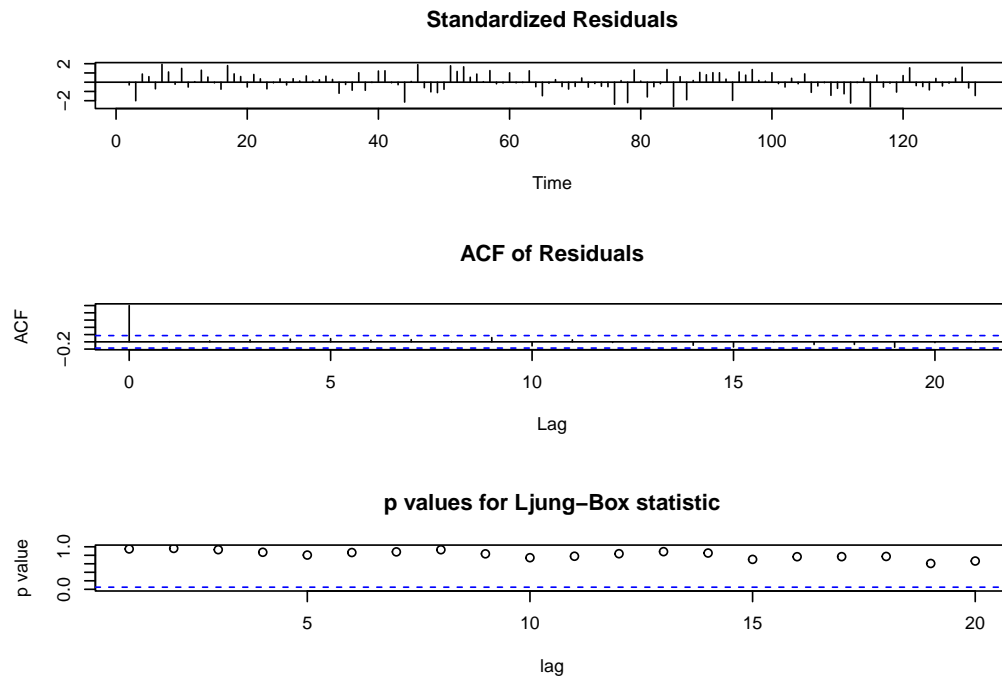
Nasdaq



```
##
```

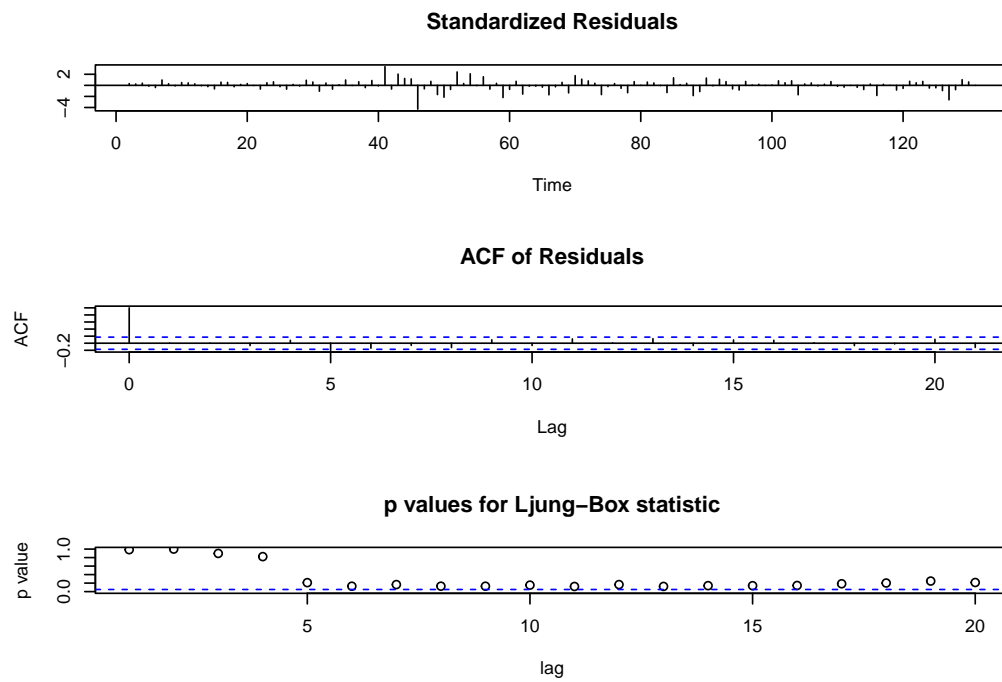
```
## Box-Ljung test
##
## data:  rstandard(modelo.arma)
## X-squared = 20.125, df = 20, p-value = 0.4501
```

IBOVESPA



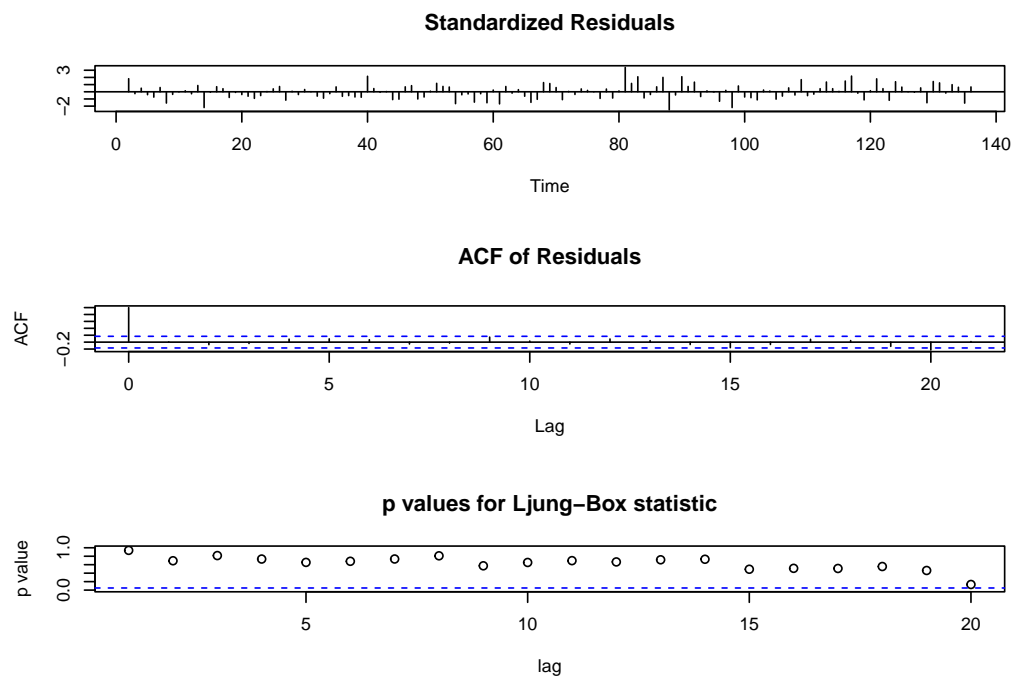
```
##
## Box-Ljung test
##
## data:  rstandard(modelo.arma)
## X-squared = 16.819, df = 20, p-value = 0.6647
```

Petróleo Brent



```
##  
## Box-Ljung test  
##  
## data: rstandard(modelo.arma)  
## X-squared = 24.671, df = 20, p-value = 0.2143
```

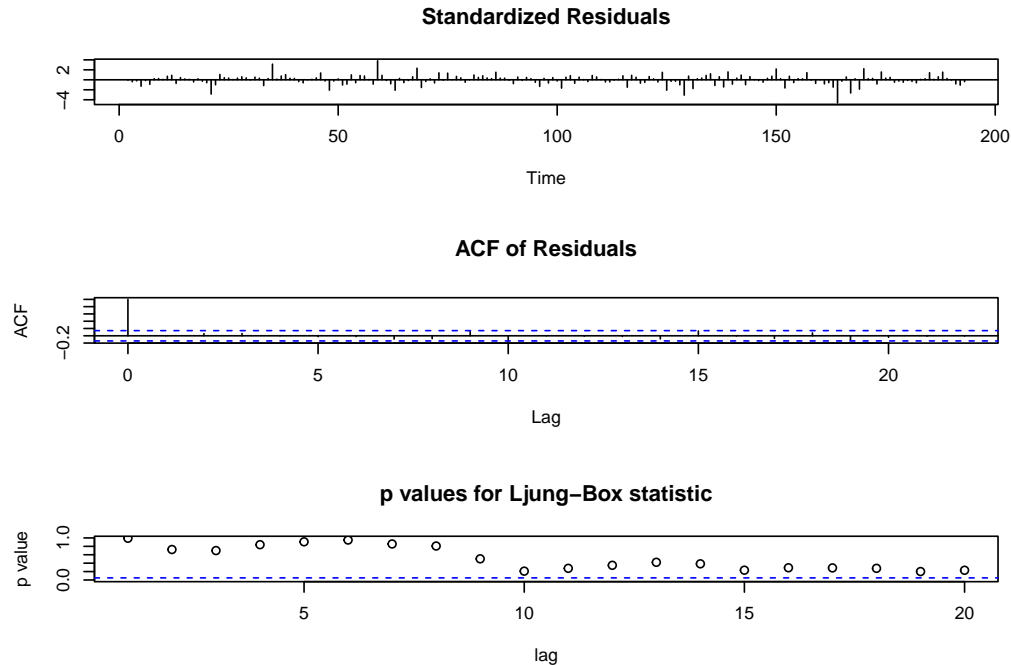
Dólar



```
##  
## Box-Ljung test
```

```
##
## data:  rstandard(modelo.arma)
## X-squared = 27.099, df = 20, p-value = 0.1325
```

Bitcoin



```
##
## Box-Ljung test
##
## data:  rstandard(modelo.arma)
## X-squared = 24.258, df = 20, p-value = 0.2313
```

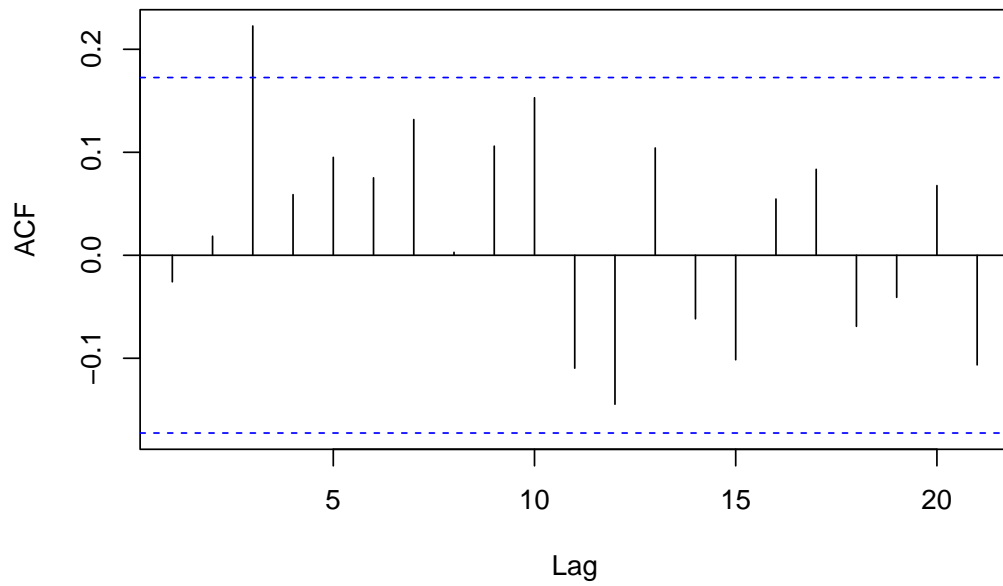
Portanto, analisando-se os gráficos gerados acima, constata-se que todos os modelos supercedem o requisito dos p-valores serem superiores a 5% e, portanto, são adequados para serem utilizados.

Ademais, temos que os resultados dos testes adicionais realizados nos dizem para não rejeitarmos a Hipótese Nula de que todas as funções de autocorrelação até 20 são zero, para todas as séries analisadas.

