Spatio-Temporal Data Analysis Project

2020-04-27

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
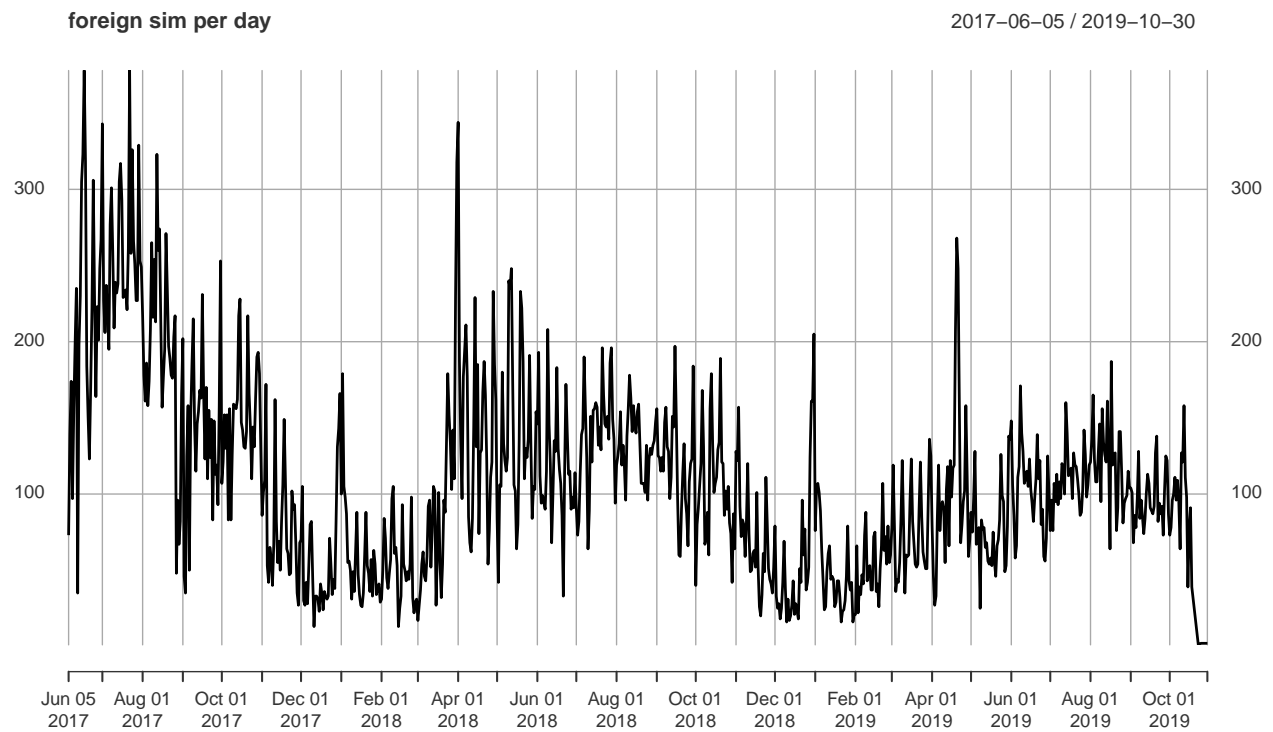
3 Exploration of the Data

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

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

Histogram of data$total.foreign.sim
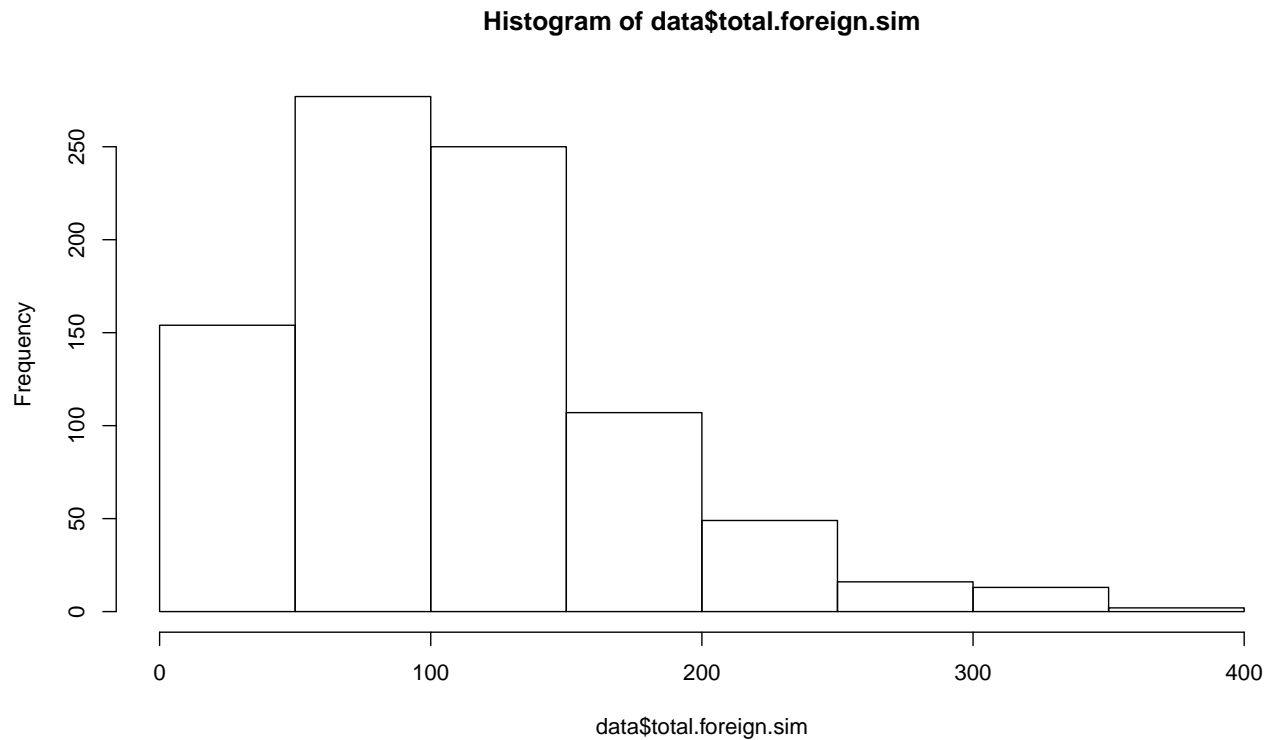
We loaded the dataset from the various datasets aggregating into only one dataset with 655 rows representing 2 years of data gathered. Starting from 01.01.2018 to 30.10.2019. Data is here:

foreign sim per day   2017−06−05 / 2019−10−30

4

4 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] "2017-06-17" "2017-07-22"
```

- 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]
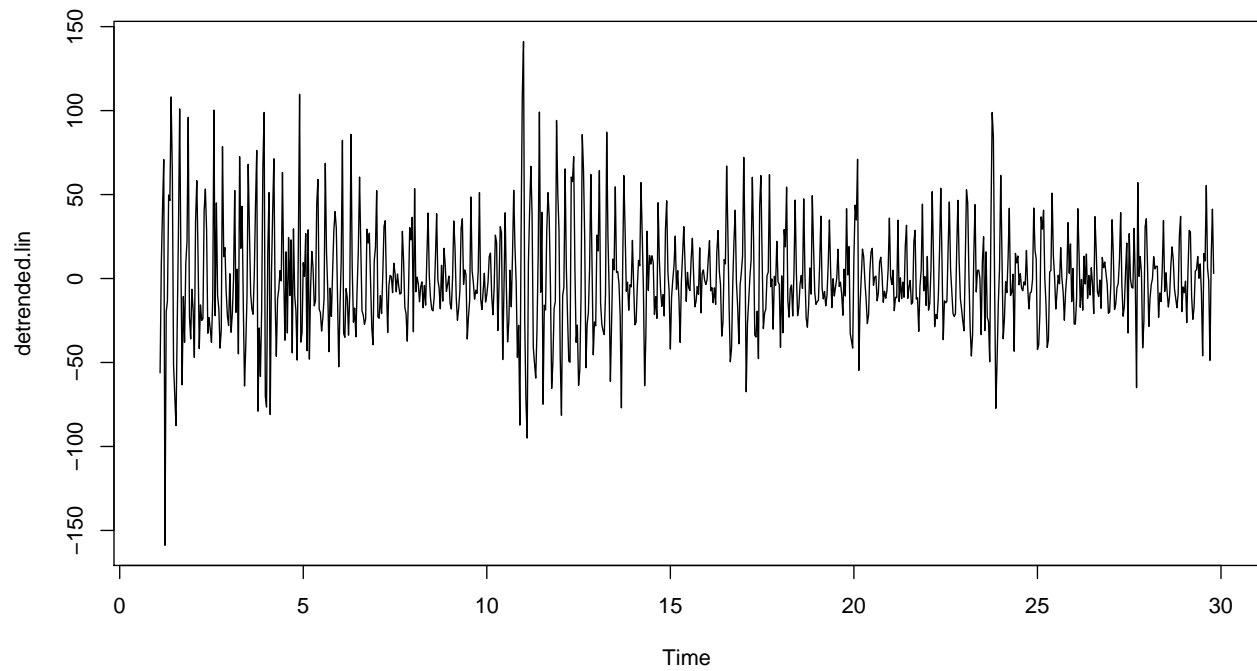
5 Outlier detection and removal

Here is not ready, should be completed asap

6 Trend recognition
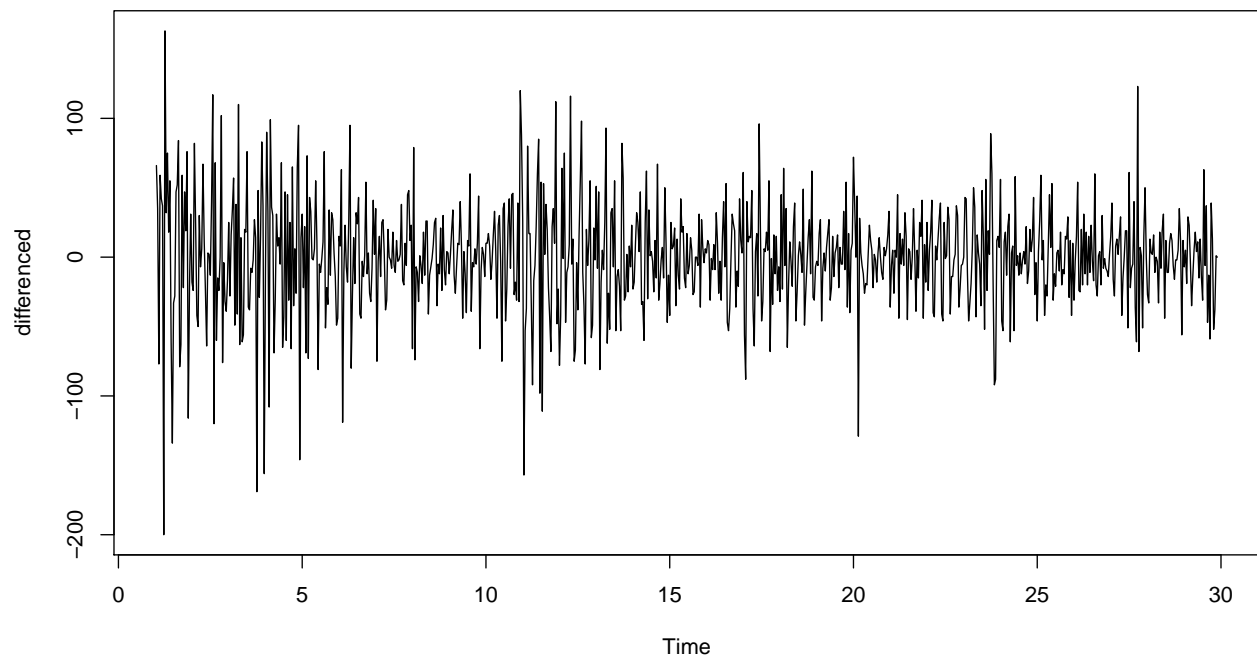
foreign sim per day
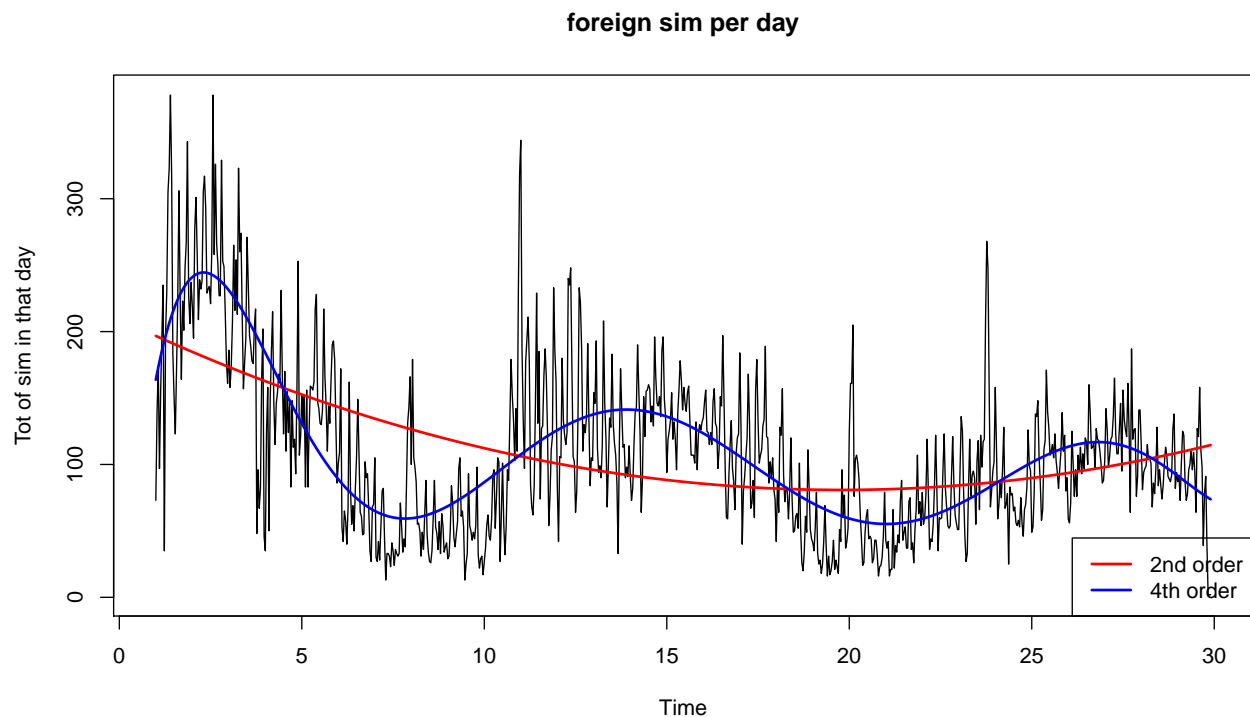
6.1 Detrending using LM

7 Removing seasonality

A good idea is to differenciate before decomposing. With the multiplicative model
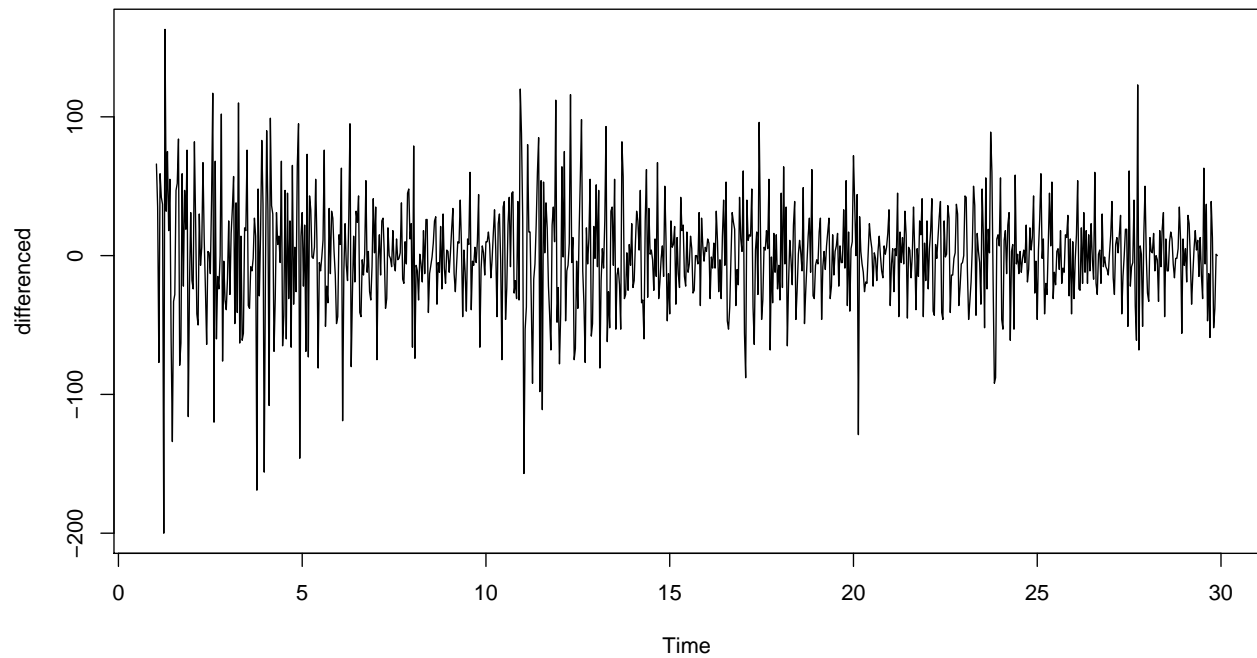


