Spatio-Temporal Data Analysis Project

2020-04-28

Patterns in foreign sims connected to OpenWiFi-Milan

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Contents

1 Introduction & Motivation

The dataset that I've chosen is about the presence of foreign smartphone's sims to the OpenWifi of the Municipality of Milan. This data is open and available on the website data.gov.it. The reasons why I would like to go further with this project is that I strongly believe that are present seasonalities that can be interesting to be analysed but also can be more interesting to relate the outliers to some events that happened in the past with a certain mediatic relevance. In practice I would like to both analyse trend and seasonalities to know in which months there are more foreign people and if the trend is increasing in time and both search for outlier peaks to be related to important happenings in the Milan city. Finally I would like to forecast the possible presences in the new year in the city of Milan.

2 The Data

The dataset comes from the open data provided by all the municipalities of Milan. This repository is available at dati.gov.it. From this repository I selected the data going from January of 2018 to October of the 2019.

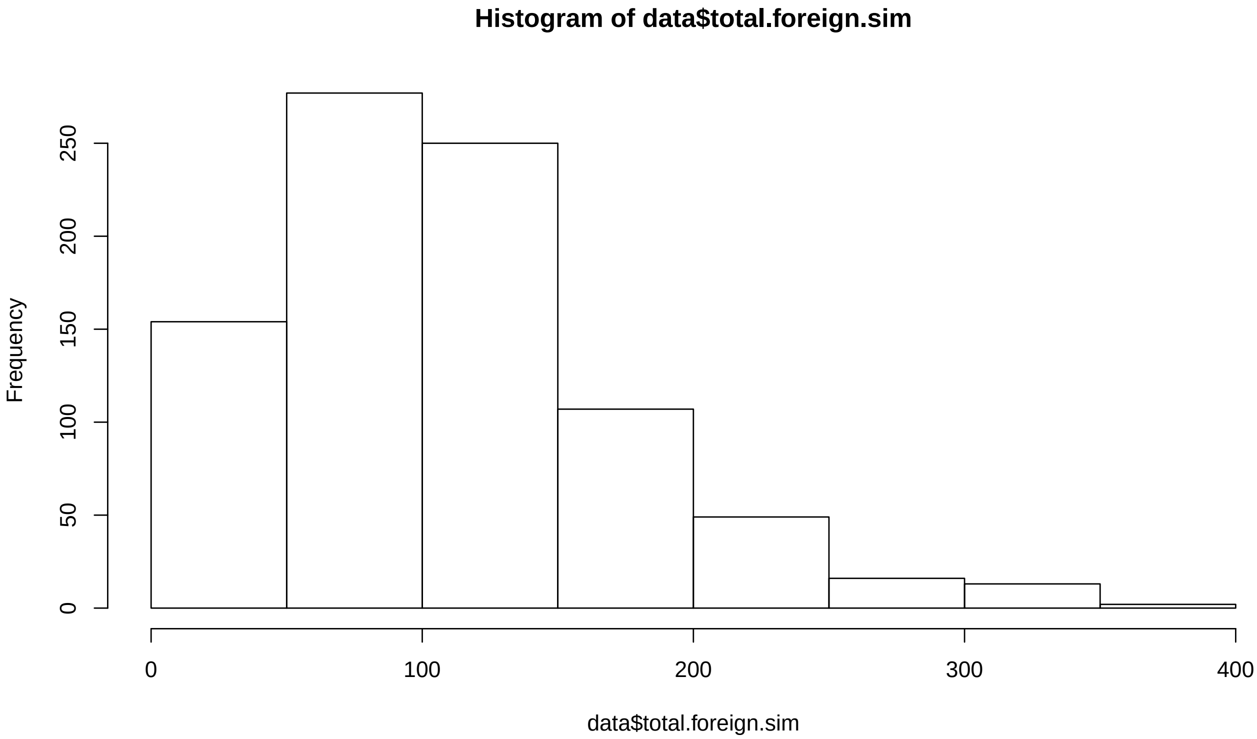
Characteristics of the DataSet:

- the dataset contains 2 columns "Date, Number_of_Foreign_Sims"
- has 658 rows
- Dates goes from from 01/01/18 to 30/10/19 (~2 years)
- the datasets have no NA
- no lacking days
- the "Number_of_Foreign_Sims" is a discrete variable about total number of foreign sims in a certain Date connected to the OpenWifi of Milan

3 Exploration of the Data

```
## [1] "minimum, lower-hinge, median, upper-hinge, maximum)"
```

```
## [1]   1.0  61.5 101.0 141.0 378.0
```



4 Preprocessing

Checking Nans

```
## [1] 0
```

```
## [1] 0
```

Checking limit values

```
## [1] 1
```

```
## [1] 378
```

```
## [1] 109.9228
```

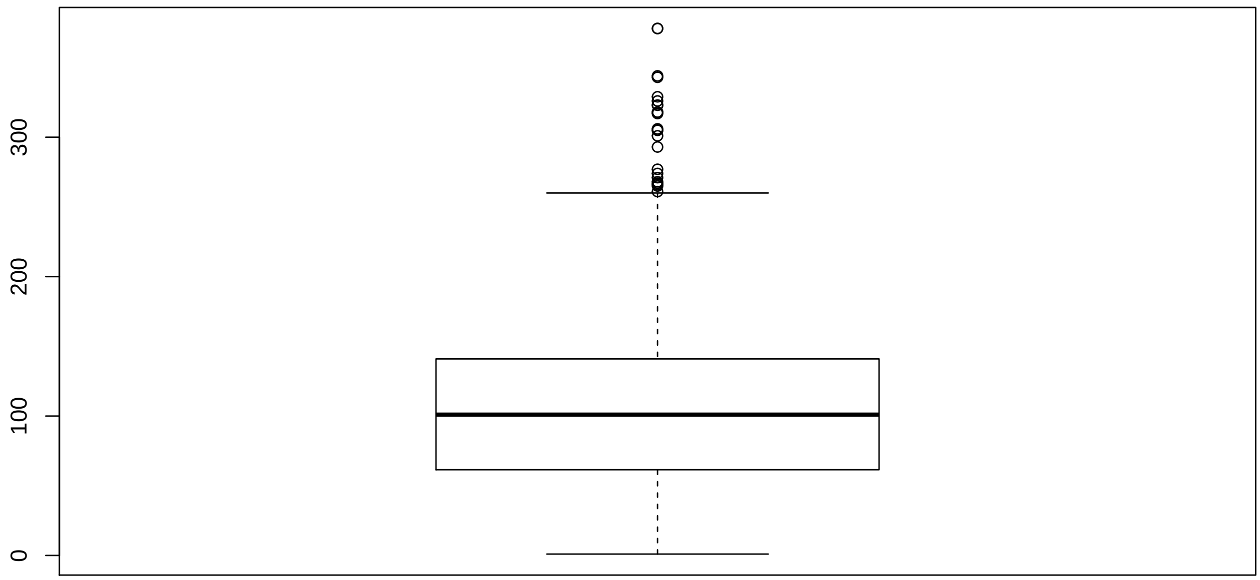
```
## [1] 63.63468
```

Elements that are good in our ts stand between mean$\pm$std

```
## [1] 173.5575
```

```
## [1] 46.28813
```

boxplot to check outliers




```
##      0%     25%     50%     75%    100%
##   1.00   61.75 101.00 141.00 378.00
```

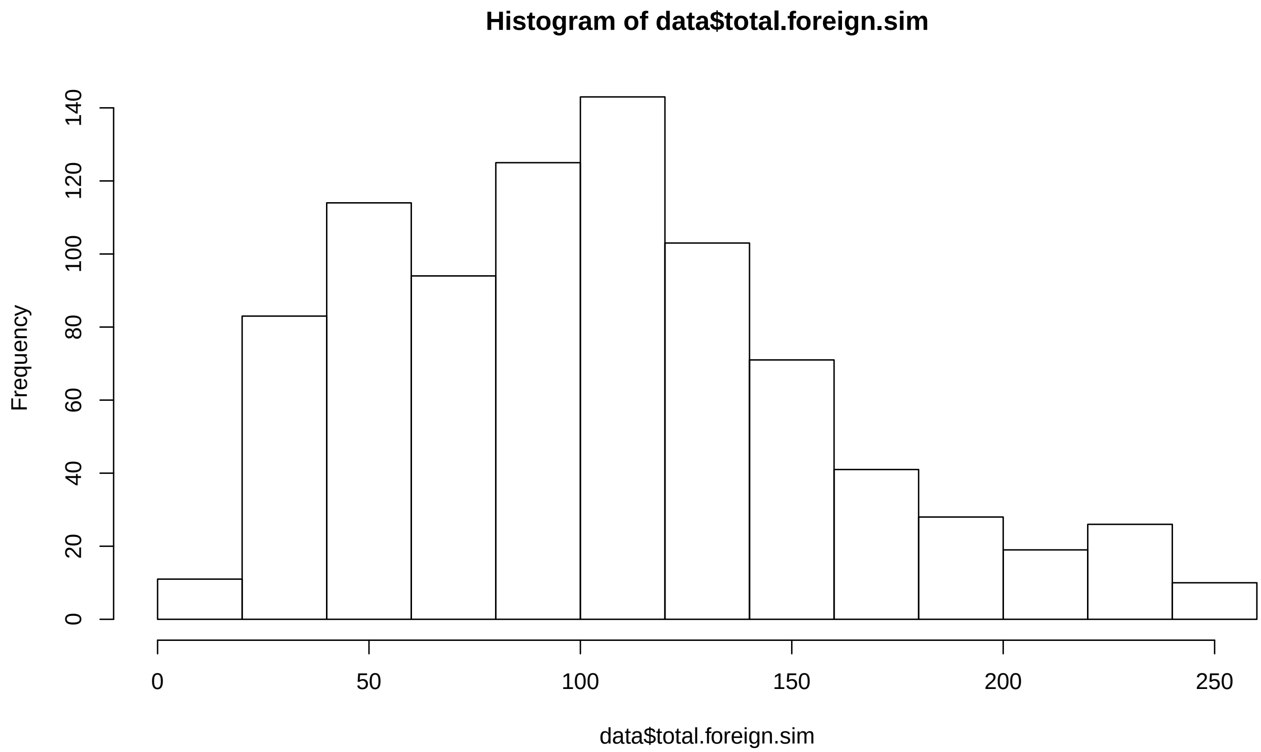
```
##      25%
## -57.125
```

```
##     75%
## 259.875
```

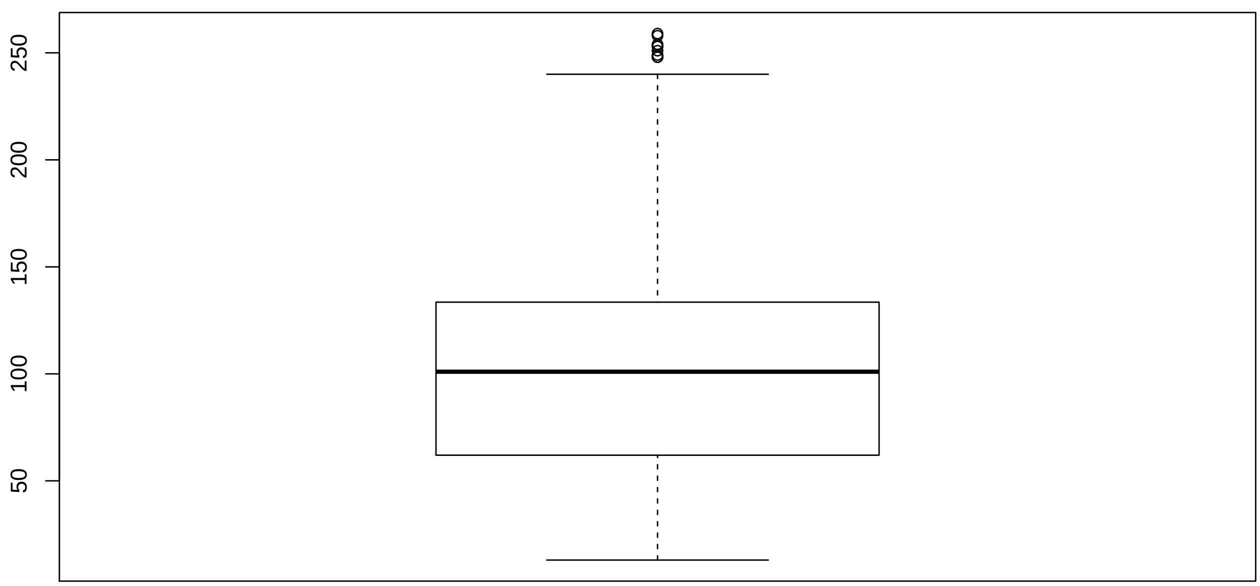
Checking last elements of the serie

5 Using a boxCox transform

6 Hist after the transformation



7 Boxplot after the transformation

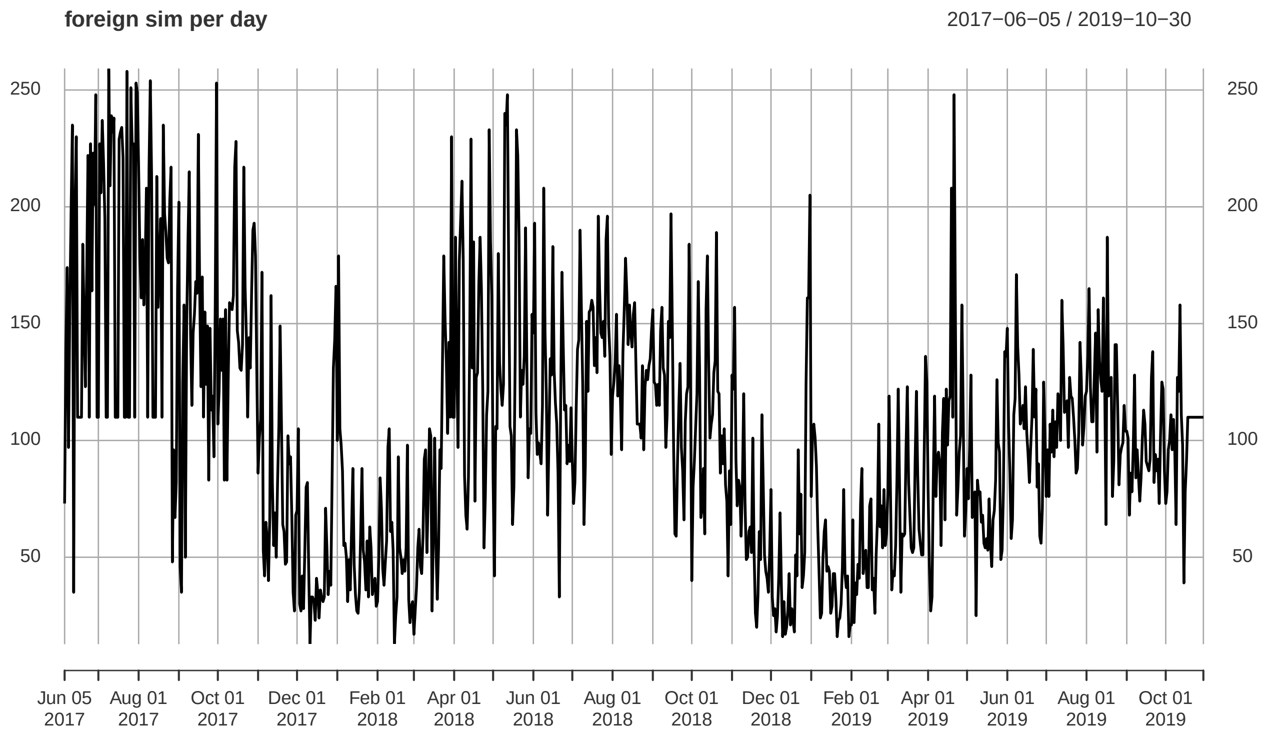


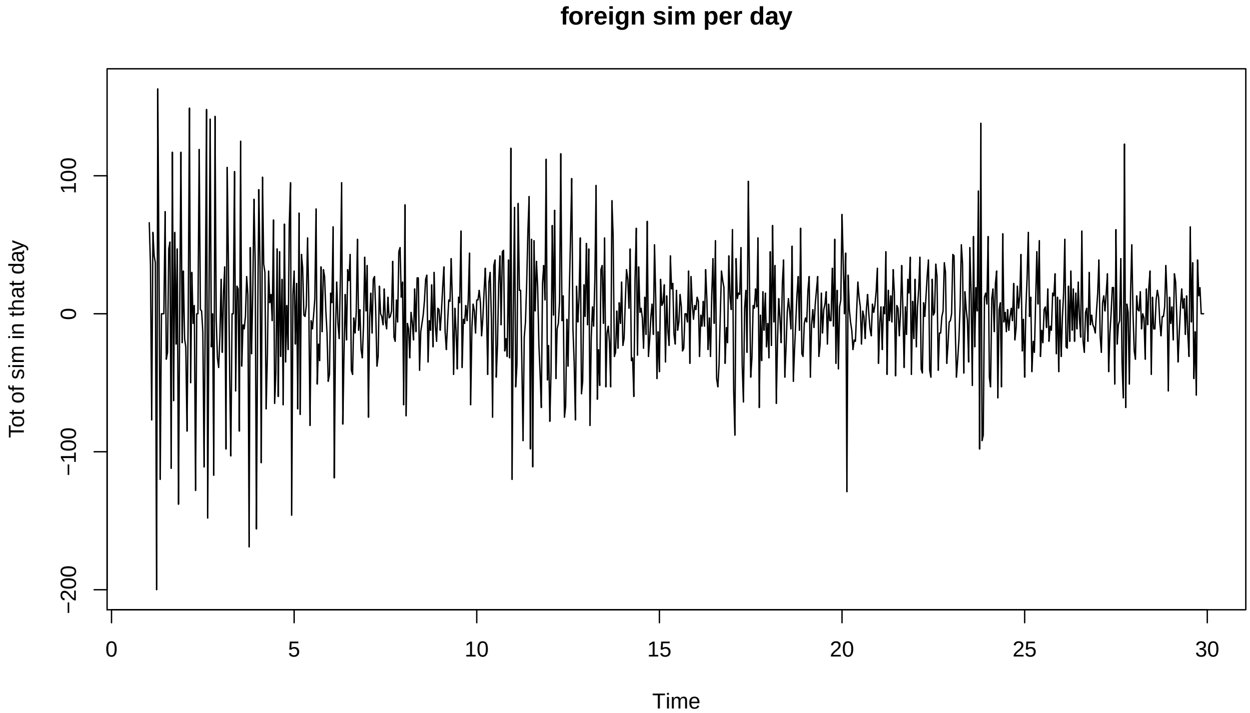
8 Time serie is built

Here the time serie is built

9 Derivative of the data to reach the stationarity

We loaded the dataset from the various datasets aggregating into only one dataset with 655 rows representing 2 years of data gathered. Starting from 05.06.2017 to 30.10.2019. Data is here:





10 Peaks Explanation

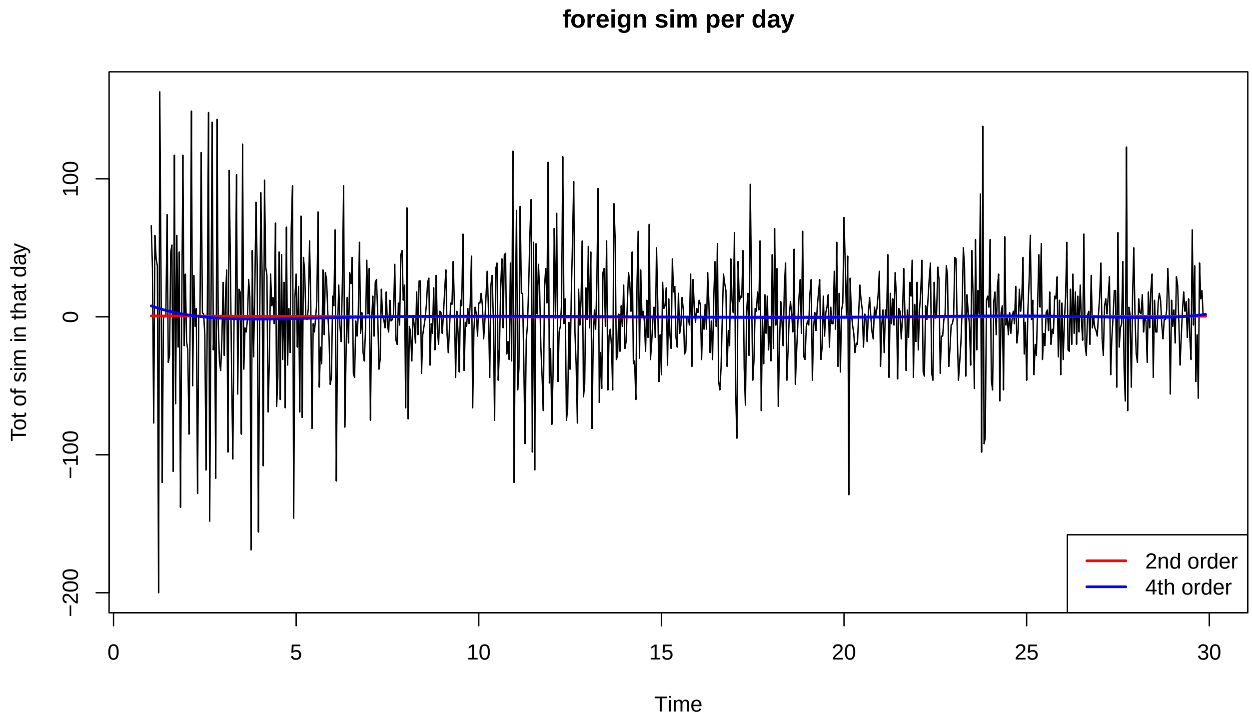
Many peaks are present we would like to exaplin them and to cut them out to be able to predict with a simple arima

- automatic roaming [https://www.mobileworld.it/2017/08/07/roaming-gratis-europa-condizioni-fair-us
- fashion week [https://www.cameramoda.it/it/milano-moda-donna/] february
- fashion week 2017 [https://www.milanoweekend.it/articoli/milano-fashion-week-2017-eventi-programm february

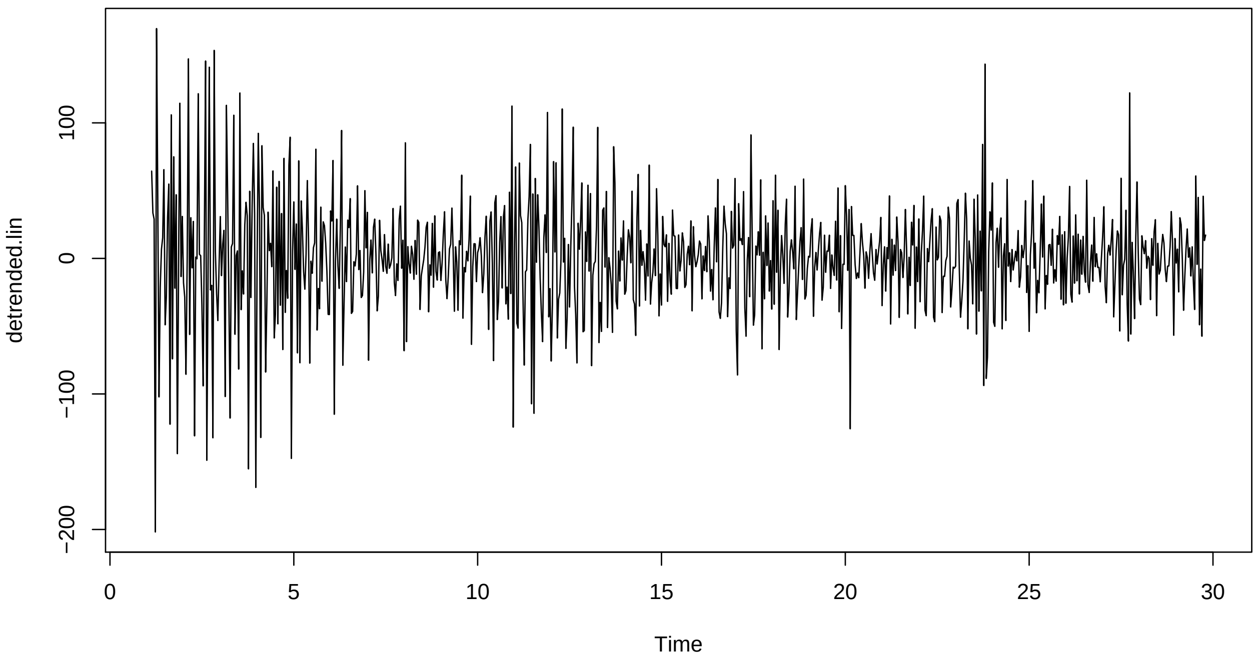
```
## [1] "2017-07-09"
```

- arch week [https://www.lastampa.it/milano/2017/06/17/news/milano-smart-city-del-futuro-se-ne-par 34584894?refresh_ce]
- it was a saturday!!
- it was the orient festival [https://www.wikieventi.it/milano/index.php?data_selezionata=2017-06-17]
- many mucis events, samsara of papetee and others, folk's festivals, discounts [https://www.wikieventi.it/milano/index.php?data_selezionata=2017-07-22]