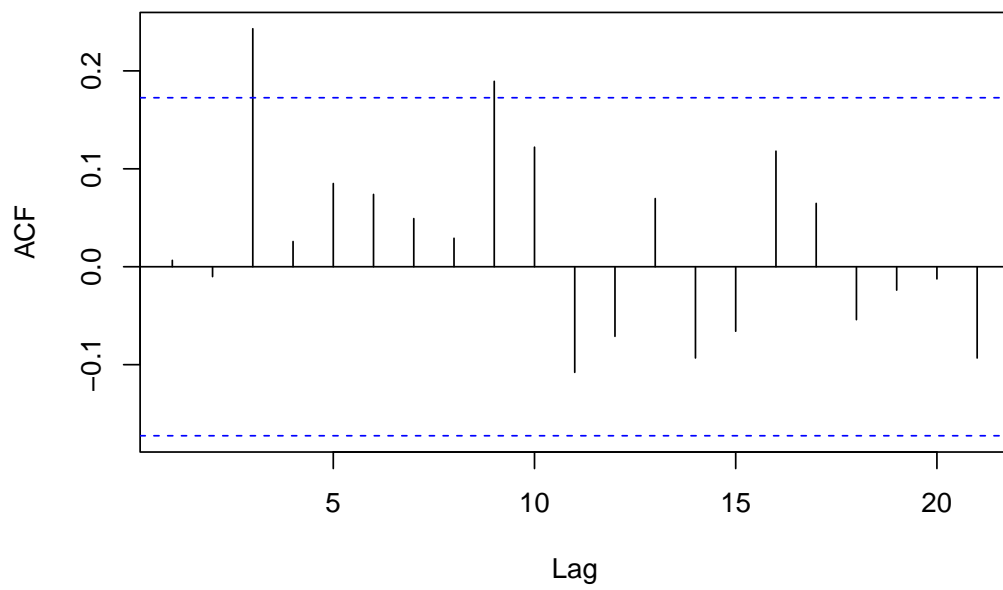
Correlograma dos Resíduos ao Quadrado

Portanto, temos o correlograma dos resíduos ao quadrado para cada uma das séries analisadas.

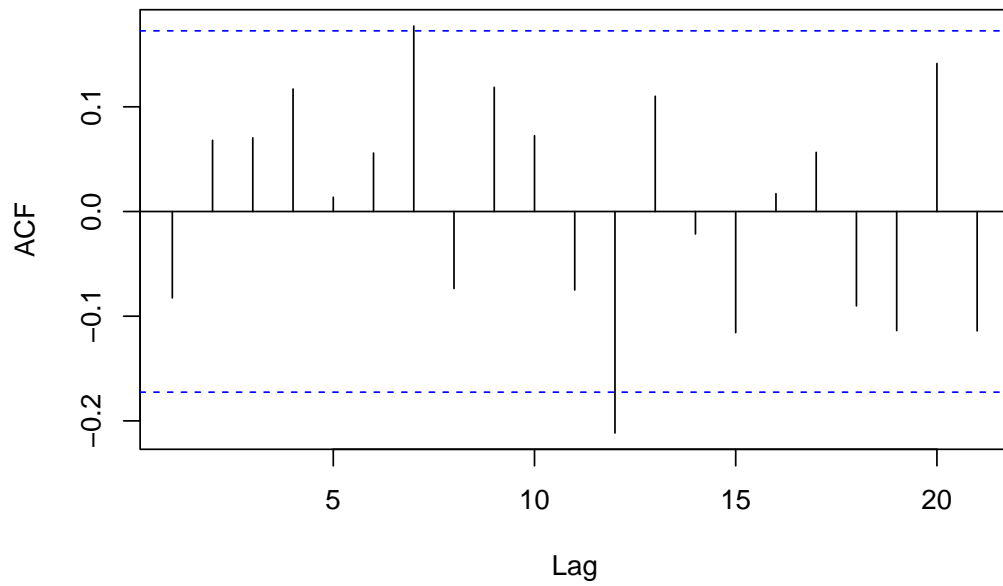
Correlograma dos Resíduos ao Quadrado (S&P500)



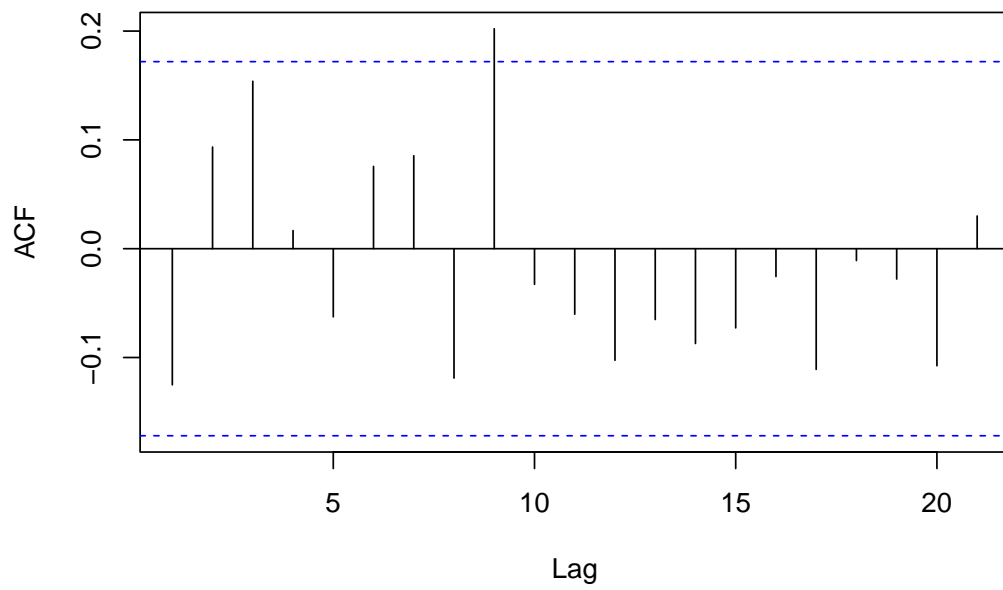
Correlograma dos Resíduos ao Quadrado (Dow Jones)



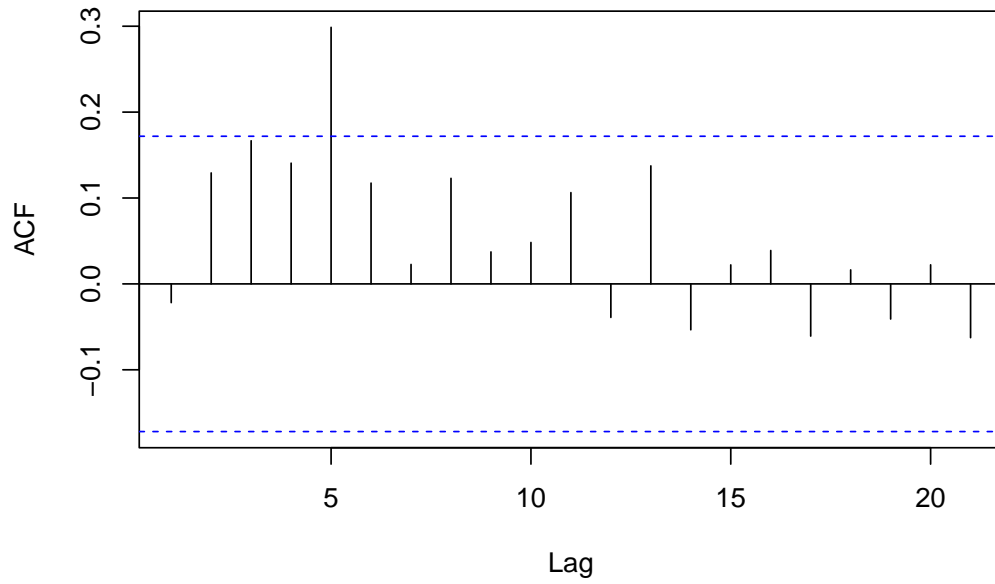
Correlograma dos Resíduos ao Quadrado (Nasdaq)



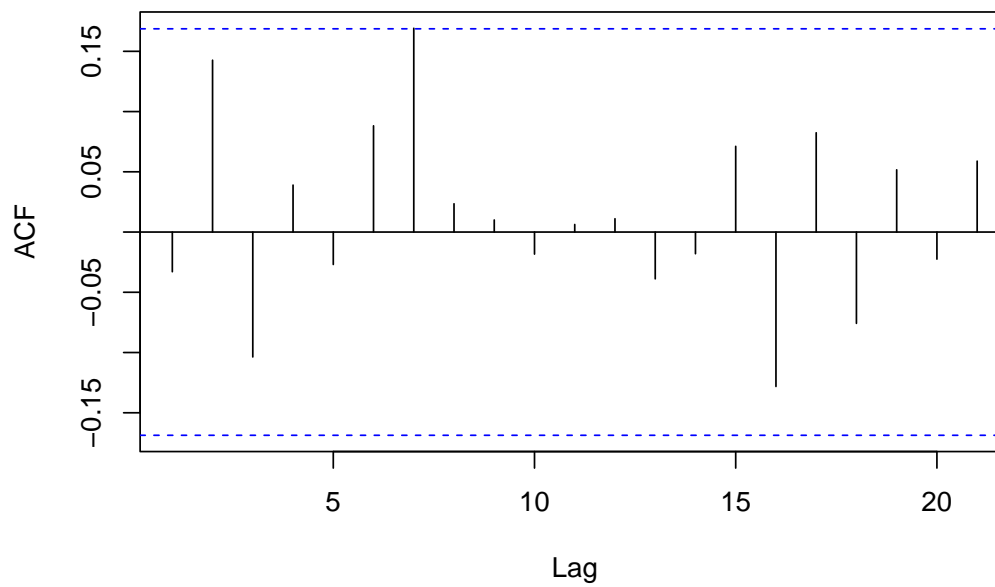
Correlograma dos Resíduos ao Quadrado (IBOVESPA)

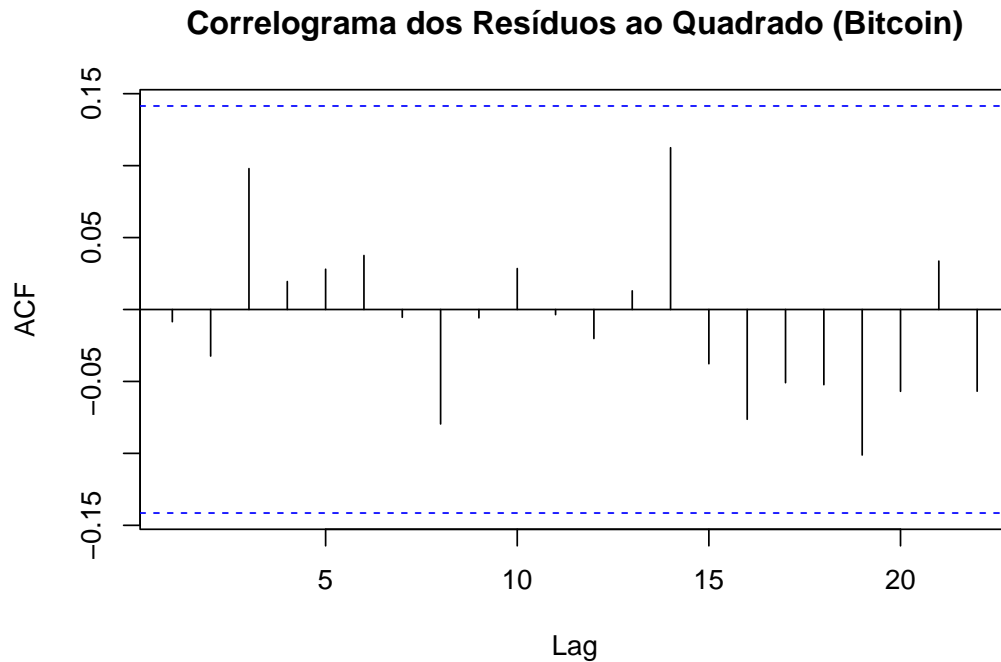


Correlograma dos Resíduos ao Quadrado (Petróleo Brent)



Correlograma dos Resíduos ao Quadrado (Dólar)





Portanto, podem ser utilizados os correlogramas gerados para auxiliar na escolha dos modelos ARCH/GARCH que será feita a seguir.

