

Spatio-Temporal Data Analysis Project

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Patterns in foreign sims connected to OpenWiFi-Milan

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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.

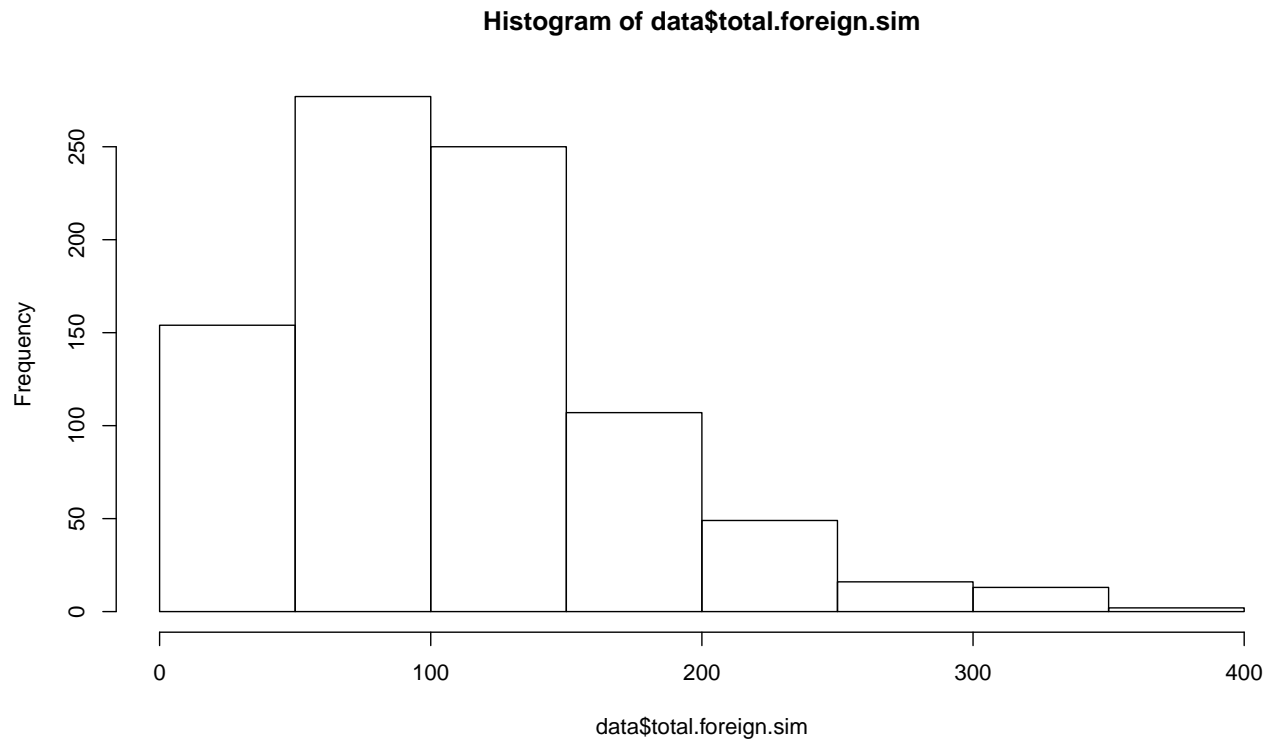
Characteristics of the DataSet:

- 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
```

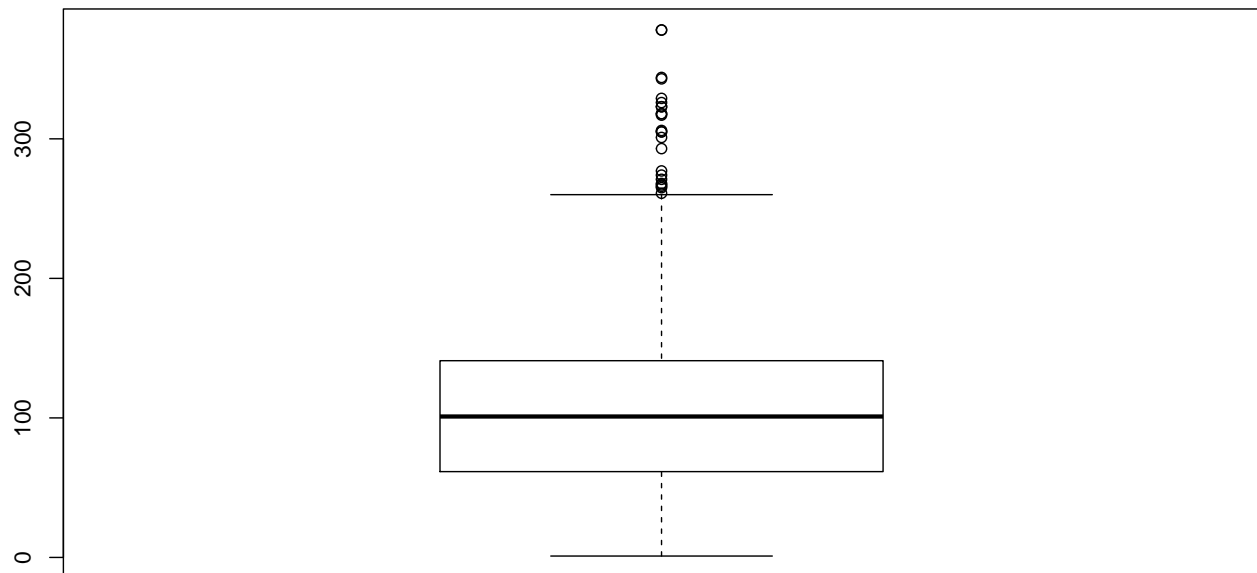
```
## [1] 63.63468
```

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

```
## [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

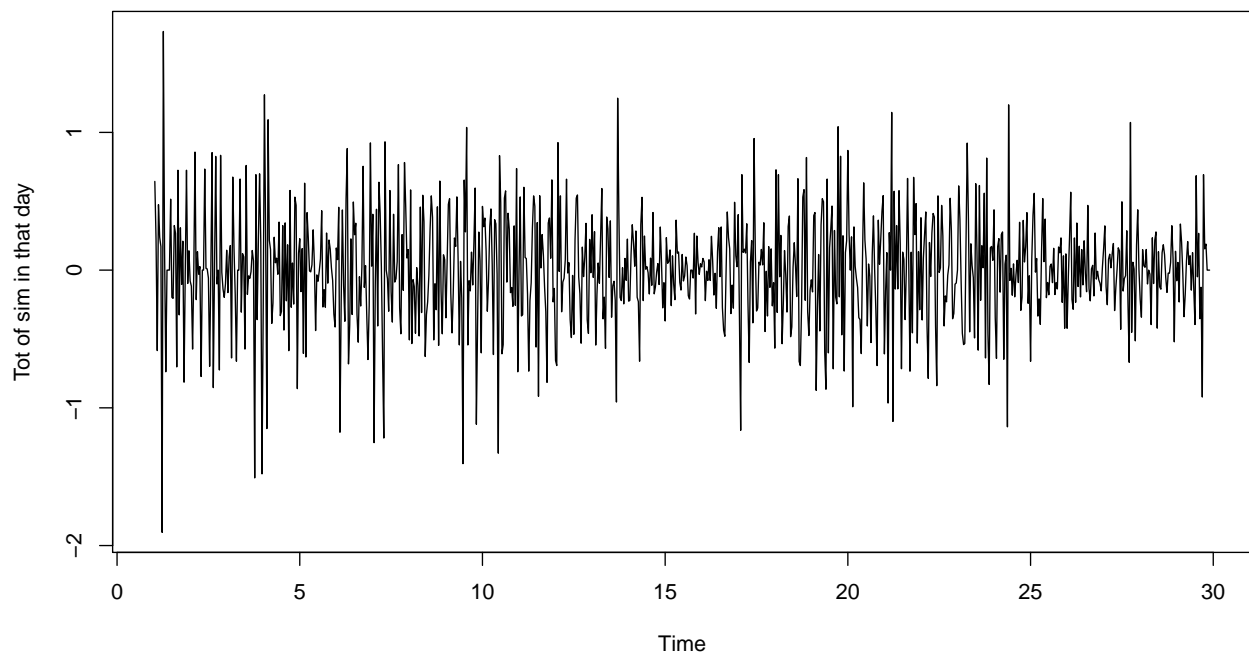
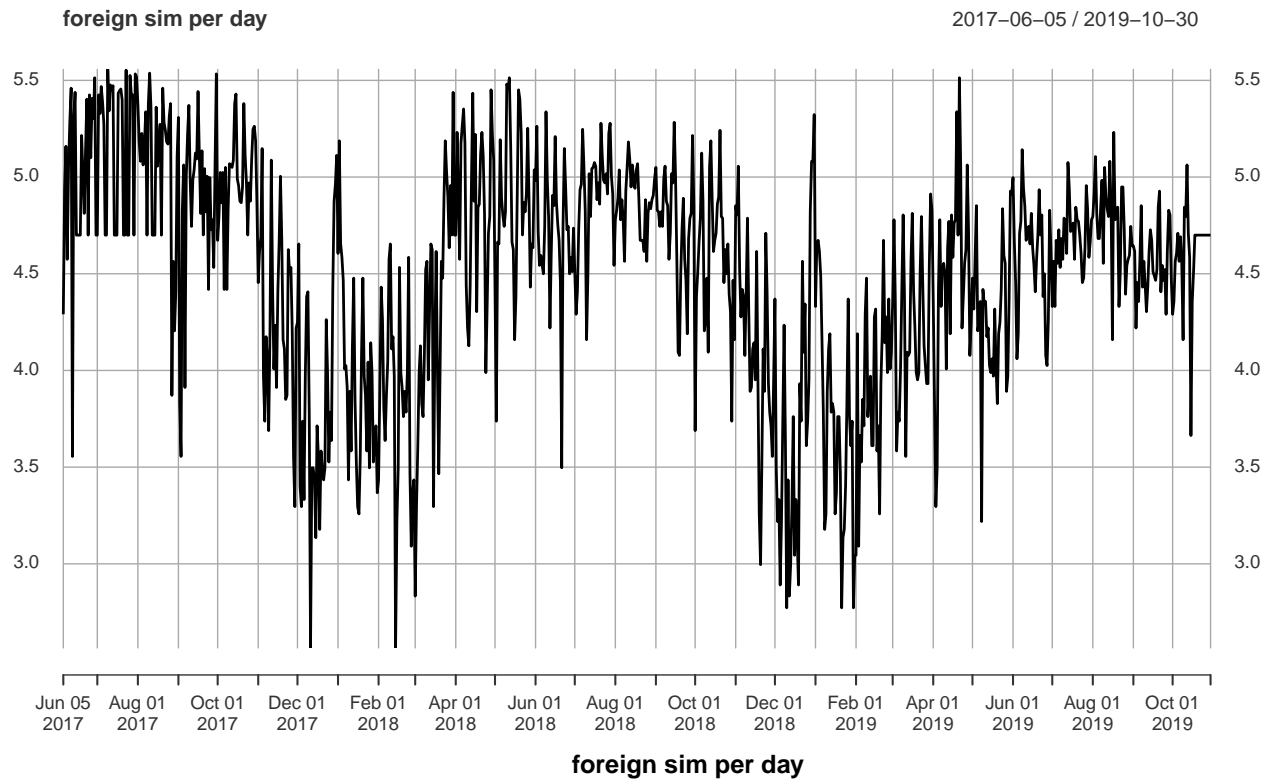
5 Using a boxCox transform