11 Trend recognition

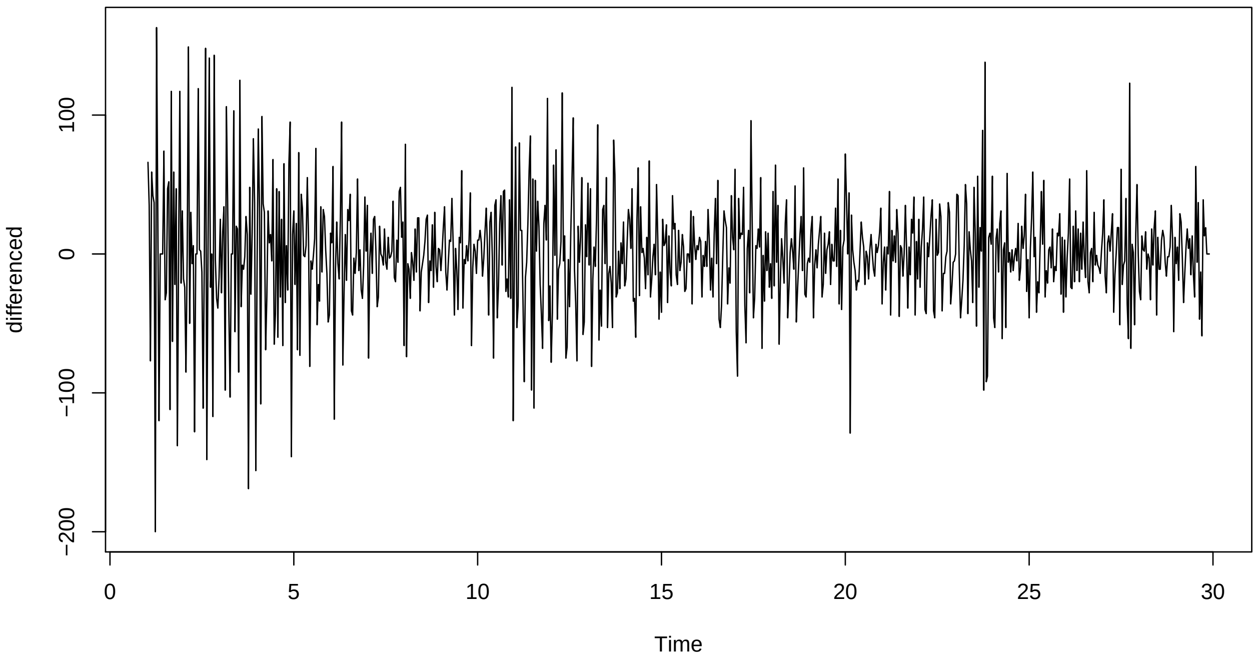


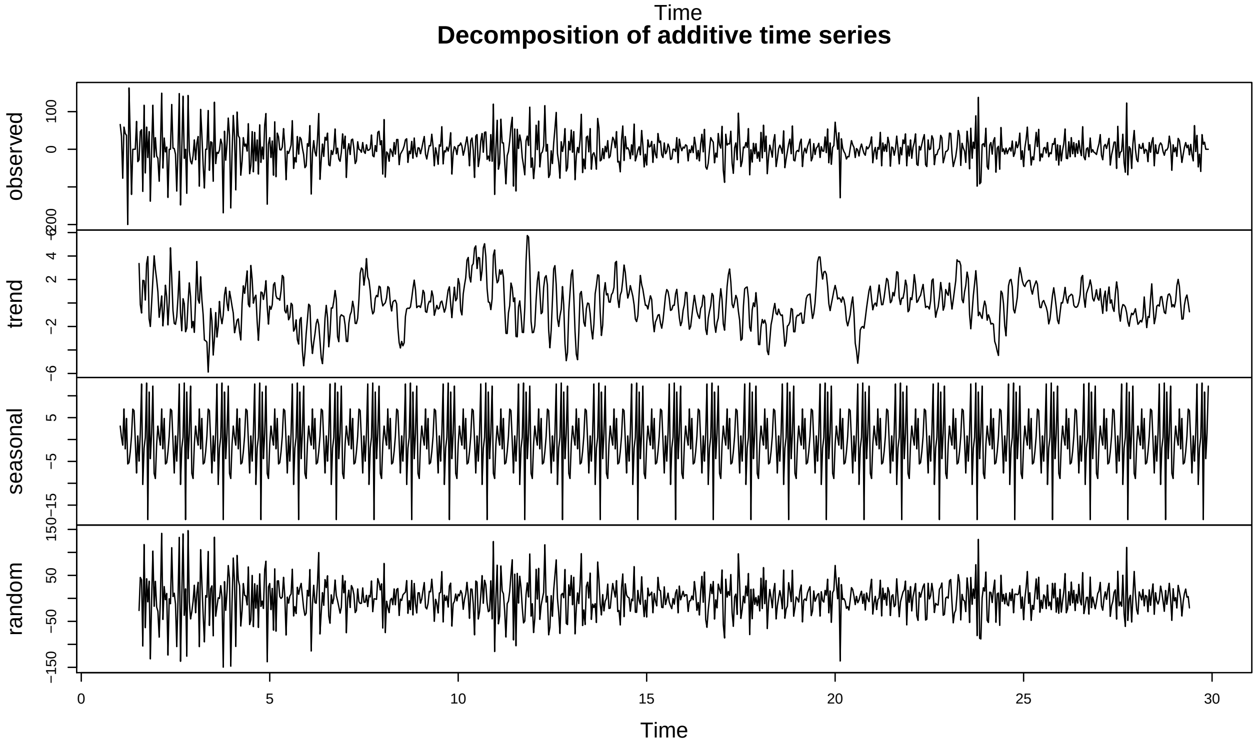
11.1 Detrending using LM

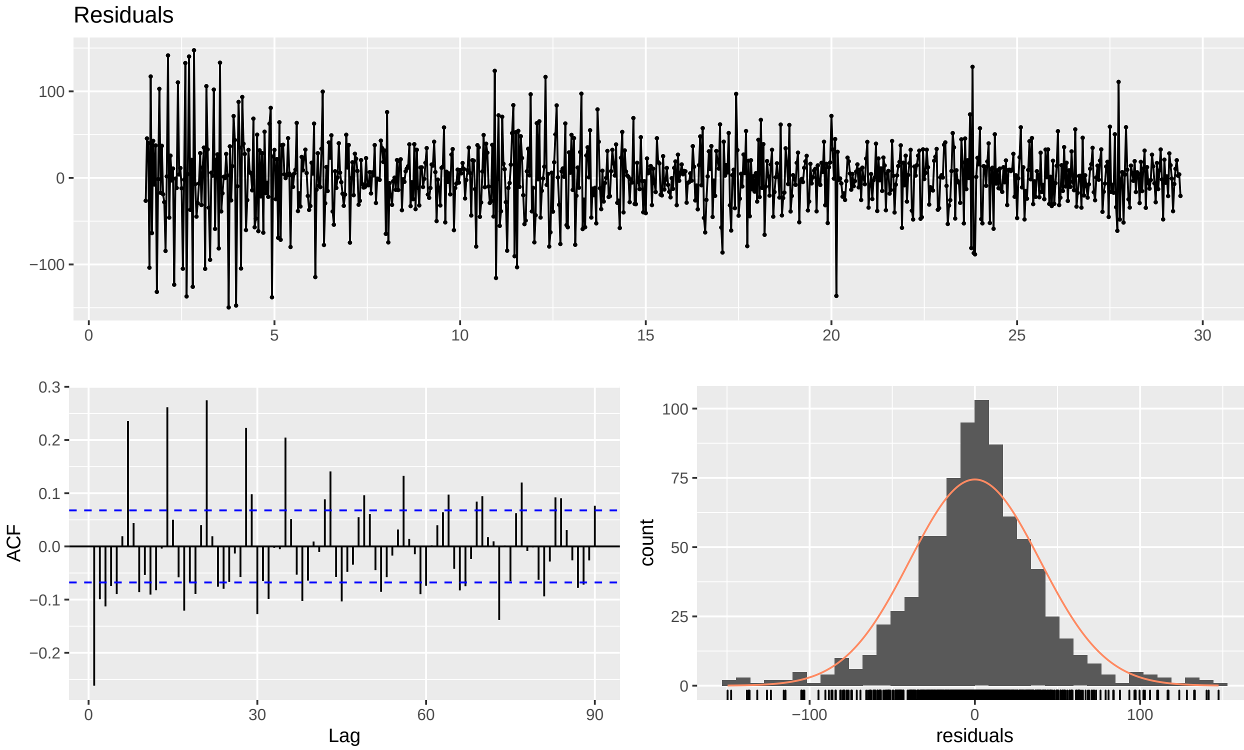


12 The additive model doesn't work for us

With the additive model This model doesn't work at all


differenced
100
0
−100
−200
0
5
10
15
20
25
30
Time


Decomposition of additive time series
observed
trend
seasonal
random
Time



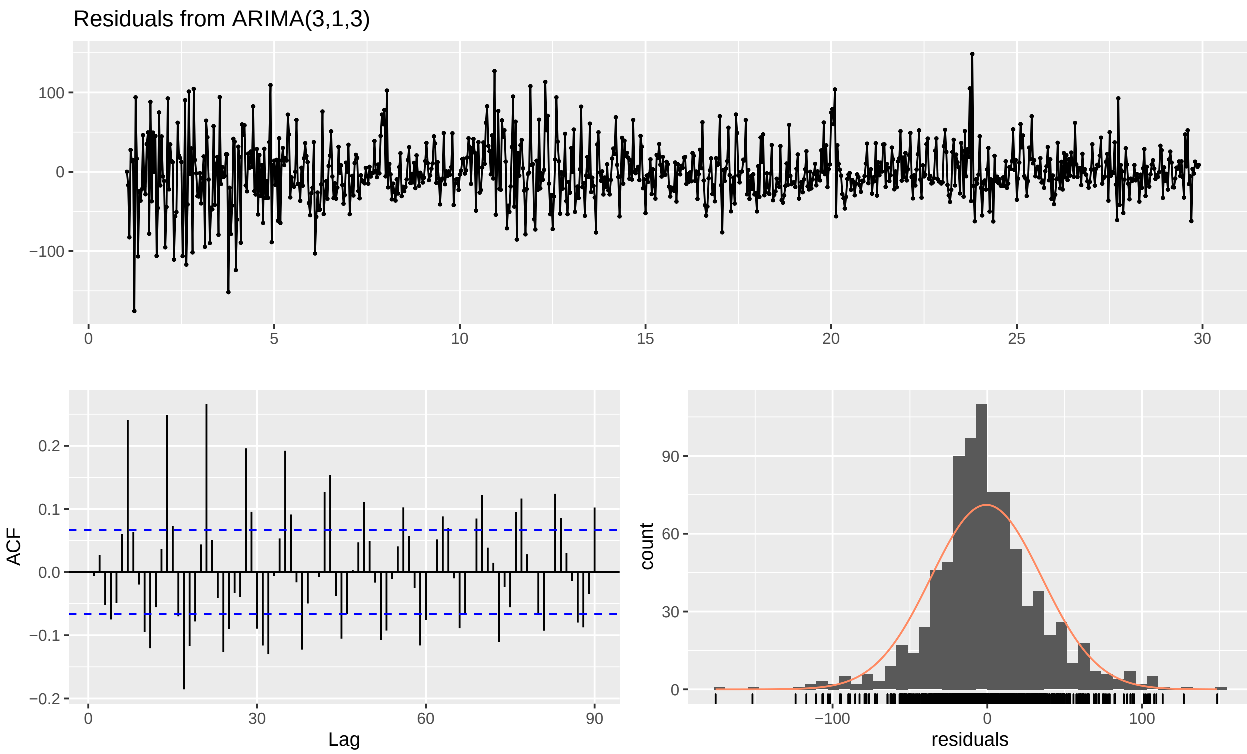

```
##
##  Box-Pierce test
##
## data:  decomposed$random
## X-squared = 87.63, df = 5, p-value < 2.2e-16
```

```
##
##  Box-Ljung test
##
## data:  decomposed$random
## X-squared = 88.029, df = 5, p-value < 2.2e-16
```

13 Arima

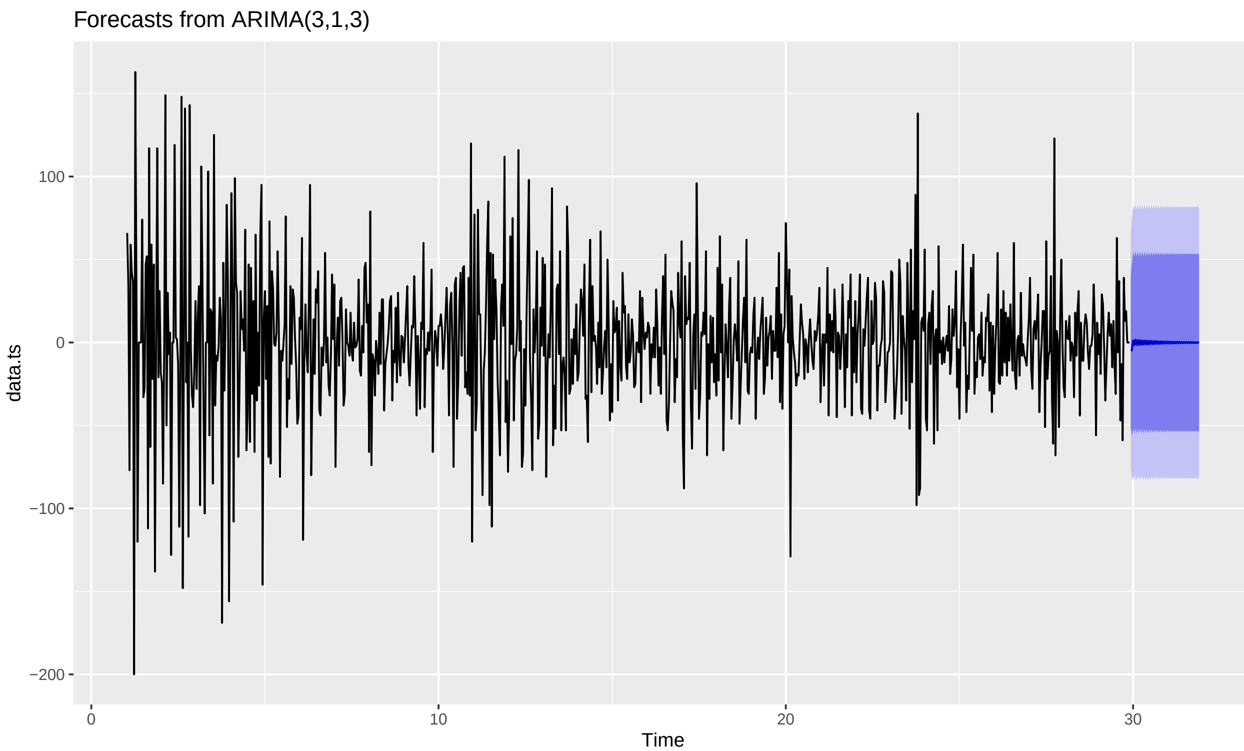
```
## Series: data.ts
## ARIMA(3,1,3)
##
## Coefficients:
##           ar1     ar2      ar3     ma1      ma2     ma3
##       -0.5721  0.2793  -0.1006  -0.935  -0.9105  0.8455
## s.e.      NaN  0.0325   0.0359     NaN      NaN     NaN
##
## sigma^2 estimated as 1292:  log likelihood=-4333.64
## AIC=8681.27   AICc=8681.4   BIC=8714.62
##
```

```
## Training set error measures:
##                      ME     RMSE      MAE MPE MAPE      MASE         ACF1
## Training set -0.6238148 35.80279 25.94447 NaN  Inf 0.5746165 -0.006201867
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(3,1,3)
## Q* = 553.28, df = 54, p-value < 2.2e-16
##
## Model df: 6.   Total lags used: 60
```

Every 7 bins a peak occurs

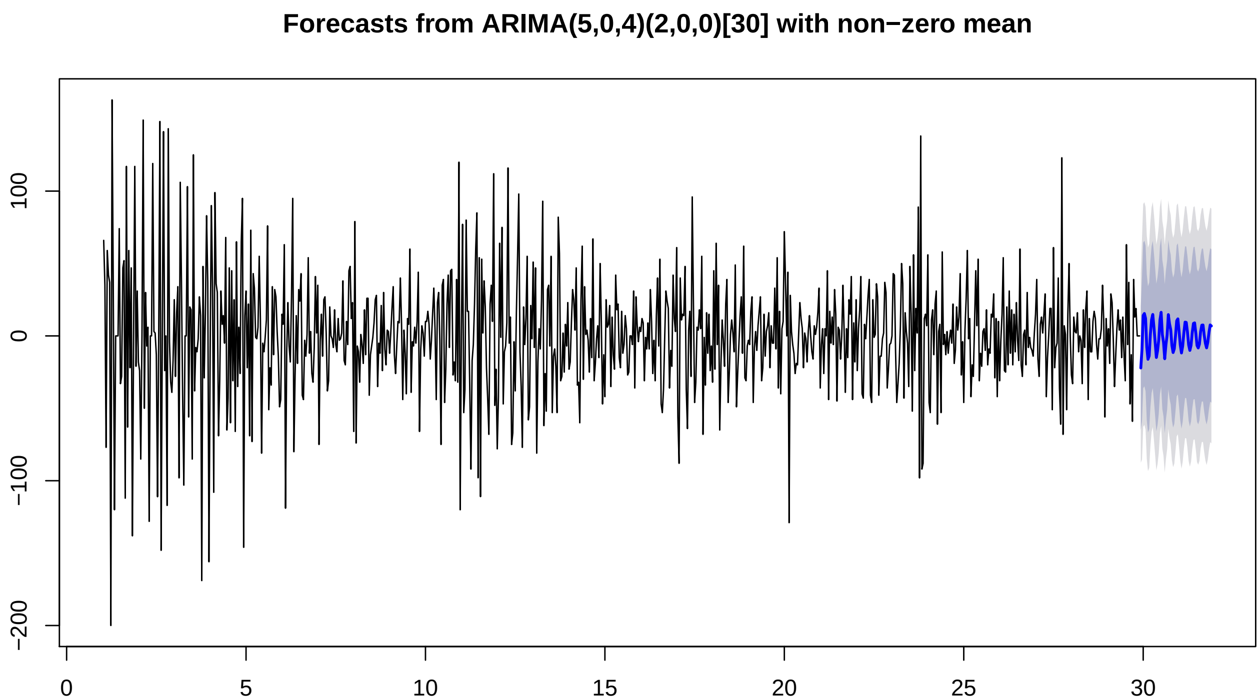


14 Auto Arima

```
##
##  Fitting models using approximations to speed things up...
##
##  ARIMA(2,0,2)(1,0,1)[30] with non-zero mean : 8663.813
##  ARIMA(0,0,0)            with non-zero mean : 8935.378
##  ARIMA(1,0,0)(1,0,0)[30] with non-zero mean : 8807.148
##  ARIMA(0,0,1)(0,0,1)[30] with non-zero mean : 8782.497
##  ARIMA(0,0,0)            with zero mean     : 8928.614
##  ARIMA(2,0,2)(0,0,1)[30] with non-zero mean : 8692.718
##  ARIMA(2,0,2)(1,0,0)[30] with non-zero mean : 8658.911
##  ARIMA(2,0,2)            with non-zero mean : 8694.686
##  ARIMA(2,0,2)(2,0,0)[30] with non-zero mean : 8552.932
##  ARIMA(2,0,2)(2,0,1)[30] with non-zero mean : 8550.925
##  ARIMA(2,0,2)(2,0,2)[30] with non-zero mean : 8556.85
##  ARIMA(2,0,2)(1,0,2)[30] with non-zero mean : 8666.356
##  ARIMA(1,0,2)(2,0,1)[30] with non-zero mean : 8558.03
##  ARIMA(2,0,1)(2,0,1)[30] with non-zero mean : 8557.03
##  ARIMA(3,0,2)(2,0,1)[30] with non-zero mean : 8539.628
##  ARIMA(3,0,2)(1,0,1)[30] with non-zero mean : 8620.286
##  ARIMA(3,0,2)(2,0,0)[30] with non-zero mean : 8539.936
##  ARIMA(3,0,2)(2,0,2)[30] with non-zero mean : 8543.912
##  ARIMA(3,0,2)(1,0,0)[30] with non-zero mean : 8618.343
```

```
##  ARIMA(3,0,2)(1,0,2)[30] with non-zero mean : 8626.493
##  ARIMA(3,0,1)(2,0,1)[30] with non-zero mean : 8542.713
##  ARIMA(4,0,2)(2,0,1)[30] with non-zero mean : 8543.894
##  ARIMA(3,0,3)(2,0,1)[30] with non-zero mean : Inf
##  ARIMA(2,0,3)(2,0,1)[30] with non-zero mean : Inf
##  ARIMA(4,0,1)(2,0,1)[30] with non-zero mean : 8539.443
##  ARIMA(4,0,1)(1,0,1)[30] with non-zero mean : 8619.134
##  ARIMA(4,0,1)(2,0,0)[30] with non-zero mean : 8544.122
##  ARIMA(4,0,1)(2,0,2)[30] with non-zero mean : 8542.931
##  ARIMA(4,0,1)(1,0,0)[30] with non-zero mean : 8612.547
##  ARIMA(4,0,1)(1,0,2)[30] with non-zero mean : 8622.61
##  ARIMA(4,0,0)(2,0,1)[30] with non-zero mean : 8616.219
##  ARIMA(5,0,1)(2,0,1)[30] with non-zero mean : 8518.913
##  ARIMA(5,0,1)(1,0,1)[30] with non-zero mean : 8597.996
##  ARIMA(5,0,1)(2,0,0)[30] with non-zero mean : 8514.745
##  ARIMA(5,0,1)(1,0,0)[30] with non-zero mean : 8591.423
##  ARIMA(5,0,0)(2,0,0)[30] with non-zero mean : 8539.191
##  ARIMA(5,0,2)(2,0,0)[30] with non-zero mean : 8486.887
##  ARIMA(5,0,2)(1,0,0)[30] with non-zero mean : 8592.958
##  ARIMA(5,0,2)(2,0,1)[30] with non-zero mean : 8486.373
##  ARIMA(5,0,2)(1,0,1)[30] with non-zero mean : 8598.725
##  ARIMA(5,0,2)(2,0,2)[30] with non-zero mean : 8491.305
##  ARIMA(5,0,2)(1,0,2)[30] with non-zero mean : 8605.233
##  ARIMA(5,0,3)(2,0,1)[30] with non-zero mean : 8481.375
##  ARIMA(5,0,3)(1,0,1)[30] with non-zero mean : 8590.645
##  ARIMA(5,0,3)(2,0,0)[30] with non-zero mean : Inf
##  ARIMA(5,0,3)(2,0,2)[30] with non-zero mean : 8486.796
##  ARIMA(5,0,3)(1,0,0)[30] with non-zero mean : 8585.559
##  ARIMA(5,0,3)(1,0,2)[30] with non-zero mean : 8596.863
##  ARIMA(4,0,3)(2,0,1)[30] with non-zero mean : 8550.888
##  ARIMA(5,0,4)(2,0,1)[30] with non-zero mean : 8476.119
##  ARIMA(5,0,4)(1,0,1)[30] with non-zero mean : 8569.669
##  ARIMA(5,0,4)(2,0,0)[30] with non-zero mean : 8475.588
##  ARIMA(5,0,4)(1,0,0)[30] with non-zero mean : 8565.536
##  ARIMA(4,0,4)(2,0,0)[30] with non-zero mean : 8511.699
##  ARIMA(5,0,5)(2,0,0)[30] with non-zero mean : Inf
##  ARIMA(4,0,3)(2,0,0)[30] with non-zero mean : 8552.847
##  ARIMA(4,0,5)(2,0,0)[30] with non-zero mean : Inf
##  ARIMA(5,0,4)(2,0,0)[30] with zero mean     : 8469.048
##  ARIMA(5,0,4)(1,0,0)[30] with zero mean     : 8558.813
##  ARIMA(5,0,4)(2,0,1)[30] with zero mean     : 8469.634
##  ARIMA(5,0,4)(1,0,1)[30] with zero mean     : 8562.931
##  ARIMA(4,0,4)(2,0,0)[30] with zero mean     : 8505.03
##  ARIMA(5,0,3)(2,0,0)[30] with zero mean     : Inf
##  ARIMA(5,0,5)(2,0,0)[30] with zero mean     : Inf
```

```
##  ARIMA(4,0,3)(2,0,0)[30] with zero mean     : 8546.18
##  ARIMA(4,0,5)(2,0,0)[30] with zero mean     : Inf
##
##  Now re-fitting the best model(s) without approximations...
##
##  ARIMA(5,0,4)(2,0,0)[30] with zero mean     : Inf
##  ARIMA(5,0,4)(2,0,1)[30] with zero mean     : Inf
##  ARIMA(5,0,4)(2,0,0)[30] with non-zero mean : 8620.614
##
##  Best model: ARIMA(5,0,4)(2,0,0)[30] with non-zero mean
```