```
## [1] -200
```

```
## [1] 163
```

```
##
##   Box-Pierce test
##
## data:  decomposed$random
## X-squared = NA, df = 5, p-value = NA

##
##   Box-Ljung test
##
## data:  decomposed$random
## X-squared = NA, df = 5, p-value = NA
```
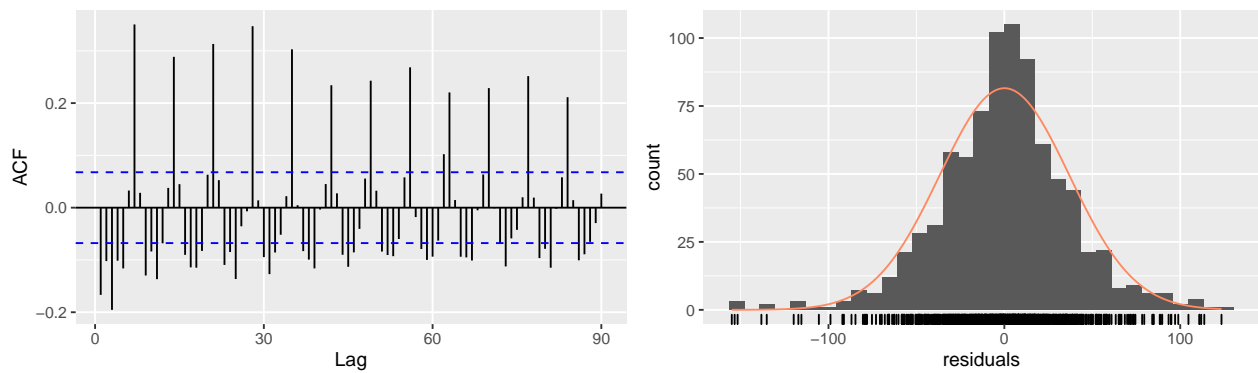
8 The additive model doesn't work for us

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

Decomposition of additive time series

Residuals
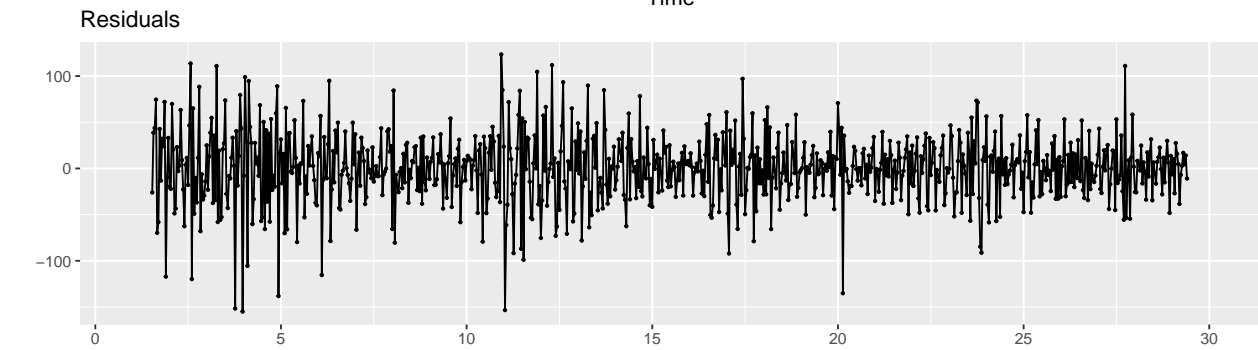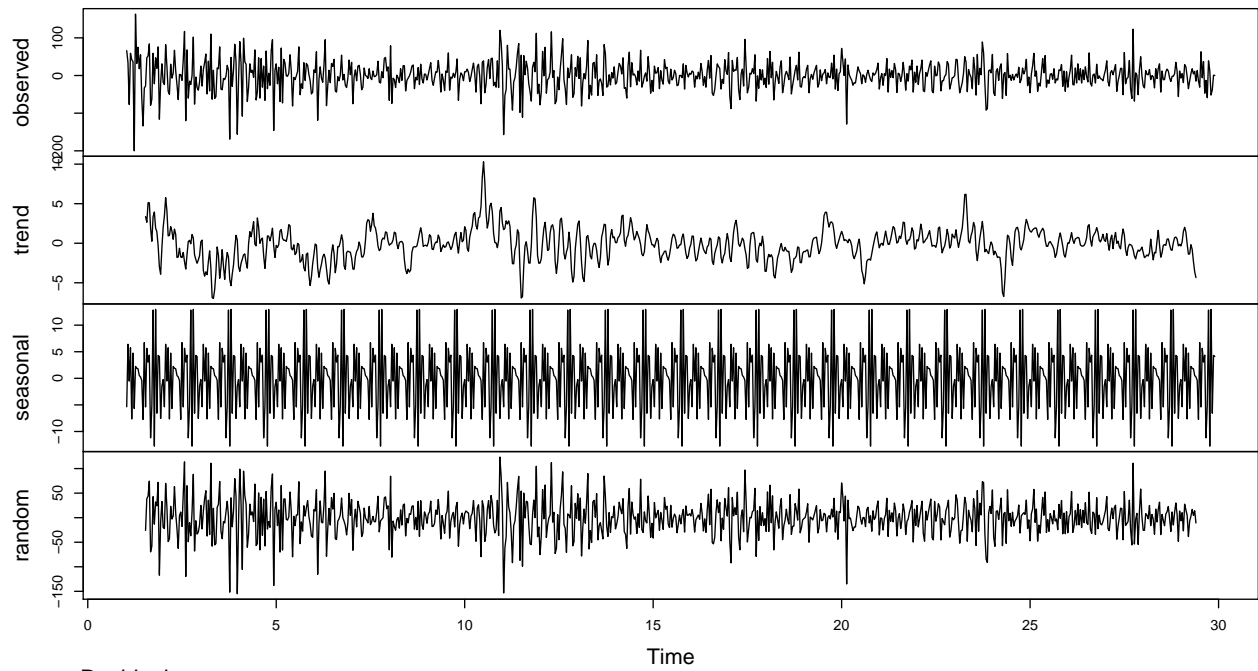

```
##
##   Box-Pierce test
##
## data:  decomposed$random
## X-squared = 83.893, df = 5, p-value < 2.2e-16
```

```
##
##  Box-Ljung test
##
## data:  decomposed$random
## X-squared = 84.367, df = 5, p-value < 2.2e-16
```

Without the first differentiation the result will have been much worse:

Decomposition of multiplicative time series

```
##
##  Box-Pierce test
##
## data:  decomposed$random
## X-squared = 244, df = 5, p-value < 2.2e-16

##
##  Box-Ljung test
##
## data:  decomposed$random
## X-squared = 244.99, df = 5, p-value < 2.2e-16
```
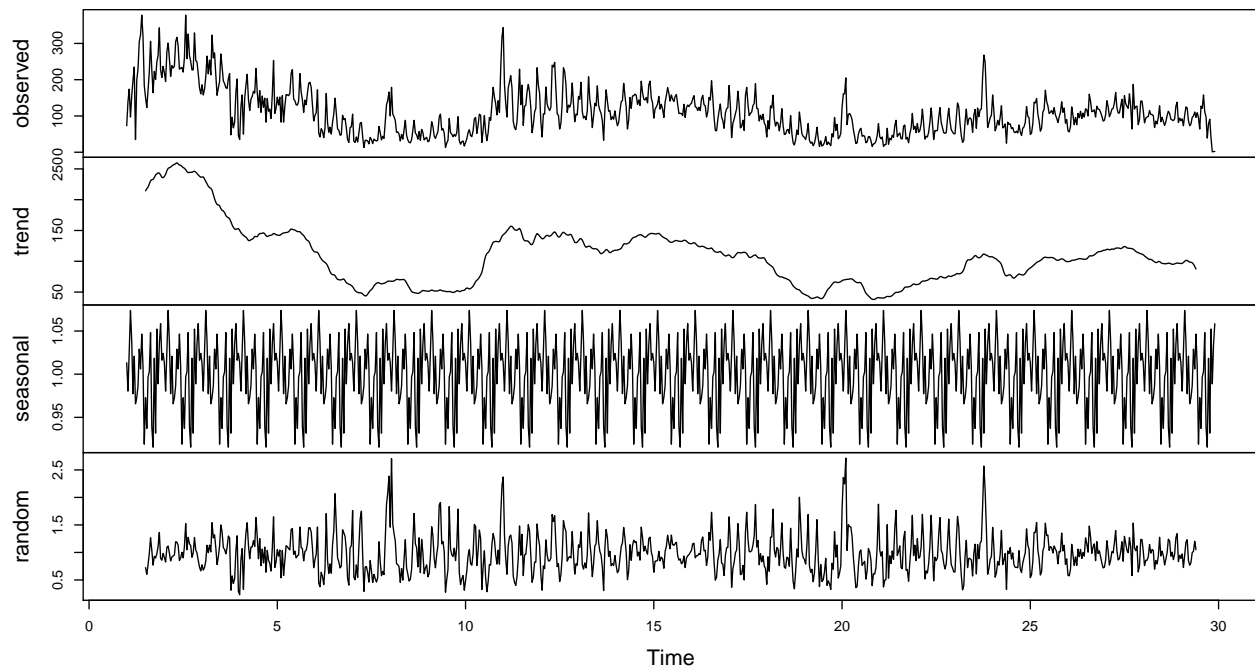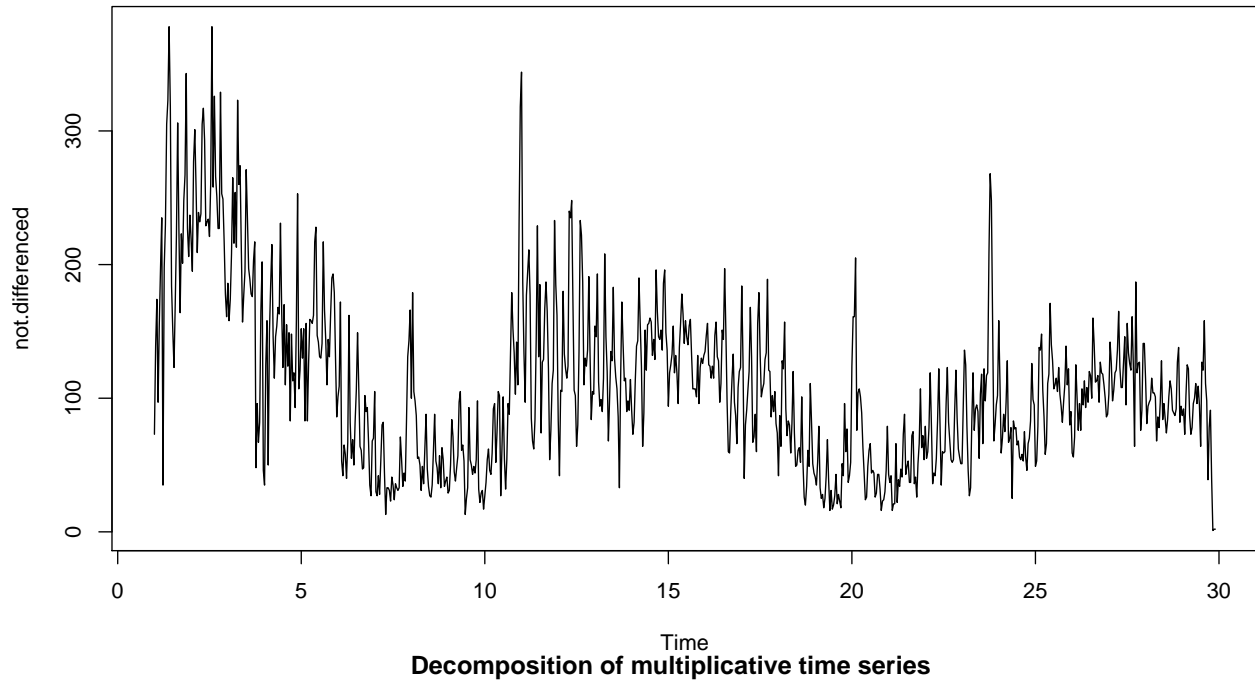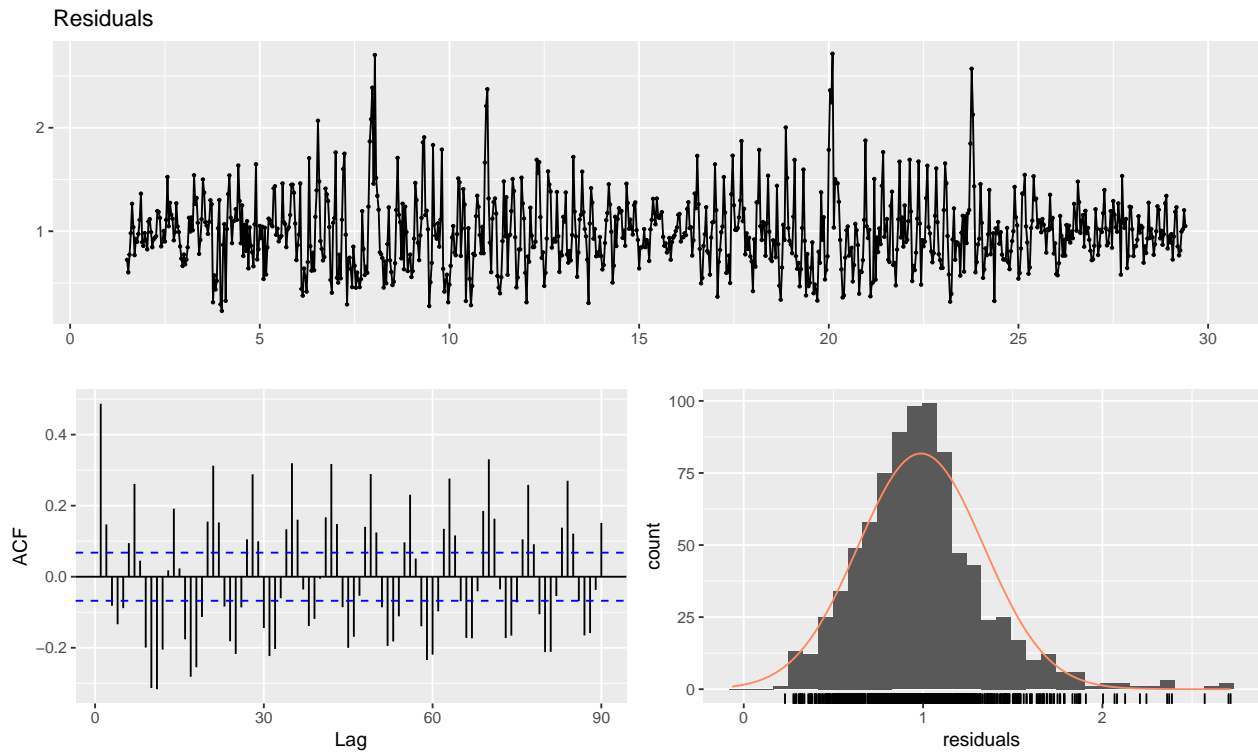
Every 7 lags the peak recurs

9 Check Residuals

Standardized Residuals

Standardized Residuals
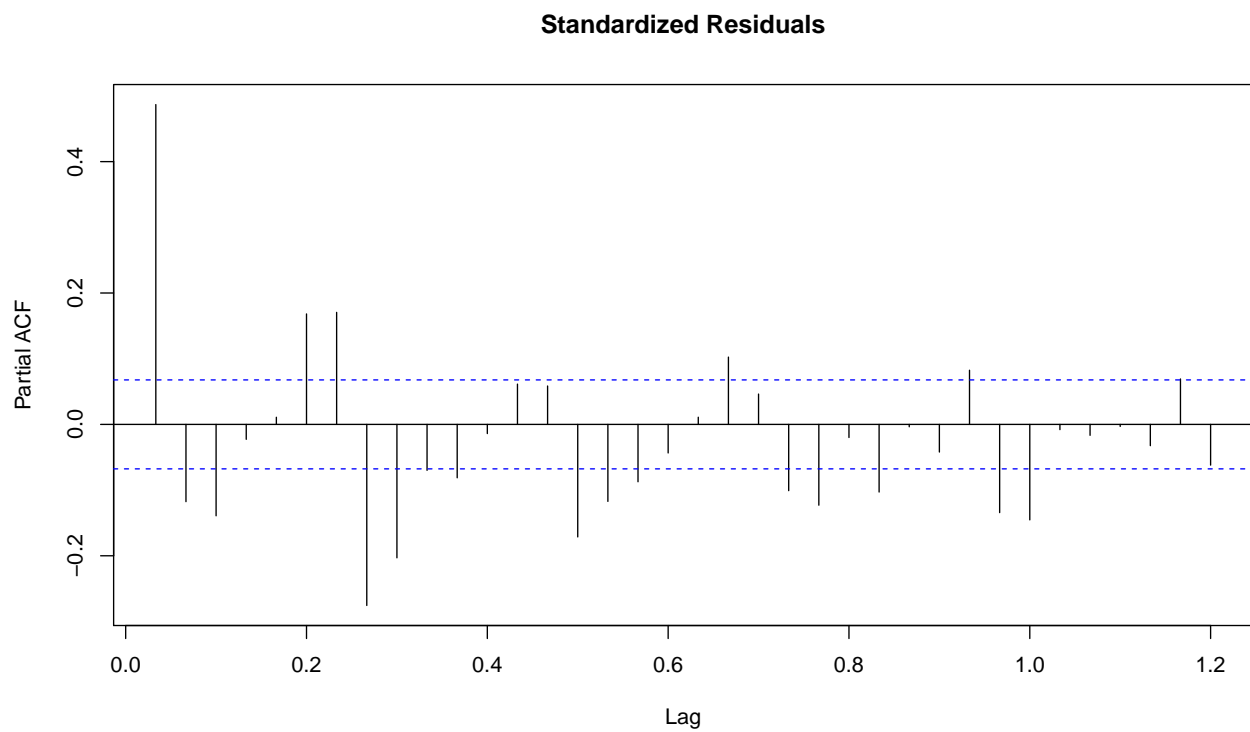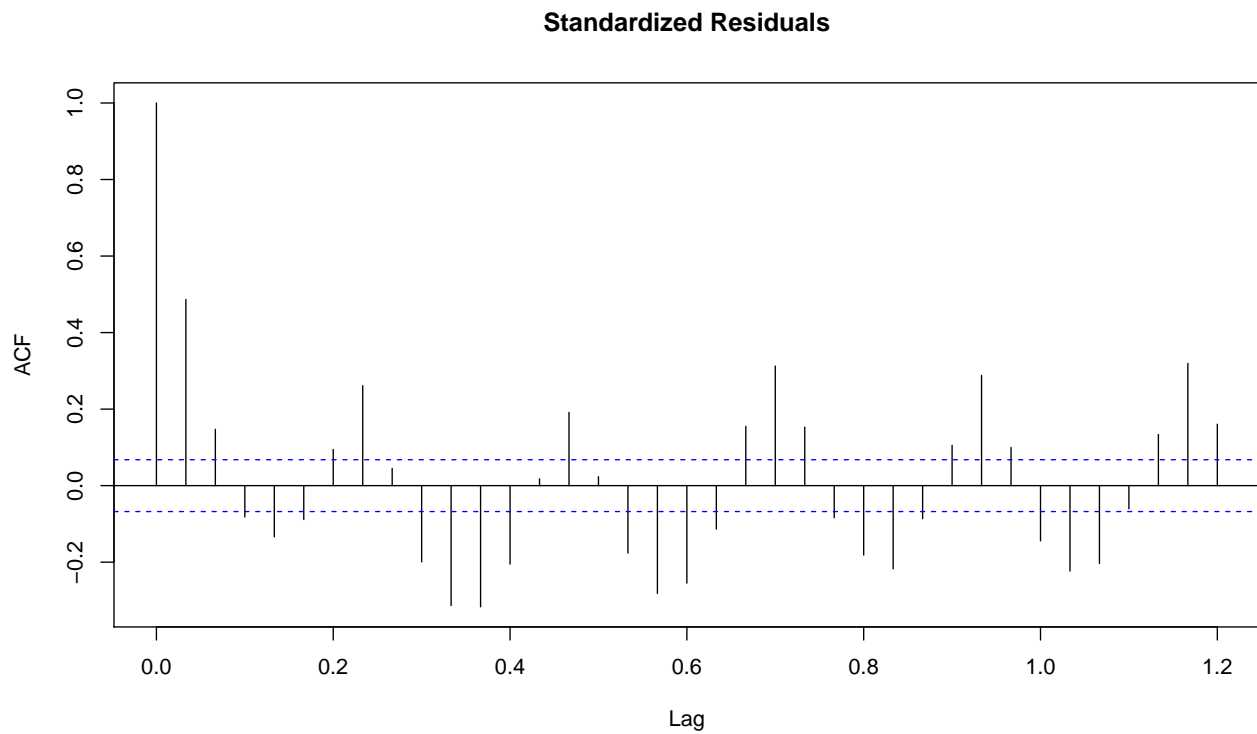
10 Arima