6 Time serie is built

Here the time serie is built

7 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:



8 Peaks Explanation

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

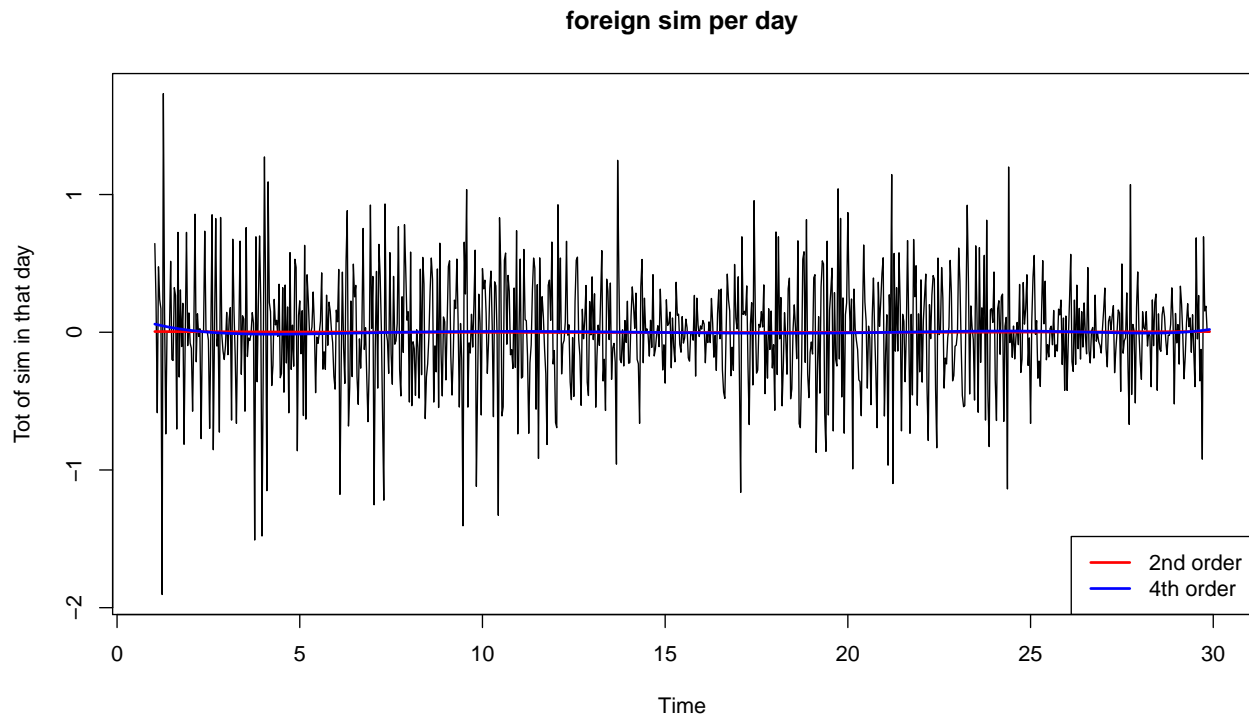
- automatic roaming [<https://www.mobileworld.it/2017/08/07/roaming-gratis-europa-condizioni-fair-us>]

- fashion week [<https://www.cameramoda.it/it/milano-moda-donna/>] february
- fashion week 2017 [<https://www.milanoweekend.it/articoli/milano-fashion-week-2017-eventi-programma-february>]

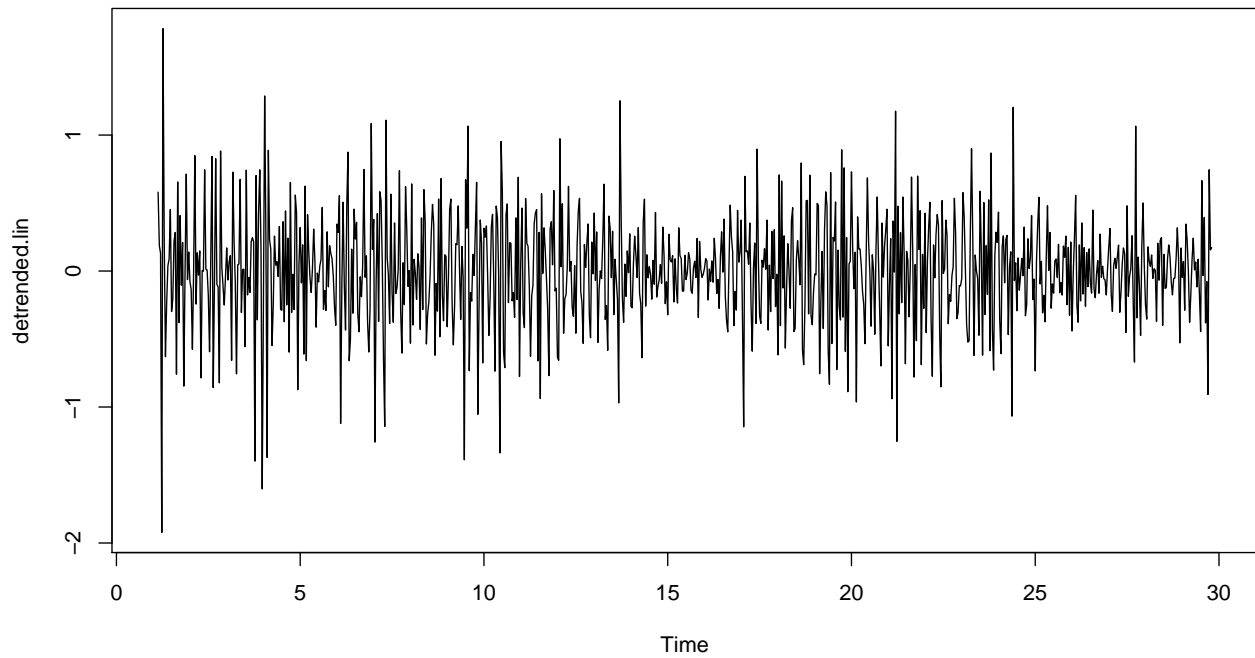
[1] "2017-07-09"

- arch week [https://www.lastampa.it/milano/2017/06/17/news/milano-smart-city-del-futuro-se-ne-parla-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]