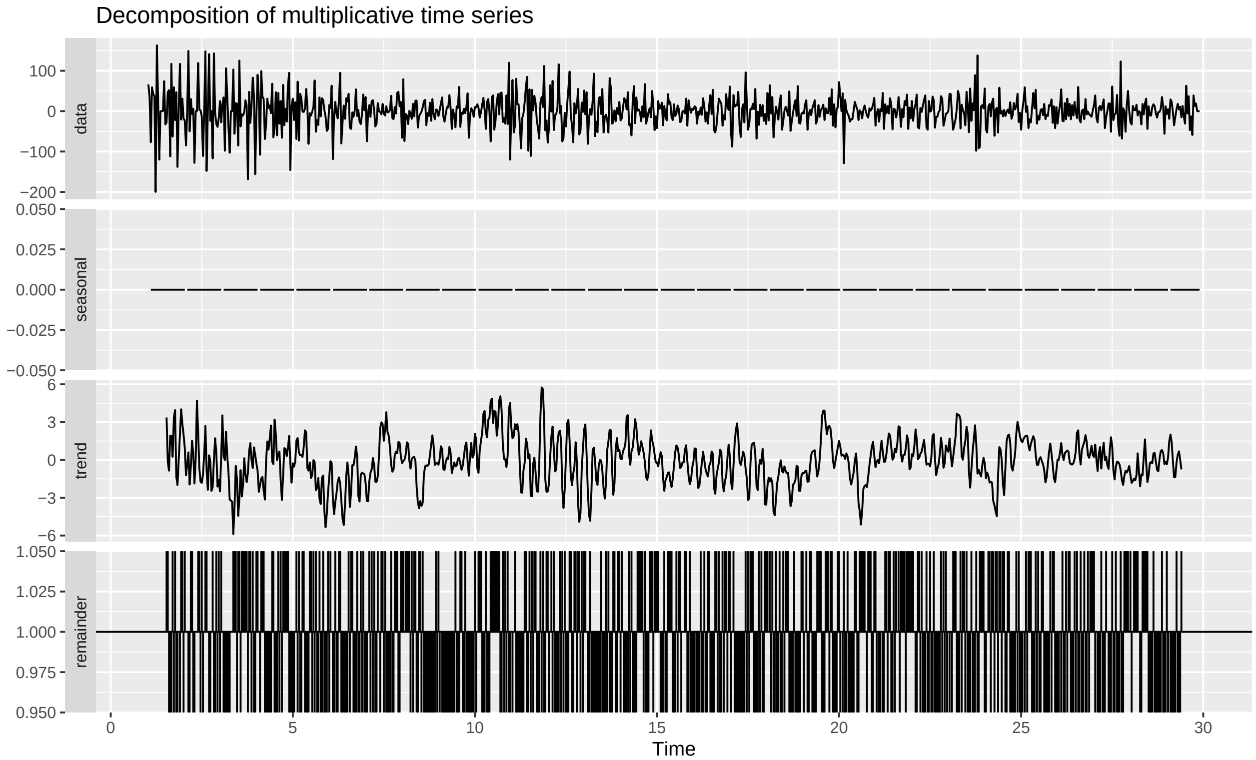


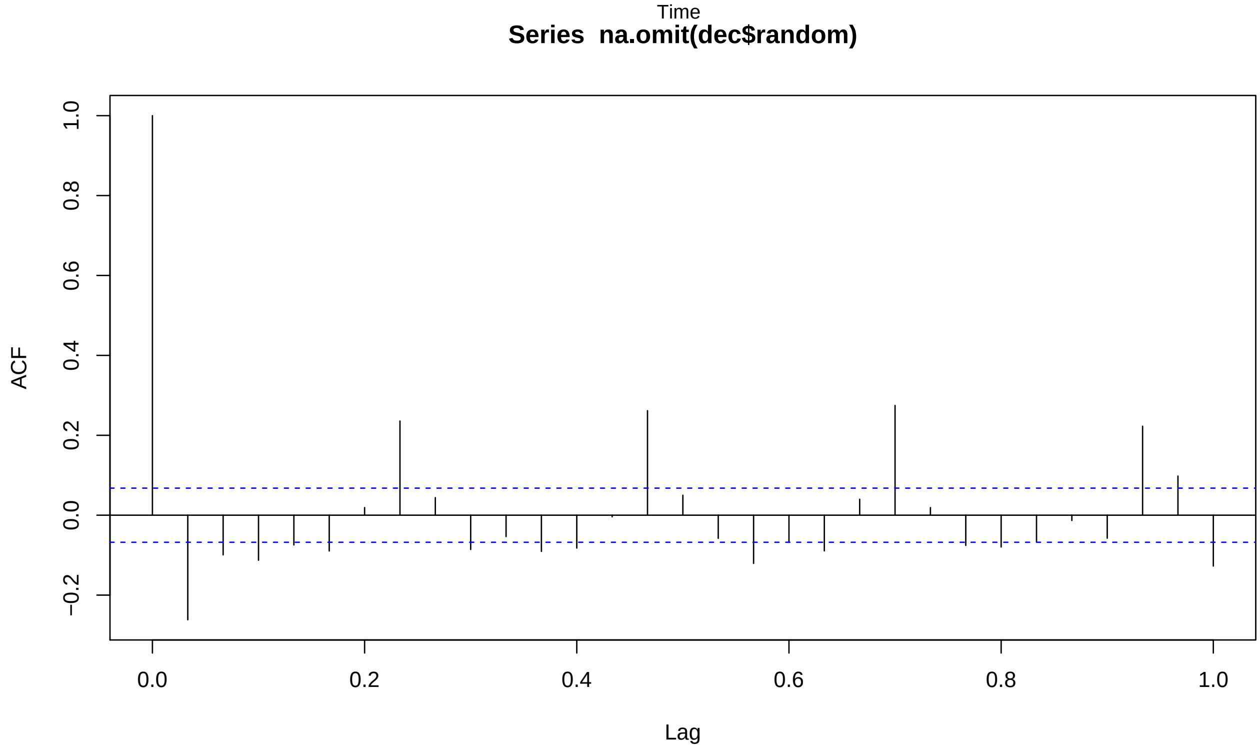
The plot is not good but AIC and BIC are very high, we should try with a multi seasonal decomposition

```
## [1] 30
```

15 Searching for multi seasonalities

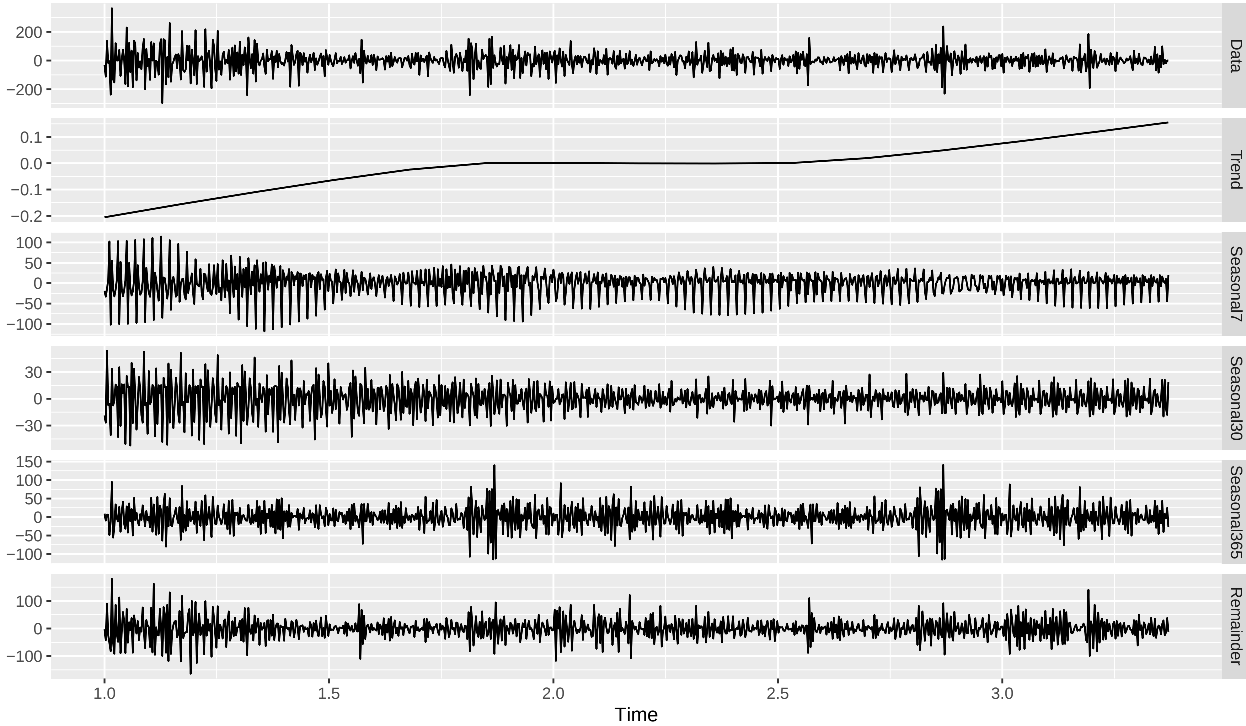
without differentiation residuals looks pretty bad

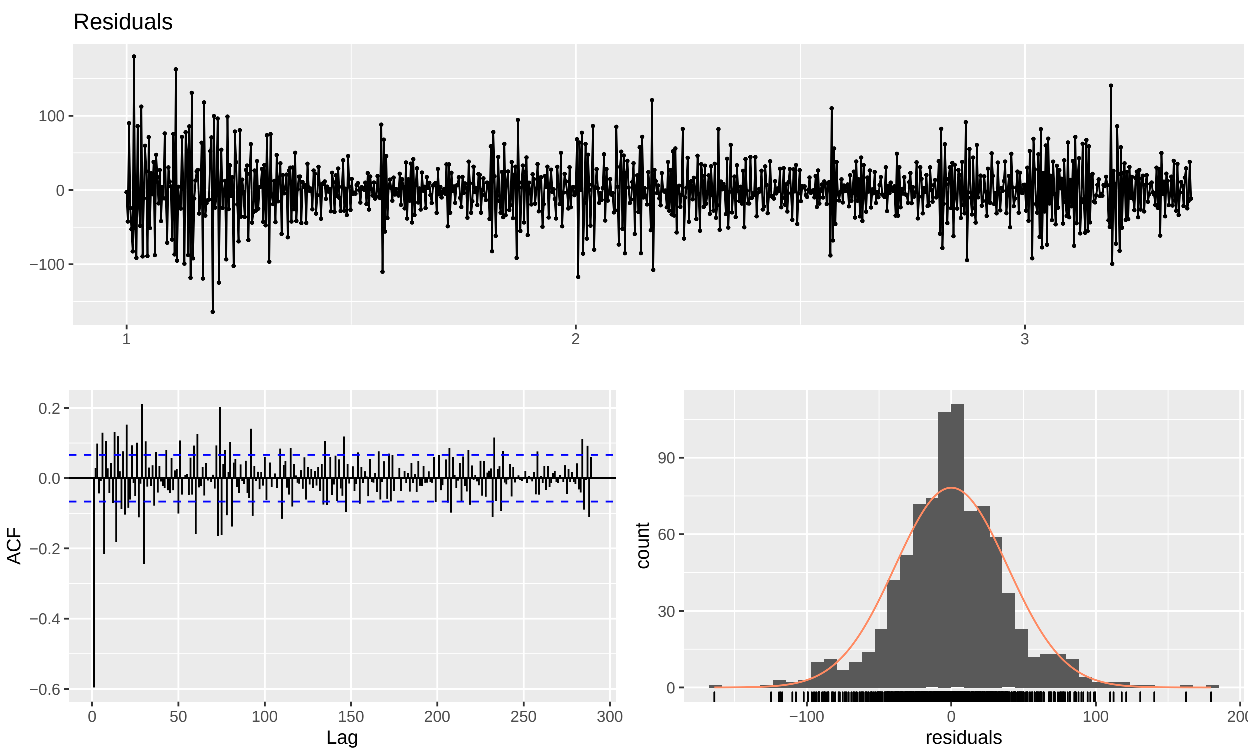




Looks better than before but we can still see every 5(*7) a seasonality/trend left. 5*7 is about a month, probably there is a monthly seasonality

16 Transforming into msts

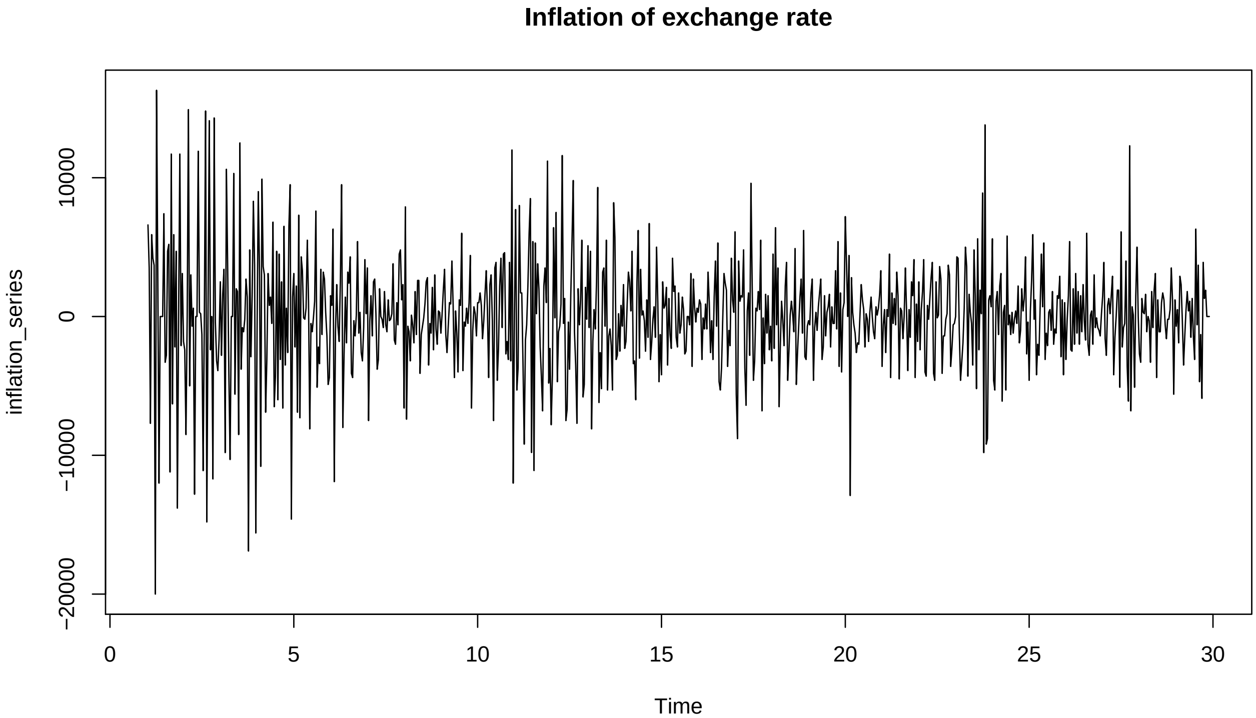




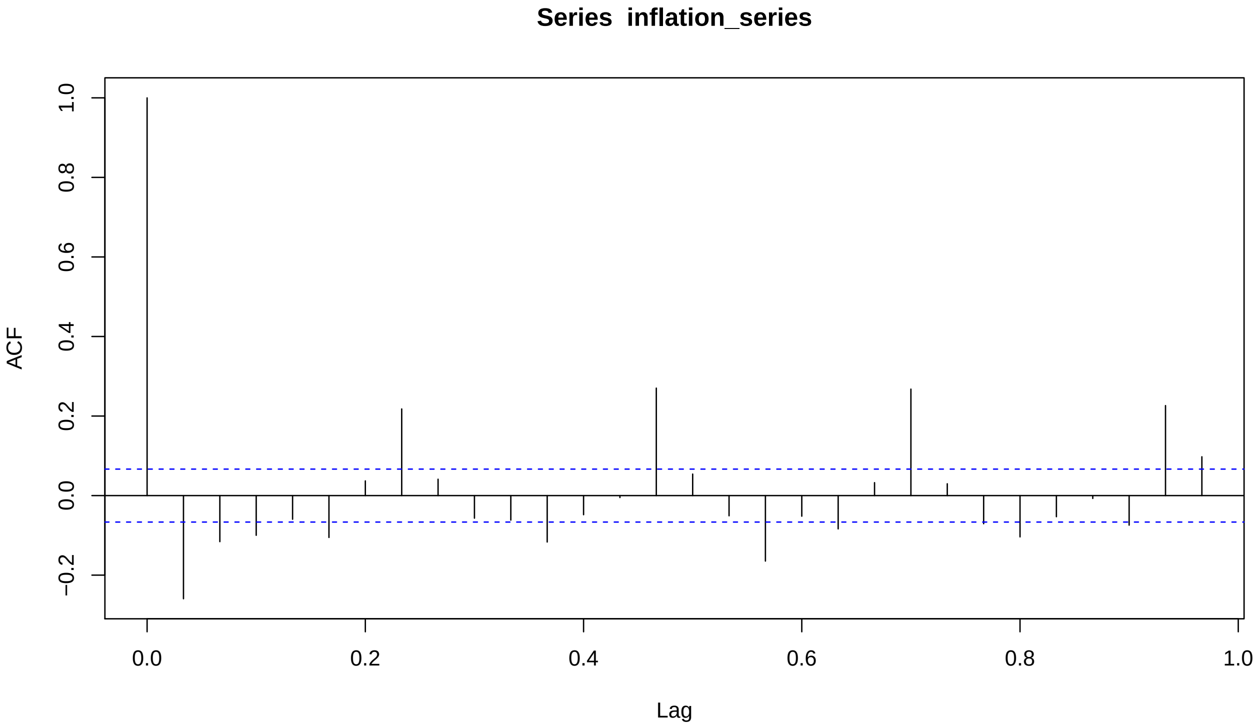

```
##
##  Box-Pierce test
##
## data:  remainder(decomposed)
```