```
## Series: differenced
```

```
## ARIMA(3,1,3)
##
## Coefficients:
##           ar1      ar2      ar3      ma1      ma2      ma3
##       -0.4107   0.4209  -0.1268  -0.9264  -0.9235   0.8499
## s.e.   0.3868   0.2064   0.0512   0.4041   0.7835   0.3810
##
## sigma^2 estimated as 1273:  log likelihood=-4326.94
## AIC=8667.87   AICc=8668   BIC=8701.22
##
## Training set error measures:
##                     ME     RMSE      MAE MPE MAPE      MASE       ACF1
## Training set -1.314353 35.54053 25.84148 NaN  Inf 0.5948003 -0.01590064
```


Residuals from ARIMA(3,1,3)
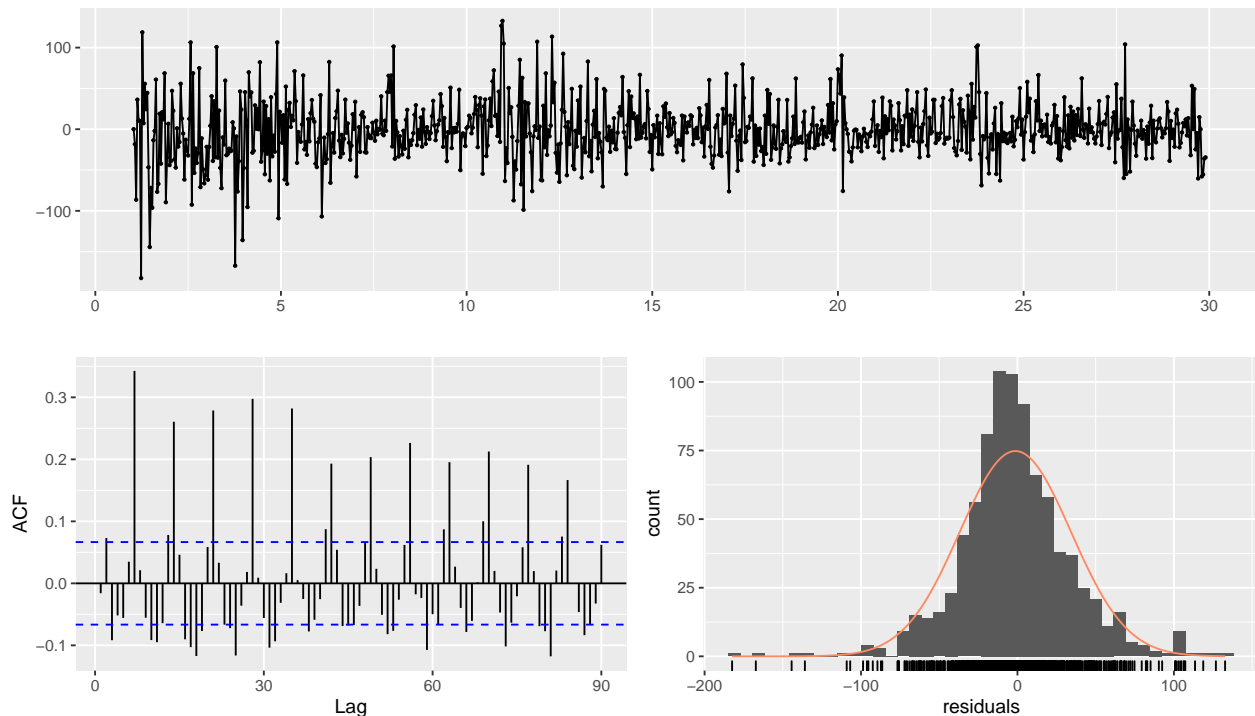
```
##
##   Ljung-Box test
##
## data:  Residuals from ARIMA(3,1,3)
## Q* = 702.82, df = 54, p-value < 2.2e-16
##
## Model df: 6.   Total lags used: 60
```

Forecasts from ARIMA(3,1,3)
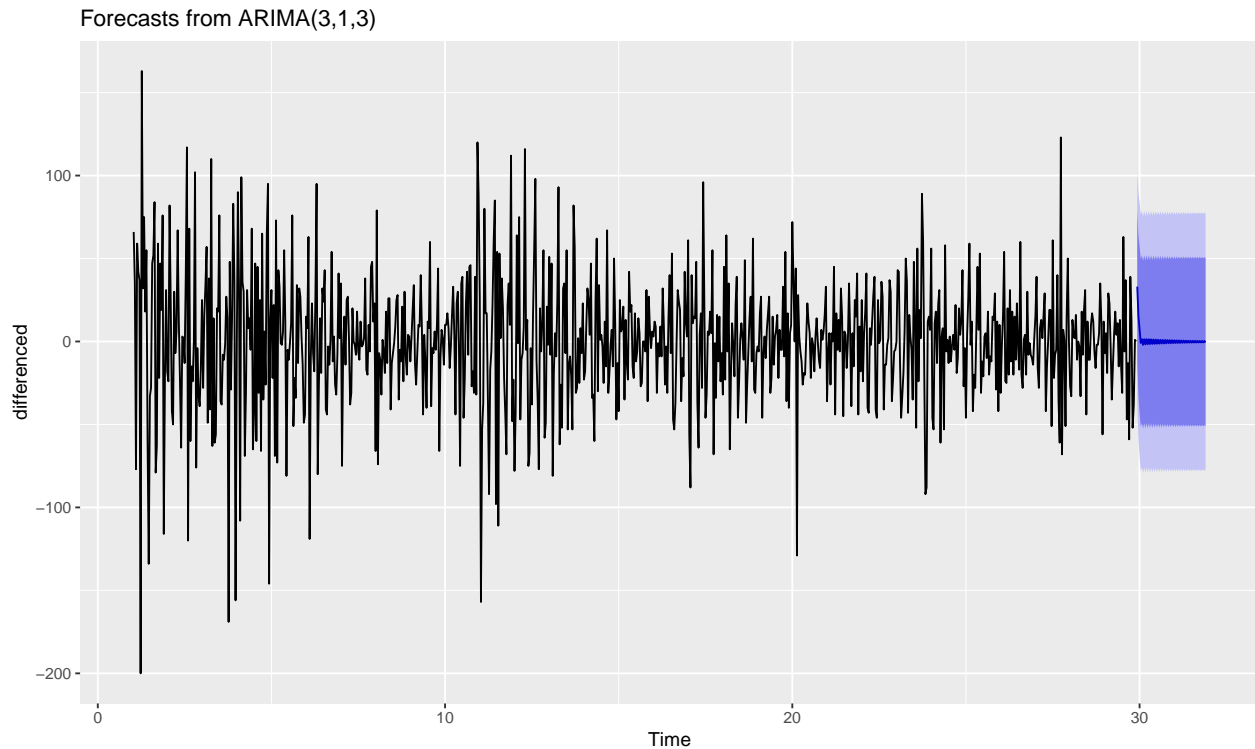
11 Auto Arima

```
##
## Fitting models using approximations to speed things up...
##
##  ARIMA(2,1,2)(1,0,1)[30] with drift         : 8610.806
##  ARIMA(0,1,0)            with drift          : 8834.014
##  ARIMA(1,1,0)(1,0,0)[30] with drift          : 8730.36
##  ARIMA(0,1,1)(0,0,1)[30] with drift          : 8800.342
##  ARIMA(0,1,0)                                : 8827.253
##  ARIMA(2,1,2)(0,0,1)[30] with drift          : Inf
##  ARIMA(2,1,2)(1,0,0)[30] with drift          : 8610.141
##  ARIMA(2,1,2)            with drift          : 8671.879
##  ARIMA(2,1,2)(2,0,0)[30] with drift          : Inf
##  ARIMA(2,1,2)(2,0,1)[30] with drift          : Inf
##  ARIMA(1,1,2)(1,0,0)[30] with drift          : 8608.827
##  ARIMA(1,1,2)            with drift          : 8678.032
##  ARIMA(1,1,2)(2,0,0)[30] with drift          : 8579.411
##  ARIMA(1,1,2)(2,0,1)[30] with drift          : 8583.577
##  ARIMA(1,1,2)(1,0,1)[30] with drift          : 8609.229
##  ARIMA(0,1,2)(2,0,0)[30] with drift          : Inf
##  ARIMA(1,1,1)(2,0,0)[30] with drift          : 8575.506
##  ARIMA(1,1,1)(1,0,0)[30] with drift          : 8606.677
##  ARIMA(1,1,1)(2,0,1)[30] with drift          : 8580.196
```

```
##   ARIMA(1,1,1)(1,0,1)[30] with drift      : 8607.332
##   ARIMA(0,1,1)(2,0,0)[30] with drift      : 8665.059
##   ARIMA(1,1,0)(2,0,0)[30] with drift      : 8689.61
##   ARIMA(2,1,1)(2,0,0)[30] with drift      : 8567.804
##   ARIMA(2,1,1)(1,0,0)[30] with drift      : 8603.453
##   ARIMA(2,1,1)(2,0,1)[30] with drift      : 8574.386
##   ARIMA(2,1,1)(1,0,1)[30] with drift      : 8604.228
##   ARIMA(2,1,0)(2,0,0)[30] with drift      : 8688.443
##   ARIMA(3,1,1)(2,0,0)[30] with drift      : 8540.098
##   ARIMA(3,1,1)(1,0,0)[30] with drift      : 8566.621
##   ARIMA(3,1,1)(2,0,1)[30] with drift      : 8546.123
##   ARIMA(3,1,1)(1,0,1)[30] with drift      : 8571.574
##   ARIMA(3,1,0)(2,0,0)[30] with drift      : 8638.097
##   ARIMA(4,1,1)(2,0,0)[30] with drift      : 8538.185
##   ARIMA(4,1,1)(1,0,0)[30] with drift      : 8561.636
##   ARIMA(4,1,1)(2,0,1)[30] with drift      : 8541.546
##   ARIMA(4,1,1)(1,0,1)[30] with drift      : 8566.49
##   ARIMA(4,1,0)(2,0,0)[30] with drift      : 8593.136
##   ARIMA(5,1,1)(2,0,0)[30] with drift      : 8527.192
##   ARIMA(5,1,1)(1,0,0)[30] with drift      : 8548.369
##   ARIMA(5,1,1)(2,0,1)[30] with drift      : 8532.352
##   ARIMA(5,1,1)(1,0,1)[30] with drift      : 8553.149
##   ARIMA(5,1,0)(2,0,0)[30] with drift      : 8537.623
##   ARIMA(5,1,2)(2,0,0)[30] with drift      : 8499.702
##   ARIMA(5,1,2)(1,0,0)[30] with drift      : Inf
##   ARIMA(5,1,2)(2,0,1)[30] with drift      : 8506.464
##   ARIMA(5,1,2)(1,0,1)[30] with drift      : Inf
##   ARIMA(4,1,2)(2,0,0)[30] with drift      : 8546.42
##   ARIMA(5,1,3)(2,0,0)[30] with drift      : 8505.967
##   ARIMA(4,1,3)(2,0,0)[30] with drift      : 8543.06
##   ARIMA(5,1,2)(2,0,0)[30]                 : 8493.095
##   ARIMA(5,1,2)(1,0,0)[30]                 : Inf
##   ARIMA(5,1,2)(2,0,1)[30]                 : 8499.858
##   ARIMA(5,1,2)(1,0,1)[30]                 : Inf
##   ARIMA(4,1,2)(2,0,0)[30]                 : 8540.416
##   ARIMA(5,1,1)(2,0,0)[30]                 : 8520.844
##   ARIMA(5,1,3)(2,0,0)[30]                 : 8499.324
##   ARIMA(4,1,1)(2,0,0)[30]                 : 8532.057
##   ARIMA(4,1,3)(2,0,0)[30]                 : 8536.662
## 
##   Now re-fitting the best model(s) without approximations...
## 
##   ARIMA(5,1,2)(2,0,0)[30]                 : Inf
##   ARIMA(5,1,3)(2,0,0)[30]                 : Inf
##   ARIMA(5,1,2)(2,0,0)[30] with drift      : Inf
```