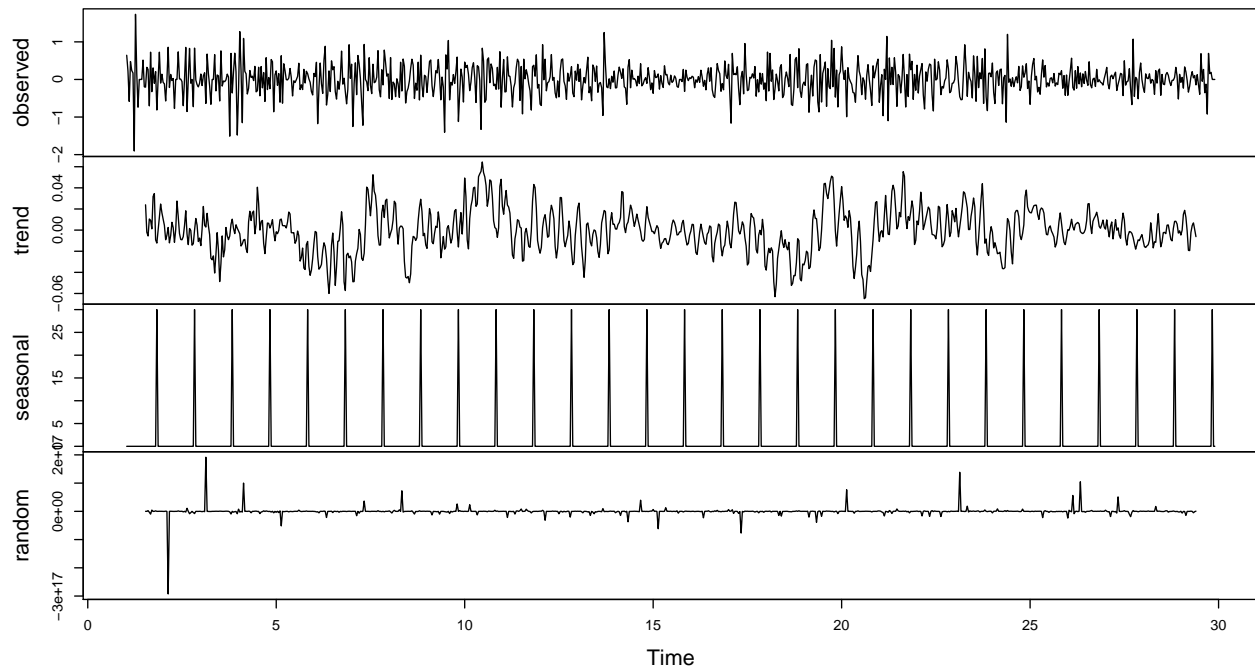
9 Trend recognition



9.1 Detrending using LM



Decomposition of multiplicative time series



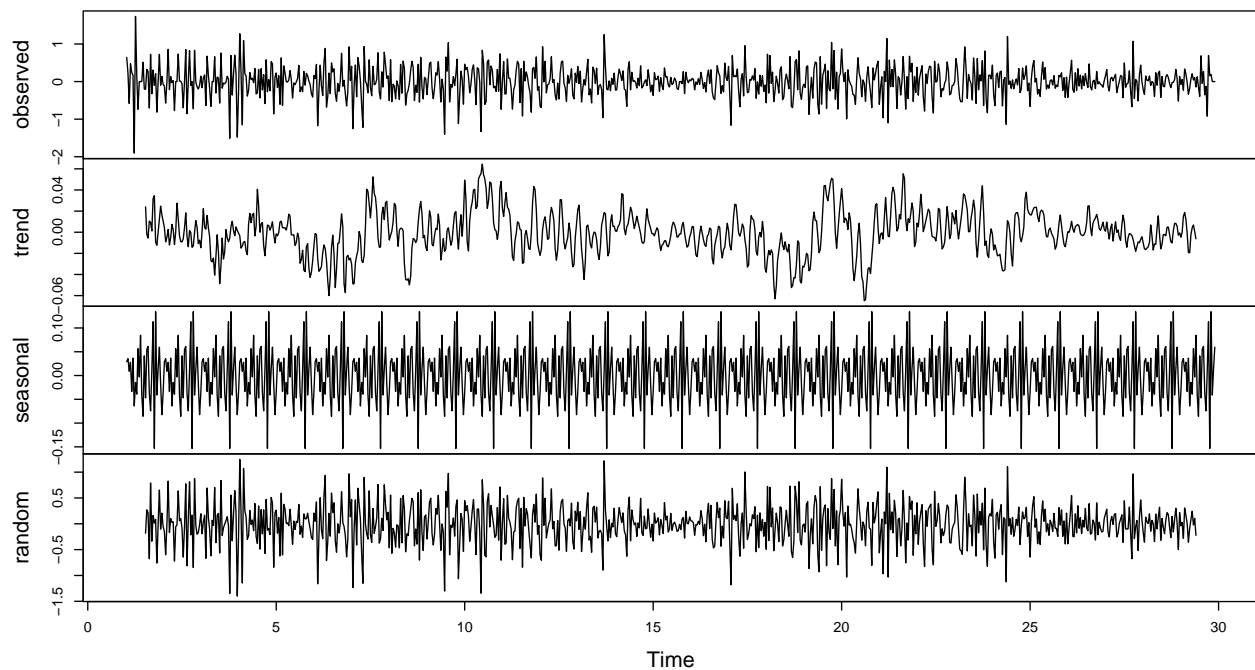
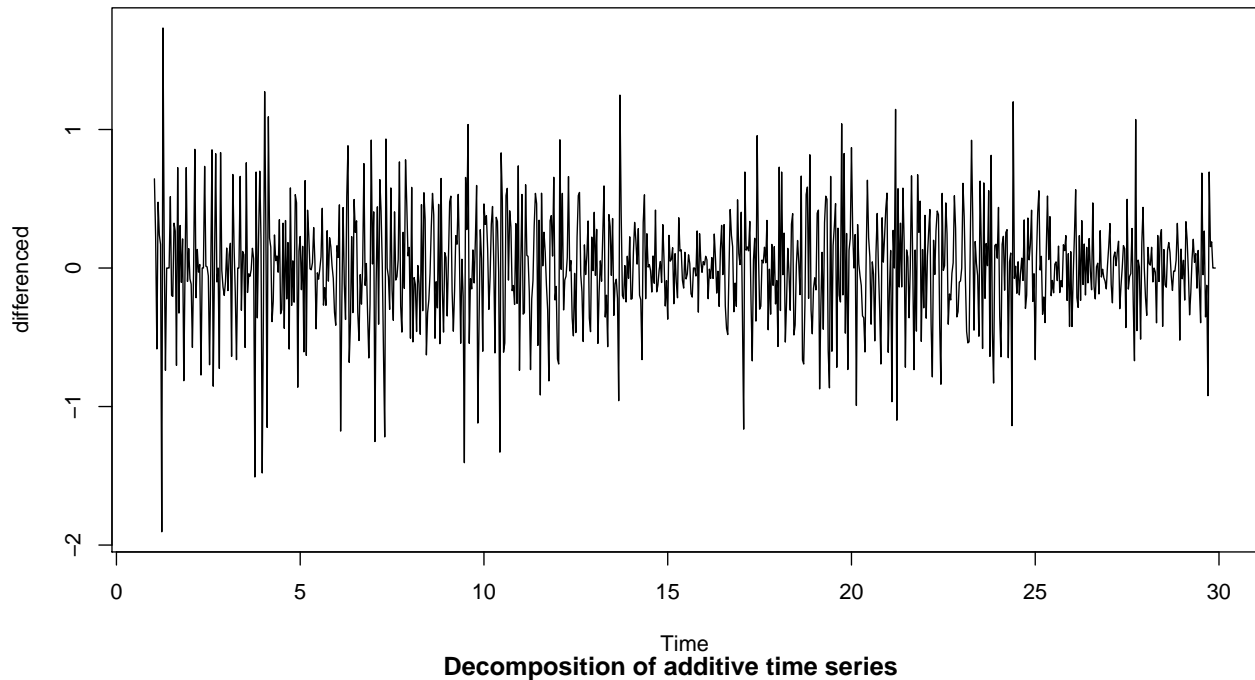
```
##
## Box-Pierce test
##
## data:  decomposed$random
## X-squared = 0.11788, df = 5, p-value = 0.9998
##
```

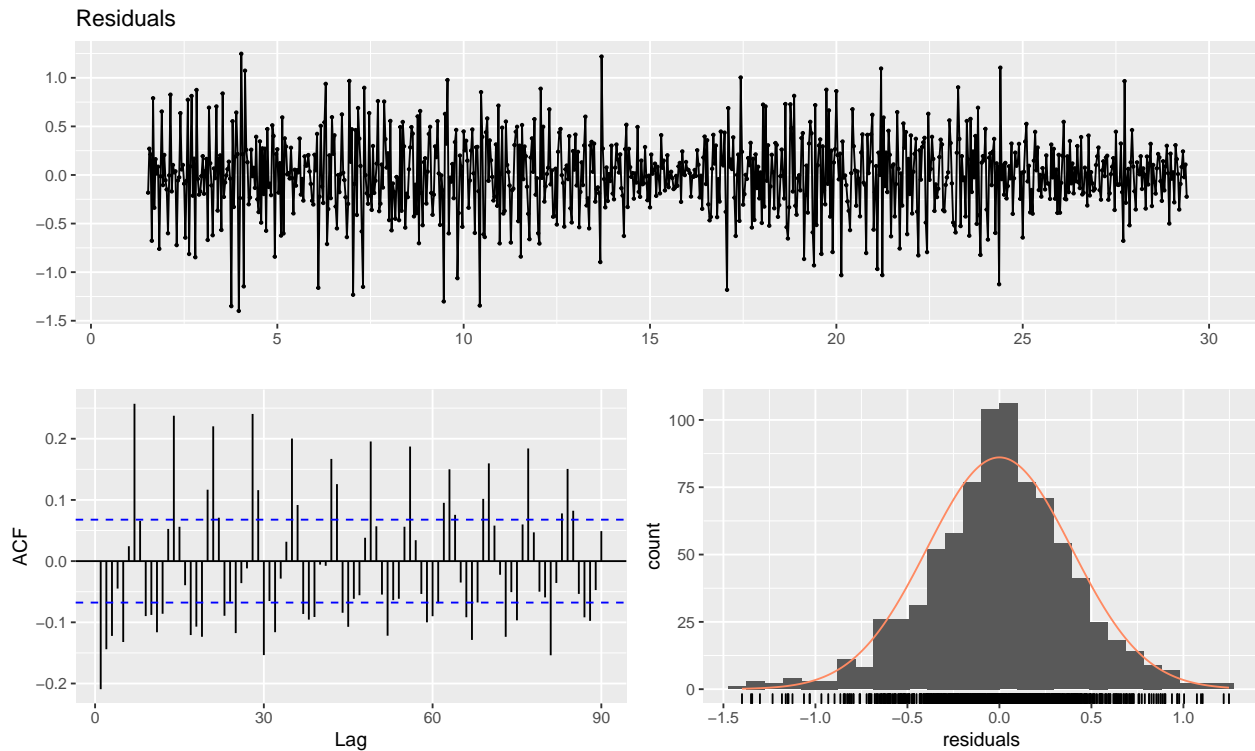


```
## Box-Ljung test
##
## data: decomposed$random
## X-squared = 0.11856, df = 5, p-value = 0.9998
```

10 The additive model doesn't work for us

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





```
##
## Box-Pierce test
##
## data: decomposed$random
## X-squared = 82.821, df = 5, p-value = 2.22e-16
##
## Box-Ljung test
##
## data: decomposed$random
## X-squared = 83.245, df = 5, p-value = 2.22e-16
```

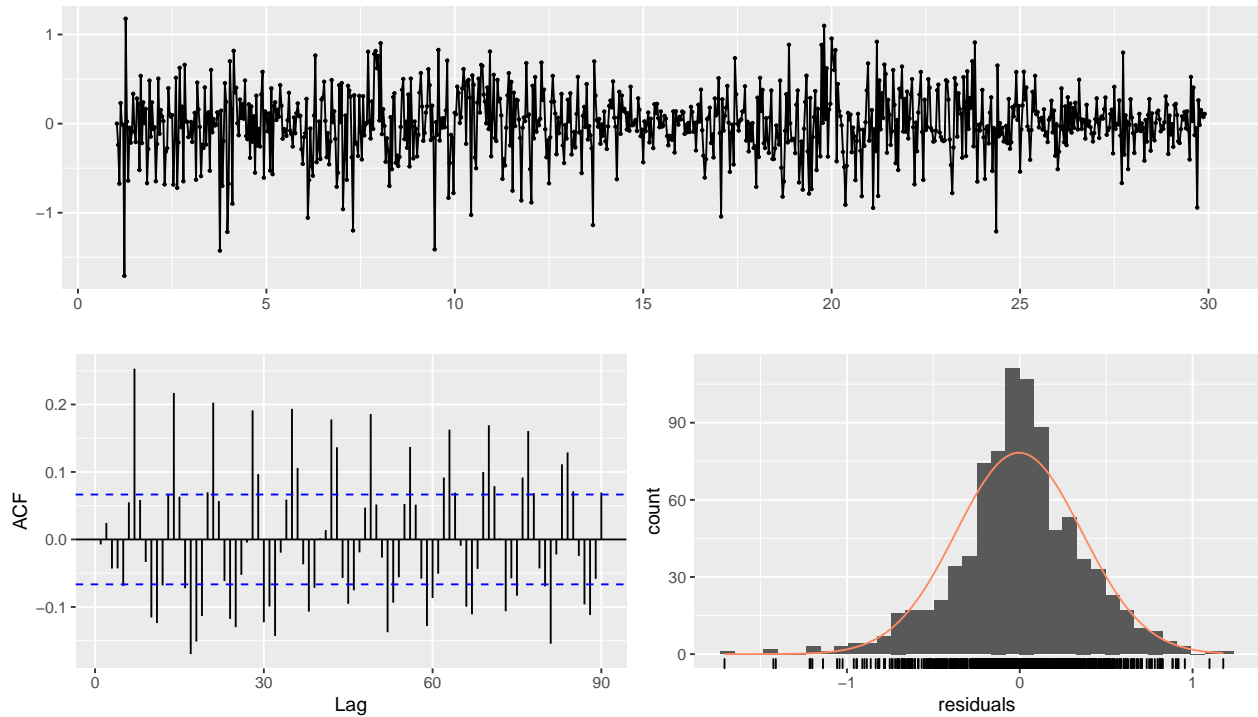
11 Arima

```
## Series: data.ts
## ARIMA(3,1,3)
##
## Coefficients:
##          ar1      ar2      ar3      ma1      ma2      ma3
##      -0.5238  0.3127 -0.1288 -0.8950 -0.9297  0.8248
## s.e.   0.0596  0.0581  0.0389  0.0513  0.0850  0.0500
##
## sigma^2 estimated as 0.1335: log likelihood=-359.39
## AIC=732.77 AICc=732.9 BIC=766.12
##
```

```
## Training set error measures:
```