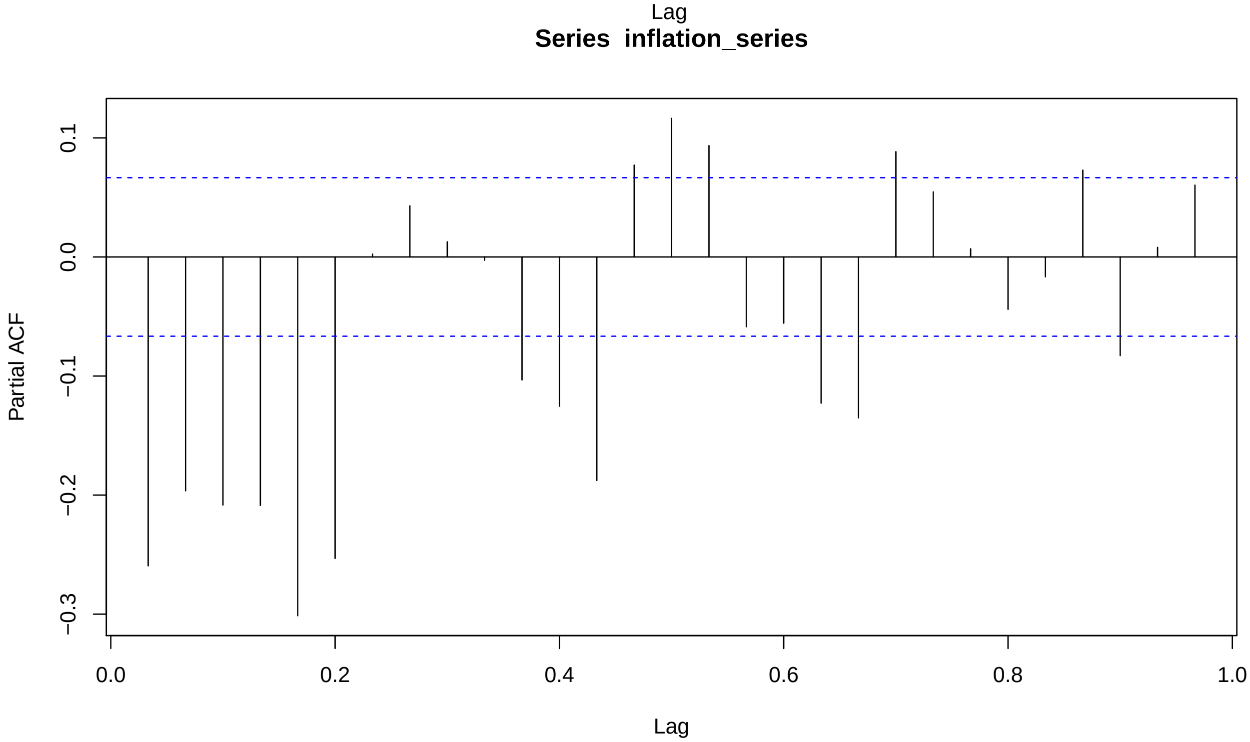
```
## X-squared = 318.35, df = 5, p-value < 2.2e-16
##
##  Box-Ljung test
##
## data:  remainder(decomposed)
## X-squared = 319.48, df = 5, p-value < 2.2e-16
```

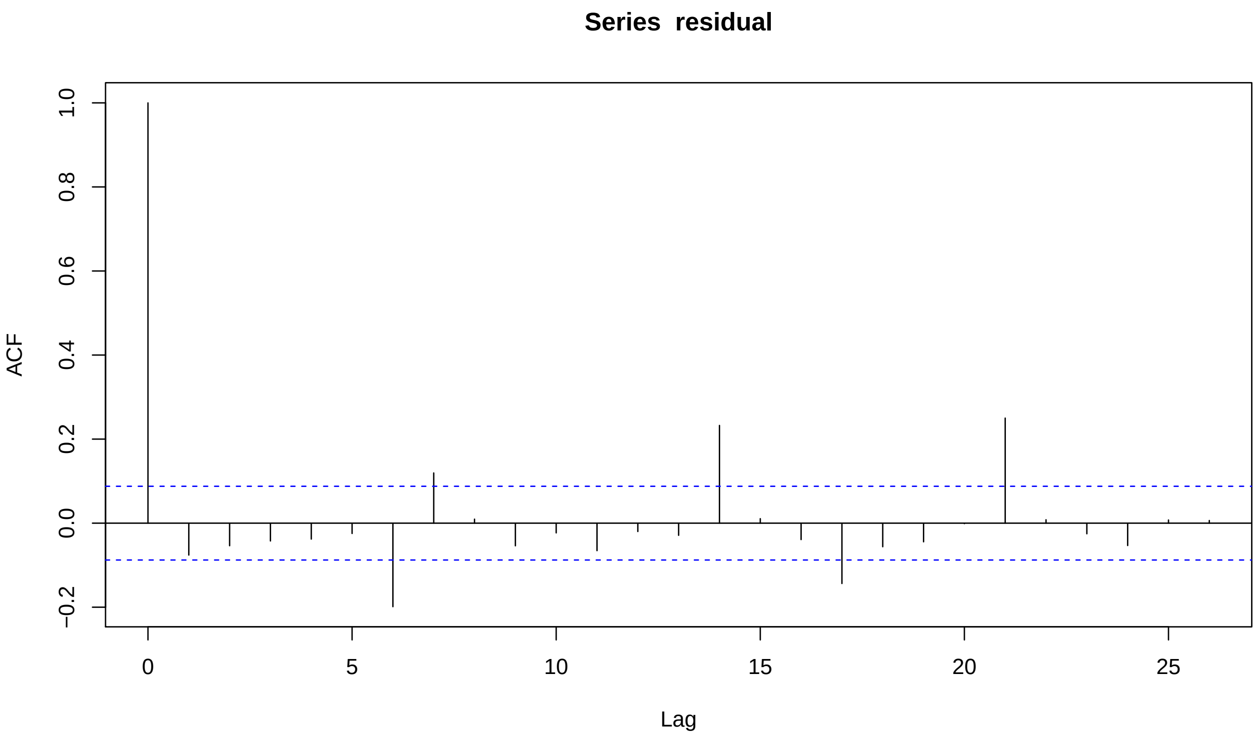
17 Garch

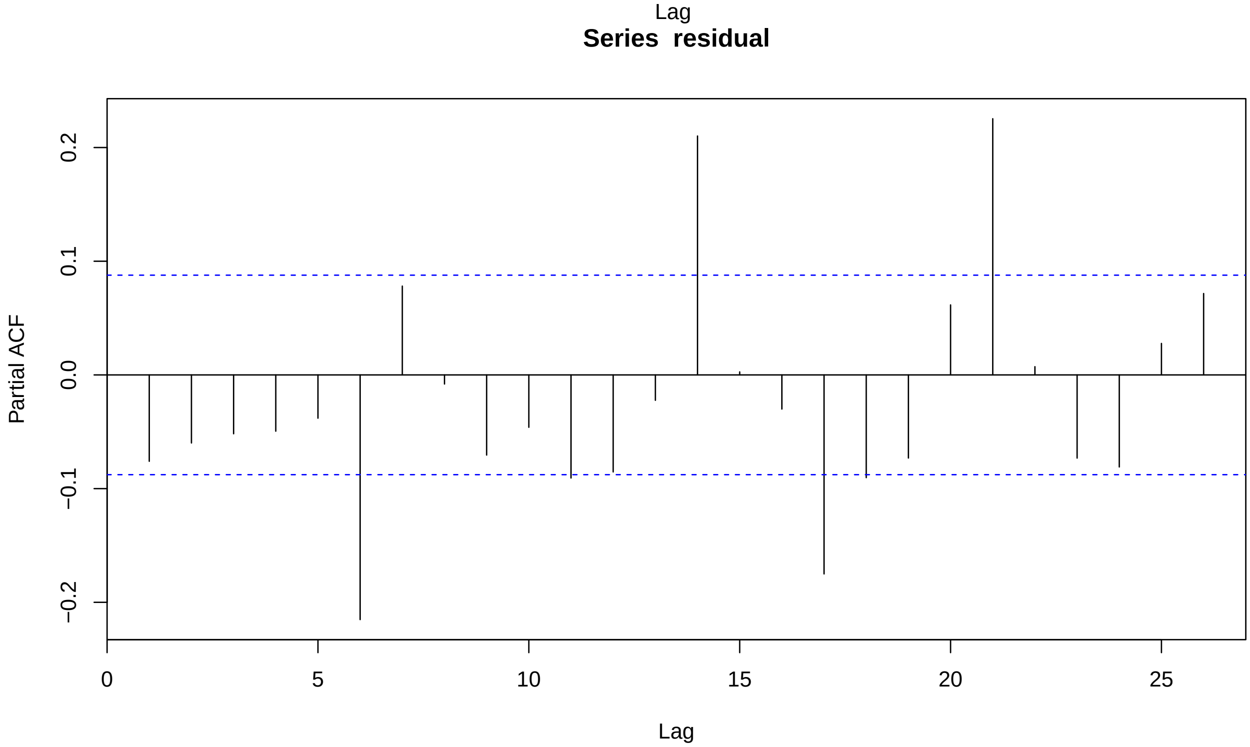



```
##       Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
## -20000.000  -2100.000      0.000      4.259   2000.000  16300.000
```


Series inflation_series
ACF
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
Lag


Series inflation_series
Partial ACF
0.1
0.0
−0.1
−0.2
−0.3
0.0
0.2
0.4
0.6
0.8
1.0
Lag





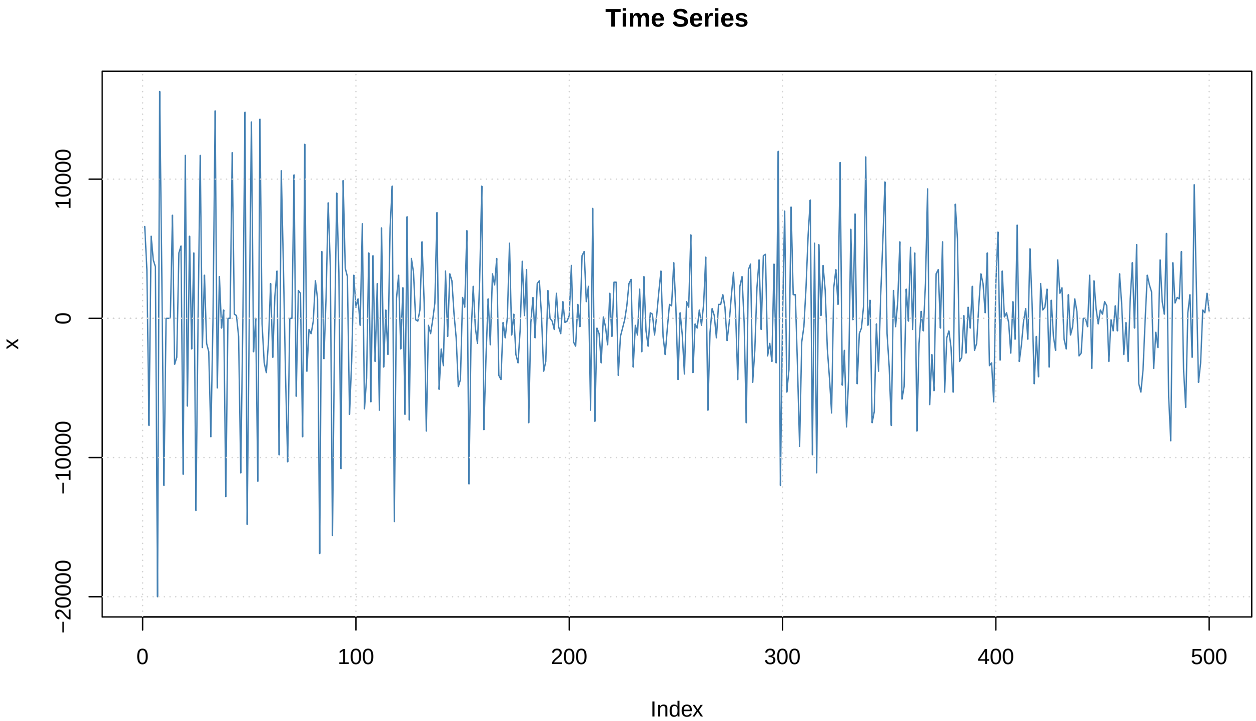

```
##
##  Box-Ljung test
##
## data:  residual
## X-squared = 80.32, df = 20, p-value = 3.465e-09

##
```

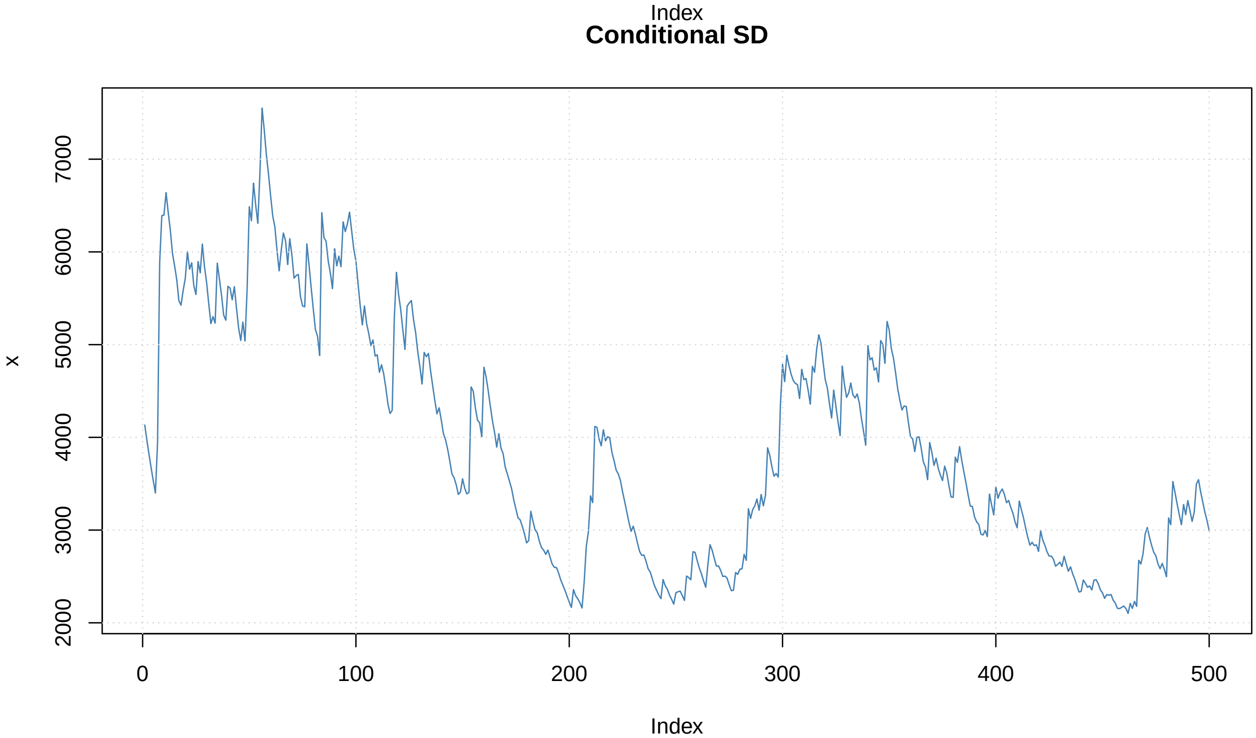
```
## Series Initialization:
##  ARMA Model:                arma
##  Formula Mean:              ~ arma(5, 0)
##  GARCH Model:               garch
##  Formula Variance:          ~ garch(1, 1)
##  ARMA Order:                5 0
##  Max ARMA Order:            5
##  GARCH Order:               1 1
##  Max GARCH Order:           1
##  Maximum Order:             5
##  Conditional Dist:          norm
##  h.start:                   6
##  llh.start:                 1
##  Length of Series:          500
##  Recursion Init:            mci
##  Series Scale:              4806.199
##
## Parameter Initialization:
##  Initial Parameters:          $params
##  Limits of Transformations:   $U, $V
##  Which Parameters are Fixed?  $includes
##  Parameter Matrix:
##                       U            V        params includes
##     mu     -0.02538388   0.02538388 -3.946469e-05     TRUE
##     ar1    -0.99999999   0.99999999 -4.626914e-01     TRUE
##     ar2    -0.99999999   0.99999999 -4.349010e-01     TRUE
##     ar3    -0.99999999   0.99999999 -3.854059e-01     TRUE
##     ar4    -0.99999999   0.99999999 -3.193767e-01     TRUE
##     ar5    -0.99999999   0.99999999 -2.774935e-01     TRUE
##     omega   0.00000100 100.00000000  1.000000e-01     TRUE
##     alpha1  0.00000001   0.99999999  1.000000e-01     TRUE
##     gamma1 -0.99999999   0.99999999  1.000000e-01    FALSE
##     beta1   0.00000001   0.99999999  8.000000e-01     TRUE
##     delta   0.00000000   2.00000000  2.000000e+00    FALSE
##     skew    0.10000000  10.00000000  1.000000e+00    FALSE
##     shape   1.00000000  10.00000000  4.000000e+00    FALSE
##  Index List of Parameters to be Optimized:
##     mu    ar1    ar2    ar3    ar4    ar5  omega alpha1  beta1
##      1      2      3      4      5      6      7      8     10
##  Persistence:                  0.9
##
##
## --- START OF TRACE ---
## Selected Algorithm: nlminb
##
```