```
##   ARIMA(5,1,2)(2,0,1)[30]                     : Inf
##   ARIMA(5,1,3)(2,0,0)[30] with drift          : Inf
##   ARIMA(5,1,2)(2,0,1)[30] with drift          : Inf
##   ARIMA(5,1,1)(2,0,0)[30]                     : 8644.43
##
##   Best model: ARIMA(5,1,1)(2,0,0)[30]

## Series: data.ts
## ARIMA(5,1,1)(2,0,0)[30]
##
## Coefficients:
##           ar1      ar2      ar3      ar4      ar5      ma1      sar1      sar2
##       -0.0582  -0.2057  -0.3041  -0.2182  -0.2583  -0.3268  -0.0639  -0.0228
## s.e.   0.0683   0.0385   0.0338   0.0382   0.0391   0.0663   0.0383   0.0386
##
## sigma^2 estimated as 1176:   log likelihood=-4291.77
## AIC=8601.54   AICc=8601.75   BIC=8644.43
```
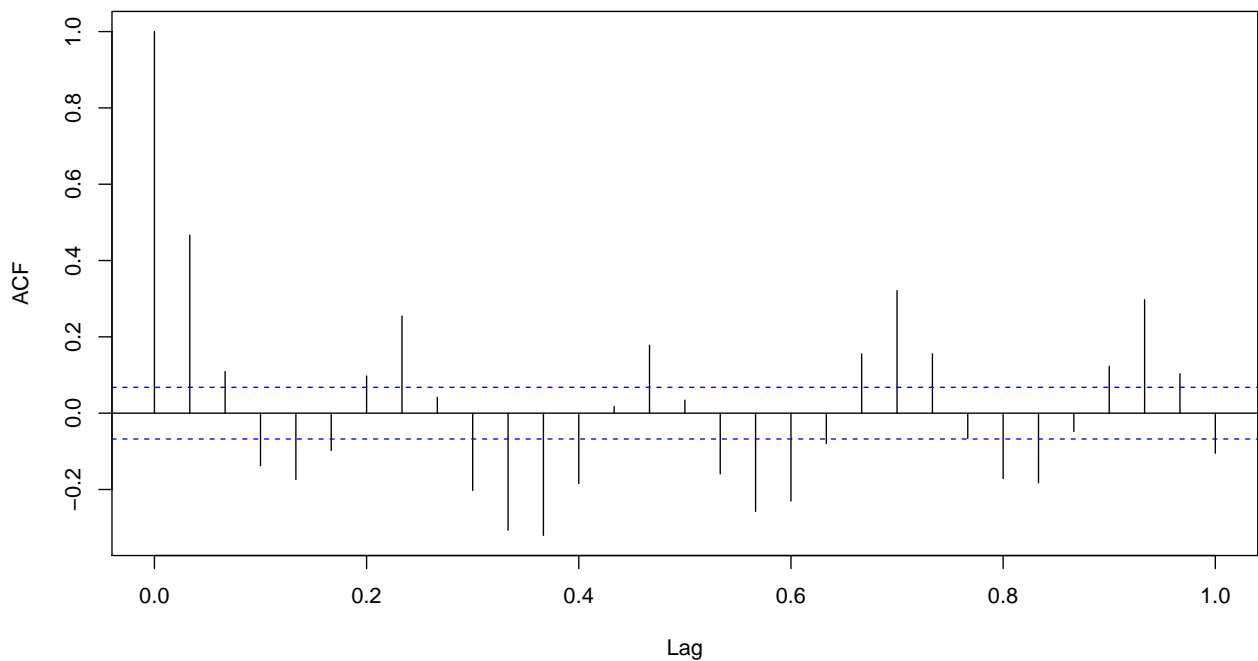
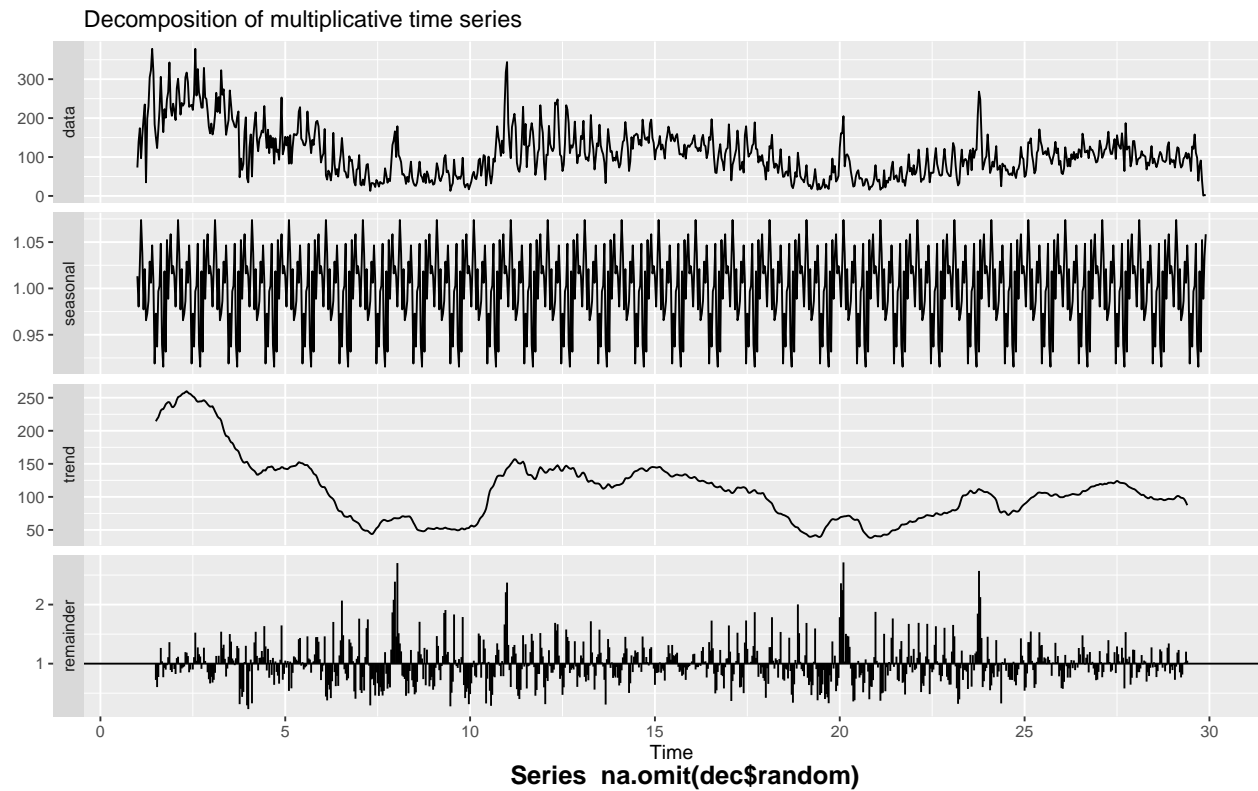**Forecasts from ARIMA(3,1,1)(2,0,0)[30]**
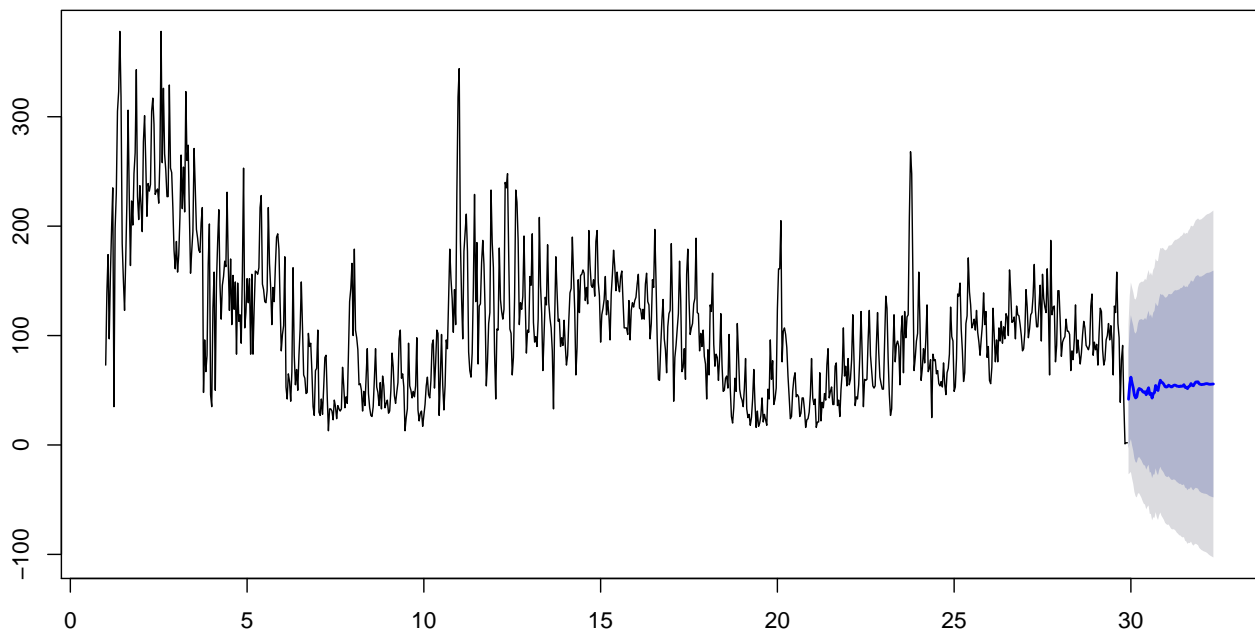
The plot is not good but AIC and BIC are very high, we should try with a multi seasonal decomposition

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

12 Searching for multi seasonalities

without differentiation residuals looks pretty bad

Decomposition of multiplicative time series

Series na.omit(dec$random)

trying with differentiation and a multiplicative model:

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

13   Transforming into msts


```
##
##   Box-Pierce test
##
```

17
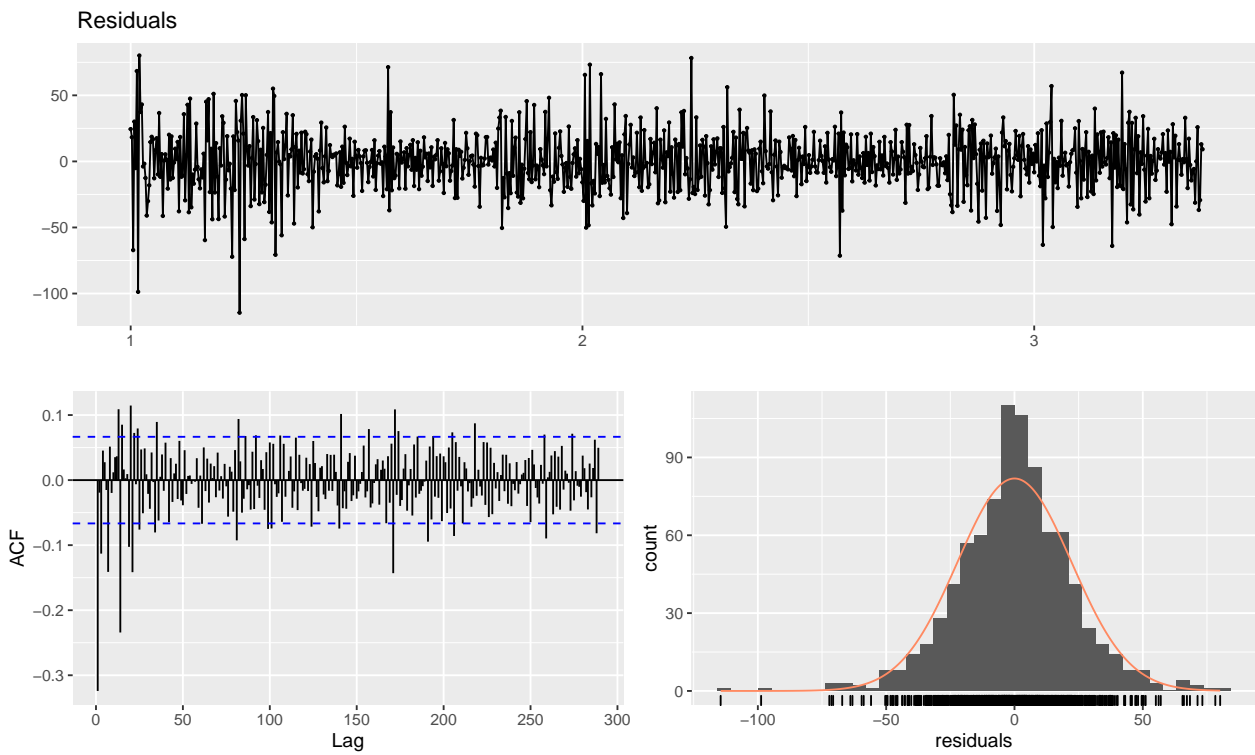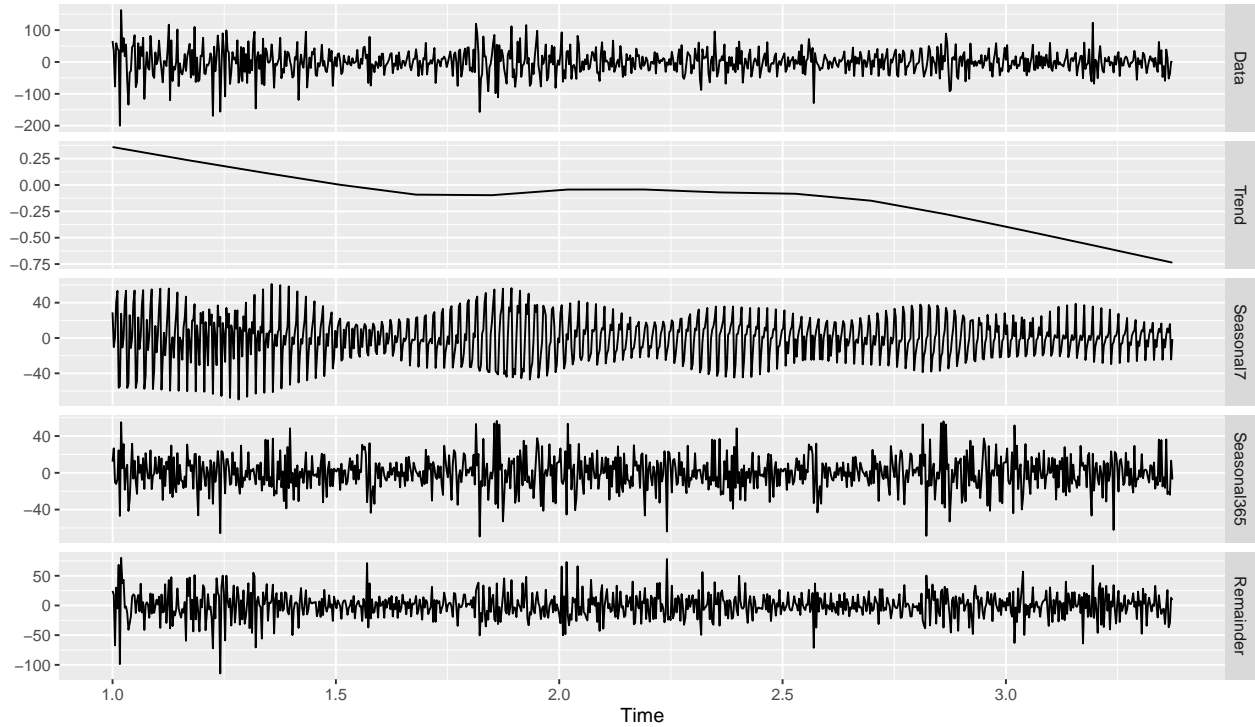
```
## data:  remainder(decomposed)
## X-squared = 104.9, df = 5, p-value < 2.2e-16