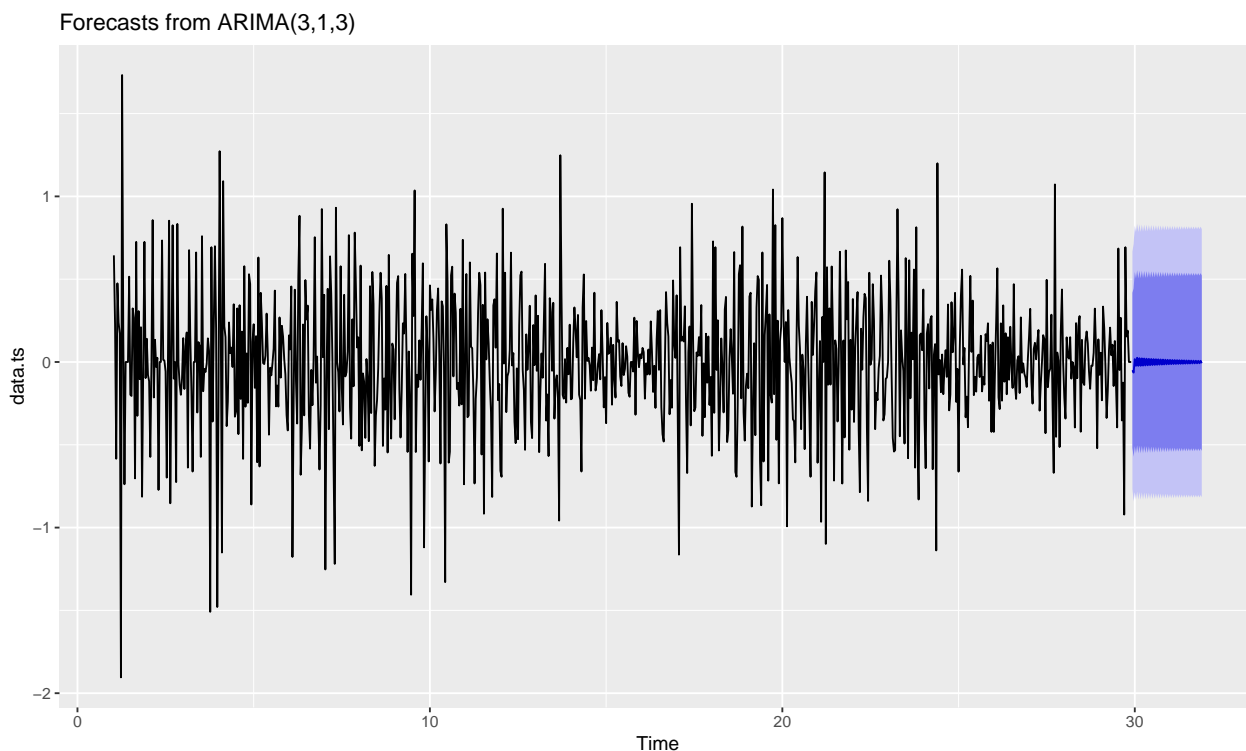
```
##               ME      RMSE      MAE MPE MAPE      MASE      ACF1
## Training set -0.003852611 0.3639435 0.2689911 NaN  Inf 0.5694373 -0.007322947
```

Residuals from ARIMA(3,1,3)



```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(3,1,3)
## Q* = 610.79, df = 54, p-value < 2.2e-16
##
## Model df: 6. Total lags used: 60
```

Every 7 bins a peak occurs



12 Auto Arima

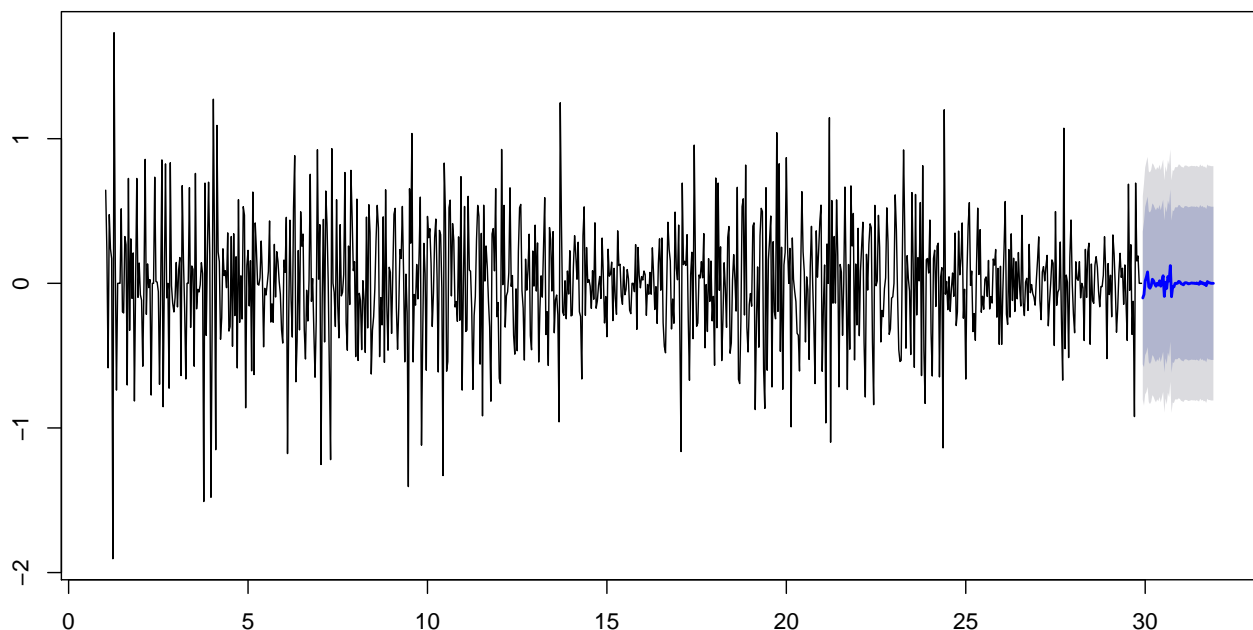
```
##
## Fitting models using approximations to speed things up...
##
## ARIMA(2,0,2)(1,0,1)[30] with non-zero mean : 724.9293
## ARIMA(0,0,0) with non-zero mean : 934.8101
## ARIMA(1,0,0)(1,0,0)[30] with non-zero mean : 861.179
## ARIMA(0,0,1)(0,0,1)[30] with non-zero mean : 833.2352
## ARIMA(0,0,0) with zero mean : 928.0462
## ARIMA(2,0,2)(0,0,1)[30] with non-zero mean : 732.5242
## ARIMA(2,0,2)(1,0,0)[30] with non-zero mean : 721.5047
## ARIMA(2,0,2) with non-zero mean : 739.5021
## ARIMA(2,0,2)(2,0,0)[30] with non-zero mean : 702.9164
## ARIMA(2,0,2)(2,0,1)[30] with non-zero mean : 705.4422
## ARIMA(1,0,2)(2,0,0)[30] with non-zero mean : 705.4284
## ARIMA(2,0,1)(2,0,0)[30] with non-zero mean : 705.0605
## ARIMA(3,0,2)(2,0,0)[30] with non-zero mean : 699.2801
## ARIMA(3,0,2)(1,0,0)[30] with non-zero mean : 699.7676
## ARIMA(3,0,2)(2,0,1)[30] with non-zero mean : 702.4877
## ARIMA(3,0,2)(1,0,1)[30] with non-zero mean : 702.5142
## ARIMA(3,0,1)(2,0,0)[30] with non-zero mean : 701.8751
## ARIMA(4,0,2)(2,0,0)[30] with non-zero mean : 714.8849
## ARIMA(3,0,3)(2,0,0)[30] with non-zero mean : Inf
```

```

## ARIMA(2,0,3)(2,0,0)[30] with non-zero mean : 713.6209
## ARIMA(4,0,1)(2,0,0)[30] with non-zero mean : 705.521
## ARIMA(4,0,3)(2,0,0)[30] with non-zero mean : 714.3103
## ARIMA(3,0,2)(2,0,0)[30] with zero mean : 692.5672
## ARIMA(3,0,2)(1,0,0)[30] with zero mean : 693.0428
## ARIMA(3,0,2)(2,0,1)[30] with zero mean : 695.7968
## ARIMA(3,0,2)(1,0,1)[30] with zero mean : 695.8076
## ARIMA(2,0,2)(2,0,0)[30] with zero mean : 696.2188
## ARIMA(3,0,1)(2,0,0)[30] with zero mean : 695.1976
## ARIMA(4,0,2)(2,0,0)[30] with zero mean : 708.1668
## ARIMA(3,0,3)(2,0,0)[30] with zero mean : Inf
## ARIMA(2,0,1)(2,0,0)[30] with zero mean : 698.3924
## ARIMA(2,0,3)(2,0,0)[30] with zero mean : 706.9431
## ARIMA(4,0,1)(2,0,0)[30] with zero mean : 698.7863
## ARIMA(4,0,3)(2,0,0)[30] with zero mean : 707.5733
##
## Now re-fitting the best model(s) without approximations...
##
## ARIMA(3,0,2)(2,0,0)[30] with zero mean : Inf
## ARIMA(3,0,2)(1,0,0)[30] with zero mean : 724.8936
##
## Best model: ARIMA(3,0,2)(1,0,0)[30] with zero mean