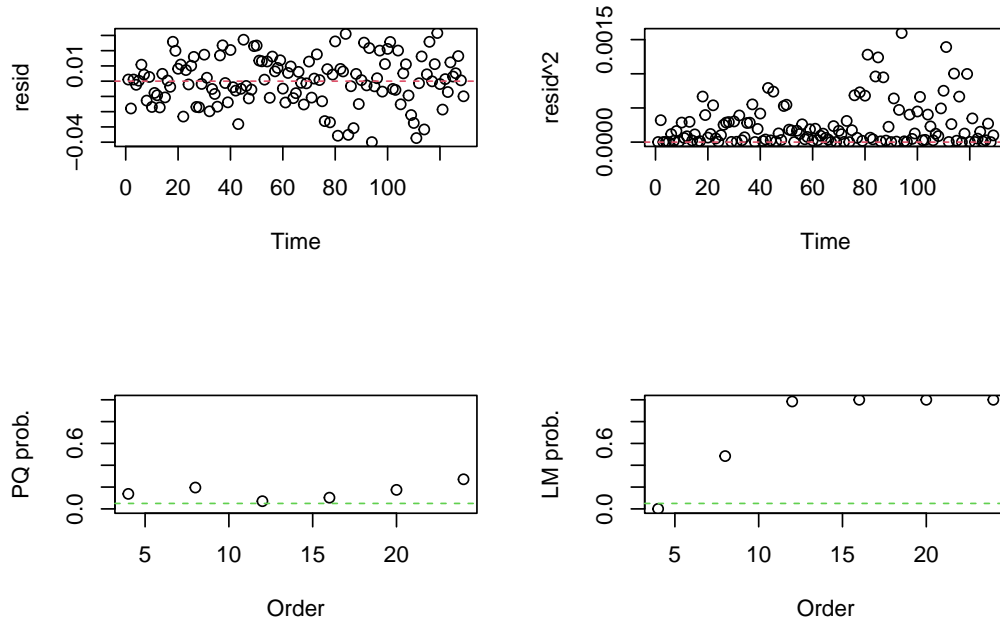
Teste de Efeitos ARCH e Escolha do Processo

Para tal, usaremos as funções fornecidas nas bibliotecas do R. Temos os seguintes resultados para cada uma das séries temporais estudadas:

S&P500

```
##
##  ARCH LM-test; Null hypothesis: no ARCH effects
##
## data:  sqresidual
## Chi-squared = 6.7513, df = 6, p-value = 0.3445
## ARCH heteroscedasticity test for residuals
## alternative: heteroscedastic
##
## Portmanteau-Q test:
##      order    PQ p.value
## [1,]     4   6.97  0.1375
## [2,]     8  11.11  0.1956
## [3,]    12  19.82  0.0705
## [4,]    16  23.43  0.1028
## [5,]    20  25.75  0.1743
## [6,]    24  27.73  0.2715
## Lagrange-Multiplier test:
##      order    LM p.value
## [1,]     4 17.303 0.000612
## [2,]     8   6.487 0.484134
## [3,]    12   3.395 0.984402
## [4,]    16   1.606 0.999993
```

```
## [5,]    20  1.031 1.000000
## [6,]    24  0.634 1.000000
```



```
##
## Box-Ljung test
##
## data: y^2
## X-squared = 571.32, df = 6, p-value < 2.2e-16
## alternative hypothesis: y is heteroscedastic
```

Do primeiro teste, temos um p-valor superior a 5%, portanto, não rejeitamos que haja efeito ARCH. Do segundo teste, temos que há valores superiores a 5%, então, rejeitamos que haja heterocedasticidade no modelo. Do terceiro teste, temos que o p-valor é inferior a 5%, então não rejeitamos a hipótese de que a série seja heterocedástica.

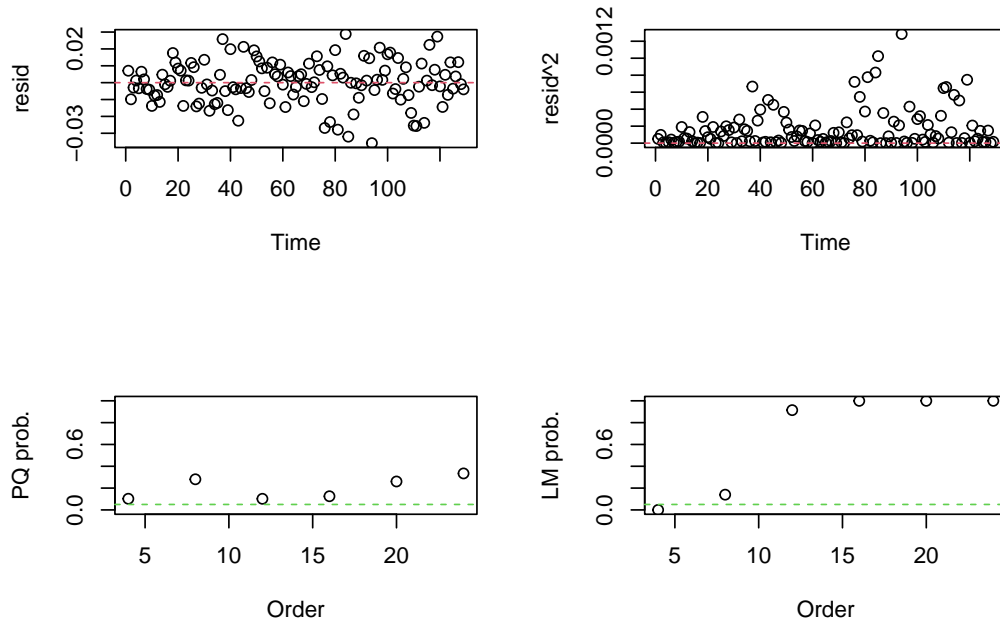
Assim, tomamos um modelo GARCH para representar a série.

Dow Jones

```
##
## ARCH LM-test; Null hypothesis: no ARCH effects
##
## data: sqresidual
## Chi-squared = 3.6166, df = 6, p-value = 0.7284

## ARCH heteroscedasticity test for residuals
## alternative: heteroscedastic
##
## Portmanteau-Q test:
##      order    PQ p.value
## [1,]     4   7.72  0.102
## [2,]     8   9.78  0.281
## [3,]    12  18.48  0.102
## [4,]    16  22.58  0.125
## [5,]    20  23.59  0.261
## [6,]    24  26.38  0.334
```

```
## Lagrange-Multiplier test:
##      order    LM  p.value
## [1,]     4 26.29 8.29e-06
## [2,]     8 10.98 1.40e-01
## [3,]    12  5.32 9.15e-01
## [4,]    16  2.94 1.00e+00
## [5,]    20  1.74 1.00e+00
## [6,]    24  1.16 1.00e+00
```



```
##
## Box-Ljung test
##
## data: y^2
## X-squared = 545.94, df = 6, p-value < 2.2e-16
## alternative hypothesis: y is heteroscedastic
```

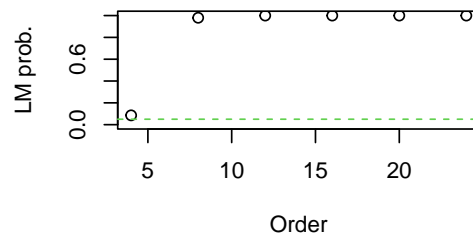
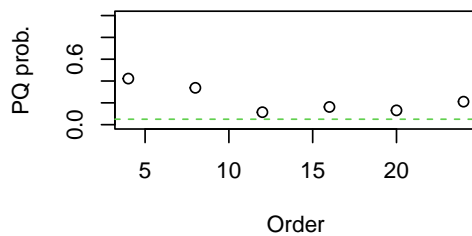
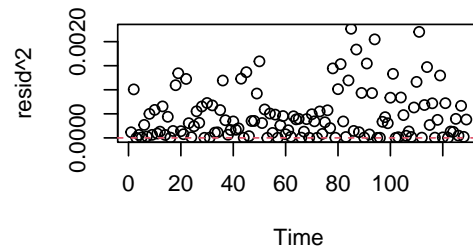
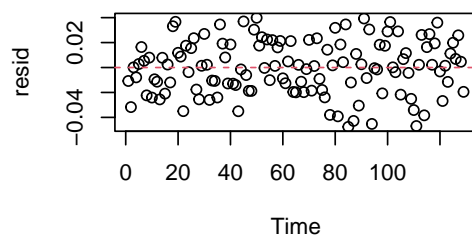
Do primeiro teste, temos um p-valor superior a 5%, portanto, não rejeitamos que haja efeito ARCH. Do segundo teste, temos que há valores superiores a 5%, então, rejeitamos que haja heterocedasticidade no modelo. Do terceiro teste, temos que o p-valor é inferior a 5%, então não rejeitamos a hipótese de que a série seja heterocedástica.

Assim, tomamos um modelo GARCH para representar a série.

Nasdaq

```
##
## ARCH LM-test; Null hypothesis: no ARCH effects
##
## data: sqresidual
## Chi-squared = 4.7651, df = 6, p-value = 0.5743
## ARCH heteroscedasticity test for residuals
## alternative: heteroscedastic
##
## Portmanteau-Q test:
##      order    PQ  p.value
```

```
## [1,]      4  3.88  0.422
## [2,]      8  9.06  0.338
## [3,]     12 18.05  0.114
## [4,]     16 21.44  0.162
## [5,]     20 27.15  0.131
## [6,]     24 29.25  0.211
## Lagrange-Multiplier test:
##      order      LM p.value
## [1,]      4  6.6124  0.0853
## [2,]      8  1.5667  0.9799
## [3,]     12  0.6612  1.0000
## [4,]     16 -0.0212  1.0000
## [5,]     20 -0.0856  1.0000
## [6,]     24 -0.1311  1.0000
```



```
##
## Box-Ljung test
##
## data:  y^2
## X-squared = 584.14, df = 6, p-value < 2.2e-16
## alternative hypothesis: y is heteroscedastic
```

Do primeiro teste, temos um p-valor superior a 5%, portanto, não rejeitamos que haja efeito ARCH. Do segundo teste, temos que há valores superiores a 5%, então, rejeitamos que haja heterocedasticidade no modelo. Do terceiro teste, temos que o p-valor é inferior a 5%, então não rejeitamos a hipótese de que a série seja heterocedástica.

Assim, tomamos um modelo ARCH para representar a série.

IBOVESPA

```
##
## ARCH LM-test; Null hypothesis: no ARCH effects
##
## data:  sqresidual
## Chi-squared = 6.215, df = 6, p-value = 0.3995
```

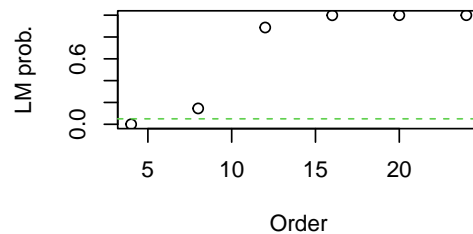
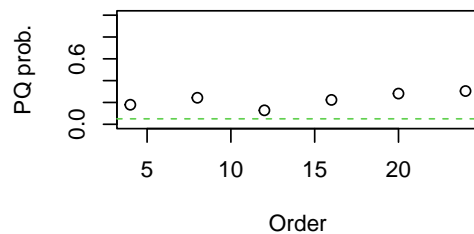
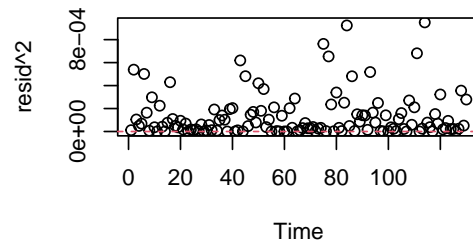
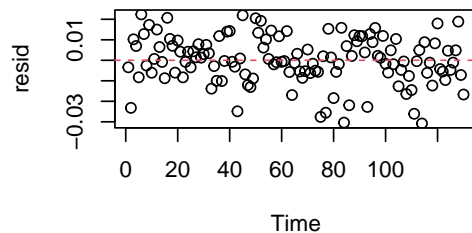
```
## ARCH heteroscedasticity test for residuals
## alternative: heteroscedastic
##
```

```
## Portmanteau-Q test:
```

	order	PQ	p.value
## [1,]	4	6.28	0.179
## [2,]	8	10.33	0.243
## [3,]	12	17.62	0.128
## [4,]	16	19.93	0.223
## [5,]	20	23.15	0.281
## [6,]	24	27.00	0.305

```
## Lagrange-Multiplier test:
```

	order	LM	p.value
## [1,]	4	25.40	1.27e-05
## [2,]	8	10.85	1.45e-01
## [3,]	12	5.79	8.87e-01
## [4,]	16	3.33	9.99e-01
## [5,]	20	2.39	1.00e+00
## [6,]	24	1.37	1.00e+00