##
##  Box-Ljung test
##
## data:  remainder(decomposed)
## X-squared = 105.3, df = 5, p-value < 2.2e-16
```

14 Garch

Inflation of exchange rate
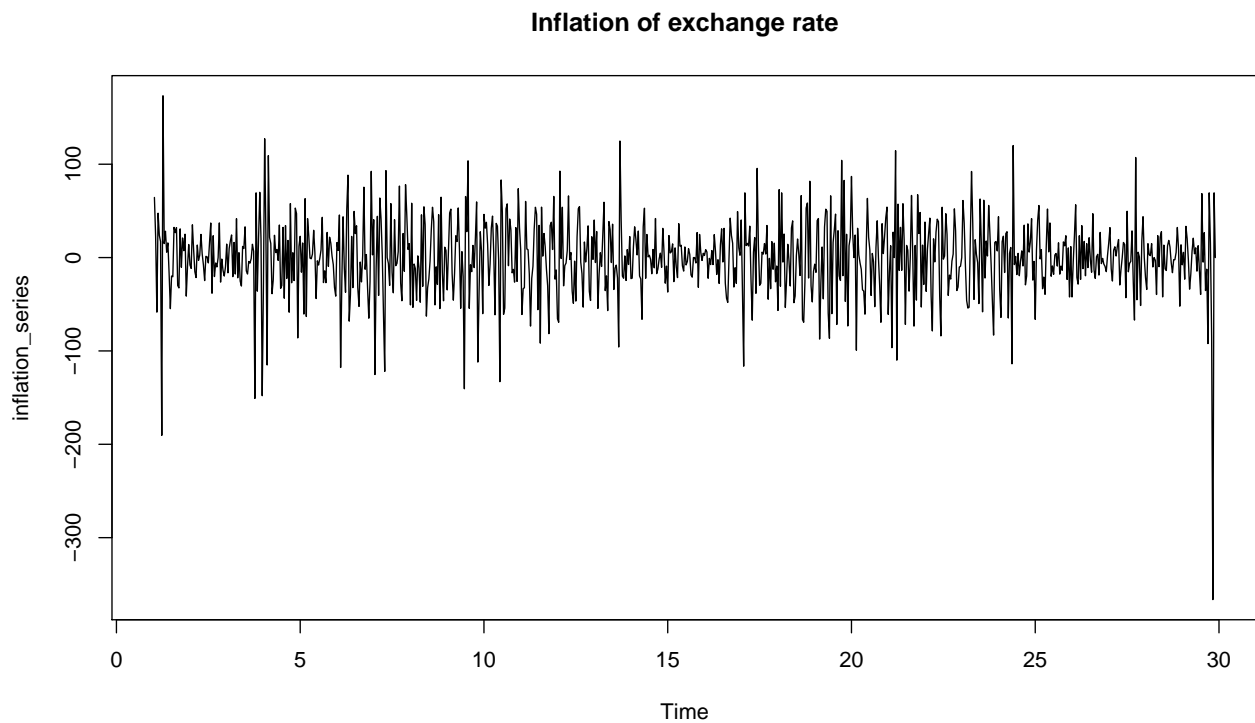

```
##      Min.   1st Qu.   Median      Mean   3rd Qu.      Max.
## -366.3562  -22.2343   1.2903   -0.4149   23.6858  173.2919
```

Series inflation_series

Series inflation_series
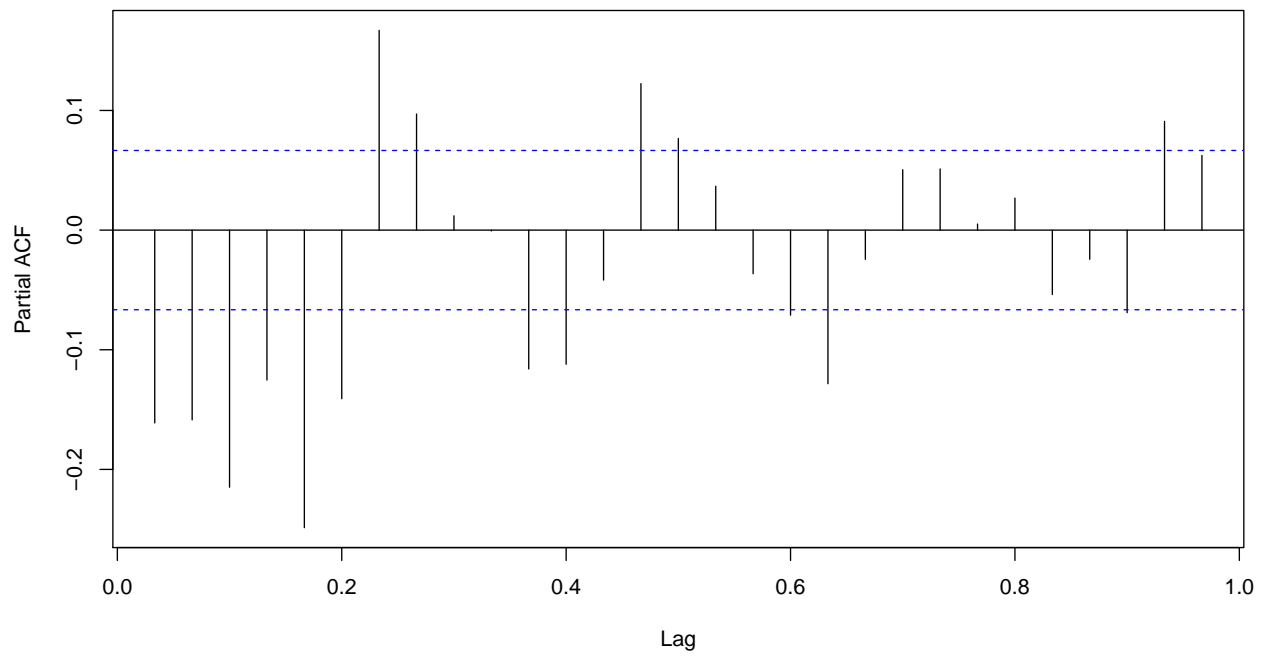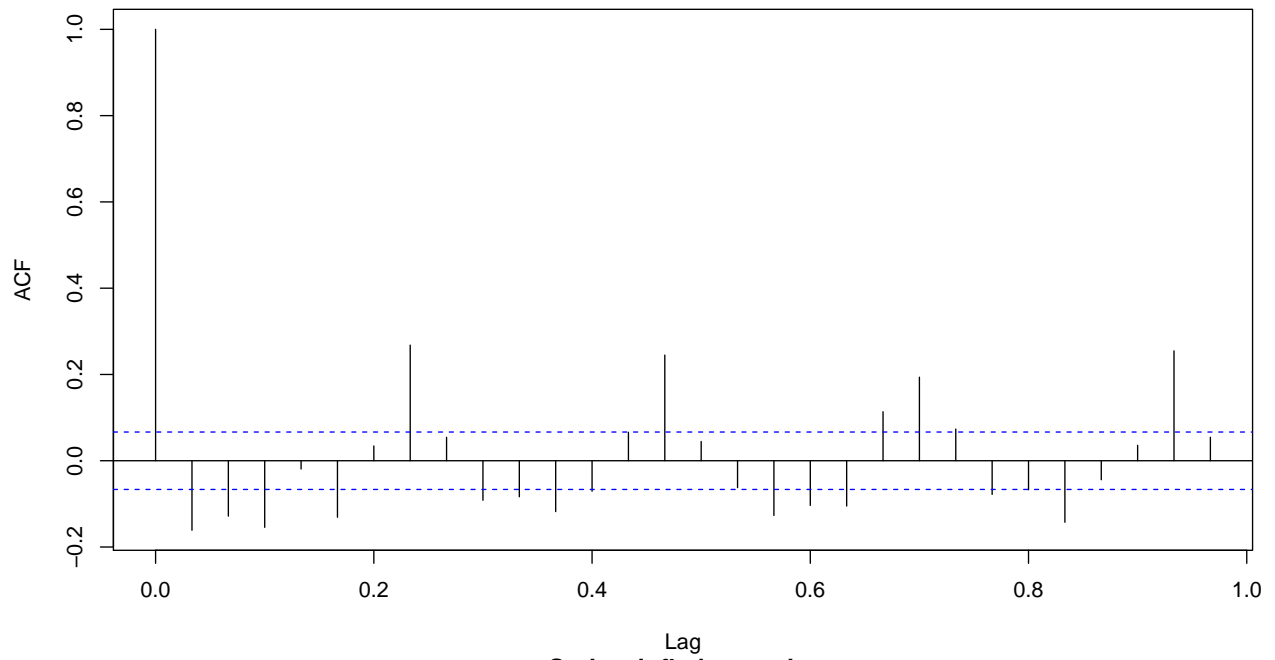
Series residual
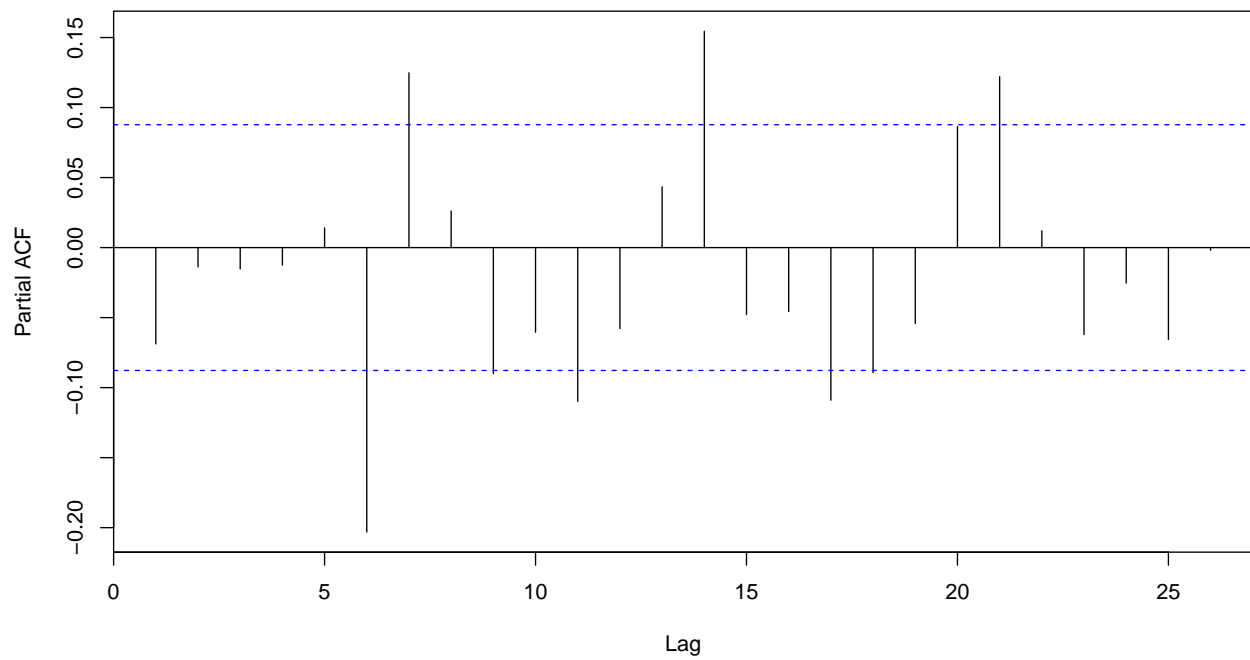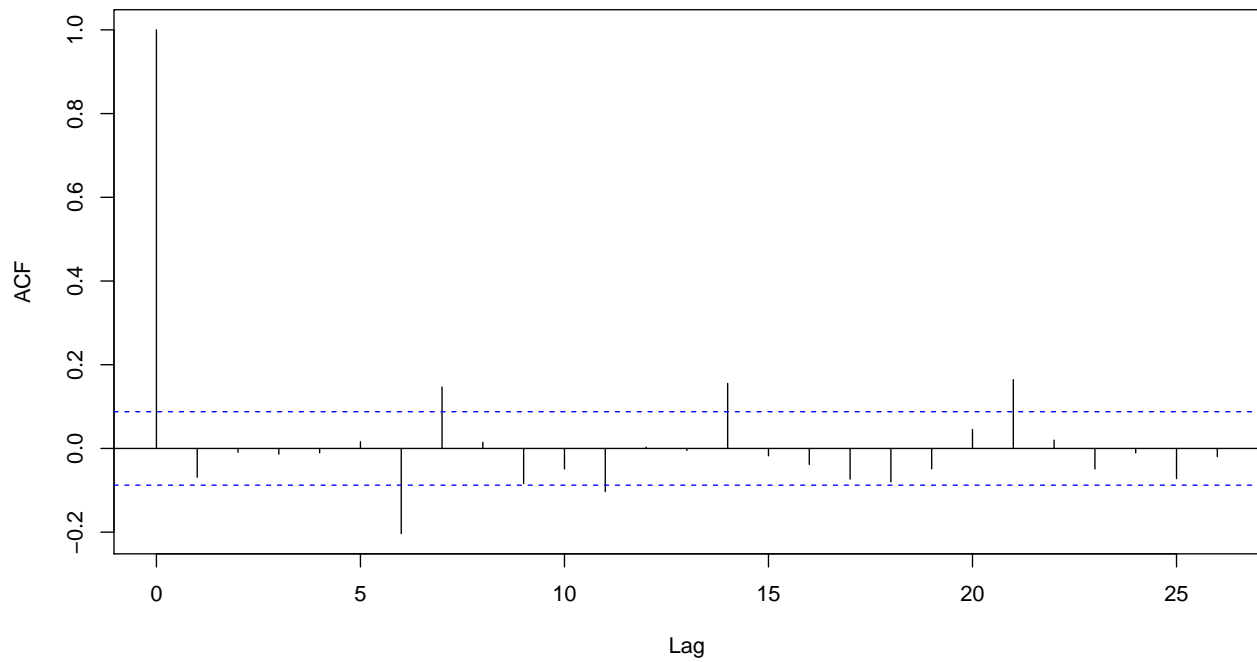
Series residual


```
##
##   Box-Ljung test
##
## data:  residual
## X-squared = 66.837, df = 20, p-value = 5.929e-07