```

Forecasts from ARIMA(3,0,2)(1,0,0)[30] with zero mean

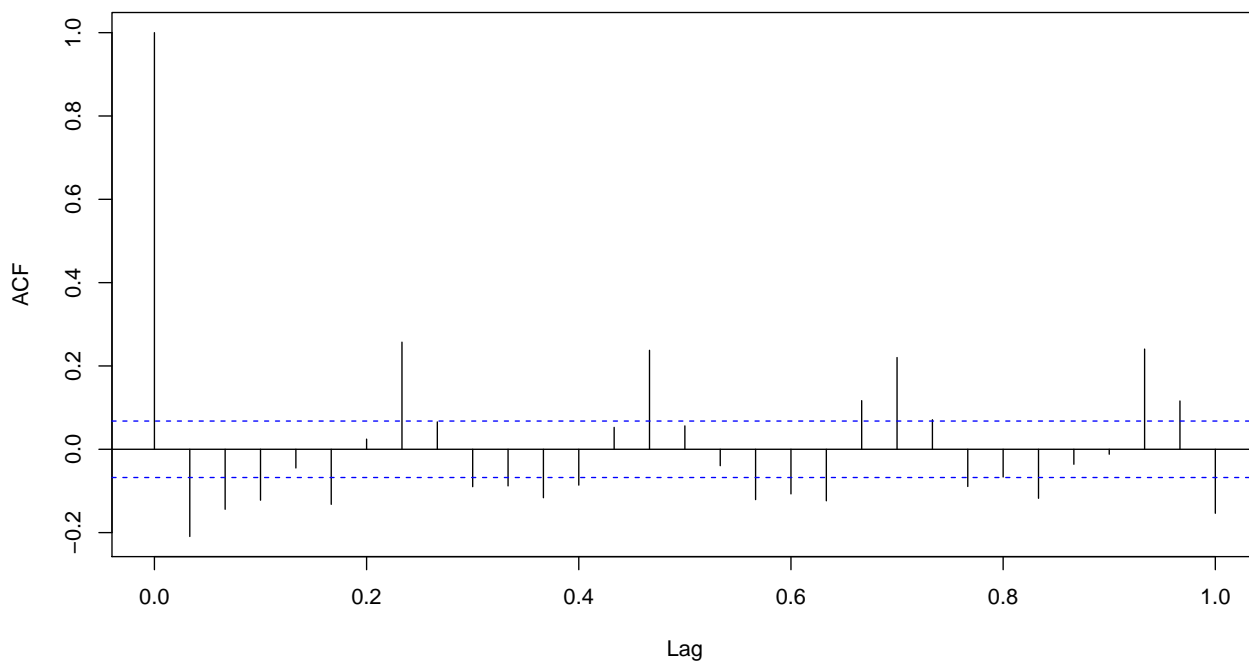
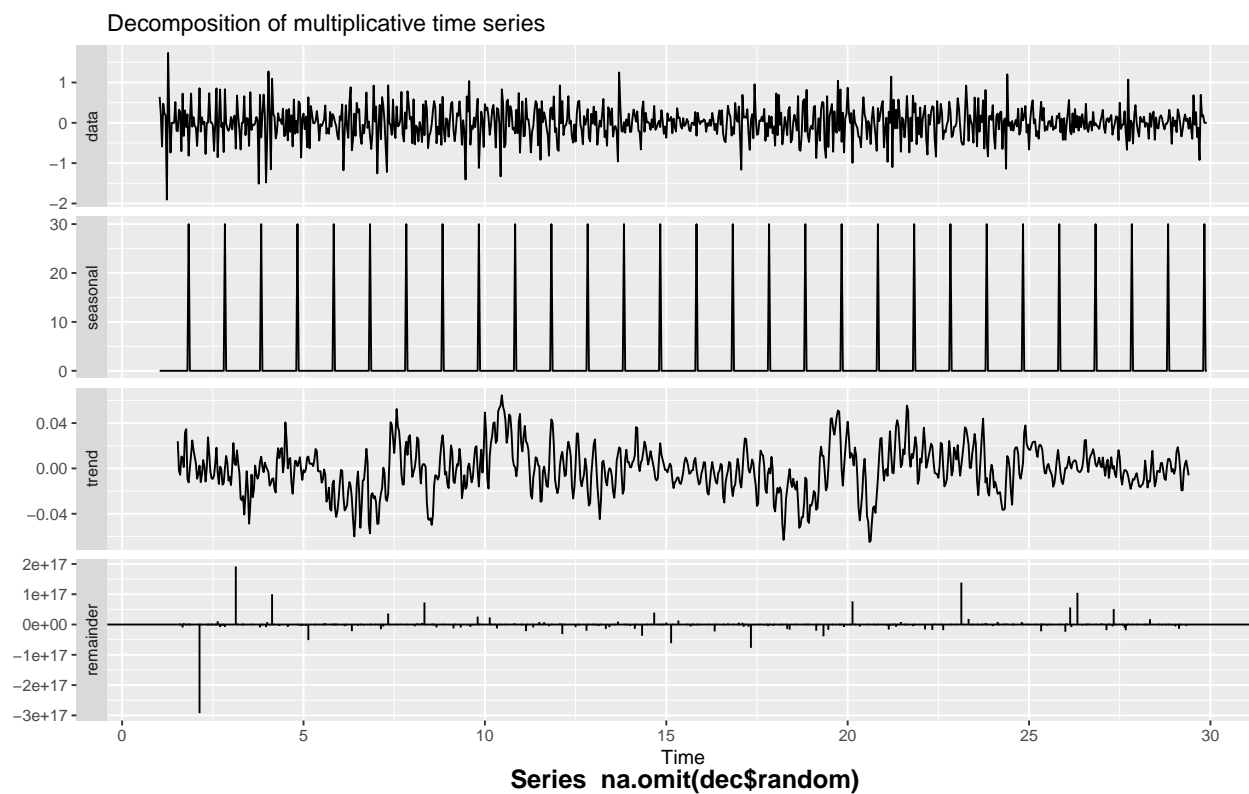


The plot is not good but AIC and BIC are very high, we should try with a multi seasonal decomposition

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

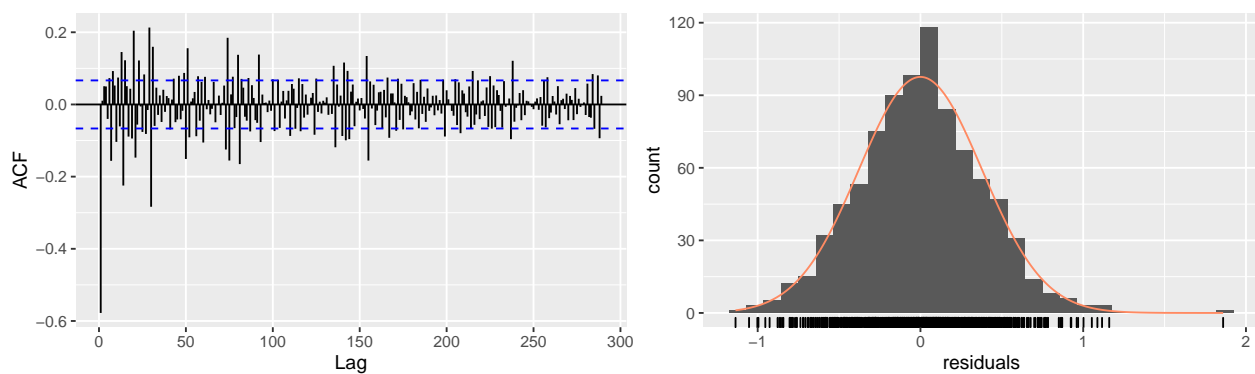
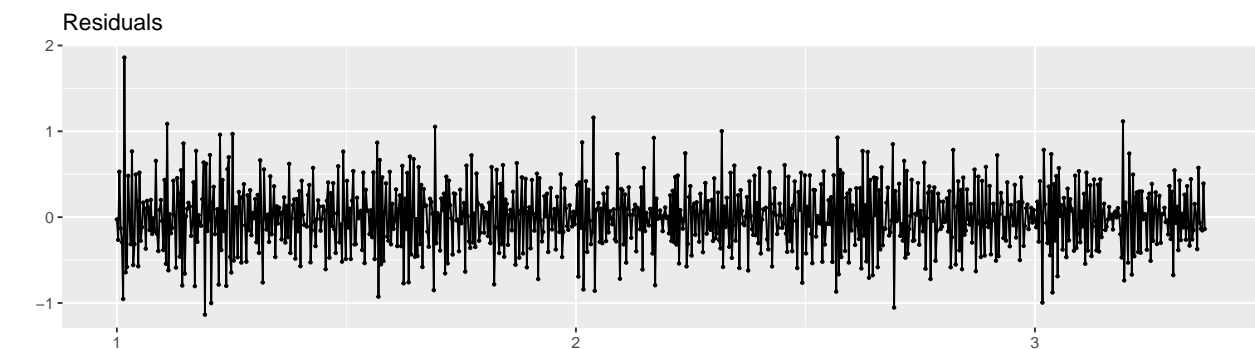
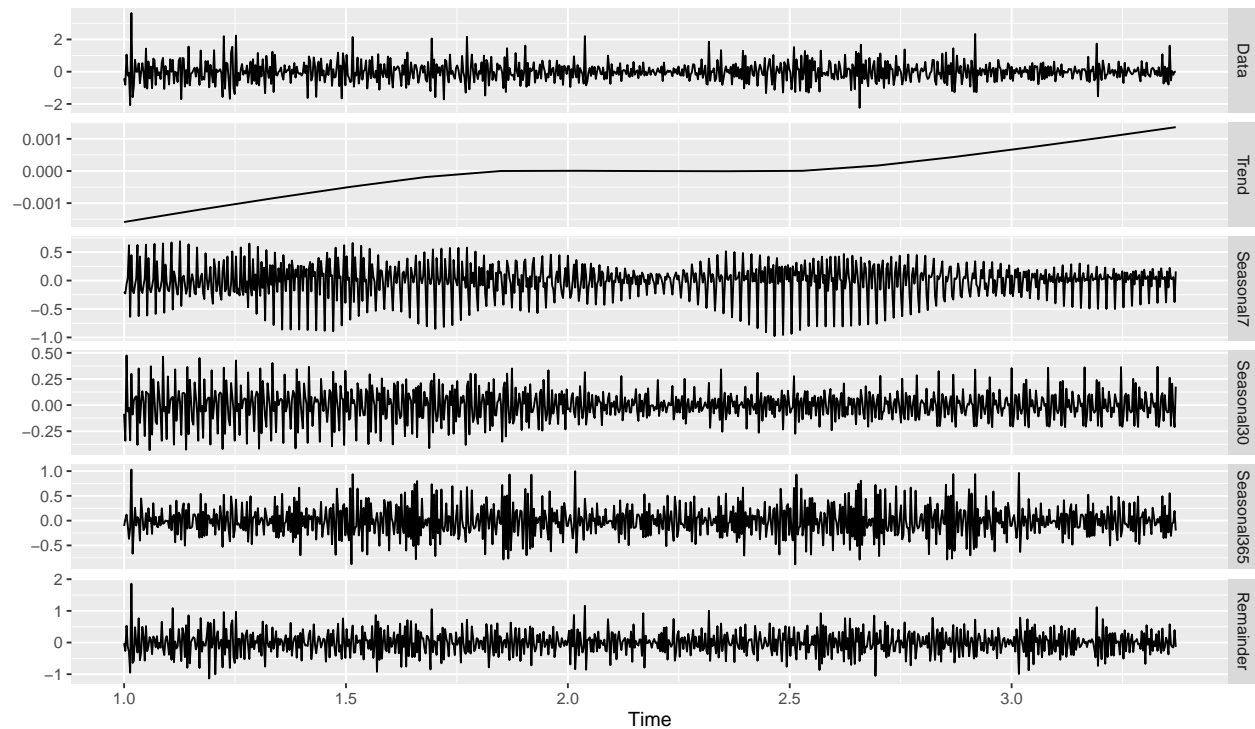
13 Searching for multi seasonalities