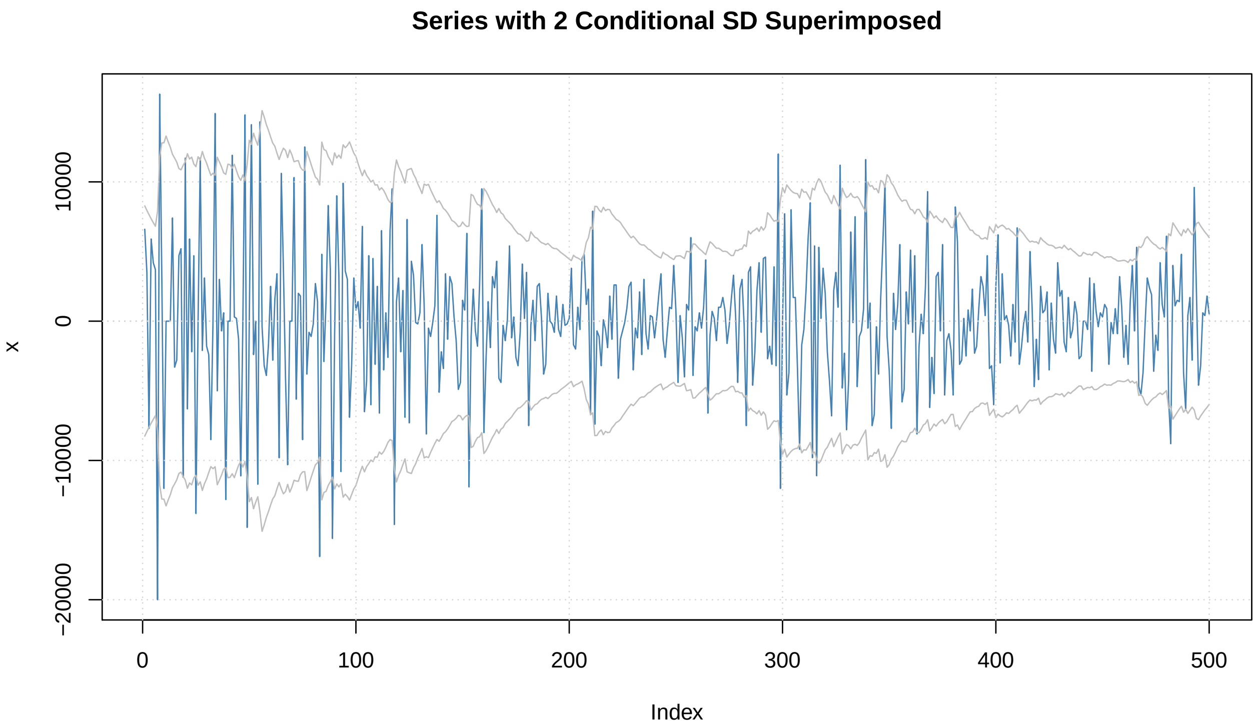
```
## R coded nlminb Solver:
##
##   0:     610.77533: -3.94647e-05 -0.462691 -0.434901 -0.385406 -0.319377 -0.277493 0.
##   1:     604.45223: -3.94655e-05 -0.462157 -0.434322 -0.385569 -0.319881 -0.277830 0.
##   2:     601.91127: -3.94672e-05 -0.460994 -0.433161 -0.385899 -0.320951 -0.278591 0.
##   3:     599.79875: -3.94692e-05 -0.459126 -0.431548 -0.386337 -0.322539 -0.279867 0.
##   4:     597.38479: -3.94738e-05 -0.454553 -0.428119 -0.387053 -0.325998 -0.282972 0.
##   5:     592.48462: -3.94776e-05 -0.445781 -0.423636 -0.387170 -0.331032 -0.288975 0.
##   6:     590.52956: -3.94817e-05 -0.435899 -0.418927 -0.386069 -0.336044 -0.295138 0.
##   7:     589.57187: -3.94914e-05 -0.420890 -0.407195 -0.384298 -0.345973 -0.303241 0.
##   8:     588.06573: -3.95154e-05 -0.405736 -0.391703 -0.380641 -0.356682 -0.310054 0.
##   9:     587.55035: -3.95767e-05 -0.411686 -0.387329 -0.372823 -0.351104 -0.301200 0.
##  10:     587.47759: -3.95768e-05 -0.411676 -0.387316 -0.372808 -0.351094 -0.301190 0.
##  11:     587.45033: -3.95773e-05 -0.411652 -0.387282 -0.372774 -0.351068 -0.301162 0.
##  12:     587.40885: -3.95867e-05 -0.411549 -0.386761 -0.372194 -0.350501 -0.300534 0.
##  13:     587.36507: -3.96104e-05 -0.410982 -0.385498 -0.370877 -0.349207 -0.299131 0.
##  14:     587.32887: -3.96815e-05 -0.408309 -0.382384 -0.367681 -0.346349 -0.296129 0.
##  15:     587.31261: -3.98258e-05 -0.404793 -0.378458 -0.363829 -0.343405 -0.293532 0.
##  16:     587.30765: -4.07656e-05 -0.405391 -0.374385 -0.363855 -0.338989 -0.289824 0.
##  17:     587.30154: -4.11120e-05 -0.404029 -0.376303 -0.361307 -0.339700 -0.289646 0.
##  18:     587.30085: -4.11123e-05 -0.404023 -0.376301 -0.361308 -0.339706 -0.289653 0.
##  19:     587.30026: -4.11224e-05 -0.403970 -0.376228 -0.361313 -0.339733 -0.289707 0.
##  20:     587.29972: -4.11457e-05 -0.403841 -0.376072 -0.361321 -0.339792 -0.289817 0.
##  21:     587.29894: -4.12093e-05 -0.403502 -0.375734 -0.361314 -0.339883 -0.289966 0.
##  22:     587.29818: -4.14604e-05 -0.402785 -0.375206 -0.361195 -0.339950 -0.289873 0.
##  23:     587.29753: -4.17707e-05 -0.403411 -0.375268 -0.361368 -0.339811 -0.290642 0.
##  24:     587.29706: -4.20397e-05 -0.403478 -0.375652 -0.362093 -0.340354 -0.290310 0.
##  25:     587.29672: -4.25967e-05 -0.403214 -0.376200 -0.361316 -0.340559 -0.290249 0.
##  26:     587.29665: -4.25970e-05 -0.403213 -0.376199 -0.361318 -0.340561 -0.290254 0.
##  27:     587.29659: -4.26135e-05 -0.403203 -0.376208 -0.361328 -0.340560 -0.290291 0.
##  28:     587.29653: -4.26396e-05 -0.403182 -0.376216 -0.361353 -0.340573 -0.290366 0.
##  29:     587.29642: -4.27343e-05 -0.403169 -0.376238 -0.361400 -0.340596 -0.290532 0.
##  30:     587.29629: -4.29438e-05 -0.403365 -0.376120 -0.361483 -0.340832 -0.290657 0.
##  31:     587.29607: -4.34020e-05 -0.403197 -0.376394 -0.361972 -0.340508 -0.290855 0.
##  32:     587.29606: -4.34024e-05 -0.403195 -0.376393 -0.361972 -0.340514 -0.290859 0.
##  33:     587.29605: -4.34120e-05 -0.403196 -0.376394 -0.361966 -0.340515 -0.290862 0.
##  34:     587.29603: -4.34398e-05 -0.403199 -0.376395 -0.361951 -0.340513 -0.290871 0.
##  35:     587.29600: -4.35211e-05 -0.403204 -0.376401 -0.361916 -0.340499 -0.290884 0.
##  36:     587.29569: -4.54946e-05 -0.402949 -0.376367 -0.361745 -0.340713 -0.290909 0.
##  37:     587.29560: -4.69646e-05 -0.402750 -0.376405 -0.362099 -0.341248 -0.291123 0.
##  38:     587.29539: -4.88450e-05 -0.403119 -0.376614 -0.362223 -0.341438 -0.291404 0.
##  39:     587.29537: -5.06825e-05 -0.403528 -0.376686 -0.362510 -0.341636 -0.291294 0.
##  40:     587.29523: -5.14749e-05 -0.403512 -0.376770 -0.362383 -0.341605 -0.291602 0.
##  41:     587.29523: -5.19882e-05 -0.403500 -0.376779 -0.362356 -0.341596 -0.291682 0.
##  42:     587.29521: -5.25279e-05 -0.403504 -0.376756 -0.362385 -0.341602 -0.291652 0.
```

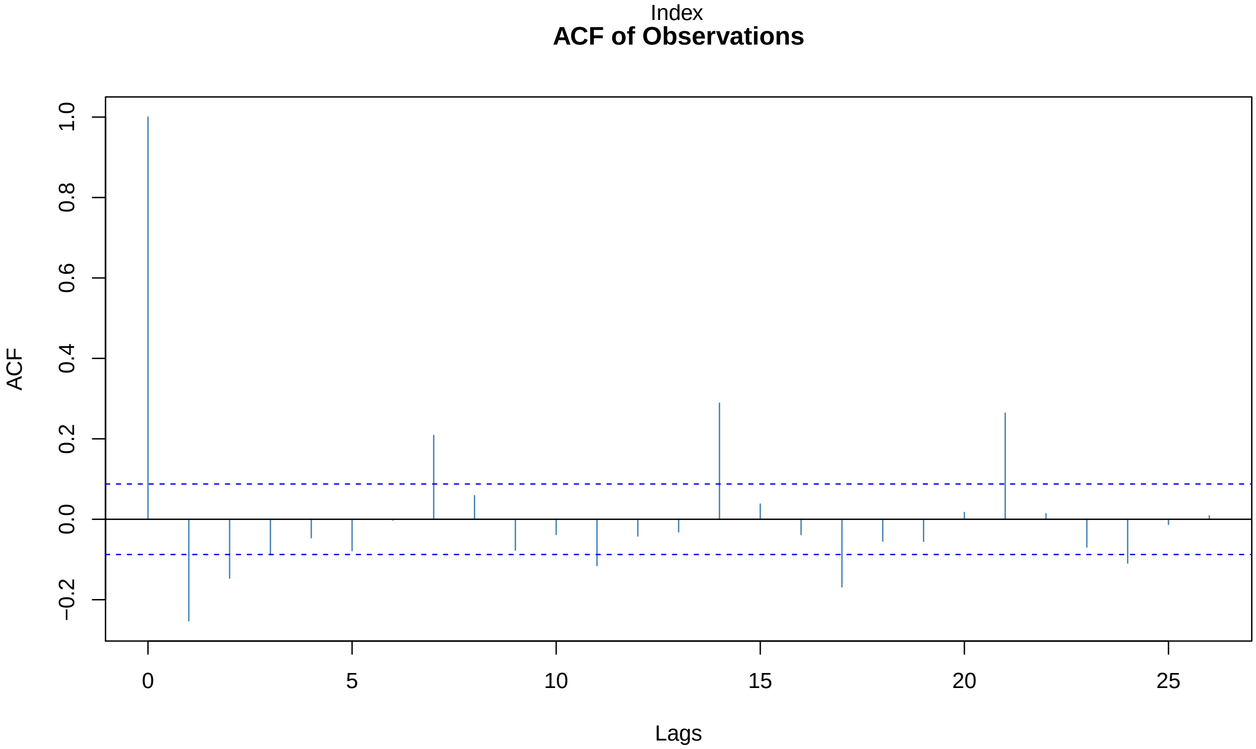
```
## 43:     587.29519: -5.36048e-05 -0.403508 -0.376713 -0.362444 -0.341620 -0.291593 0.
## 44:     587.29510: -7.26785e-05 -0.403410 -0.376893 -0.362415 -0.341633 -0.292174 0.
## 45:     587.29494: -9.18063e-05 -0.403389 -0.376898 -0.362593 -0.341724 -0.292202 0.
## 46:     587.29463: -0.000168358 -0.403045 -0.376753 -0.362289 -0.342237 -0.292039 0.
## 47:     587.29383: -0.000375169 -0.403432 -0.376531 -0.362221 -0.342501 -0.291974 0.
## 48:     587.29249: -0.000796411 -0.402518 -0.376600 -0.362203 -0.342174 -0.291221 0.
## 49:     587.28996: -0.00192733 -0.401970 -0.374291 -0.362391 -0.342022 -0.291244 0.0
## 50:     587.28662: -0.00305824 -0.403200 -0.375805 -0.363143 -0.343291 -0.291345 0.0
## 51:     587.28292: -0.00493408 -0.403181 -0.375889 -0.361053 -0.342037 -0.290702 0.0
## 52:     587.28153: -0.00531578 -0.403364 -0.377096 -0.363043 -0.342400 -0.292111 0.0
## 53:     587.28138: -0.00505242 -0.403283 -0.376686 -0.362503 -0.342024 -0.291878 0.0
## 54:     587.28137: -0.00504745 -0.403259 -0.376639 -0.362501 -0.342067 -0.291896 0.0
## 55:     587.28137: -0.00505248 -0.403264 -0.376654 -0.362505 -0.342054 -0.291896 0.0
## 56:     587.28137: -0.00505238 -0.403264 -0.376654 -0.362505 -0.342054 -0.291896 0.0
##
## Final Estimate of the Negative LLH:
##  LLH:  4826.112    norm LLH:  9.652225
##            mu           ar1           ar2           ar3           ar4
## -2.428272e+01 -4.032638e-01 -3.766543e-01 -3.625048e-01 -3.420538e-01
##           ar5         omega        alpha1         beta1
## -2.918959e-01  1.807480e+05  7.564802e-02  9.124303e-01
##
## R-optimhess Difference Approximated Hessian Matrix:
##                   mu           ar1           ar2           ar3           ar4
## mu     -4.768606e-05 -2.964231e-03 -2.707136e-03  4.624630e-04  6.524598e-03
## ar1    -2.964231e-03 -6.177652e+02  1.248805e+02  9.260837e+01  7.795532e+01
## ar2    -2.707136e-03  1.248805e+02 -5.870936e+02  1.246926e+02  5.374366e+01
## ar3     4.624630e-04  9.260837e+01  1.246926e+02 -6.286416e+02  1.131009e+02
## ar4     6.524598e-03  7.795532e+01  5.374366e+01  1.131009e+02 -5.909806e+02
## ar5    -5.720242e-04  5.953900e+01  7.040710e+01  9.264864e+01  1.334550e+02
## omega  -3.251541e-09 -7.322456e-06 -4.178298e-06 -1.248122e-05  7.256022e-06
## alpha1 -1.235062e-02 -3.460577e+01  1.896724e+01 -3.186932e+01  1.975131e+01
## beta1  -2.069983e-02 -6.868159e+01  1.175393e+02 -1.171400e+01  1.544394e+01
##                  ar5         omega        alpha1         beta1
## mu     -5.720242e-04 -3.251541e-09 -1.235062e-02 -2.069983e-02
## ar1     5.953900e+01 -7.322456e-06 -3.460577e+01 -6.868159e+01
## ar2     7.040710e+01 -4.178298e-06  1.896724e+01  1.175393e+02
## ar3     9.264864e+01 -1.248122e-05 -3.186932e+01 -1.171400e+01
## ar4     1.334550e+02  7.256022e-06  1.975131e+01  1.544394e+01
## ar5    -6.240032e+02  9.985461e-06  3.982418e+01  1.119287e+02
## omega   9.985461e-06 -3.434998e-10 -2.395714e-03 -3.079911e-03
## alpha1  3.982418e+01 -2.395714e-03 -2.855277e+04 -3.208824e+04
## beta1   1.119287e+02 -3.079911e-03 -3.208824e+04 -3.900660e+04
## attr(,"time")
## Time difference of 0.03055596 secs
```