##
```

```
## 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:                41.0543
##
## Parameter Initialization:
##   Initial Parameters:          $params
##   Limits of Transformations:   $U, $V
##   Which Parameters are Fixed?  $includes
##   Parameter Matrix:
##                      U               V         params includes
##      mu       -0.02958912    0.02958912  0.0004379123    TRUE
##      ar1      -0.99999999    0.99999999 -0.3416401219    TRUE
##      ar2      -0.99999999    0.99999999 -0.3773843846    TRUE
##      ar3      -0.99999999    0.99999999 -0.3537906753    TRUE
##      ar4      -0.99999999    0.99999999 -0.2437663341    TRUE
##      ar5      -0.99999999    0.99999999 -0.2757320301    TRUE
##      omega     0.00000100  100.00000000  0.1000000000    TRUE
##      alpha1    0.00000001    0.99999999  0.1000000000    TRUE
##      gamma1   -0.99999999    0.99999999  0.1000000000    FALSE
##      beta1     0.00000001    0.99999999  0.8000000000    TRUE
##      delta     0.00000000    2.00000000  2.0000000000    FALSE
##      skew      0.10000000   10.00000000  1.0000000000    FALSE
##      shape     1.00000000   10.00000000  4.0000000000    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:    637.07469: 0.000437912 -0.341640 -0.377384 -0.353791 -0.243766 -0.275732 0.1
##    1:    635.12577: 0.000437904 -0.341341 -0.376830 -0.354027 -0.244424 -0.276033 0.0
##    2:    634.80126: 0.000437818 -0.338443 -0.371898 -0.356251 -0.250399 -0.278932 0.0
##    3:    634.59553: 0.000437685 -0.335492 -0.366346 -0.358949 -0.257304 -0.282403 0.0
##    4:    634.43531: 0.000437440 -0.334945 -0.363242 -0.361368 -0.262225 -0.285280 0.0
##    5:    634.29527: 0.000437110 -0.336695 -0.363922 -0.362277 -0.263617 -0.287243 0.0
##    6:    634.10259: 0.000435251 -0.342599 -0.370069 -0.363278 -0.265341 -0.288119 0.0
##    7:    634.09567: 0.000435222 -0.342438 -0.369369 -0.363385 -0.265907 -0.288684 0.0
##    8:    633.95285: 0.000435217 -0.342408 -0.369244 -0.363411 -0.266009 -0.288767 0.0
##    9:    633.92536: 0.000435170 -0.342377 -0.368797 -0.363507 -0.266411 -0.289143 0.0
##   10:    633.88249: 0.000434986 -0.343018 -0.368924 -0.363452 -0.266446 -0.289435 0.0
##   11:    633.85447: 0.000434730 -0.343809 -0.368578 -0.363355 -0.266495 -0.289856 0.0
##   12:    633.83116: 0.000434129 -0.344500 -0.365659 -0.363329 -0.267284 -0.290947 0.0
##   13:    633.81312: 0.000433561 -0.342646 -0.363251 -0.363958 -0.269531 -0.291648 0.0
##   14:    633.80956: 0.000432571 -0.339600 -0.365153 -0.365672 -0.272564 -0.291857 0.0
##   15:    633.79963: 0.000430781 -0.342500 -0.363870 -0.367087 -0.273552 -0.295338 0.0
##   16:    633.79769: 0.000428904 -0.343519 -0.361462 -0.365682 -0.274480 -0.292216 0.0
##   17:    633.79762: 0.000428896 -0.343474 -0.361441 -0.365702 -0.274491 -0.292271 0.0
##   18:    633.79658: 0.000428893 -0.343455 -0.361432 -0.365711 -0.274496 -0.292296 0.0
##   19:    633.79503: 0.000428776 -0.342811 -0.361125 -0.366001 -0.274654 -0.293094 0.0
##   20:    633.79351: 0.000427443 -0.341675 -0.360864 -0.365444 -0.273360 -0.293438 0.0
##   21:    633.79313: 0.000424208 -0.342252 -0.362235 -0.366231 -0.274030 -0.294301 0.0
##   22:    633.79228: 0.000420478 -0.342806 -0.361849 -0.366941 -0.274341 -0.295331 0.0
##   23:    633.79226: 0.000415090 -0.341786 -0.361096 -0.365972 -0.274747 -0.294907 0.0
##   24:    633.79170: 0.000412525 -0.341499 -0.360951 -0.366486 -0.274835 -0.294343 0.0
##   25:    633.79152: 0.000410155 -0.341405 -0.360781 -0.367274 -0.274666 -0.293930 0.0
##   26:    633.79105: 0.000408301 -0.341656 -0.361189 -0.366587 -0.275147 -0.294405 0.0
##   27:    633.79099: 0.000408297 -0.341656 -0.361184 -0.366588 -0.275147 -0.294412 0.0
##   28:    633.79094: 0.000408235 -0.341660 -0.361110 -0.366617 -0.275151 -0.294524 0.0
##   29:    633.79085: 0.000407299 -0.341653 -0.361063 -0.366584 -0.275064 -0.294567 0.0
##   30:    633.78976: 0.000362647 -0.342148 -0.361117 -0.366722 -0.274607 -0.294925 0.0
##   31:    633.78922: 0.000317842 -0.342332 -0.361735 -0.367411 -0.275965 -0.294633 0.0
##   32:    633.78405: -6.51134e-05 -0.338943 -0.358712 -0.365868 -0.276065 -0.295330 0.
##   33:    633.77528: -0.000448109 -0.340934 -0.358869 -0.367827 -0.277582 -0.298220 0.
##   34:    633.76623: -0.000831325 -0.341745 -0.358715 -0.367301 -0.277351 -0.297903 0.
##   35:    633.68345: -0.00644891 -0.342576 -0.369286 -0.369043 -0.273869 -0.305214 0.0
##   36:    633.60773: -0.0125805 -0.352816 -0.363819 -0.363643 -0.273048 -0.302214 0.04
##   37:    633.49362: -0.0187121 -0.352985 -0.362901 -0.365004 -0.274065 -0.303516 0.04
##   38:    633.39483: -0.0248438 -0.348931 -0.362193 -0.366597 -0.275890 -0.301235 0.04
##   39:    633.36183: -0.0295891 -0.335642 -0.358716 -0.368295 -0.278140 -0.290324 0.04
##   40:    633.33878: -0.0295891 -0.342120 -0.360181 -0.367410 -0.277158 -0.295485 0.04
##   41:    633.33877: -0.0295891 -0.342129 -0.360224 -0.367430 -0.277163 -0.295509 0.04
##   42:    633.33876: -0.0295891 -0.342131 -0.360224 -0.367425 -0.277160 -0.295503 0.04
```

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```
## 43:     633.33876: -0.0295891 -0.342132 -0.360224 -0.367425 -0.277159 -0.295503 0.04
##
## Final Estimate of the Negative LLH:
##  LLH:  2490.787    norm LLH:  4.981573
##          mu           ar1          ar2          ar3          ar4          ar5
## -1.21476072 -0.34213169 -0.36022407 -0.36742497 -0.27715949 -0.29550303
##       omega       alpha1        beta1
## 79.03691998  0.06601148  0.87205266
##
## R-optimhess Difference Approximated Hessian Matrix:
##                   mu           ar1          ar2           ar3           ar4
## mu      -0.457472849    0.15895878 -3.477774e-01    0.11047855  6.144113e-01
## ar1      0.158958784 -548.91316020  8.400644e+01   79.35724952  9.829975e+01
## ar2     -0.347777398   84.00643955 -5.196965e+02   88.64784166  5.481826e+01
## ar3      0.110478554   79.35724952  8.864784e+01 -567.65566137  9.577744e+01
## ar4      0.614411331   98.29975099  5.481826e+01   95.77744069 -5.374288e+02
## ar5     -0.257030691   35.02504586  8.889707e+01   95.36704488  1.022688e+02
## omega    0.004791553    0.01125851 -7.489342e-04   -0.03392825  2.506991e-03
## alpha1  -2.093524959  -40.03538677 -1.062704e+01   37.89851129  1.020662e+01
## beta1    4.286530629  -67.50809470 -3.862055e+01   20.72436214  4.337998e+01
##                  ar5          omega        alpha1          beta1
## mu        -0.25703069  4.791553e-03     -2.093525       4.286531
## ar1       35.02504586  1.125851e-02    -40.035387     -67.508095
## ar2       88.89706962 -7.489342e-04    -10.627045     -38.620549
## ar3       95.36704488 -3.392825e-02     37.898511      20.724362
## ar4      102.26884743  2.506991e-03     10.206617      43.379978
## ar5     -579.38482493  6.908145e-02    -68.159641      43.852679
## omega      0.06908145 -1.202629e-02    -10.157877     -13.712071
## alpha1   -68.15964056 -1.015788e+01 -13543.451549 -13587.644372
## beta1     43.85267923 -1.371207e+01 -13587.644372 -16805.902479
## attr(,"time")
## Time difference of 0.03096199 secs
##
## --- END OF TRACE ---
##
##
## Time to Estimate Parameters:
##  Time difference of 0.1206801 secs
```
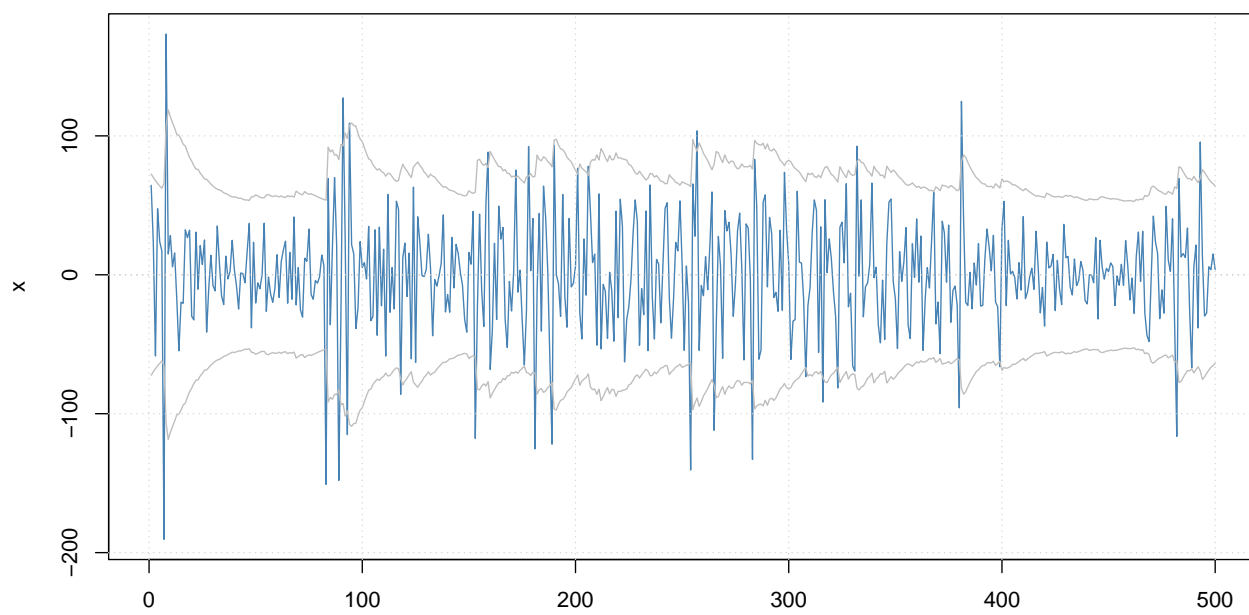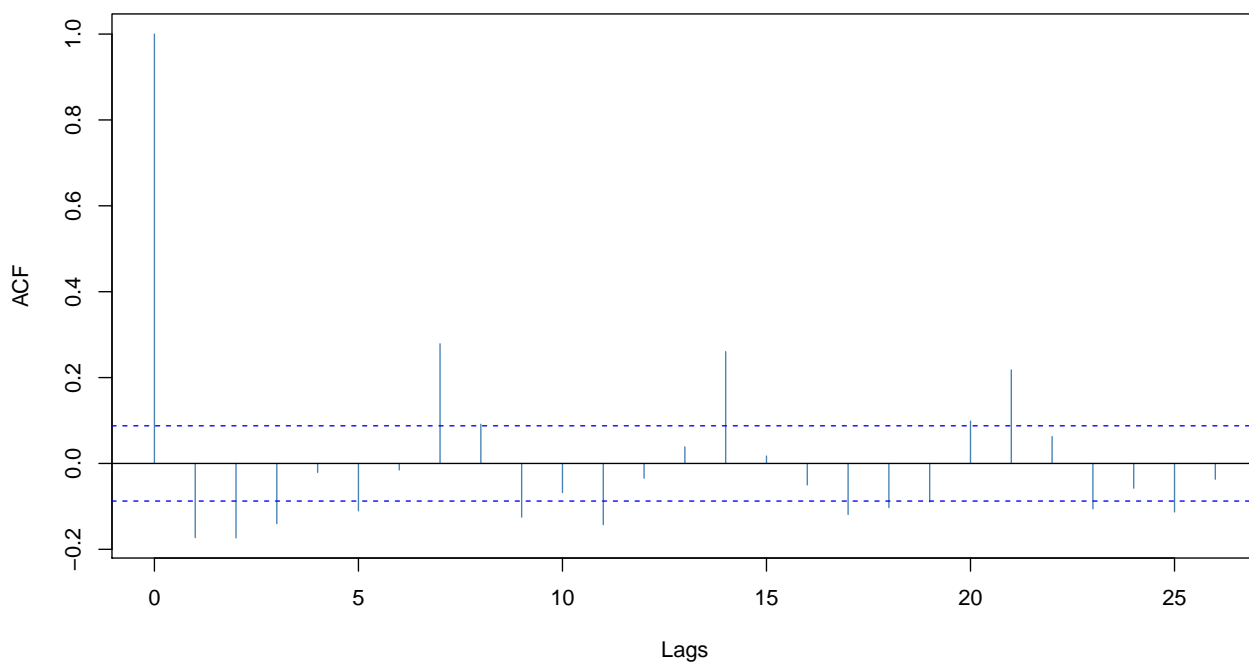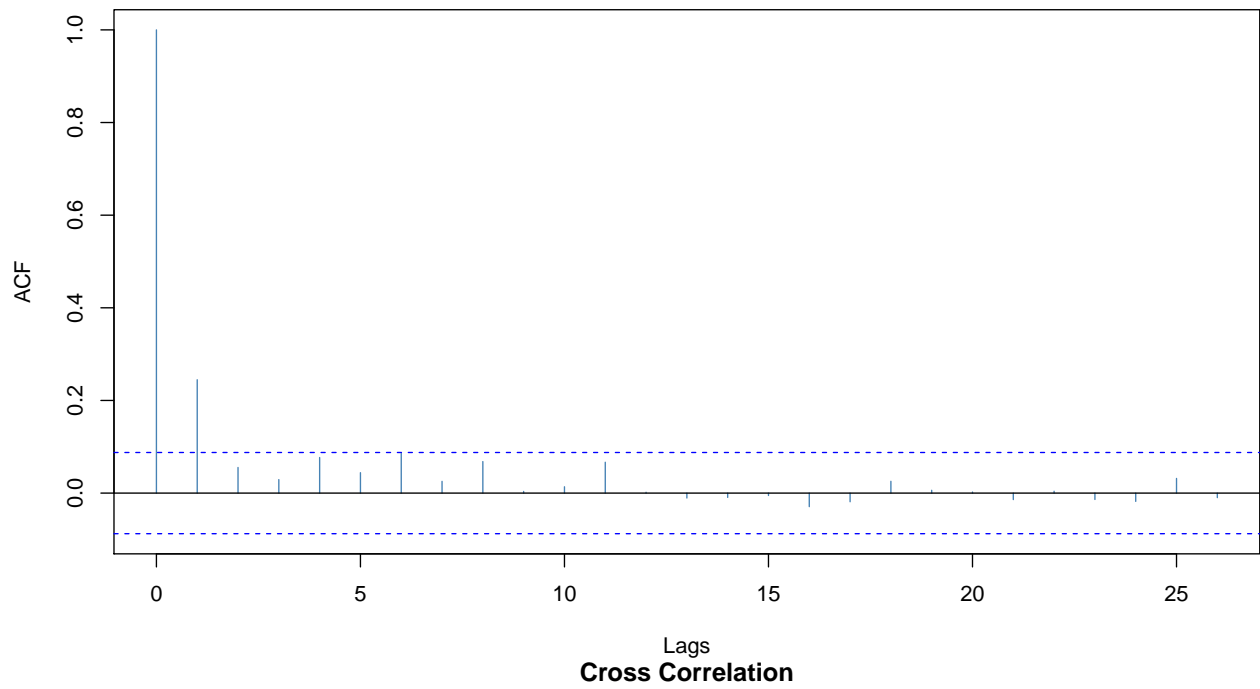
Time Series