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

14 Transforming into msts

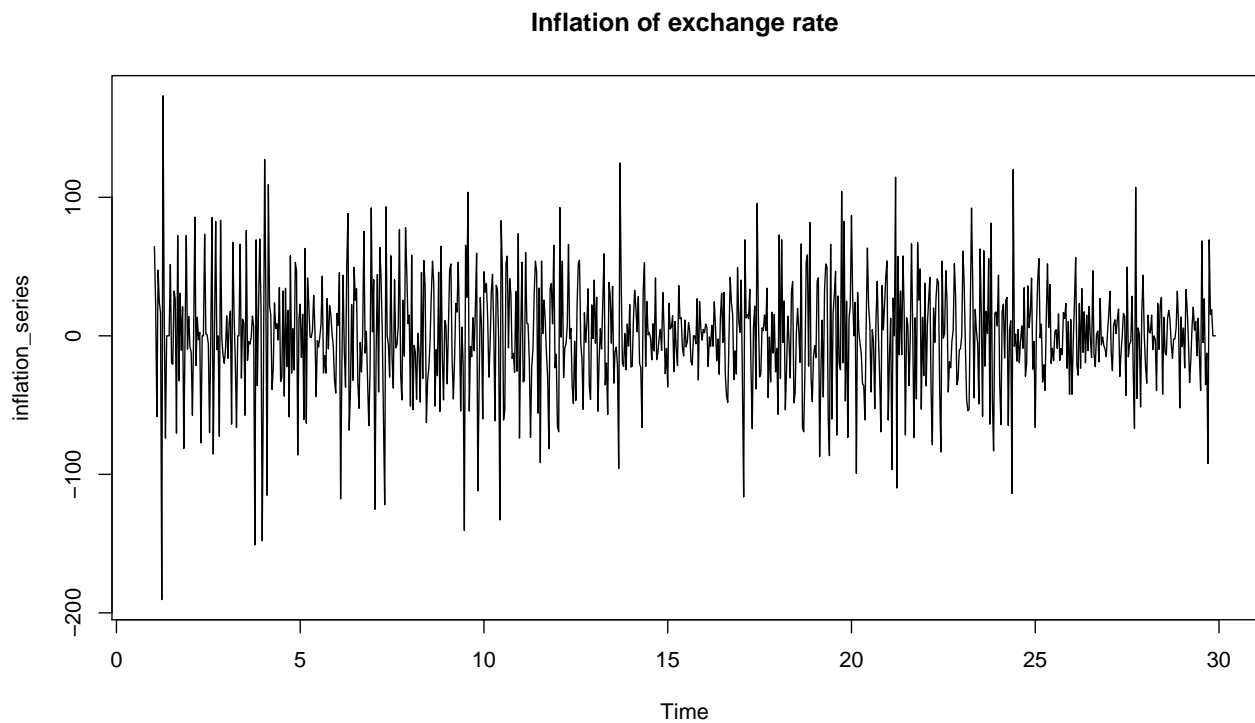


```
##
## Box-Pierce test
##
```

```
## data: remainder(decomposed)
## X-squared = 294.88, df = 5, p-value < 2.2e-16

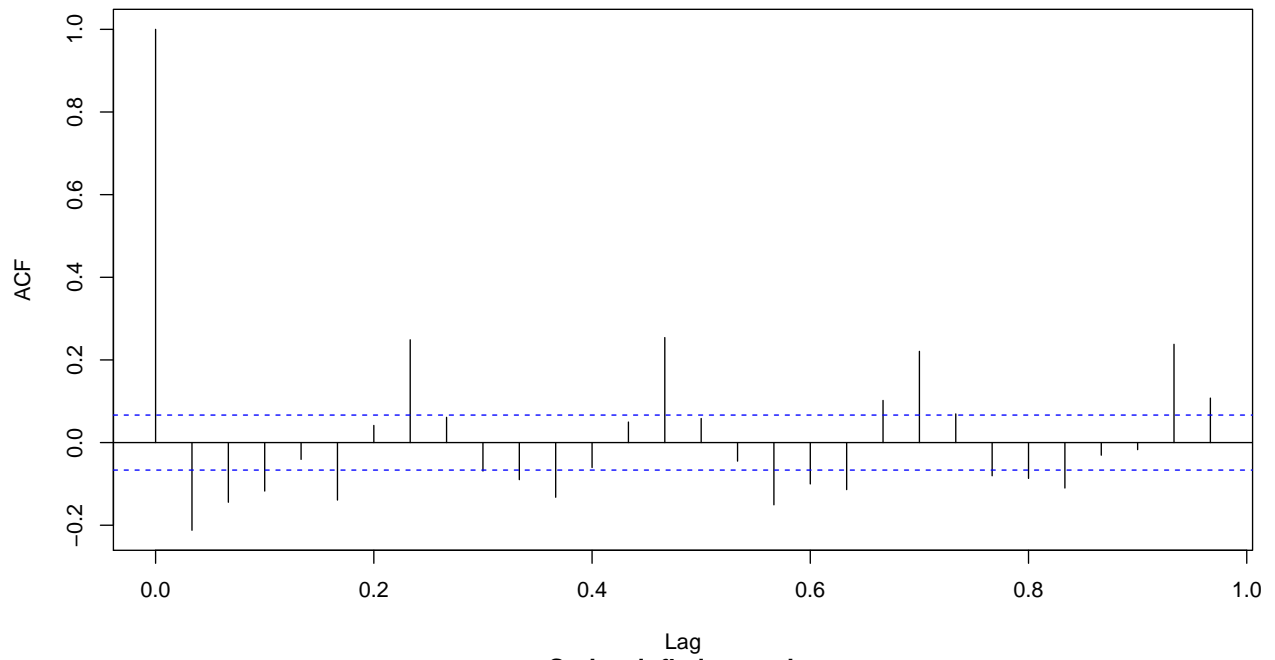
##
## Box-Ljung test
##
## data: remainder(decomposed)
## X-squared = 295.92, df = 5, p-value < 2.2e-16
```

15 Garch

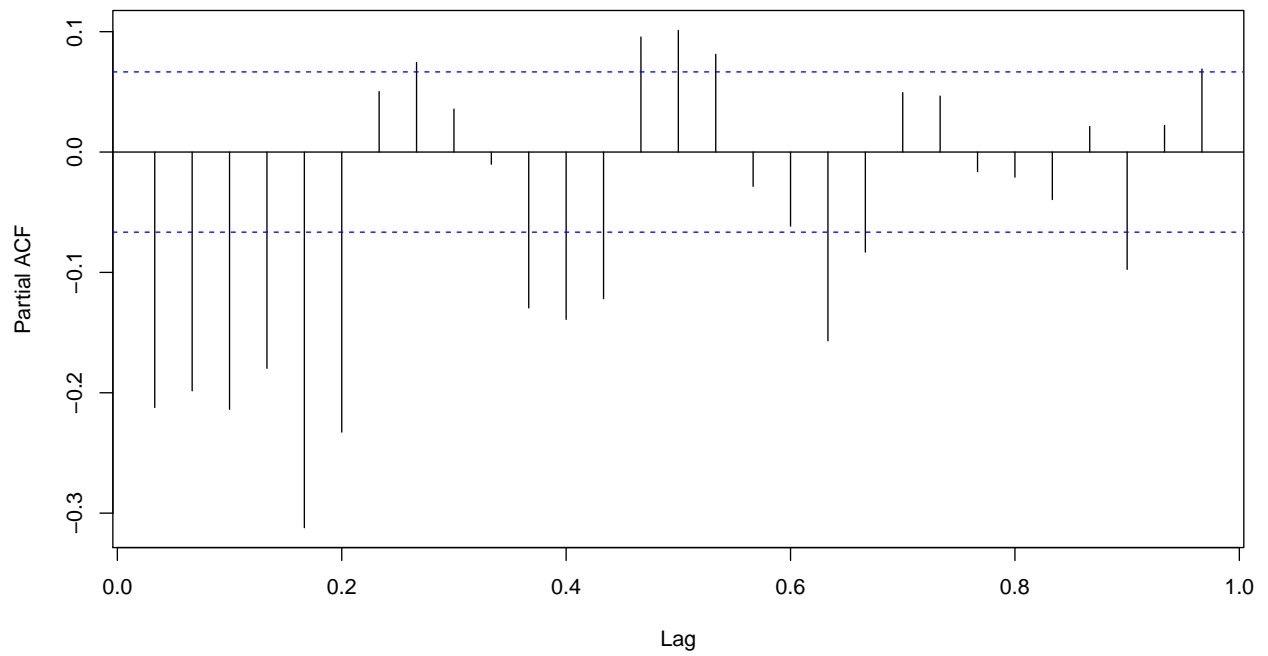


##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	-190.42375	-22.42412	0.00000	0.04721	23.68585	173.29190

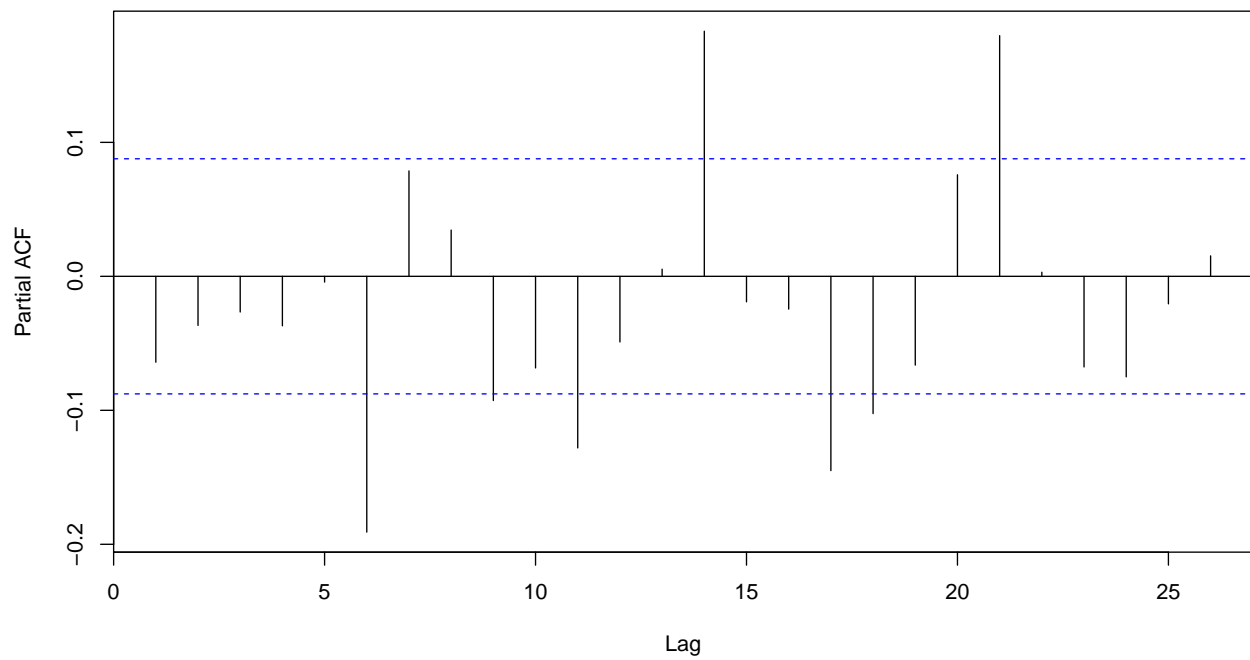
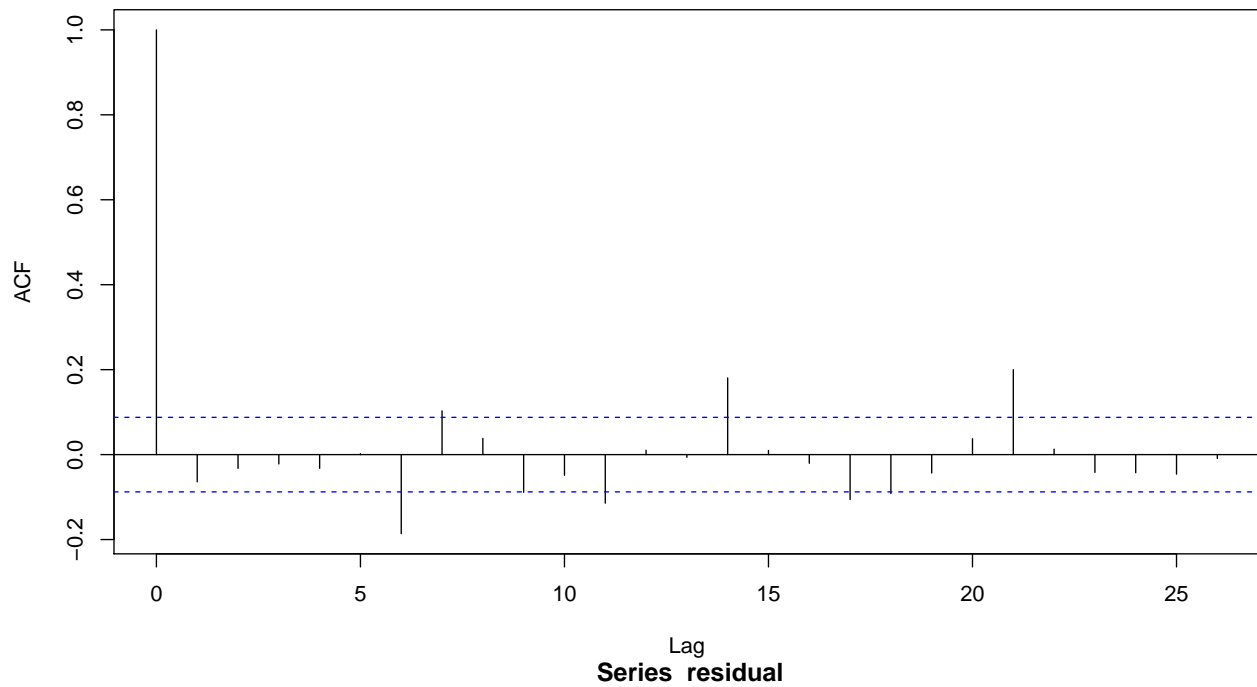
Series inflation_series