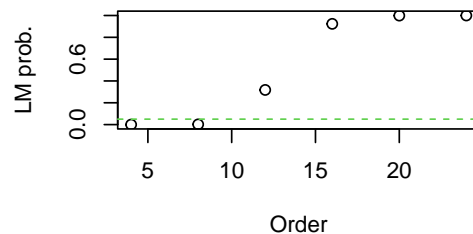
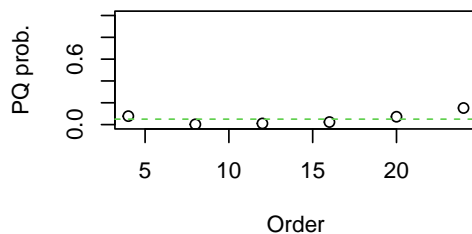
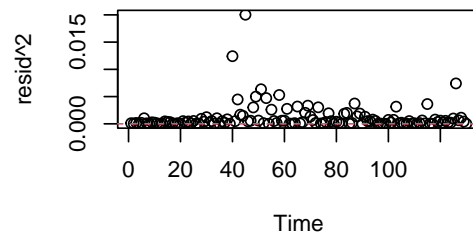
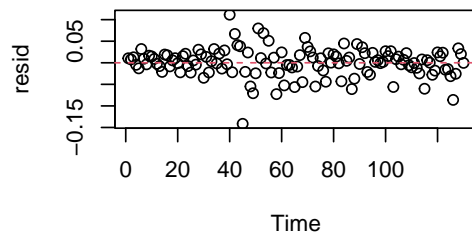
```
##
## Box-Ljung test
##
## data: y^2
## X-squared = 588.25, df = 6, p-value < 2.2e-16
## alternative hypothesis: y is heteroscedastic
```

Do primeiro teste, temos um p-valor superior a 5%, portanto, não rejeitamos que haja efeito ARCH. Do segundo teste, temos que há valores superiores a 5%, então, rejeitamos que haja heterocedasticidade no modelo. Do terceiro teste, temos que o p-valor é inferior a 5%, então não rejeitamos a hipótese de que a série seja heterocedástica.

Assim, tomamos um modelo ARCH para representar a série.

Petróleo Brent

```
##
## ARCH LM-test; Null hypothesis: no ARCH effects
##
## data: sqresidual
## Chi-squared = 13.105, df = 6, p-value = 0.0414
## ARCH heteroscedasticity test for residuals
## alternative: heteroscedastic
##
## Portmanteau-Q test:
##      order    PQ p.value
## [1,]      4  8.41 0.07754
## [2,]      8 23.84 0.00244
## [3,]     12 25.99 0.01078
## [4,]     16 29.07 0.02344
## [5,]     20 29.87 0.07197
## [6,]     24 31.06 0.15211
## Lagrange-Multiplier test:
##      order    LM p.value
## [1,]      4 85.33 0.00000
## [2,]      8 22.57 0.00202
## [3,]     12 12.64 0.31771
## [4,]     16  8.01 0.92337
## [5,]     20  5.38 0.99904
## [6,]     24  3.93 1.00000
```



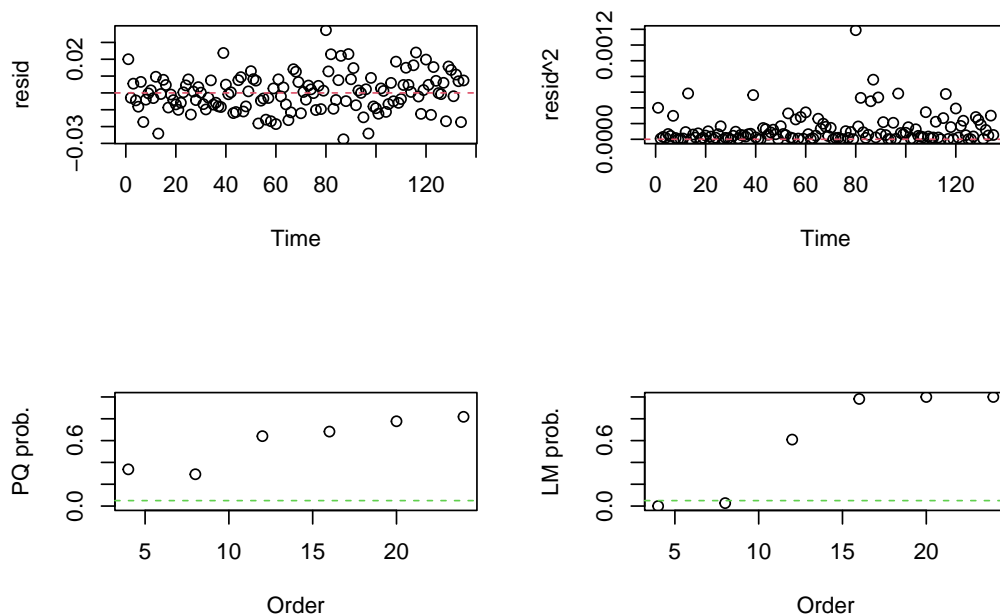
```
##
## Box-Ljung test
##
## data: y^2
## X-squared = 499.15, df = 6, p-value < 2.2e-16
## alternative hypothesis: y is heteroscedastic
```

Do primeiro teste, temos um p-valor inferior a 5%, portanto, rejeitamos que haja efeito ARCH. Do segundo teste, nota-se que há p-valores inferiores a 5% apenas para os casos de ordem 8, 12 e 16. Do terceiro teste,

temos que o p-valor é inferior a 5%, então não rejeitamos a hipótese de que a série seja heterocedástica. Assim, tomamos um modelo ARCH para representar a série.

Dólar

```
##
## ARCH LM-test; Null hypothesis: no ARCH effects
##
## data: sqresidual
## Chi-squared = 2.2599, df = 6, p-value = 0.8943
## ARCH heteroscedasticity test for residuals
## alternative: heteroscedastic
##
## Portmanteau-Q test:
##      order    PQ p.value
## [1,]     4  4.55  0.337
## [2,]     8  9.64  0.292
## [3,]    12  9.72  0.641
## [4,]    16 12.87  0.683
## [5,]    20 14.99  0.777
## [6,]    24 17.68  0.818
## Lagrange-Multiplier test:
##      order    LM p.value
## [1,]     4 38.48 2.24e-08
## [2,]     8 15.80 2.70e-02
## [3,]    12  9.14 6.09e-01
## [4,]    16  5.86 9.82e-01
## [5,]    20  3.80 1.00e+00
## [6,]    24  2.54 1.00e+00
```



```
##
## Box-Ljung test
##
## data: y^2
```

```
## X-squared = 624.66, df = 6, p-value < 2.2e-16
## alternative hypothesis: y is heteroscedastic
```

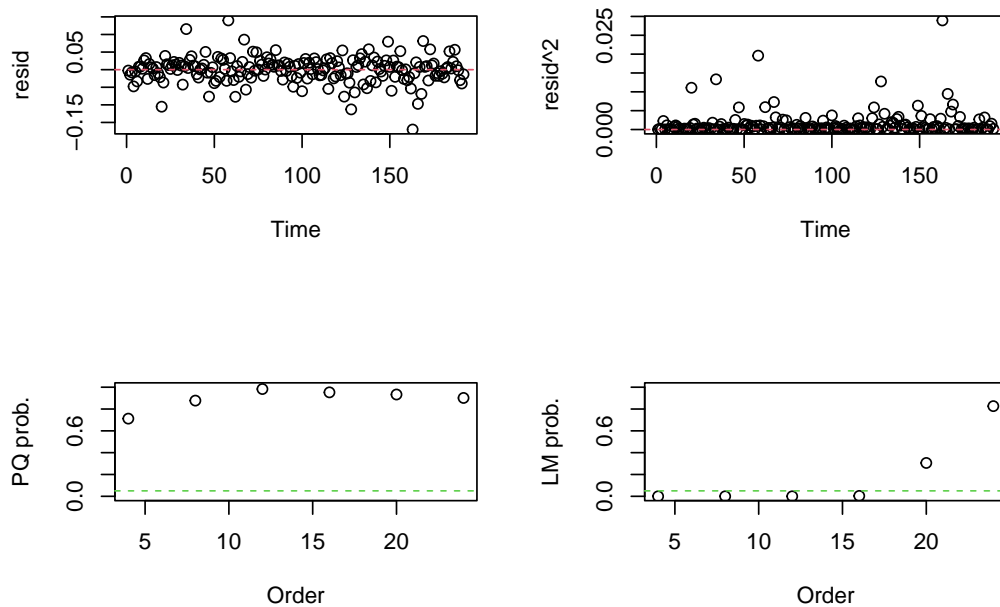
Do primeiro teste, temos um p-valor superior a 5%, portanto, não rejeitamos que haja efeito ARCH. Do segundo teste, temos que há valores superiores a 5%, então, rejeitamos que haja heterocedasticidade no modelo. Do terceiro teste, temos que o p-valor é inferior a 5%, então não rejeitamos a hipótese de que a série seja heterocedástica.

Assim, tomamos um modelo GARCH para representar a série.

Bitcoin

```
##
## ARCH LM-test; Null hypothesis: no ARCH effects
##
## data: sqresidual
## Chi-squared = 0.79726, df = 6, p-value = 0.9921

## ARCH heteroscedasticity test for residuals
## alternative: heteroscedastic
##
## Portmanteau-Q test:
##      order    PQ p.value
## [1,]      4  2.13  0.712
## [2,]      8  3.77  0.877
## [3,]     12  4.01  0.983
## [4,]     16  7.86  0.953
## [5,]     20 11.47  0.933
## [6,]     24 15.61  0.902
## Lagrange-Multiplier test:
##      order    LM p.value
## [1,]      4 186.4 0.00e+00
## [2,]      8  88.0 3.33e-16
## [3,]     12  52.7 2.04e-07
## [4,]     16  33.8 3.65e-03
## [5,]     20  21.6 3.06e-01
## [6,]     24  16.6 8.27e-01
```

```
##
## Box-Ljung test
##
## data: y^2
## X-squared = 955.53, df = 6, p-value < 2.2e-16
## alternative hypothesis: y is heteroscedastic
```

Do primeiro teste, temos um p-valor superior a 5%, portanto, não rejeitamos que haja efeito ARCH. Do segundo teste, temos que há valores superiores a 5%, então, rejeitamos que haja heterocedasticidade no modelo. Do terceiro teste, temos que o p-valor é inferior a 5%, então não rejeitamos a hipótese de que a série seja heterocedástica.

Assim, tomamos um modelo ARCH para representar a série.

Estimação do Modelo ARCH/GARCH

De acordo com o que foi selecionado na seção anterior, temos os seguintes modelos estimados a partir das informações coletadas até então. Nota-se que todos os coeficientes escolhidos são significativos para o modelo.