Conditional SD

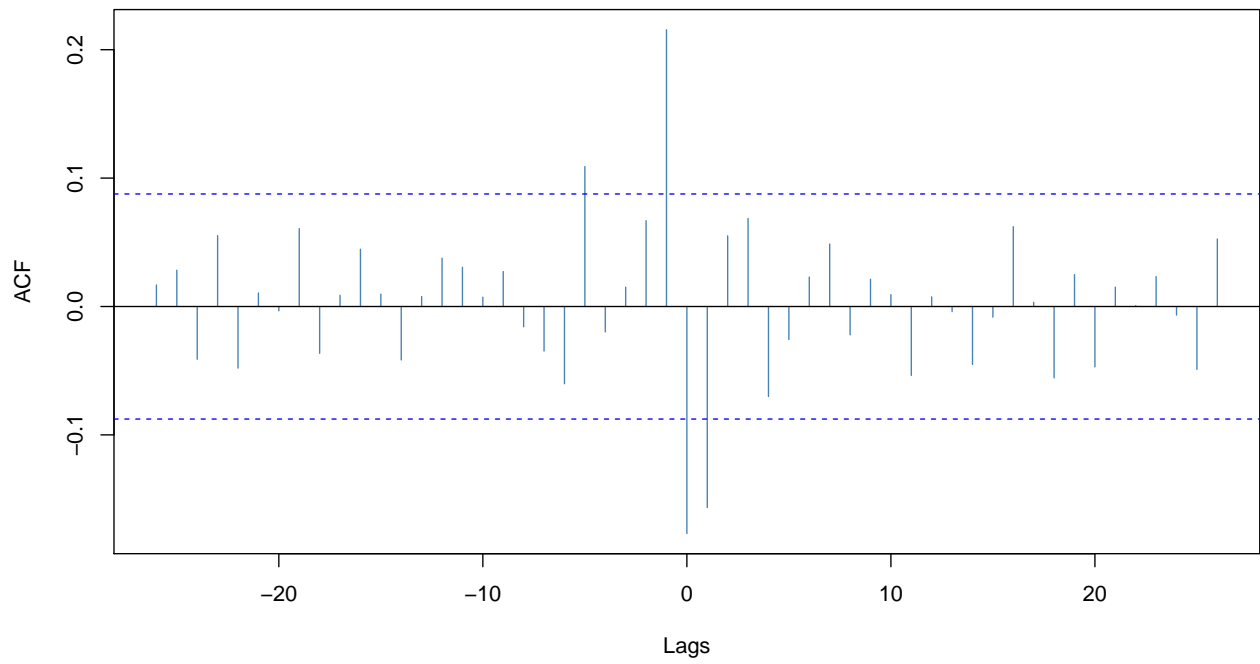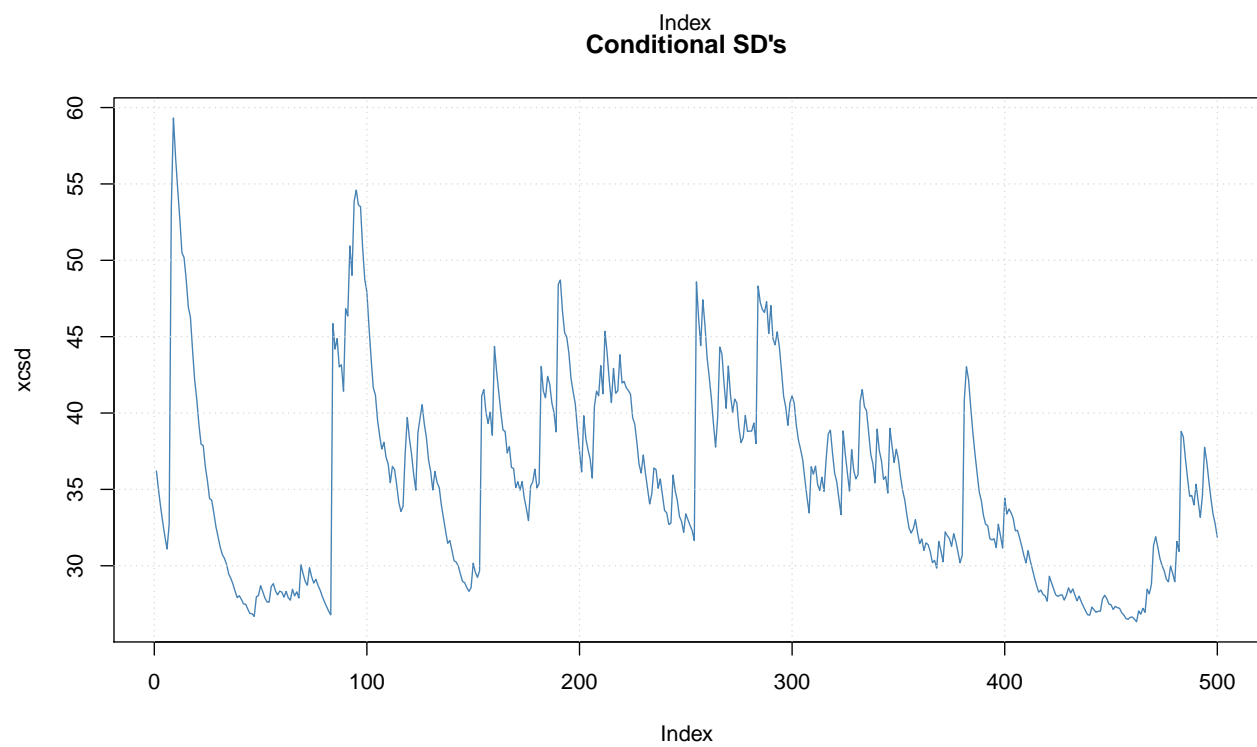24
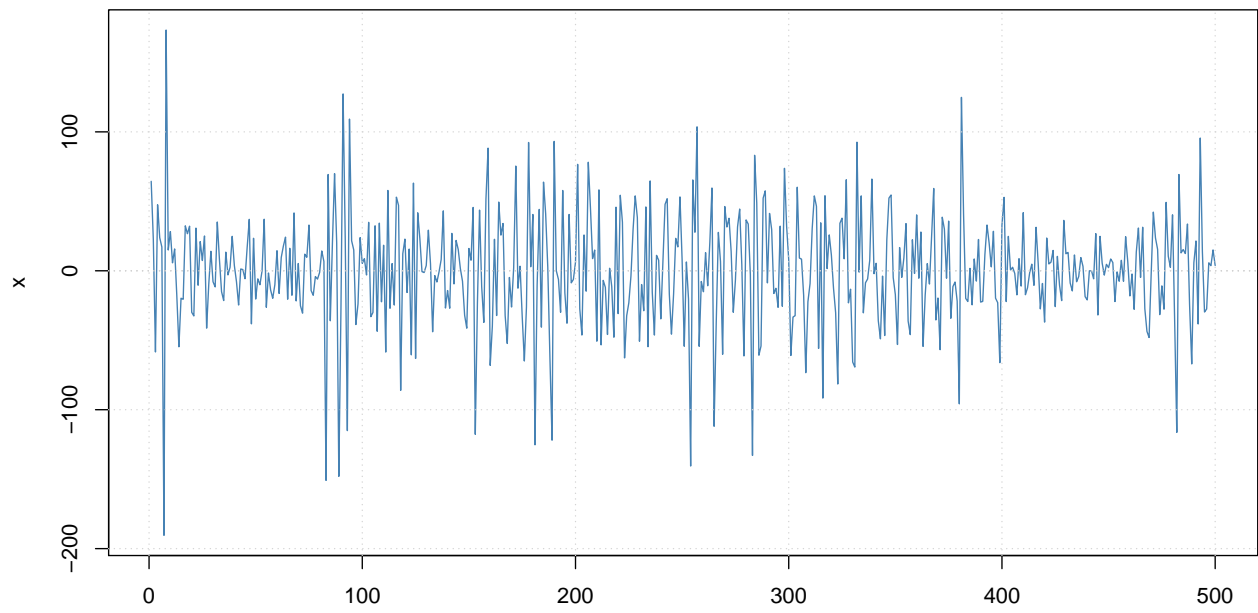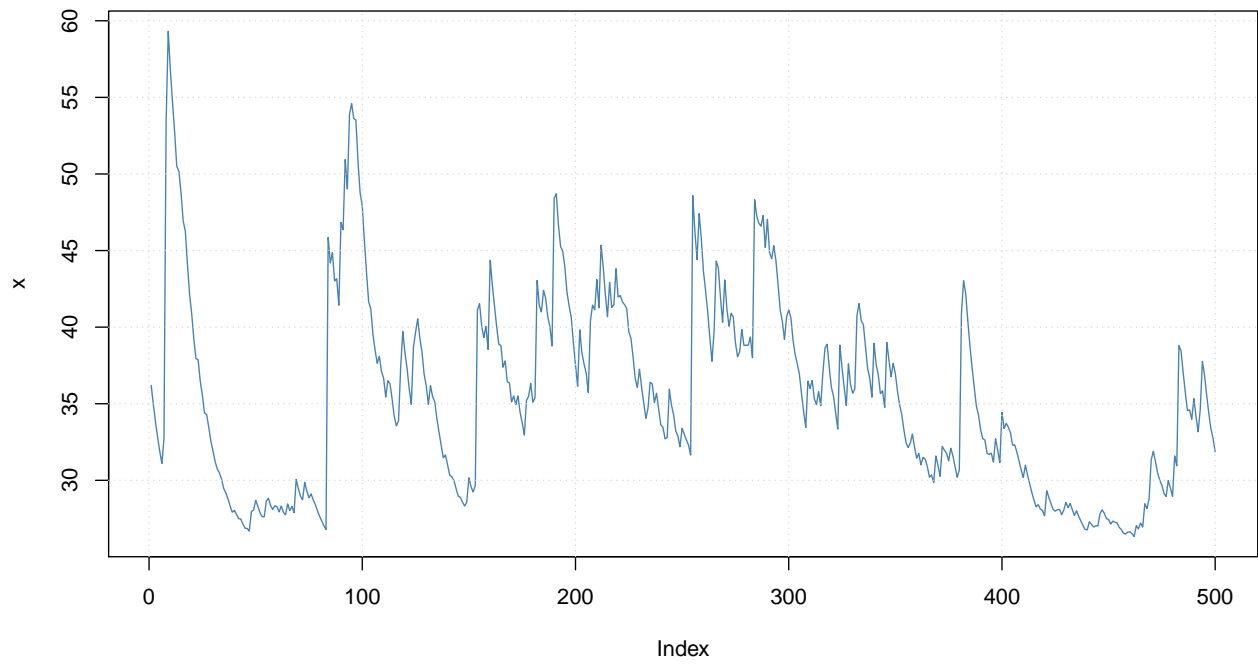
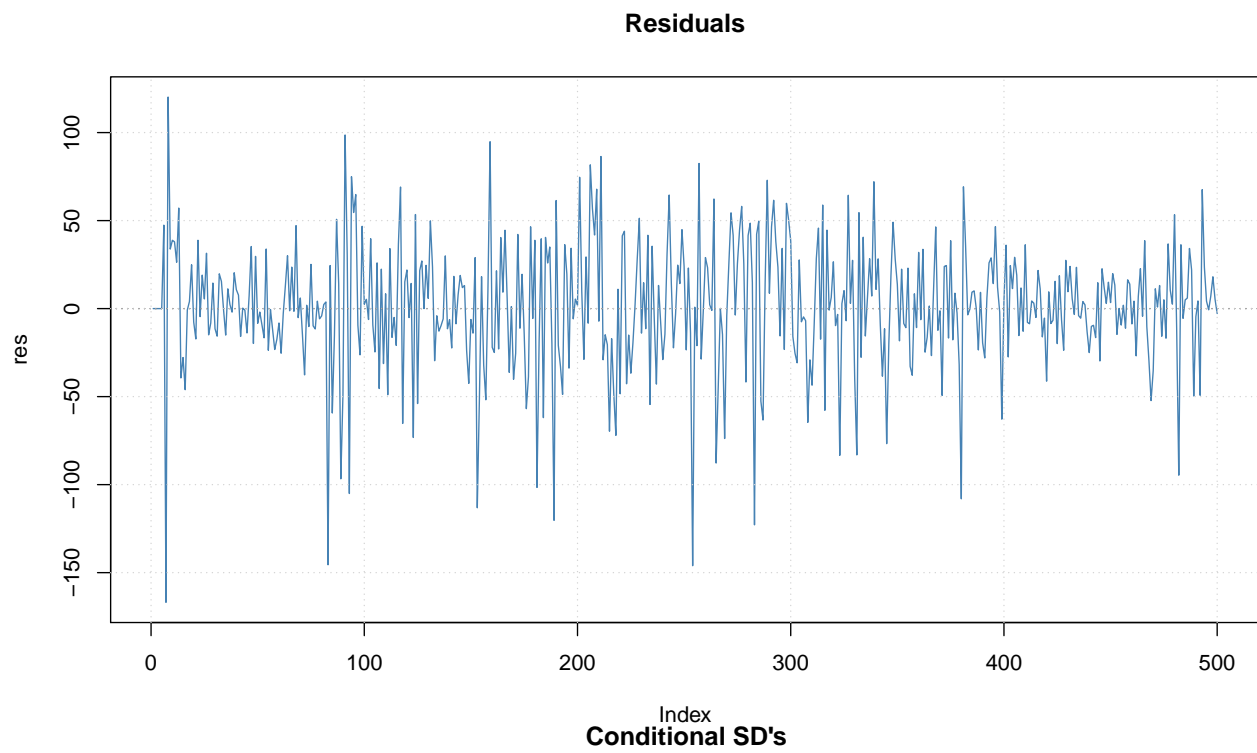## Series with 2 Conditional SD Superimposed