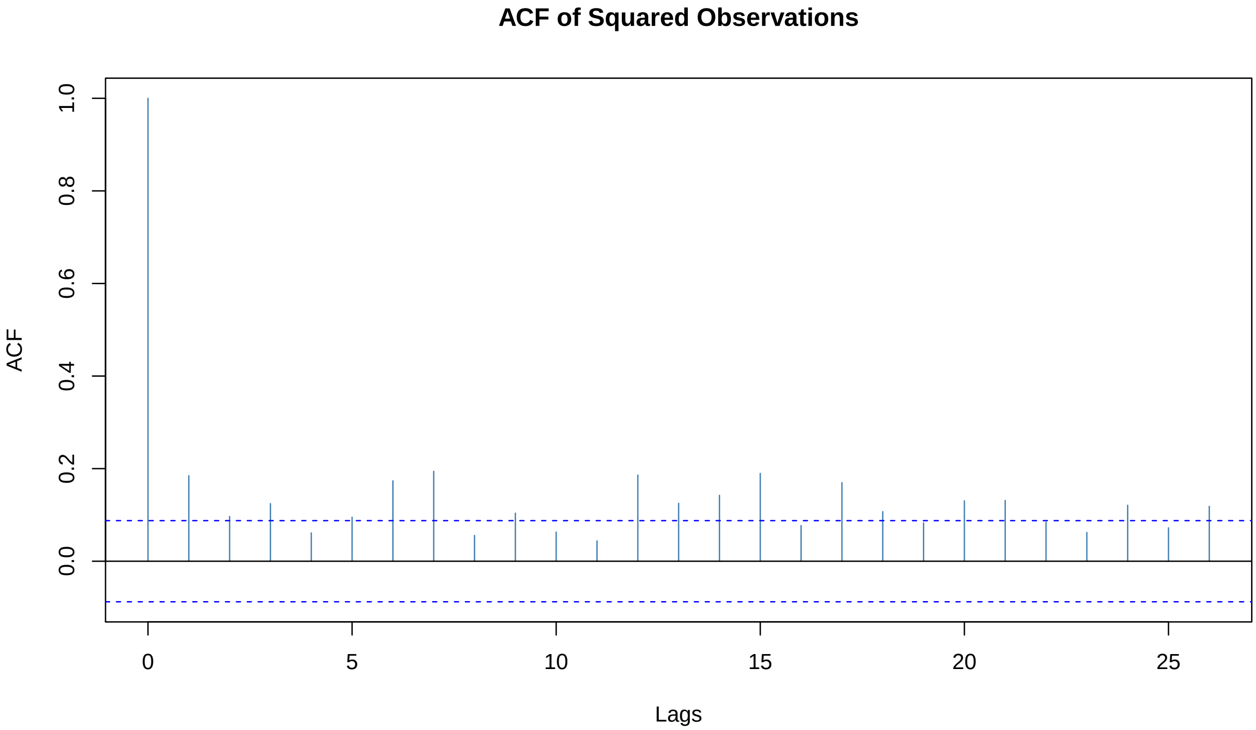
```
##
## --- END OF TRACE ---
##
##
## Time to Estimate Parameters:
##  Time difference of 0.142611 secs
```

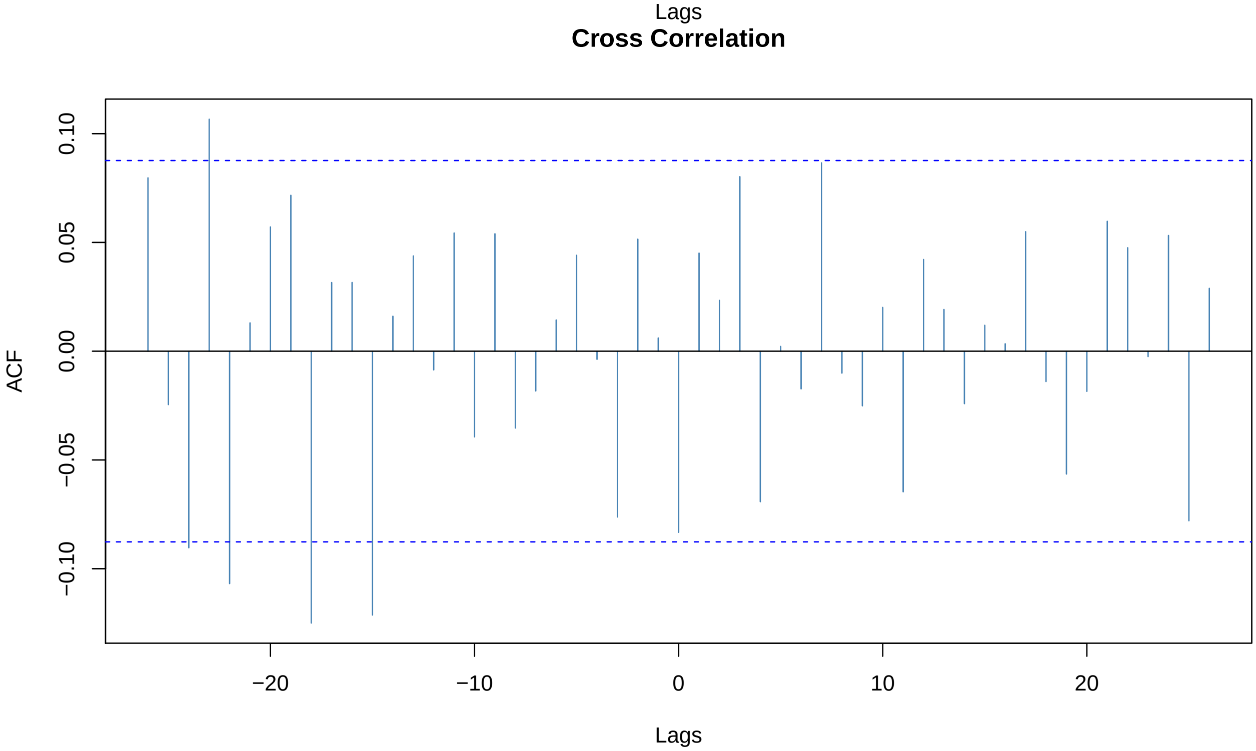


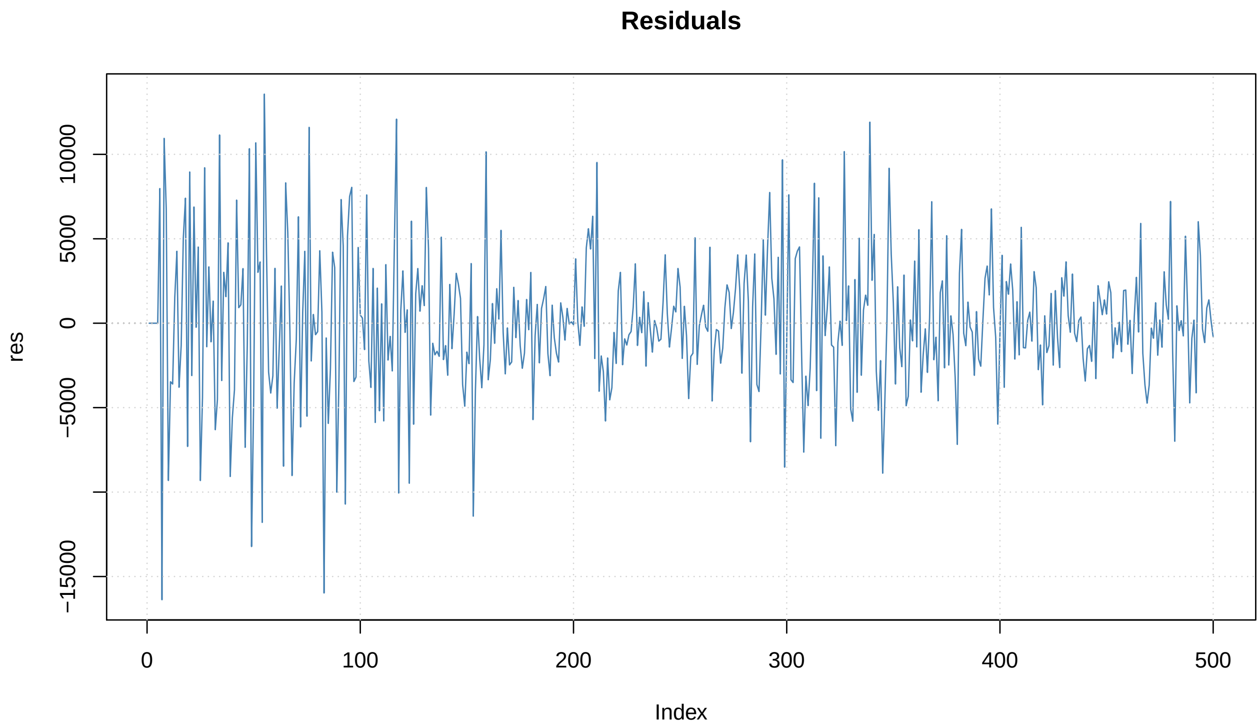


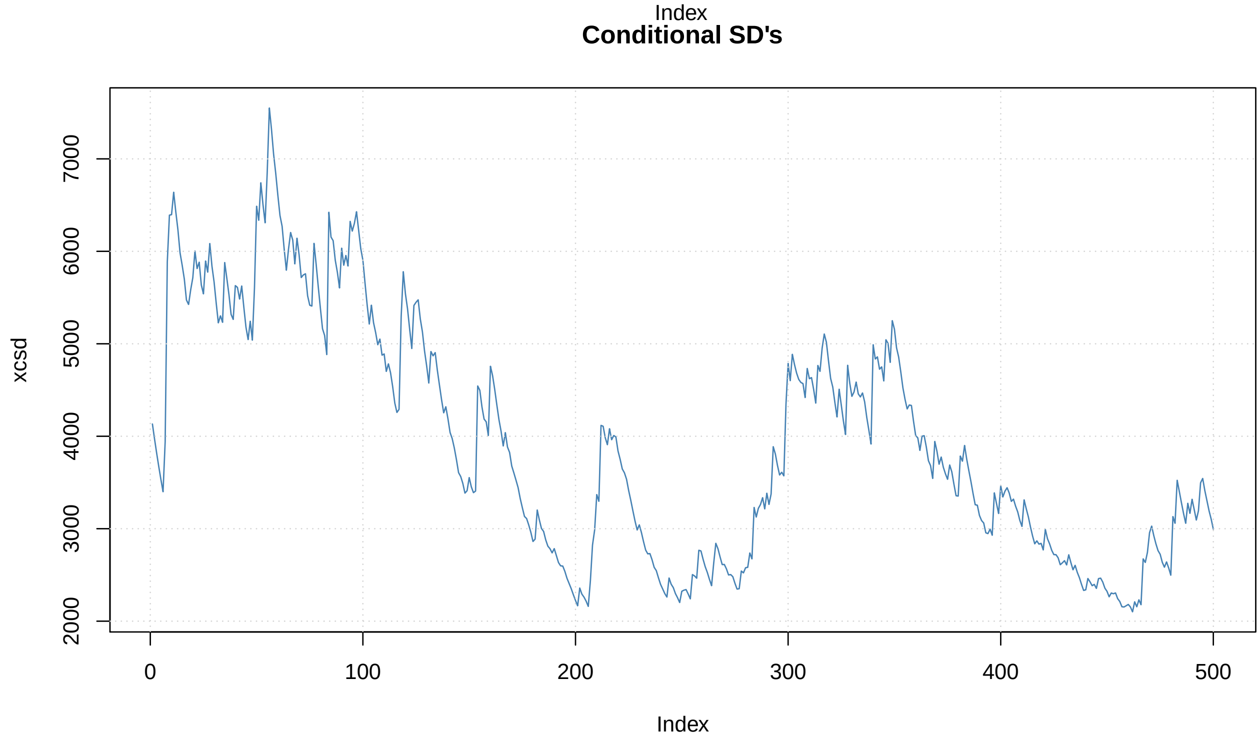

Series with 2 Conditional SD Superimposed
x
10000
0
−10000
−20000
0
100
200
300
400
500
Index

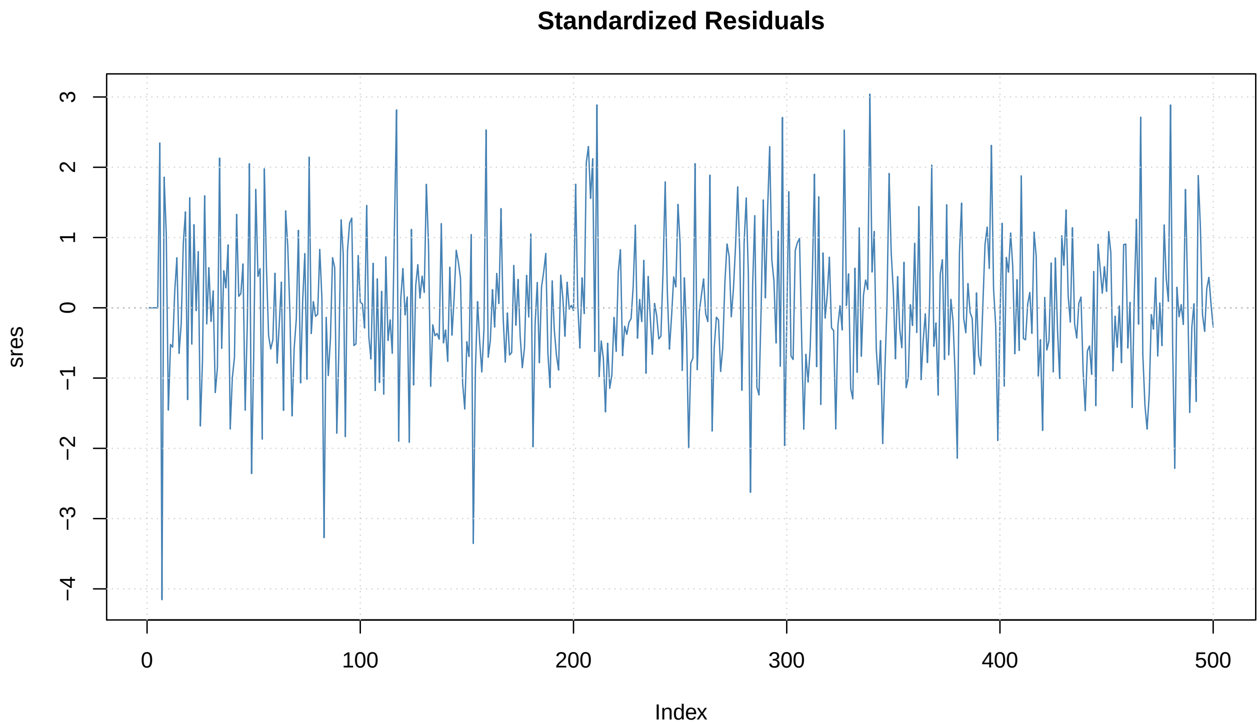

ACF of Observations
ACF
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
5
10
15
20
25
Lags