S&P500

```
##
## Series Initialization:
## ARMA Model: arma
## Formula Mean: ~ arma(0, 0)
## GARCH Model: garch
## Formula Variance: ~ garch(1, 1)
## ARMA Order: 0 0
## Max ARMA Order: 0
## GARCH Order: 1 1
## Max GARCH Order: 1
## Maximum Order: 1
## Conditional Dist: norm
## h.start: 2
## llh.start: 1
```

```

## Length of Series:          130
## Recursion Init:           mci
## Series Scale:             281.7138
##
## Parameter Initialization:
## Initial Parameters:       $params
## Limits of Transformations: $U, $V
## Which Parameters are Fixed? $includes
## Parameter Matrix:
##           U           V   params includes
## mu      -151.39987478 151.3999 15.13999    TRUE
## omega     0.00000100 100.0000 0.10000    TRUE
## alpha1    0.00000001  1.0000 0.10000    TRUE
## gamma1   -0.99999999  1.0000 0.10000    FALSE
## beta1     0.00000001  1.0000 0.80000    TRUE
## delta     0.00000000  2.0000 2.00000    FALSE
## skew      0.10000000 10.0000 1.00000    FALSE
## shape     1.00000000 10.0000 4.00000    FALSE
## Index List of Parameters to be Optimized:
## mu omega alpha1 beta1
##   1   2   3   5
## Persistence:              0.9
##
##
## --- START OF TRACE ---
## Selected Algorithm: nlminb
##
## R coded nlminb Solver:
##
## 0:    169.92302:  15.1400 0.100000 0.100000 0.800000
## 1:    165.01499:  15.5926 0.0905762 0.100693 0.793076
## 2:    160.74947:  15.3667 0.0660338 0.109720 0.781921
## 3:    155.71179:  15.6209 0.0436858 0.124437 0.776171
## 4:    152.78916:  15.4860 0.0201081 0.144326 0.776496
## 5:    150.70905:  15.7101 0.0167092 0.172123 0.781755
## 6:    149.92751:  15.5156 0.0142042 0.201293 0.778797
## 7:    149.19110:  15.6082 0.0121688 0.201463 0.777347
## 8:    149.00225:  15.6539 0.0109124 0.203464 0.771967
## 9:    148.80893:  15.6194 0.0132326 0.206161 0.766887
## 10:   148.63450:  15.6571 0.0119287 0.208776 0.761510
## 11:   148.44879:  15.6189 0.0136125 0.212112 0.756680
## 12:   148.29730:  15.6642 0.0141160 0.215251 0.751720
## 13:   148.11967:  15.6310 0.0120828 0.218761 0.746986
## 14:   147.93431:  15.6400 0.0153866 0.222345 0.742566
## 15:   147.76159:  15.6457 0.0128171 0.225826 0.737586
## 16:   147.59620:  15.6507 0.0157603 0.229912 0.733321
## 17:   147.44312:  15.6268 0.0138640 0.233321 0.728228
## 18:   147.26235:  15.6672 0.0148172 0.237355 0.723828
## 19:   147.08505:  15.6363 0.0151624 0.241273 0.718927
## 20:   143.46623:  15.7308 0.0152493 0.359421 0.576055
## 21:   141.99625:  15.6594 0.0524271 0.463718 0.427300
## 22:   141.55574:  15.5871 0.0453002 0.464133 0.426064
## 23:   141.04149:  15.6672 0.0417262 0.469978 0.425476
## 24:   140.72914:  15.6149 0.0355220 0.474947 0.425119

```

```

## 25:      140.41485:  15.6775 0.0330341 0.482108 0.425940
## 26:      140.24088:  15.6445 0.0294198 0.489655 0.426626
## 27:      140.08943:  15.6829 0.0277246 0.497773 0.426868
## 28:      139.97073:  15.6624 0.0259600 0.505929 0.424921
## 29:      138.13741:  15.7097 0.0220184 0.661351 0.261587
## 30:      137.77885:  15.7067 0.0260066 0.749137 0.264597
## 31:      137.42456:  15.6725 0.0389830 0.759769 0.178313
## 32:      136.94687:  15.6925 0.0370334 0.830029 0.125500
## 33:      136.74135:  15.7039 0.0371639 0.893384 0.0937262
## 34:      136.56765:  15.7344 0.0330781 0.914662 0.0647693
## 35:      136.47162:  15.7391 0.0314967 0.998113 0.0199112
## 36:      136.47087:  15.7463 0.0317560 1.00000 0.0356148
## 37:      136.45914:  15.7406 0.0314311 1.00000 0.0304421
## 38:      136.45910:  15.7412 0.0312881 1.00000 0.0302693
## 39:      136.45909:  15.7411 0.0313150 1.00000 0.0303327
## 40:      136.45909:  15.7411 0.0313148 1.00000 0.0303331
##
## Final Estimate of the Negative LLH:
## LLH: 869.775      norm LLH: 6.690577
##      mu      omega      alpha1      beta1
## 4.434475e+03 2.485226e+03 1.000000e+00 3.033312e-02
##
## R-optimhess Difference Approximated Hessian Matrix:
##      mu      omega      alpha1      beta1
## mu      -3.038520e-03 -2.613396e-05 -0.015793076 -2.870430e-01
## omega -2.613396e-05 -1.104215e-06 -0.002550427 -8.776022e-03
## alpha1 -1.579308e-02 -2.550427e-03 -45.728118451 -6.028913e+01
## beta1 -2.870430e-01 -8.776022e-03 -60.289134780 -1.880734e+02
## attr("time")
## Time difference of 0.005200624 secs
##
## --- END OF TRACE ---
##
##
## Time to Estimate Parameters:
## Time difference of 0.03535891 secs
##
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.
##
## Title:
## GARCH Modelling
##
## Call:
## garchFit(formula = ~garch(1, 1), data = stdpoors.ts, trace = T)
##
## Mean and Variance Equation:
## data ~ garch(1, 1)
## <environment: 0x563458f61d48>
## [data = stdpoors.ts]
##
## Conditional Distribution:
## norm
##

```

```

## Coefficient(s):
##      mu      omega      alpha1      beta1
## 4.4345e+03 2.4852e+03 1.0000e+00 3.0333e-02
##
## Std. Errors:
## based on Hessian
##
## Error Analysis:
##      Estimate Std. Error t value Pr(>|t|)
## mu      4.434e+03 2.145e+01 206.713 < 2e-16 ***
## omega  2.485e+03 1.258e+03   1.975  0.0482 *
## alpha1 1.000e+00 2.035e-01   4.914 8.92e-07 ***
## beta1  3.033e-02 1.182e-01   0.257  0.7974
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
## -869.775      normalized: -6.690577
##
## Description:
## Tue Jul 12 16:45:39 2022 by user: stevenson
##
##
## Standardised Residuals Tests:
##
##      Statistic p-Value
## Jarque-Bera Test  R      Chi^2  9.389576 0.009142805
## Shapiro-Wilk Test  R      W      0.9073156 1.927483e-07
## Ljung-Box Test     R      Q(10) 363.5365 0
## Ljung-Box Test     R      Q(15) 370.3866 0
## Ljung-Box Test     R      Q(20) 371.0373 0
## Ljung-Box Test     R^2  Q(10) 15.24529 0.1233716
## Ljung-Box Test     R^2  Q(15) 21.3739 0.1253024
## Ljung-Box Test     R^2  Q(20) 24.99033 0.2018012
## LM Arch Test       R      TR^2   14.74789 0.255514
##
## Information Criterion Statistics:
##      AIC      BIC      SIC      HQIC
## 13.44269 13.53092 13.44087 13.47854

```

Dow Jones

```

##
## Series Initialization:
## ARMA Model:      arma
## Formula Mean:     ~ arma(0, 0)
## GARCH Model:      garch
## Formula Variance: ~ garch(1, 1)
## ARMA Order:       0 0
## Max ARMA Order:   0
## GARCH Order:      1 1
## Max GARCH Order:  1
## Maximum Order:    1
## Conditional Dist:  norm
## h.start:          2

```

```

## llh.start:          1
## Length of Series:   130
## Recursion Init:     mci
## Series Scale:       1657.502
##
## Parameter Initialization:
## Initial Parameters:  $params
## Limits of Transformations:  $U, $V
## Which Parameters are Fixed? $includes
## Parameter Matrix:
##           U          V  params includes
## mu      -202.51865692 202.5187 20.25187    TRUE
## omega    0.00000100 100.0000 0.10000    TRUE
## alpha1   0.00000001 1.0000 0.10000    TRUE
## gamma1   -0.99999999 1.0000 0.10000    FALSE
## beta1    0.00000001 1.0000 0.80000    TRUE
## delta    0.00000000 2.0000 2.00000    FALSE
## skew     0.10000000 10.0000 1.00000    FALSE
## shape    1.00000000 10.0000 4.00000    FALSE
## Index List of Parameters to be Optimized:
## mu omega alpha1 beta1
## 1 2 3 5
## Persistence:          0.9
##
## --- START OF TRACE ---
## Selected Algorithm: nlminb
##
## R coded nlminb Solver:
##
## 0: 168.69308: 20.2519 0.100000 0.100000 0.800000
## 1: 165.14826: 20.5260 0.0961688 0.100215 0.797199
## 2: 158.98158: 20.4975 0.0469705 0.111274 0.769843
## 3: 157.72829: 20.6446 0.0465757 0.114894 0.770448
## 4: 156.29630: 20.5374 0.0377502 0.131046 0.771739
## 5: 154.11389: 20.7699 0.0291718 0.143811 0.771446
## 6: 152.50908: 20.6898 0.0165060 0.157681 0.771311
## 7: 151.19851: 20.8346 0.0112696 0.173775 0.765753
## 8: 150.17183: 20.7539 0.0151653 0.185990 0.752035
## 9: 147.44881: 20.8642 0.0183629 0.244032 0.692033
## 10: 146.12846: 20.7920 0.00936855 0.262848 0.680739
## 11: 145.80383: 20.8603 0.00812615 0.269061 0.676967
## 12: 145.45861: 20.8257 0.00786607 0.274494 0.671202
## 13: 145.21297: 20.8429 0.0118898 0.276312 0.664456
## 14: 144.95970: 20.8190 0.0109285 0.282119 0.659008
## 15: 144.09845: 20.8616 0.00630392 0.314942 0.627479
## 16: 142.80121: 20.8136 0.0104342 0.338184 0.588309
## 17: 142.07445: 20.8739 0.0146593 0.360123 0.548445
## 18: 137.73874: 20.8610 0.0139648 0.525751 0.341408
## 19: 136.07973: 20.8166 0.00923350 0.790631 0.351857
## 20: 134.17211: 20.8320 0.0155993 0.939519 0.132564
## 21: 134.05887: 20.8611 0.0156667 0.939527 0.132588
## 22: 133.99782: 20.8503 0.0155139 0.939237 0.133882
## 23: 133.95400: 20.8510 0.0123801 0.938415 0.154546

```

```

## 24:      133.92319:  20.8507 0.0126582 0.926627 0.171822
## 25:      133.92104:  20.8509 0.0128484 0.932285 0.169257
## 26:      133.91993:  20.8509 0.0128997 0.940186 0.167032
## 27:      133.91992:  20.8509 0.0128795 0.940878 0.166909
## 28:      133.91992:  20.8509 0.0128750 0.940906 0.166916
## 29:      133.91992:  20.8509 0.0128748 0.940902 0.166918
##
## Final Estimate of the Negative LLH:
## LLH: 1097.619      norm LLH: 8.44322
##      mu      omega      alpha1      beta1
## 3.456043e+04 3.537102e+04 9.409021e-01 1.669177e-01
##
## R-optimhess Difference Approximated Hessian Matrix:
##      mu      omega      alpha1      beta1
## mu      -3.897995e-04 -1.647294e-07 -4.639142e-03 -2.807536e-02
## omega -1.647294e-07 -2.635658e-09 -1.637251e-04 -5.258003e-04
## alpha1 -4.639142e-03 -1.637251e-04 -5.728208e+01 -8.491416e+01
## beta1 -2.807536e-02 -5.258003e-04 -8.491416e+01 -2.450046e+02
## attr("time")
## Time difference of 0.005016088 secs
##
## --- END OF TRACE ---
##
##
## Time to Estimate Parameters:
## Time difference of 0.02533913 secs
##
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.
##
## Title:
## GARCH Modelling
##
## Call:
## garchFit(formula = ~garch(1, 1), data = dowjones.ts, trace = T)
##
## Mean and Variance Equation:
## data ~ garch(1, 1)
## <environment: 0x56345a7a1aa0>
## [data = dowjones.ts]
##
## Conditional Distribution:
## norm
##
## Coefficient(s):
##      mu      omega      alpha1      beta1
## 3.4560e+04 3.5371e+04 9.4090e-01 1.6692e-01
##
## Std. Errors:
## based on Hessian
##
## Error Analysis:
##      Estimate Std. Error t value Pr(>|t|)
## mu      3.456e+04 5.138e+01 672.656 < 2e-16 ***