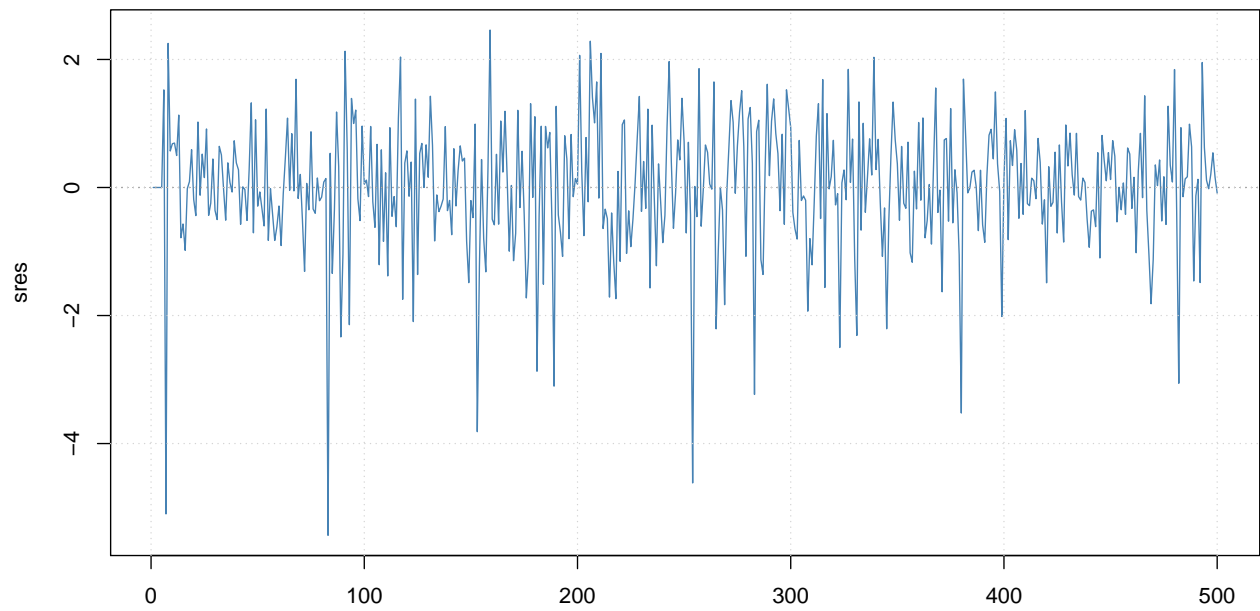## ACF of Observations

ACF of Squared Observations

Cross Correlation

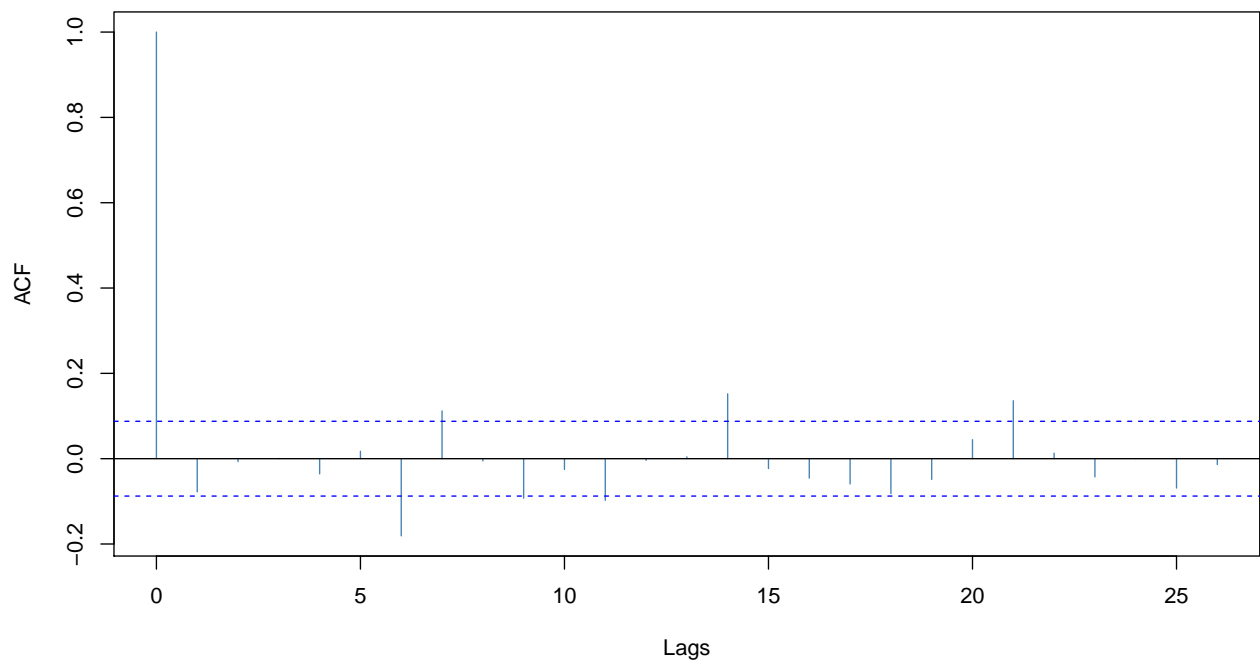**Residuals**

Conditional SD's

Standardized Residuals

ACF of Standardized Residuals

ACF of Squared Standardized Residuals

Lags

Cross Correlation

Lags

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qnorm – QQ Plot
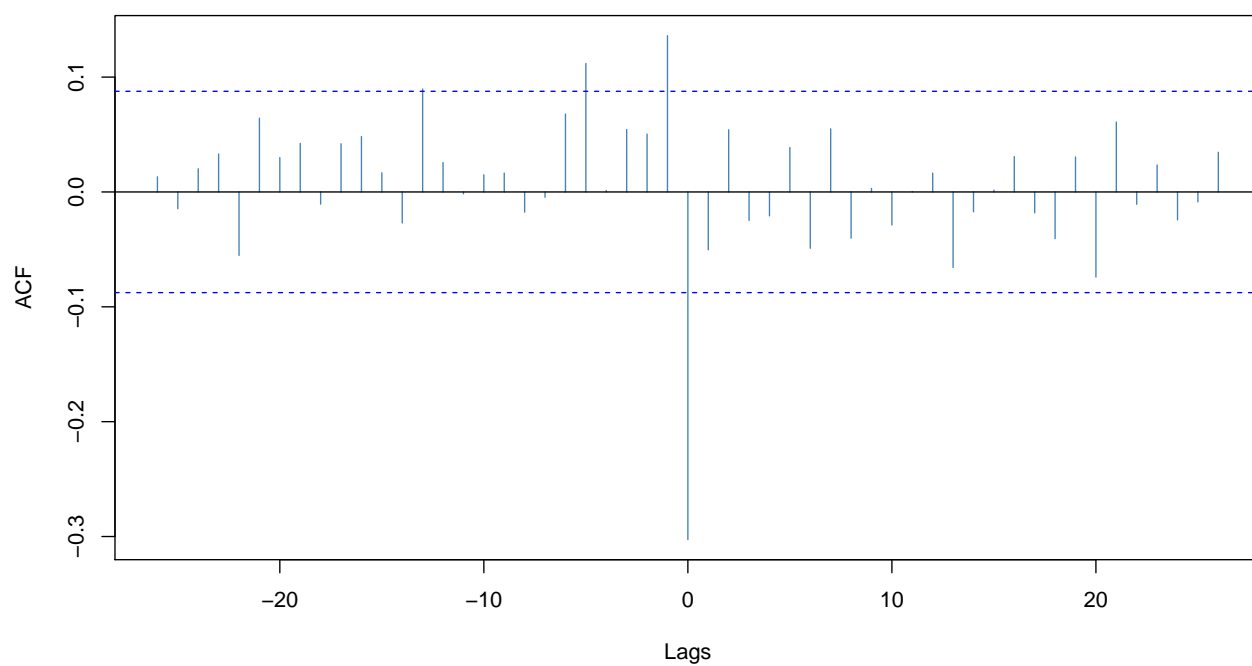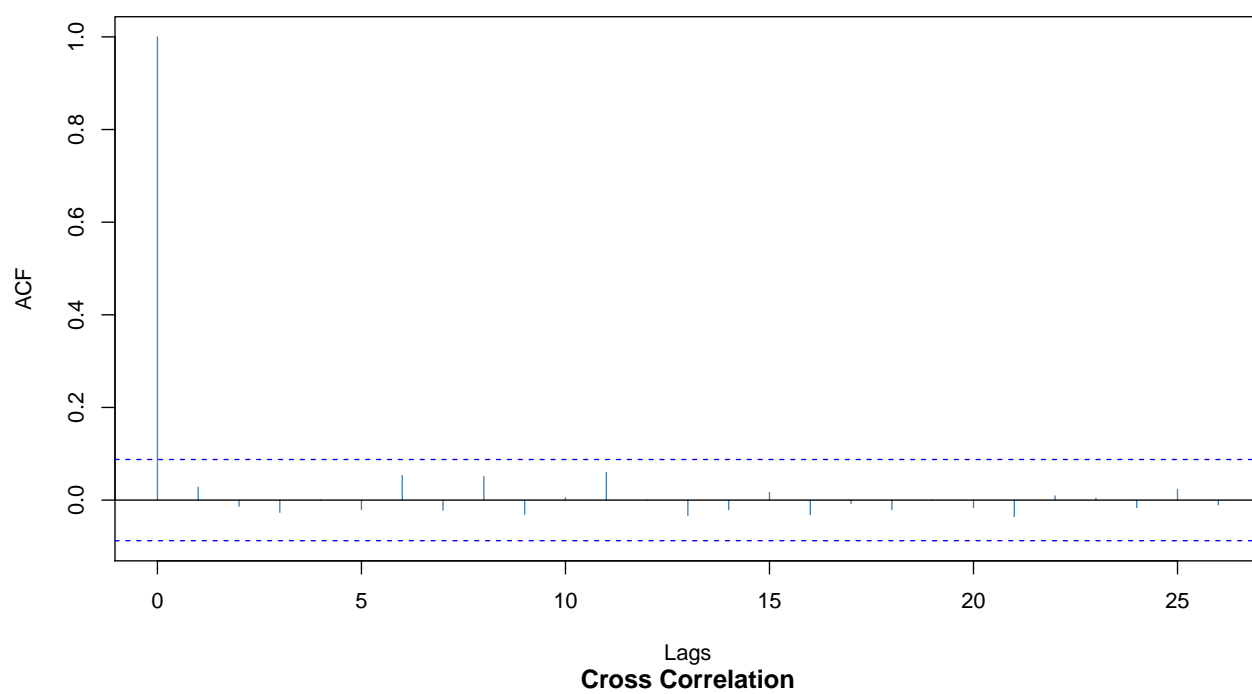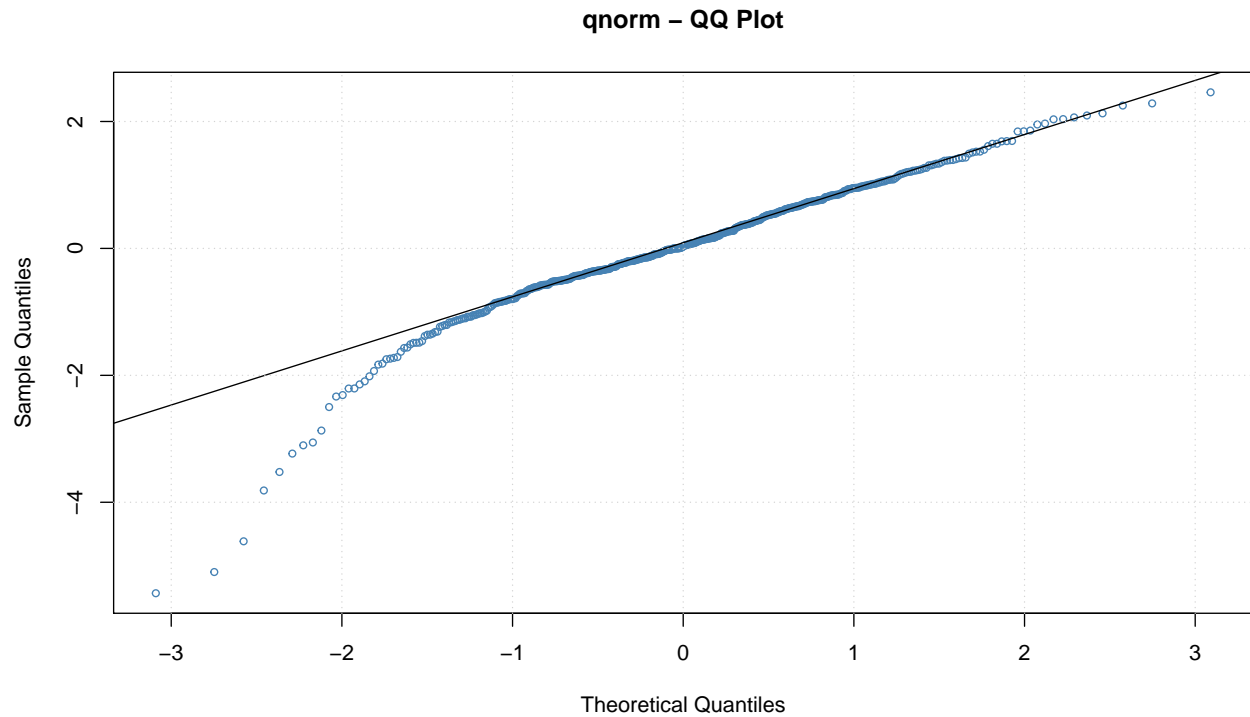
15 RUGARCH

```
##
## *---------------------------------*
## *          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      92.935489    6.047734  15.3670 0.000000
## ar1      0.851444    0.026395  32.2581 0.000000
## ma1     -0.136906    0.054949  -2.4915 0.012720
## omega   25.314547   10.476892   2.4162 0.015682
## alpha1   0.095629    0.021829   4.3808 0.000012
## beta1    0.886987    0.023000  38.5649 0.000000
##
## Robust Standard Errors:
```

```
##            Estimate  Std. Error  t value Pr(>|t|)
## mu        92.935489    6.424697  14.4653 0.000000
## ar1        0.851444    0.037383  22.7760 0.000000
## ma1       -0.136906    0.073914  -1.8522 0.063994
## omega     25.314547   11.426045   2.2155 0.026725
## alpha1     0.095629    0.031321   3.0532 0.002264
## beta1      0.886987    0.032785  27.0547 0.000000
##
## LogLikelihood : -4292.431
##
## Information Criteria
## ------------------------------------
##
## Akaike        9.9042
## Bayes         9.9372
## Shibata       9.9041
## Hannan-Quinn  9.9168
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                             statistic p-value
## Lag[1]                         0.1995  0.6551
## Lag[2*(p+q)+(p+q)-1][5]       20.8124  0.0000
## Lag[4*(p+q)+(p+q)-1][9]       83.6559  0.0000
## d.o.f=2
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                             statistic p-value
## Lag[1]                          3.531 0.06024
## Lag[2*(p+q)+(p+q)-1][5]         4.513 0.19661
## Lag[4*(p+q)+(p+q)-1][9]         8.617 0.09723
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##              Statistic Shape Scale P-Value
## ARCH Lag[3]     0.4624 0.500 2.000  0.4965
## ARCH Lag[5]     1.3939 1.440 1.667  0.6207
## ARCH Lag[7]     5.7397 2.315 1.543  0.1597
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  1.6817
```

```
## Individual Statistics:
## mu      0.1933
## ar1     0.3639
## ma1     0.1105
## omega   0.1285
## alpha1  0.2779
## beta1   0.3644
##
## 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           2.5727 0.0102569  **
## Negative Sign Bias  0.4720 0.6370780
## Positive Sign Bias  0.9759 0.3294052
## Joint Effect       18.9665 0.0002778 ***
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##    group statistic p-value(g-1)
## 1     20    33.24      0.022526
## 2     30    51.42      0.006316
## 3     40    50.53      0.102265
## 4     50    75.55      0.008792
##
##
## Elapsed time : 0.1036069

##
## please wait...calculating quantiles...
```
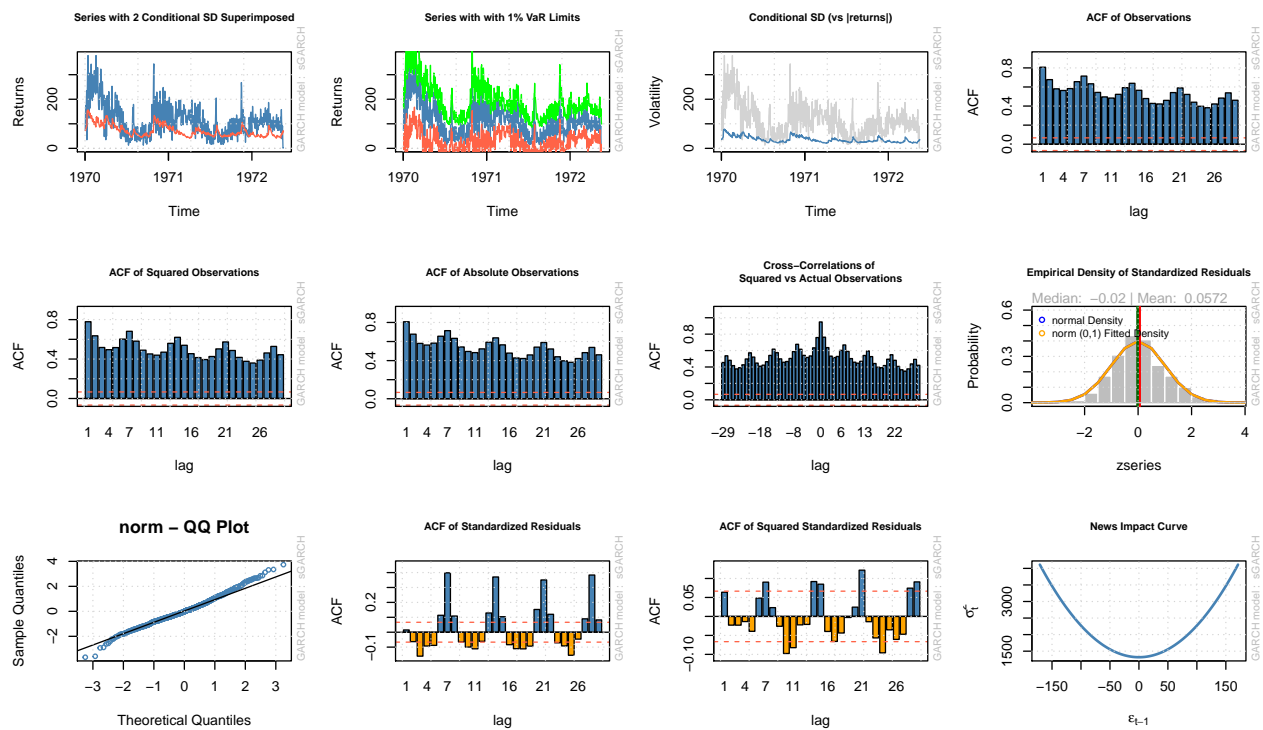
16 Conclusions

It was really interesting!

17 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