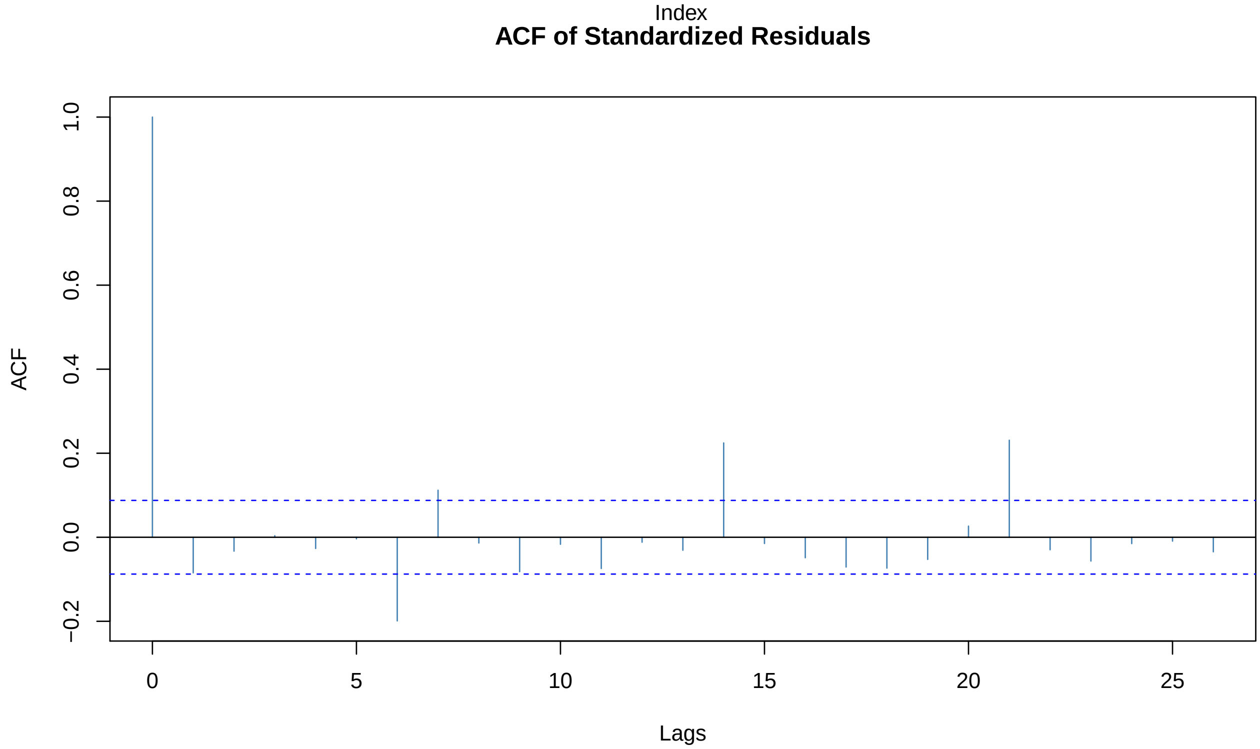

ACF of Squared Observations
ACF
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25
Lags

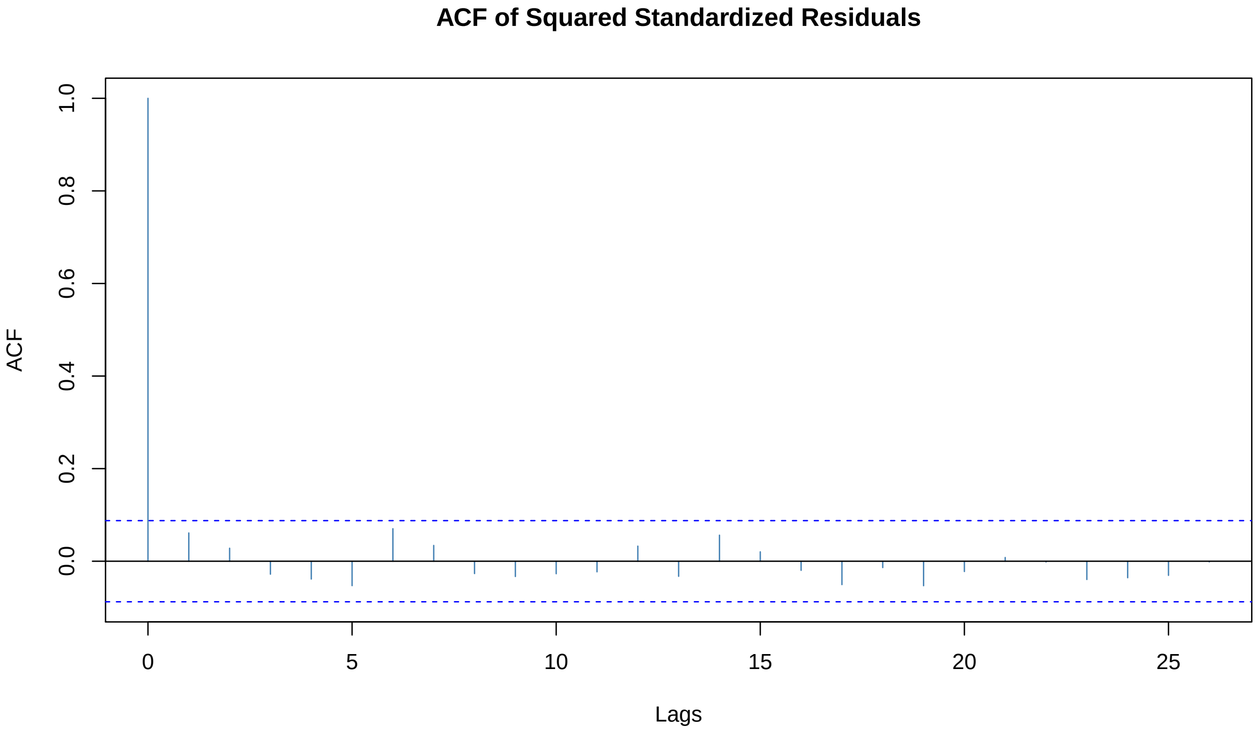

Cross Correlation
ACF
0.10
0.05
0.00
−0.05
−0.10
−20
−10
0
10
20
Lags

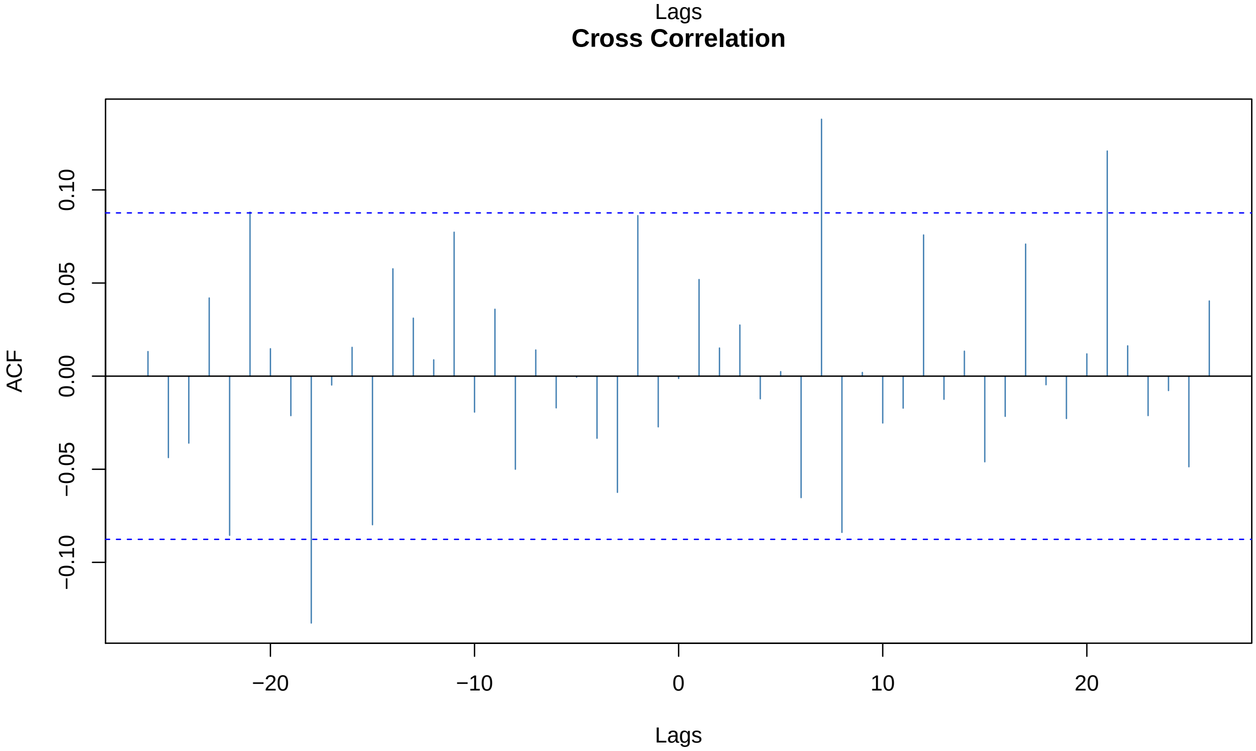

Residuals
res
10000
5000
0
−5000
−15000
0
100
200
300
400
500
Index

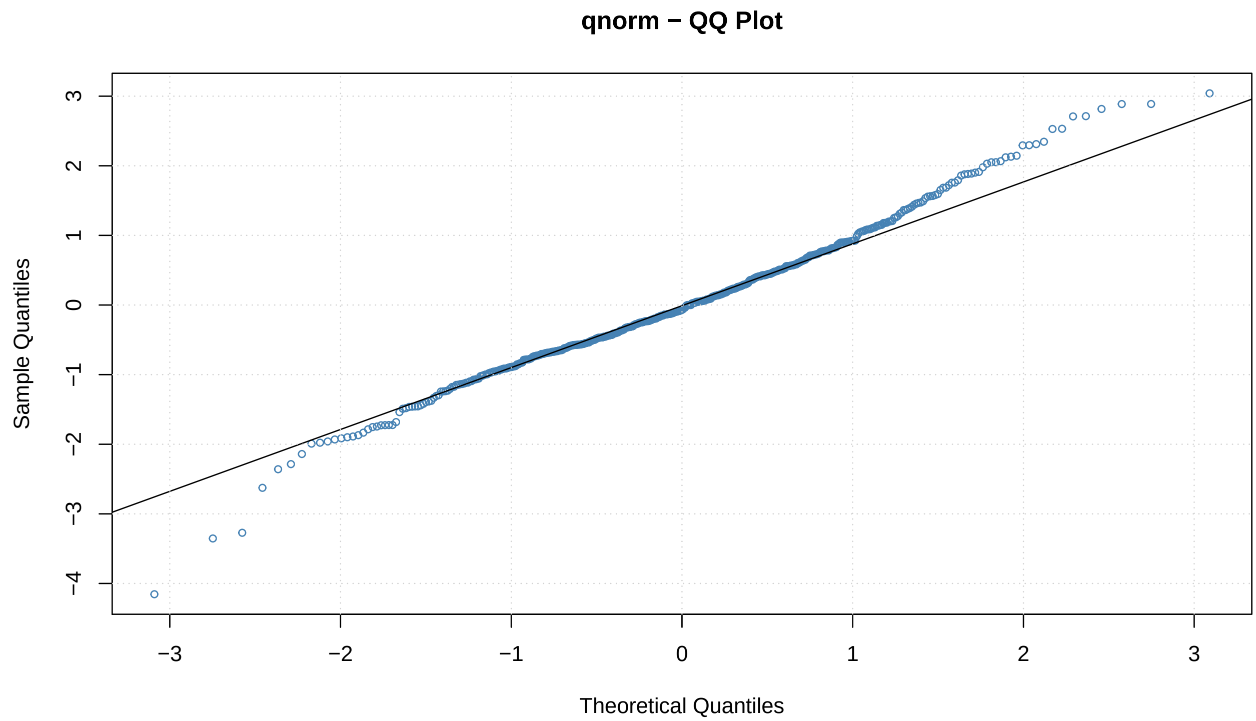

Conditional SD's
xcsd
7000
6000
5000
4000
3000
2000
0
100
200
300
400
500
Index


Standardized Residuals
sres
Index
3
2
1
0
−1
−2
−3
−4
0
100
200
300
400
500


ACF of Standardized Residuals
ACF
Lags
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
5
10
15
20
25


ACF of Squared Standardized Residuals
ACF
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
25
Lags


Cross Correlation
ACF
−0.10
−0.05
0.00
0.05
0.10
−20
−10
0
10
20
Lags

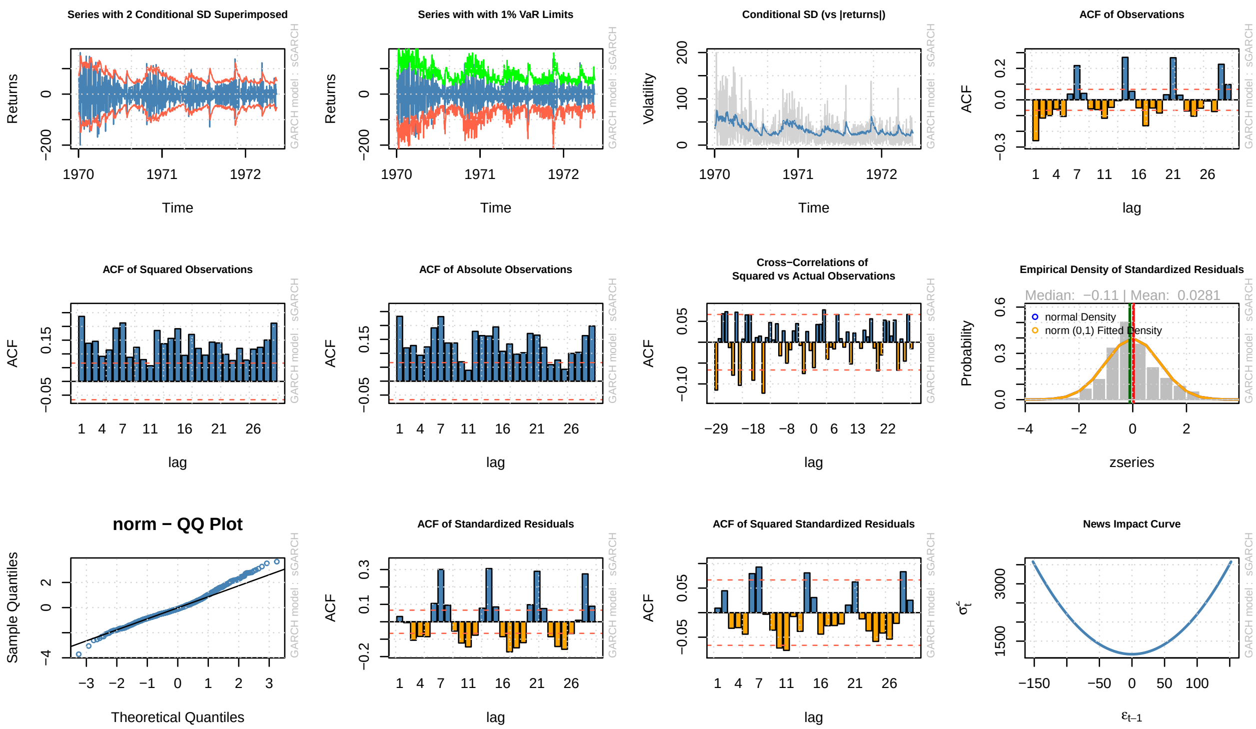


18 RUGARCH

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model   : sGARCH(1,1)
## Mean Model    : ARFIMA(1,0,1)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error   t value Pr(>|t|)
## mu      -0.05679    0.168273  -0.33748 0.735751
## ar1      0.43986    0.040780  10.78621 0.000000
## ma1     -0.90573    0.018309 -49.46943 0.000000
## omega   28.35396   10.382186   2.73102 0.006314
## alpha1   0.10488    0.021651   4.84395 0.000001
## beta1    0.87319    0.023545  37.08631 0.000000
##
## Robust Standard Errors:
```

```
##         Estimate  Std. Error   t value Pr(>|t|)
## mu      -0.05679    0.163392  -0.34757 0.728165
## ar1      0.43986    0.041878  10.50322 0.000000
## ma1     -0.90573    0.017155 -52.79577 0.000000
## omega   28.35396   12.020825   2.35874 0.018337
## alpha1   0.10488    0.026920   3.89586 0.000098
## beta1    0.87319    0.031090  28.08592 0.000000
##
## LogLikelihood : -4252.697
##
## Information Criteria
## ------------------------------------
##
## Akaike       9.8240
## Bayes        9.8570
## Shibata      9.8239
## Hannan-Quinn 9.8366
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                     0.7954 3.725e-01
## Lag[2*(p+q)+(p+q)-1][5]   10.4501 2.798e-14
## Lag[4*(p+q)+(p+q)-1][9]   48.8726 0.000e+00
## d.o.f=2
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                    0.07401 0.78558
## Lag[2*(p+q)+(p+q)-1][5]   2.64279 0.47615
## Lag[4*(p+q)+(p+q)-1][9]   8.86282 0.08671
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.8774 0.500 2.000 0.34892
## ARCH Lag[5]    2.5226 1.440 1.667 0.36691
## ARCH Lag[7]    9.0865 2.315 1.543 0.02987
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  1.3521
```

```
## Individual Statistics:
## mu     0.13071
## ar1    0.40120
## ma1    0.06599
## omega  0.11264
## alpha1 0.31711
## beta1  0.37213
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.49 1.68 2.12
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value    prob sig
## Sign Bias           2.5181 0.01198  **
## Negative Sign Bias  0.1978 0.84327
## Positive Sign Bias  0.4413 0.65909
## Joint Effect       10.4825 0.01488  **
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     63.82    9.486e-07
## 2    30     82.58    4.817e-07
## 3    40     89.72    7.148e-06
## 4    50    107.34    3.022e-06
##
##
## Elapsed time : 0.2653909
##
## please wait...calculating quantiles...
```



19 Conclusions

It was really interesting!

20 TODO

prima diff, poi prima diff seasonal, check acf pacf, check no trend(trend se con decadono a 0 velocemente) identificare i picchi identificare l estate doppia seasonality una settimanale e una annuale ARCH GARCH VAR<—- stabilizzare con trasformazioni