Series inflation_series



Series residual



```
##
## Box-Ljung test
##
## data:  residual
## X-squared = 68.026, df = 20, p-value = 3.813e-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:        43.3731
##
## Parameter Initialization:
## Initial Parameters:   $params
## Limits of Transformations: $U, $V
## Which Parameters are Fixed? $includes
## Parameter Matrix:
##           U           V      params includes
## mu      -0.02800724  0.02800724  0.0003397276    TRUE
## ar1      -0.99999999  0.99999999 -0.3983890274    TRUE
## ar2      -0.99999999  0.99999999 -0.4322784794    TRUE
## ar3      -0.99999999  0.99999999 -0.3600753018    TRUE
## ar4      -0.99999999  0.99999999 -0.2633705040    TRUE
## ar5      -0.99999999  0.99999999 -0.2649479256    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:	638.83173:	0.000339728	-0.398389	-0.432278	-0.360075	-0.263371	-0.264948	0.1
##	1:	637.07263:	0.000339720	-0.398147	-0.431676	-0.360429	-0.263906	-0.265395	0.0
##	2:	636.72688:	0.000339673	-0.396648	-0.428151	-0.362606	-0.267076	-0.268208	0.0
##	3:	636.18771:	0.000339545	-0.393194	-0.419844	-0.367888	-0.274947	-0.274637	0.0
##	4:	635.91318:	0.000339283	-0.391525	-0.414698	-0.372941	-0.283546	-0.278163	0.0
##	5:	635.48127:	0.000339004	-0.391359	-0.413498	-0.375282	-0.287369	-0.282310	0.0
##	6:	633.55993:	0.000338026	-0.397239	-0.427600	-0.370754	-0.279874	-0.293164	0.0
##	7:	633.21336:	0.000338024	-0.397215	-0.427543	-0.370777	-0.279933	-0.293150	0.0
##	8:	633.13212:	0.000338015	-0.397071	-0.427227	-0.370899	-0.280259	-0.293095	0.0
##	9:	633.08771:	0.000338121	-0.397778	-0.427522	-0.373055	-0.281146	-0.296919	0.0
##	10:	633.00350:	0.000337901	-0.396178	-0.426489	-0.369014	-0.279943	-0.289312	0.0
##	11:	632.95332:	0.000338339	-0.399140	-0.427859	-0.377745	-0.283388	-0.304935	0.0
##	12:	632.90058:	0.000338330	-0.398993	-0.427623	-0.377756	-0.283753	-0.304605	0.0
##	13:	632.80565:	0.000338383	-0.399324	-0.427731	-0.378854	-0.284302	-0.306455	0.0
##	14:	632.64940:	0.000338388	-0.399183	-0.427361	-0.379306	-0.285243	-0.306554	0.0
##	15:	632.51643:	0.000338631	-0.400762	-0.428005	-0.384219	-0.287457	-0.315067	0.0
##	16:	631.51307:	0.000338560	-0.399589	-0.426893	-0.383341	-0.290378	-0.310638	0.0
##	17:	631.15666:	0.000338968	-0.402100	-0.427815	-0.391676	-0.294784	-0.324532	0.0
##	18:	630.95071:	0.000338919	-0.400901	-0.427970	-0.389923	-0.296595	-0.320601	0.0
##	19:	630.87296:	0.000338919	-0.400889	-0.427974	-0.389903	-0.296614	-0.320542	0.0
##	20:	630.80364:	0.000338920	-0.400884	-0.427980	-0.389915	-0.296652	-0.320534	0.0
##	21:	630.73237:	0.000338949	-0.401047	-0.428052	-0.390492	-0.297004	-0.321467	0.0
##	22:	630.66226:	0.000339013	-0.401418	-0.428208	-0.391783	-0.297760	-0.323580	0.0
##	23:	630.60536:	0.000339145	-0.402196	-0.428524	-0.394451	-0.299283	-0.327978	0.0
##	24:	630.57872:	0.000338878	-0.400582	-0.427923	-0.388999	-0.296270	-0.318939	0.0
##	25:	630.48058:	0.000338876	-0.400525	-0.427929	-0.388925	-0.296345	-0.318742	0.0
##	26:	630.40657:	0.000338906	-0.400694	-0.428005	-0.389533	-0.296717	-0.319732	0.0
##	27:	630.34821:	0.000338972	-0.401059	-0.428169	-0.390833	-0.297503	-0.321857	0.0
##	28:	630.32174:	0.000339106	-0.401831	-0.428500	-0.393527	-0.299079	-0.326289	0.0
##	29:	630.31413:	0.000339154	-0.402106	-0.428622	-0.394485	-0.299641	-0.327866	0.0
##	30:	630.28690:	0.000339105	-0.401800	-0.428516	-0.393470	-0.299088	-0.326192	0.0
##	31:	630.28021:	0.000339005	-0.401038	-0.428466	-0.391238	-0.298037	-0.322642	0.0
##	32:	630.23801:	0.000339079	-0.401305	-0.428840	-0.392520	-0.298964	-0.324919	0.0
##	33:	630.23603:	0.000339079	-0.401284	-0.428846	-0.392490	-0.298989	-0.324855	0.0
##	34:	630.23306:	0.000339081	-0.401279	-0.428862	-0.392511	-0.299026	-0.324892	0.0
##	35:	630.22986:	0.000339084	-0.401261	-0.428900	-0.392542	-0.299114	-0.324944	0.0
##	36:	630.22589:	0.000339095	-0.401256	-0.428999	-0.392676	-0.299259	-0.325240	0.0
##	37:	630.21917:	0.000339069	-0.401049	-0.429012	-0.392096	-0.298923	-0.324438	0.0
##	38:	630.20059:	0.000339100	-0.400732	-0.429642	-0.392124	-0.299325	-0.325206	0.0
##	39:	630.19812:	0.000339099	-0.400724	-0.429644	-0.392112	-0.299335	-0.325181	0.0
##	40:	630.19600:	0.000339099	-0.400713	-0.429646	-0.392097	-0.299349	-0.325146	0.0
##	41:	630.19249:	0.000339097	-0.400657	-0.429685	-0.392002	-0.299333	-0.325049	0.0
##	42:	630.11405:	0.000338950	-0.397220	-0.432488	-0.386003	-0.296966	-0.320468	0.0

```

## 43:      630.08218: 0.000338635 -0.395583 -0.431831 -0.380172 -0.292292 -0.315046 0.0
## 44:      630.05600: 0.000338635 -0.395578 -0.431824 -0.380170 -0.292305 -0.315027 0.0
## 45:      630.03584: 0.000338593 -0.395559 -0.431559 -0.379995 -0.292046 -0.314799 0.0
## 46:      630.02724: 0.000338588 -0.395434 -0.431410 -0.379957 -0.292327 -0.314379 0.0
## 47:      630.02393: 0.000338480 -0.395153 -0.430992 -0.379490 -0.291829 -0.313837 0.0
## 48:      630.01486: 0.000338347 -0.394724 -0.430683 -0.378948 -0.291429 -0.313297 0.0
## 49:      629.96097: 0.000335702 -0.389864 -0.429235 -0.371350 -0.290525 -0.305753 0.0
## 50:      629.94161: 0.000334367 -0.391410 -0.426579 -0.373488 -0.286781 -0.300367 0.0
## 51:      629.90840: 0.000332108 -0.390637 -0.423482 -0.373455 -0.293107 -0.302887 0.0
## 52:      629.90790: 0.000332108 -0.390634 -0.423481 -0.373455 -0.293111 -0.302882 0.0
## 53:      629.90744: 0.000332107 -0.390609 -0.423473 -0.373458 -0.293142 -0.302838 0.0
## 54:      629.90666: 0.000332077 -0.390471 -0.423530 -0.373580 -0.293186 -0.302839 0.0
## 55:      629.90578: 0.000332013 -0.390192 -0.423640 -0.373822 -0.293286 -0.302820 0.0
## 56:      629.90465: 0.000331827 -0.389683 -0.423892 -0.374355 -0.293469 -0.302819 0.0
## 57:      629.90294: 0.000331105 -0.389820 -0.424071 -0.374904 -0.293775 -0.302458 0.0
## 58:      629.90189: 0.000330558 -0.389911 -0.423480 -0.374681 -0.293446 -0.302163 0.0
## 59:      629.90125: 0.000329384 -0.389464 -0.422320 -0.374296 -0.292680 -0.301813 0.0
## 60:      629.89969: 0.000327896 -0.390530 -0.422944 -0.374592 -0.293404 -0.301412 0.0
## 61:      629.89671: 0.000323286 -0.387956 -0.423082 -0.375576 -0.293512 -0.301432 0.0
## 62:      629.89633: 0.000323284 -0.387947 -0.423072 -0.375545 -0.293559 -0.301378 0.0
## 63:      629.89587: 0.000322982 -0.387956 -0.423086 -0.375551 -0.293586 -0.301354 0.0
## 64:      629.89540: 0.000322446 -0.387965 -0.423101 -0.375536 -0.293666 -0.301271 0.0
## 65:      629.89472: 0.000321169 -0.387991 -0.423137 -0.375546 -0.293744 -0.301184 0.0
## 66:      629.88231: 0.000254269 -0.387559 -0.422133 -0.373909 -0.295284 -0.297143 0.0
## 67:      629.88085: 0.000243714 -0.386409 -0.420315 -0.372391 -0.294054 -0.296928 0.0
## 68:      629.87839: 0.000174566 -0.386089 -0.421609 -0.371854 -0.295603 -0.296634 0.0
## 69:      629.87661: 0.000105258 -0.385431 -0.420941 -0.371075 -0.295539 -0.296048 0.0
## 70:      629.87549: 3.58550e-05 -0.385470 -0.420679 -0.371201 -0.295467 -0.295719 0.0
## 71:      629.87019: -0.000577566 -0.385030 -0.420767 -0.369722 -0.295842 -0.295371 0.0
## 72:      629.85365: -0.00231070 -0.385478 -0.418643 -0.371097 -0.295142 -0.292926 0.0
## 73:      629.83172: -0.00476445 -0.385737 -0.417755 -0.371772 -0.294839 -0.291975 0.0
## 74:      629.77117: -0.0143807 -0.386340 -0.417304 -0.372924 -0.294586 -0.291825 0.0
## 75:      629.75426: -0.0180124 -0.386283 -0.418946 -0.372412 -0.295054 -0.293911 0.0
## 76:      629.75030: -0.0186099 -0.386091 -0.420432 -0.371706 -0.295506 -0.295686 0.0
## 77:      629.75017: -0.0183010 -0.386035 -0.420649 -0.371551 -0.295576 -0.295935 0.0
## 78:      629.75017: -0.0182347 -0.386032 -0.420660 -0.371543 -0.295580 -0.295946 0.0
## 79:      629.75017: -0.0182321 -0.386032 -0.420658 -0.371543 -0.295580 -0.295945 0.0
##
## Final Estimate of the Negative LLH:
## LLH: 2514.67      norm LLH: 5.02934
##      mu      ar1      ar2      ar3      ar4      ar5
## -0.79078293 -0.38603180 -0.42065847 -0.37154289 -0.29557968 -0.29594460
##      omega      alpha1      beta1
## 8.01000655 0.02754602 0.96546498
##