```

```
## omega 3.537e+04 2.610e+04 1.355 0.175
## alpha1 9.409e-01 1.904e-01 4.942 7.74e-07 ***
## beta1 1.669e-01 1.103e-01 1.513 0.130
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
## -1097.619 normalized: -8.44322
##
## Description:
## Tue Jul 12 16:45:39 2022 by user: stevenson
##
##
## Standardised Residuals Tests:
##
## Statistic p-Value
## Jarque-Bera Test R Chi^2 10.05235 0.006563859
## Shapiro-Wilk Test R W 0.9142264 4.752138e-07
## Ljung-Box Test R Q(10) 264.365 0
## Ljung-Box Test R Q(15) 269.913 0
## Ljung-Box Test R Q(20) 272.8326 0
## Ljung-Box Test R^2 Q(10) 25.85465 0.003940676
## Ljung-Box Test R^2 Q(15) 29.81394 0.0126104
## Ljung-Box Test R^2 Q(20) 30.81116 0.05773336
## LM Arch Test R TR^2 22.03726 0.03710437
##
## Information Criterion Statistics:
## AIC BIC SIC HQIC
## 16.94798 17.03621 16.94616 16.98383
```

Nasdaq

```
##
## Series Initialization:
## ARMA Model: arma
## Formula Mean: ~ arma(0, 0)
## GARCH Model: garch
## Formula Variance: ~ garch(1, 0)
## ARMA Order: 0 0
## Max ARMA Order: 0
## GARCH Order: 1 0
## Max GARCH Order: 1
## Maximum Order: 1
## Conditional Dist: norm
## h.start: 2
## llh.start: 1
## Length of Series: 130
## Recursion Init: mci
## Series Scale: 1270.244
##
## Parameter Initialization:
## Initial Parameters: $params
## Limits of Transformations: $U, $V
## Which Parameters are Fixed? $includes
## Parameter Matrix:
```

```

##              U      V  params includes
##  mu      -102.49908682 102.4991 10.24991      TRUE
##  omega      0.00000100 100.0000 0.10000      TRUE
##  alpha1      0.00000001 1.0000 0.10000      TRUE
##  gamma1     -0.99999999 1.0000 0.10000      FALSE
##  delta      0.00000000 2.0000 2.00000      FALSE
##  skew       0.10000000 10.0000 1.00000      FALSE
##  shape      1.00000000 10.0000 4.00000      FALSE
## Index List of Parameters to be Optimized:
##  mu  omega  alpha1
##    1    2    3
## Persistence:          0.1
##
##
## --- START OF TRACE ---
## Selected Algorithm: nlminb
##
## R coded nlminb Solver:
##
##  0:      278.99085:  10.2499 0.100000 0.100000
##  1:      274.61367:  12.2482 0.375607 0.431645
##  2:      175.06119:  9.83800 0.380651 0.457558
##  3:      148.99792:  10.6971 0.200786 0.940359
##  4:      145.51305:  10.6558 0.150362 0.936498
##  5:      138.29597:  10.6546 0.0494762 0.947328
##  6:      137.57172:  10.7642 0.0470353 0.947434
##  7:      137.25381:  10.7248 0.0368294 0.948624
##  8:      137.25064:  10.7201 0.0369655 0.948755
##  9:      137.24799:  10.7245 0.0373319 0.950097
## 10:      137.24210:  10.7194 0.0371465 0.951453
## 11:      137.22271:  10.7202 0.0354107 0.959830
## 12:      137.19620:  10.7158 0.0364266 0.968316
## 13:      137.18468:  10.7260 0.0364211 0.976814
## 14:      137.16081:  10.7174 0.0362029 0.985326
## 15:      137.15024:  10.7156 0.0344111 0.993691
## 16:      137.14129:  10.7147 0.0359654 1.00000
## 17:      137.13923:  10.7156 0.0352013 1.00000
## 18:      137.13921:  10.7150 0.0351548 1.00000
## 19:      137.13921:  10.7151 0.0351693 1.00000
## 20:      137.13921:  10.7151 0.0351692 1.00000
##
## Final Estimate of the Negative LLH:
## LLH: 1066.245      norm LLH: 8.201881
##      mu      omega      alpha1
## 13610.81 56746.10      1.00
##
## R-optimhess Difference Approximated Hessian Matrix:
##      mu      omega      alpha1
## mu      -1.743740e-04 1.868862e-07 -1.158453e-02
## omega  1.868862e-07 -2.382469e-09 -1.173147e-04
## alpha1 -1.158453e-02 -1.173147e-04 -4.633373e+01
## attr("time")
## Time difference of 0.002579689 secs
##

```



```

## --- END OF TRACE ---
##
##
## Time to Estimate Parameters:
## Time difference of 0.01601028 secs

## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.

##
## Title:
## GARCH Modelling
##
## Call:
## garchFit(formula = ~garch(1, 0), data = nasdaq.ts, trace = T)
##
## Mean and Variance Equation:
## data ~ garch(1, 0)
## <environment: 0x56346009f3c0>
## [data = nasdaq.ts]
##
## Conditional Distribution:
## norm
##
## Coefficient(s):
##      mu      omega  alpha1
## 13611   56746         1
##
## Std. Errors:
## based on Hessian
##
## Error Analysis:
##      Estimate Std. Error t value Pr(>|t|)
## mu      1.361e+04  8.191e+01 166.175 < 2e-16 ***
## omega   5.675e+04  2.349e+04   2.416  0.0157 *
## alpha1  1.000e+00  1.625e-01   6.152 7.63e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
## -1066.245      normalized: -8.201881
##
## Description:
## Tue Jul 12 16:45:40 2022 by user: stevenson
##
##
## Standardised Residuals Tests:
##
##                               Statistic p-Value
## Jarque-Bera Test      R      Chi^2 10.30584 0.005782489
## Shapiro-Wilk Test     R      W      0.9150084 5.276778e-07
## Ljung-Box Test        R      Q(10) 451.1057 0
## Ljung-Box Test        R      Q(15) 494.0965 0
## Ljung-Box Test        R      Q(20) 509.7311 0
## Ljung-Box Test        R^2 Q(10) 8.790383 0.552106
## Ljung-Box Test        R^2 Q(15) 15.8023 0.3953116

```

```
## Ljung-Box Test      R^2  Q(20)  17.75261  0.6037013
## LM Arch Test        R    TR^2   8.048057  0.7813637
##
## Information Criterion Statistics:
##      AIC      BIC      SIC      HQIC
## 16.44992 16.51609 16.44888 16.47680
```

IBOVESPA

```
##
## Series Initialization:
## ARMA Model:          arma
## Formula Mean:        ~ arma(0, 0)
## GARCH Model:         garch
## Formula Variance:    ~ garch(1, 0)
## ARMA Order:          0 0
## Max ARMA Order:      0
## GARCH Order:         1 0
## Max GARCH Order:     1
## Maximum Order:       1
## Conditional Dist:    norm
## h.start:             2
## llh.start:           1
## Length of Series:    131
## Recursion Init:      mci
## Series Scale:        6012.416
##
## Parameter Initialization:
## Initial Parameters:   $params
## Limits of Transformations: $U, $V
## Which Parameters are Fixed? $includes
## Parameter Matrix:
##      U      V  params includes
## mu    -182.17257374 182.1726 18.21726 TRUE
## omega  0.00000100 100.0000 0.10000 TRUE
## alpha1 0.00000001 1.0000 0.10000 TRUE
## gamma1 -0.99999999 1.0000 0.10000 FALSE
## delta  0.00000000 2.0000 2.00000 FALSE
## skew   0.10000000 10.0000 1.00000 FALSE
## shape  1.00000000 10.0000 4.00000 FALSE
## Index List of Parameters to be Optimized:
## mu omega alpha1
## 1 2 3
## Persistence:          0.1
##
##
## --- START OF TRACE ---
## Selected Algorithm: nlminb
##
## R coded nlminb Solver:
##
## 0: 251.93855: 18.2173 0.100000 0.100000
## 1: 235.42142: 18.9596 0.129324 0.142576
## 2: 190.29040: 18.0910 0.151868 0.181962
```

```

## 3:      166.50594:  18.5655 0.180030 0.235456
## 4:      159.58285:  18.2352 0.176240 0.298623
## 5:      151.22015:  18.5405 0.132881 0.345230
## 6:      147.71651:  18.4866 0.0809566 0.385583
## 7:      142.66055:  18.6383 0.0609858 0.447752
## 8:      140.82603:  18.4648 0.112321 0.487842
## 9:      136.43383:  18.5543 0.0654048 0.533754
## 10:     136.33013:  18.5770 0.0652078 0.534217
## 11:     136.10678:  18.5583 0.0624456 0.538716
## 12:     135.75384:  18.5870 0.0596728 0.543048
## 13:     133.22176:  18.5975 0.0369784 0.594356
## 14:     129.05687:  18.5886 0.0480436 0.749497
## 15:     127.24643:  18.6303 0.0323786 0.818081
## 16:     126.28835:  18.6194 0.0197546 0.887324
## 17:     125.59325:  18.6129 0.0227167 0.957648
## 18:     125.55398:  18.6377 0.0210874 1.00000
## 19:     125.35905:  18.6198 0.0215701 1.00000
## 20:     125.35894:  18.6202 0.0215896 1.00000
## 21:     125.35894:  18.6202 0.0215769 1.00000
## 22:     125.35894:  18.6202 0.0215762 1.00000
##
## Final Estimate of the Negative LLH:
## LLH: 1265.266      norm LLH: 9.65852
##      mu      omega      alpha1
## 111952.7 779962.0      1.0
##
## R-optimhess Difference Approximated Hessian Matrix:
##      mu      omega      alpha1
## mu      -3.652678e-05 -5.193615e-09 -1.378788e-03
## omega  -5.193615e-09 -1.186153e-11 -8.806838e-06
## alpha1 -1.378788e-03 -8.806838e-06 -5.235485e+01
## attr("time")
## Time difference of 0.002662659 secs
##
## --- END OF TRACE ---
##
## Time to Estimate Parameters:
## Time difference of 0.01652527 secs
##
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.
##
## Title:
## GARCH Modelling
##
## Call:
## garchFit(formula = ~garch(1, 0), data = bovespa.ts, trace = T)
##
## Mean and Variance Equation:
## data ~ garch(1, 0)
## <environment: 0x56345e9fb6e8>
## [data = bovespa.ts]
##

```

```

## Conditional Distribution:
## norm
##
## Coefficient(s):
##      mu      omega  alpha1
## 111953  779962      1
##
## Std. Errors:
## based on Hessian
##
## Error Analysis:
##      Estimate  Std. Error  t value Pr(>|t|)
## mu      1.120e+05  1.712e+02  653.930  < 2e-16 ***
## omega   7.800e+05  3.210e+05   2.430   0.0151 *
## alpha1  1.000e+00  1.480e-01   6.756  1.42e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
## -1265.266      normalized: -9.65852
##
## Description:
## Tue Jul 12 16:45:40 2022 by user: stevenson
##
##
## Standardised Residuals Tests:
##
##      Statistic p-Value
## Jarque-Bera Test  R      Chi^2  7.504487  0.02346504
## Shapiro-Wilk Test  R      W      0.9276877  2.89362e-06
## Ljung-Box Test     R      Q(10)  399.1648  0
## Ljung-Box Test     R      Q(15)  472.7641  0
## Ljung-Box Test     R      Q(20)  485.3374  0
## Ljung-Box Test     R^2  Q(10)  21.192    0.0197938
## Ljung-Box Test     R^2  Q(15)  25.27771  0.04633586
## Ljung-Box Test     R^2  Q(20)  29.87073  0.07197562
## LM Arch Test       R      TR^2   17.17361  0.1431826
##
## Information Criterion Statistics:
##      AIC      BIC      SIC      HQIC
## 19.36284 19.42869 19.36182 19.38960

```

Brent

```

##
## Series Initialization:
## ARMA Model:      arma
## Formula Mean:     ~ arma(0, 0)
## GARCH Model:      garch
## Formula Variance: ~ garch(1, 0)
## ARMA Order:       0 0
## Max ARMA Order:   0
## GARCH Order:      1 0
## Max GARCH Order:  1
## Maximum Order:    1

```

```

## Conditional Dist:          norm
## h.start:                  2
## llh.start:                1
## Length of Series:        131
## Recursion Init:          mci
## Series Scale:             11.82754
##
## Parameter Initialization:
## Initial Parameters:       $params
## Limits of Transformations: $U, $V
## Which Parameters are Fixed? $includes
## Parameter Matrix:
##           U           V   params includes
## mu    -88.84480729  88.84481 8.884481    TRUE
## omega  0.00000100 100.00000 0.100000    TRUE
## alpha1 0.00000001  1.00000 0.100000    TRUE
## gamma1 -0.99999999  1.00000 0.100000    FALSE
## delta  0.00000000  2.00000 2.000000    FALSE
## skew   0.10000000 10.00000 1.000000    FALSE
## shape  1.00000000 10.00000 4.000000    FALSE
## Index List of Parameters to be Optimized:
## mu  omega alpha1
##   1    2    3
## Persistence:          0.1
##
## --- START OF TRACE ---
## Selected Algorithm: nlminb
##
## R coded nlminb Solver:
##
## 0:    268.45500:  8.88448 0.100000 0.100000
## 1:    201.67614:  9.87599 0.225578 0.255771
## 2:    166.97632:  8.94479 0.230935 0.277598
## 3:    155.20346:  9.28565 0.238207 0.377427
## 4:    150.35043:  9.14109 0.164592 0.453628
## 5:    149.35571:  9.33266 0.0741616 0.506995
## 6:    144.70864:  9.27360 0.133294 0.596156
## 7:    144.64542:  9.19917 0.127976 0.600212
## 8:    144.21560:  9.25647 0.124628 0.608093
## 9:    144.00543:  9.22607 0.117176 0.614997
## 10:   143.73525:  9.26757 0.114132 0.624152
## 11:   143.53193:  9.23712 0.110296 0.633556
## 12:   143.31033:  9.27024 0.107679 0.643260
## 13:   143.12519:  9.24448 0.104701 0.653141
## 14:   142.93522:  9.27189 0.102590 0.663188
## 15:   141.44288:  9.26435 0.0776858 0.819160
## 16:   141.23127:  9.28014 0.0900582 0.893657
## 17:   141.13717:  9.28966 0.0801907 0.912090
## 18:   141.13405:  9.28608 0.0788208 0.917371
## 19:   141.13388:  9.28651 0.0790700 0.918276
## 20:   141.13388:  9.28659 0.0790615 0.918701
## 21:   141.13388:  9.28658 0.0790619 0.918727
## 22:   141.13388:  9.28658 0.0790613 0.918728

```

```

##
## Final Estimate of the Negative LLH:
## LLH: 464.7603    norm LLH: 3.547788
##      mu      omega      alpha1
## 109.8373401  11.0599393  0.9187277
##
## R-optimhess Difference Approximated Hessian Matrix:
##      mu      omega      alpha1
## mu      -1.50769951 -0.09327188  0.5783378
## omega   -0.09327188 -0.11128899 -0.7031605
## alpha1   0.57833779 -0.70316050 -44.5553759
## attr("time")
## Time difference of 0.002938986 secs
##
## --- END OF TRACE ---
##
## Time to Estimate Parameters:
## Time difference of 0.01696467 secs

## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.

##
## Title:
## GARCH Modelling
##
## Call:
## garchFit(formula = ~garch(1, 0), data = brent.ts, trace = T)
##
## Mean and Variance Equation:
## data ~ garch(1, 0)
## <environment: 0x56345d924de0>
## [data = brent.ts]
##
## Conditional Distribution:
## norm
##
## Coefficient(s):
##      mu      omega      alpha1
## 109.83734  11.05994  0.91873
##
## Std. Errors:
## based on Hessian
##
## Error Analysis:
##      Estimate Std. Error t value Pr(>|t|)
## mu      109.8373      0.8465  129.754 < 2e-16 ***
## omega   11.0599      3.2756   3.376 0.000734 ***
## alpha1   0.9187      0.1598   5.749 8.97e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
## -464.7603    normalized: -3.547788

```

```
##
## Description:
## Tue Jul 12 16:45:40 2022 by user: stevenson
##
##
## Standardised Residuals Tests:
##
##           Statistic p-Value
## Jarque-Bera Test   R   Chi^2  5.515338  0.06343948
## Shapiro-Wilk Test  R    W      0.9418788 2.646811e-05
## Ljung-Box Test     R   Q(10) 244.5538  0
## Ljung-Box Test     R   Q(15) 325.2879  0
## Ljung-Box Test     R   Q(20) 342.4151  0
## Ljung-Box Test     R^2  Q(10) 8.747982  0.5561764
## Ljung-Box Test     R^2  Q(15) 14.67914  0.474767
## Ljung-Box Test     R^2  Q(20) 15.98992  0.7172495
## LM Arch Test       R    TR^2  11.12336  0.5183776
##
## Information Criterion Statistics:
##           AIC      BIC      SIC      HQIC
## 7.141378 7.207222 7.140360 7.168134
```

Dólar

```
##
## Series Initialization:
## ARMA Model:          arma
## Formula Mean:        ~ arma(0, 0)
## GARCH Model:         garch
## Formula Variance:    ~ garch(1, 1)
## ARMA Order:          0 0
## Max ARMA Order:      0
## GARCH Order:         1 1
## Max GARCH Order:     1
## Maximum Order:       1
## Conditional Dist:    norm
## h.start:             2
## llh.start:           1
## Length of Series:    136
## Recursion Init:      mci
## Series Scale:        0.2776031
##
## Parameter Initialization:
## Initial Parameters:   $params
## Limits of Transformations: $U, $V
## Which Parameters are Fixed? $includes
## Parameter Matrix:
##
##           U      V  params includes
## mu      -183.19360162 183.1936 18.31936  TRUE
## omega    0.00000100 100.0000 0.10000  TRUE
## alpha1   0.00000001  1.0000 0.10000  TRUE
## gamma1  -0.99999999  1.0000 0.10000  FALSE
## beta1    0.00000001  1.0000 0.80000  TRUE
## delta    0.00000000  2.0000 2.00000  FALSE
## skew     0.10000000 10.0000 1.00000  FALSE
```

```

##      shape      1.00000000  10.0000  4.00000  FALSE
## Index List of Parameters to be Optimized:
##      mu omega alpha1 beta1
##      1      2      3      5
## Persistence:                0.9
##
##
## --- START OF TRACE ---
## Selected Algorithm: nlminb
##
## R coded nlminb Solver:
##
## 0:      173.12871:  18.3194 0.100000 0.100000 0.800000
## 1:      170.07868:  18.1120 0.0838948 0.100490 0.787443
## 2:      167.66231:  18.4173 0.0701685 0.103390 0.779030
## 3:      163.92841:  18.1965 0.0535332 0.109751 0.769925
## 4:      160.81396:  18.3720 0.0374133 0.121994 0.763299
## 5:      157.97408:  18.2427 0.0241707 0.139447 0.759338
## 6:      155.65652:  18.3787 0.0186134 0.160687 0.756461
## 7:      153.69152:  18.2695 0.0160893 0.181201 0.747368
## 8:      152.92678:  18.3440 0.00699912 0.191082 0.728696
## 9:      150.91002:  18.3373 0.0176895 0.204425 0.712791
## 10:     150.73933:  18.3051 0.0159996 0.205661 0.711854
## 11:     150.63945:  18.3457 0.0149780 0.206984 0.711054
## 12:     150.44274:  18.3127 0.0145145 0.208597 0.709540
## 13:     150.31388:  18.3396 0.0140343 0.210576 0.708107
## 14:     150.14428:  18.3132 0.0138353 0.212374 0.706376
## 15:     150.00916:  18.3375 0.0136995 0.214370 0.704766
## 16:     149.84999:  18.3136 0.0136068 0.216185 0.702938
## 17:     149.71547:  18.3368 0.0135643 0.218140 0.701228
## 18:     149.56274:  18.3139 0.0135161 0.219929 0.699330
## 19:     149.42986:  18.3362 0.0135052 0.221839 0.697536
## 20:     149.28283:  18.3144 0.0134814 0.223600 0.695581
## 21:     149.15204:  18.3359 0.0134865 0.225469 0.693716
## 22:     149.01018:  18.3148 0.0134800 0.227207 0.691715
## 23:     148.88174:  18.3356 0.0134953 0.229041 0.689791
## 24:     148.74461:  18.3152 0.0135020 0.230760 0.687752
## 25:     148.61864:  18.3354 0.0135241 0.232565 0.685783
## 26:     148.48583:  18.3156 0.0135407 0.234272 0.683714
## 27:     148.36238:  18.3352 0.0135670 0.236055 0.681708
## 28:     148.23352:  18.3161 0.0135905 0.237755 0.679619
## 29:     148.11255:  18.3352 0.0136187 0.239525 0.677586
## 30:     147.98730:  18.3165 0.0136465 0.241226 0.675483
## 31:     147.86874:  18.3351 0.0136748 0.242990 0.673432
## 32:     147.74677:  18.3169 0.0137048 0.244698 0.671323
## 33:     147.63051:  18.3351 0.0137316 0.246464 0.669262
## 34:     147.51155:  18.3174 0.0137623 0.248184 0.667152
## 35:     147.39750:  18.3352 0.0137866 0.249957 0.665088
## 36:     147.28133:  18.3178 0.0138171 0.251694 0.662983
## 37:     147.16943:  18.3352 0.0138387 0.253480 0.660919
## 38:     147.05588:  18.3182 0.0138692 0.255235 0.658821
## 39:     146.94610:  18.3353 0.0138888 0.257034 0.656761
## 40:     146.83508:  18.3186 0.0139203 0.258807 0.654670
## 41:     146.72742:  18.3354 0.0139391 0.260618 0.652614

```



```

## 42:      146.61888:   18.3189 0.0139729 0.262407 0.650530
## 43:      146.51336:   18.3355 0.0139924 0.264228 0.648475
## 44:      146.40724:   18.3193 0.0140300 0.266030 0.646396
## 45:      146.30384:   18.3356 0.0140513 0.267859 0.644343
## 46:      146.20007:   18.3197 0.0140935 0.269672 0.642267
## 47:      146.09876:   18.3358 0.0141174 0.271508 0.640215
## 48:      145.99725:   18.3201 0.0141644 0.273331 0.638142
## 49:      145.89799:   18.3359 0.0141912 0.275175 0.636090
## 50:      145.79866:   18.3205 0.0142430 0.277008 0.634020
## 51:      145.70141:   18.3361 0.0142727 0.278858 0.631968
## 52:      145.60421:   18.3210 0.0143288 0.280699 0.629899
## 53:      145.50892:   18.3362 0.0143613 0.282556 0.627847
## 54:      145.41380:   18.3214 0.0144210 0.284405 0.625779
## 55:      145.32046:   18.3364 0.0144560 0.286268 0.623726
## 56:      145.22737:   18.3219 0.0145187 0.288125 0.621659
## 57:      145.13594:   18.3365 0.0145562 0.289992 0.619604
## 58:      145.04483:   18.3223 0.0146210 0.291856 0.617537
## 59:      144.95529:   18.3367 0.0146609 0.293729 0.615481
## 60:      144.86611:   18.3228 0.0147273 0.295599 0.613413
## 61:      144.77843:   18.3369 0.0147694 0.297476 0.611355
## 62:      144.69114:   18.3233 0.0148369 0.299353 0.609287
## 63:      144.60528:   18.3371 0.0148814 0.301234 0.607226
## 64:      144.51983:   18.3238 0.0149493 0.303117 0.605158
## 65:      144.43576:   18.3373 0.0149962 0.305002 0.603094
## 66:      144.35211:   18.3243 0.0150640 0.306891 0.601026
## 67:      144.26979:   18.3375 0.0151134 0.308779 0.598960
## 68:      143.82273:   18.3259 0.0108321 0.331353 0.568259
## 69:      142.61444:   18.3392 0.0194853 0.347202 0.534433
## 70:      142.11208:   18.2859 0.0172605 0.384427 0.525962
## 71:      141.14092:   18.3501 0.0188808 0.399552 0.490931
## 72:      140.93995:   18.3328 0.0206917 0.406278 0.453230
## 73:      139.46083:   18.2954 0.0236205 0.517776 0.403125
## 74:      138.28985:   18.4171 0.0269535 0.596181 0.309569
## 75:      136.74051:   18.3882 0.0343669 0.770947 0.103651
## 76:      136.61995:   18.3855 0.0340901 0.803038 0.0936581
## 77:      136.50530:   18.3845 0.0321184 0.844485 0.105182
## 78:      136.49520:   18.3898 0.0317291 0.861938 0.0976415
## 79:      136.49319:   18.3926 0.0312492 0.864198 0.0994304
## 80:      136.49246:   18.3940 0.0309082 0.863232 0.100624
## 81:      136.49221:   18.3941 0.0306833 0.861292 0.101788
## 82:      136.49217:   18.3937 0.0306379 0.860563 0.102132
## 83:      136.49217:   18.3936 0.0306391 0.860520 0.102154
## 84:      136.49217:   18.3936 0.0306400 0.860541 0.102147
## 85:      136.49217:   18.3936 0.0306400 0.860544 0.102146
##
## Final Estimate of the Negative LLH:
## LLH:  -37.80039      norm LLH:  -0.2779441
##      mu      omega      alpha1      beta1
## 5.106114578 0.002361222 0.860544479 0.102146465
##
## R-optimhess Difference Approximated Hessian Matrix:
##      mu      omega      alpha1      beta1
## mu      -2462.38567  -18091.289   26.42886  -154.50976
## omega  -18091.28929 -1383847.194 -3074.14652 -11129.56734

```

```

## alpha1      26.42886      -3074.147      -64.21477      -73.57294
## beta1       -154.50976      -11129.567      -73.57294      -192.65245
## attr("time")
## Time difference of 0.005331993 secs
##
## --- END OF TRACE ---
##
##
## Time to Estimate Parameters:
## Time difference of 0.04742837 secs

## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.

##
## Title:
## GARCH Modelling
##
## Call:
## garchFit(formula = ~garch(1, 1), data = dolar.ts, trace = T)
##
## Mean and Variance Equation:
## data ~ garch(1, 1)
## <environment: 0x56345c5a2810>
## [data = dolar.ts]
##
## Conditional Distribution:
## norm
##
## Coefficient(s):
##          mu          omega      alpha1      beta1
## 5.1061146  0.0023612  0.8605445  0.1021465
##
## Std. Errors:
## based on Hessian
##
## Error Analysis:
##      Estimate Std. Error t value Pr(>|t|)
## mu      5.106115   0.021935  232.784 < 2e-16 ***
## omega   0.002361   0.001210   1.952  0.0509 .
## alpha1  0.860544   0.176798   4.867 1.13e-06 ***
## beta1   0.102146   0.129586   0.788  0.4305
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
## 37.80039      normalized: 0.2779441
##
## Description:
## Tue Jul 12 16:45:40 2022 by user: stevenson
##
##
## Standardised Residuals Tests:
##
##                               Statistic p-Value
## Jarque-Bera Test      R      Chi^2 11.46655 0.003236466

```

```
## Shapiro-Wilk Test R W 0.8979165 3.472768e-08
## Ljung-Box Test R Q(10) 553.0233 0
## Ljung-Box Test R Q(15) 662.7706 0
## Ljung-Box Test R Q(20) 703.8948 0
## Ljung-Box Test R^2 Q(10) 17.0636 0.07296837
## Ljung-Box Test R^2 Q(15) 22.48064 0.09580678
## Ljung-Box Test R^2 Q(20) 26.10934 0.162231
## LM Arch Test R TR^2 18.35161 0.105424
##
## Information Criterion Statistics:
## AIC BIC SIC HQIC
## -0.4970646 -0.4113983 -0.4987297 -0.4622520
```

Bitcoin

```
##
## Series Initialization:
## ARMA Model: arma
## Formula Mean: ~ arma(0, 0)
## GARCH Model: garch
## Formula Variance: ~ garch(1, 0)
## ARMA Order: 0 0
## Max ARMA Order: 0
## GARCH Order: 1 0
## Max GARCH Order: 1
## Maximum Order: 1
## Conditional Dist: norm
## h.start: 2
## llh.start: 1
## Length of Series: 193
## Recursion Init: mci
## Series Scale: 8210.722
##
## Parameter Initialization:
## Initial Parameters: $params
## Limits of Transformations: $U, $V
## Which Parameters are Fixed? $includes
## Parameter Matrix:
## U V params includes
## mu -43.65916304 43.65916 4.365916 TRUE
## omega 0.00000100 100.00000 0.100000 TRUE
## alpha1 0.00000001 1.00000 0.100000 TRUE
## gamma1 -0.99999999 1.00000 0.100000 FALSE
## delta 0.00000000 2.00000 2.000000 FALSE
## skew 0.10000000 10.00000 1.000000 FALSE
## shape 1.00000000 10.00000 4.000000 FALSE
## Index List of Parameters to be Optimized:
## mu omega alpha1
## 1 2 3
## Persistence: 0.1
##
##
## --- START OF TRACE ---
## Selected Algorithm: nlminb
```

```

##
## R coded nlminb Solver:
##
## 0:      381.89341:  4.36592 0.100000 0.100000
## 1:      372.18984:  6.22050 0.670928 0.802564
## 2:      267.95127:  4.03796 0.661614 0.799921
## 3:      195.25774:  4.64865 0.182868 0.835083
## 4:      186.85051:  4.76524 0.171715 0.834656
## 5:      178.51307:  5.00769 0.117075 0.833134
## 6:      160.05775:  4.82572 0.0513752 0.837361
## 7:      155.18868:  4.86078 0.0239490 0.837542
## 8:      154.63887:  4.82964 0.0228294 0.837999
## 9:      154.59999:  4.82703 0.0214924 0.838309
## 10:     154.58896:  4.82181 0.0212539 0.839176
## 11:     154.58109:  4.82626 0.0210726 0.840257
## 12:     154.56846:  4.82295 0.0215692 0.841447
## 13:     154.55631:  4.82395 0.0208760 0.842753
## 14:     154.54296:  4.82302 0.0213856 0.844145
## 15:     154.53169:  4.82396 0.0208556 0.845528
## 16:     154.51890:  4.82294 0.0213366 0.846926
## 17:     154.50777:  4.82380 0.0208223 0.848318
## 18:     154.49550:  4.82283 0.0212874 0.849723
## 19:     154.48454:  4.82365 0.0207877 0.851121
## 20:     154.47277:  4.82273 0.0212375 0.852533
## 21:     154.46203:  4.82350 0.0207514 0.853938
## 22:     154.45073:  4.82262 0.0211871 0.855356
## 23:     154.44024:  4.82335 0.0207139 0.856766
## 24:     154.42939:  4.82252 0.0211363 0.858189
## 25:     154.41917:  4.82321 0.0206753 0.859604
## 26:     154.40874:  4.82241 0.0210853 0.861032
## 27:     154.39883:  4.82307 0.0206360 0.862452
## 28:     154.38881:  4.82232 0.0210344 0.863884
## 29:     154.37921:  4.82294 0.0205967 0.865308
## 30:     154.36959:  4.82222 0.0209838 0.866745
## 31:     154.36031:  4.82282 0.0205578 0.868173
## 32:     154.35107:  4.82214 0.0209336 0.869614
## 33:     154.34212:  4.82270 0.0205200 0.871047
## 34:     154.33325:  4.82208 0.0208840 0.872492
## 35:     154.29851:  4.81860 0.0200554 0.880568
## 36:     154.25255:  4.82600 0.0206041 0.888529
## 37:     154.21650:  4.82217 0.0198923 0.896609
## 38:     154.19049:  4.82153 0.0208956 0.904703
## 39:     154.16439:  4.82526 0.0202201 0.912788
## 40:     154.12827:  4.82510 0.0204448 0.937213
## 41:     154.11943:  4.82257 0.0196797 0.937236
## 42:     154.11773:  4.82190 0.0198707 0.938164
## 43:     154.11425:  4.82137 0.0196871 0.947805
## 44:     154.11422:  4.82157 0.0197194 0.948115
## 45:     154.11422:  4.82156 0.0197174 0.948111
## 46:     154.11422:  4.82156 0.0197174 0.948112
##
## Final Estimate of the Negative LLH:
## LLH: 1893.661    norm LLH: 9.811715
##      mu      omega      alpha1

```

```

## 3.958847e+04 1.329265e+06 9.481117e-01
##
## R-optimhess Difference Approximated Hessian Matrix:
##           mu           omega          alpha1
## mu      -1.586491e-05  1.944546e-09 -3.944759e-04
## omega   1.944546e-09 -8.003546e-12 -6.180763e-06
## alpha1 -3.944759e-04 -6.180763e-06 -7.447624e+01
## attr("time")
## Time difference of 0.003099918 secs
##
## --- END OF TRACE ---
##
## Time to Estimate Parameters:
## Time difference of 0.02839732 secs

## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.

##
## Title:
## GARCH Modelling
##
## Call:
## garchFit(formula = ~garch(1, 0), data = bitcoin.ts, trace = T)
##
## Mean and Variance Equation:
## data ~ garch(1, 0)
## <environment: 0x563459f41d38>
## [data = bitcoin.ts]
##
## Conditional Distribution:
## norm
##
## Coefficient(s):
##           mu           omega          alpha1
## 3.9588e+04 1.3293e+06 9.4811e-01
##
## Std. Errors:
## based on Hessian
##
## Error Analysis:
##      Estimate Std. Error t value Pr(>|t|)
## mu      3.959e+04  2.553e+02 155.058 < 2e-16 ***
## omega   1.329e+06  3.715e+05   3.578 0.000347 ***
## alpha1  9.481e-01  1.200e-01   7.902 2.66e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
## -1893.661    normalized: -9.811715
##
## Description:
## Tue Jul 12 16:45:40 2022 by user: stevenson
##

```

```
##
## Standardised Residuals Tests:
##
##      Jarque-Bera Test    R      Chi^2  16.56077  0.0002534391
##      Shapiro-Wilk Test  R      W      0.8880755  8.046103e-11
##      Ljung-Box Test     R      Q(10)  715.3045  0
##      Ljung-Box Test     R      Q(15)  815.9507  0
##      Ljung-Box Test     R      Q(20)  877.148   0
##      Ljung-Box Test     R^2    Q(10)  5.785253  0.8329711
##      Ljung-Box Test     R^2    Q(15)  9.259751  0.8635488
##      Ljung-Box Test     R^2    Q(20)  12.85308  0.8835983
##      LM Arch Test       R      TR^2   6.818263  0.8693861
##
## Information Criterion Statistics:
##      AIC      BIC      SIC      HQIC
## 19.65452 19.70523 19.65405 19.67506
```

Por fim, percebe-se que os p-valores dos coeficientes são todos inferiores a 5%, o que configura-os como cabíveis ao modelo.

Previsões da Série

Finalmente, temos a previsão para o valor seguinte de cada uma das séries, que usa os respectivos modelos ARCH/GARCH encontrados anteriormente, considerando apenas os últimos 14 valores da série.

S&P500

```
## Warning in sqrt(diag(fit$cvar)): NaNs produced
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
##   Consider formula(paste(x, collapse = " ")) instead.
##      meanForecast meanError standardDeviation
## 1      3841.191   38.03641           38.03641
```

Dow Jones

```
## Warning in sqrt(diag(fit$cvar)): NaNs produced
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
##   Consider formula(paste(x, collapse = " ")) instead.
##      meanForecast meanError standardDeviation
## 1      31059.81   216.4632           216.4632
```

Nasdaq

```
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
##   Consider formula(paste(x, collapse = " ")) instead.
##      meanForecast meanError standardDeviation
## 1      11308.29   210.4978           210.4978
```

IBOVESPA

```
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
##   Consider formula(paste(x, collapse = " ")) instead.
```

```
## meanForecast meanError standardDeviation
## 1      99257.21  946.6562          946.6562
```

Brent

```
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.
```

```
## meanForecast meanError standardDeviation
## 1      111.1116  4.720819          4.720819
```

Dólar

```
## Warning in sqrt(diag(fit$cvar)): NaNs produced
```

```
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.
```

```
## meanForecast meanError standardDeviation
## 1       5.280812 0.07819604          0.07819604
```

Bitcoin

```
## Warning: Using formula(x) is deprecated when x is a character vector of length > 1.
## Consider formula(paste(x, collapse = " ")) instead.
```

```
## meanForecast meanError standardDeviation
## 1      19784.81  406.9124          406.9124
```