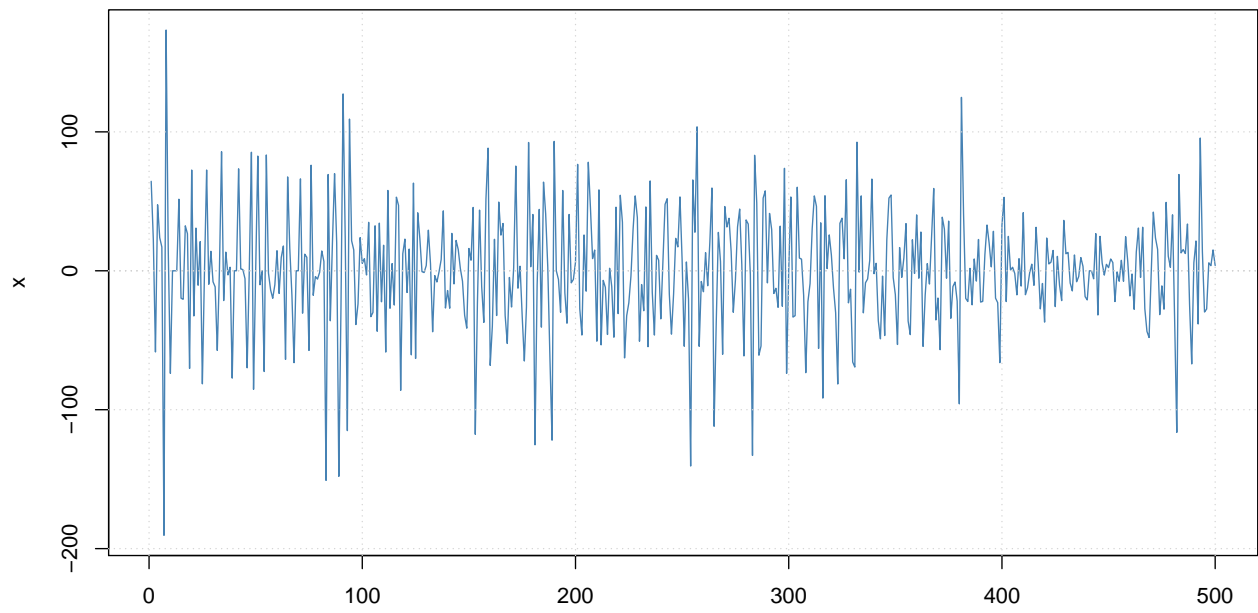
```

```

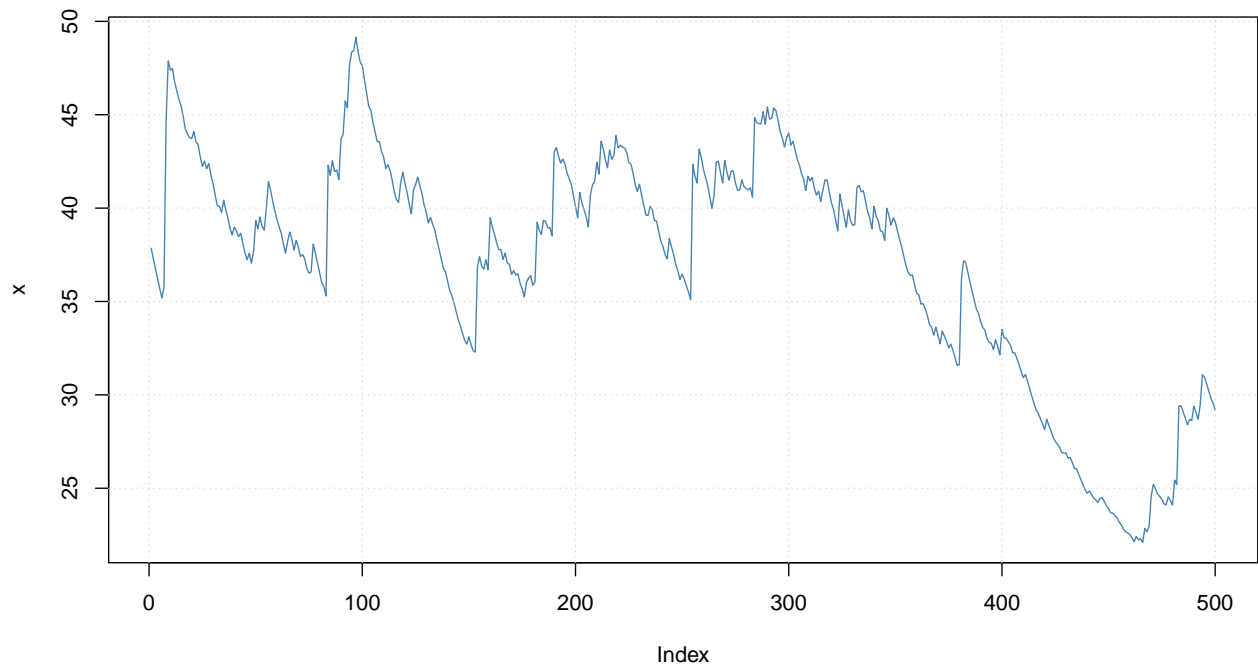
## R-optimhess Difference Approximated Hessian Matrix:
##          mu          ar1          ar2          ar3          ar4
## mu      -0.41377743    0.2012027   -0.11737143    0.04798714    0.2638166
## ar1      0.20120269  -609.8603807   127.40357272   119.71132503   54.1057565
## ar2     -0.11737143   127.4035727  -601.78735885   120.15484401   101.7546167
## ar3      0.04798714   119.7113250   120.15484401  -627.16625104   114.4813091
## ar4      0.26381655    54.1057565   101.75461671   114.48130905  -602.7266974
## ar5     -0.25718067    28.9123664    50.34321504   121.43872587   132.1392110
## omega    0.00906054   -0.4397750   -0.04514474   -0.16509678    0.2847093
## alpha1   1.30746989  -284.9512580  -95.11548438  -95.37413649   226.9324971
## beta1    12.50421555  -298.5966519  -146.22738982 -103.60649134   235.7339361
##          ar5          omega          alpha1          beta1
## mu      -0.2571807    0.00906054    1.30747    12.50422
## ar1      28.9123664   -0.43977503   -284.95126   -298.59665
## ar2      50.3432150   -0.04514474   -95.11548   -146.22739
## ar3     121.4387259   -0.16509678   -95.37414   -103.60649
## ar4     132.1392110    0.28470932    226.93250    235.73394
## ar5     -621.1199733    0.63720719    201.20831    359.78172
## omega     0.6372072   -0.15747841   -154.93221   -175.31270
## alpha1   201.2083061  -154.93220505  -201384.62477 -210287.87249
## beta1    359.7817173  -175.31270464  -210287.87249 -231474.15089
## attr(,"time")
## Time difference of 0.02955103 secs
##
## --- END OF TRACE ---
##
##
## Time to Estimate Parameters:
## Time difference of 0.1561182 secs

```

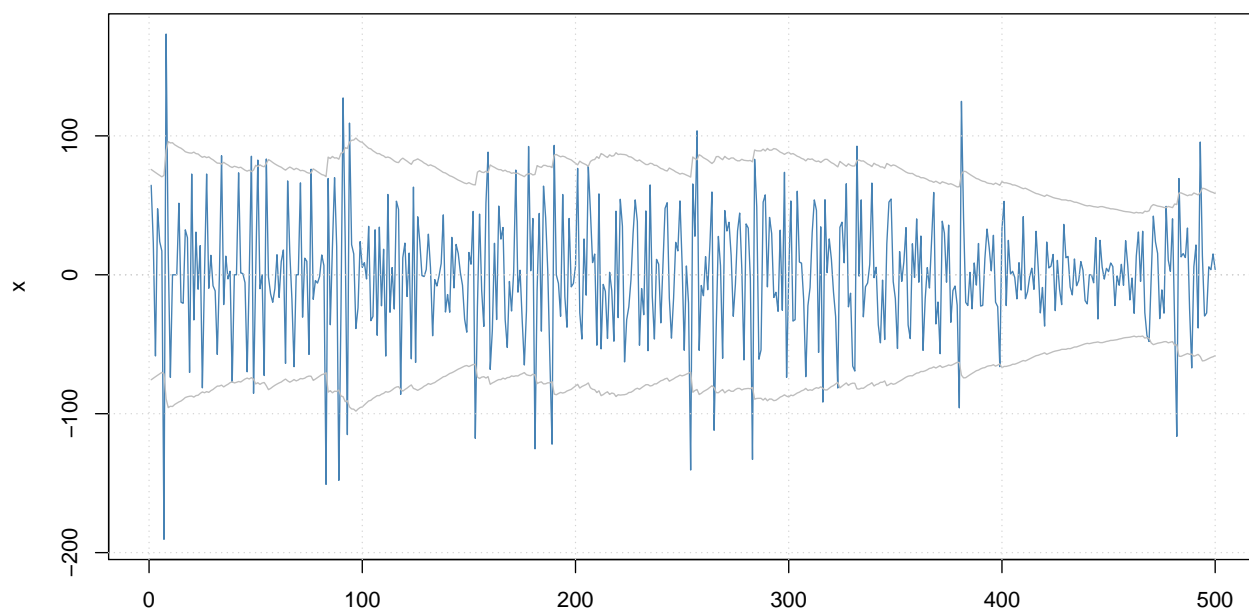
Time Series



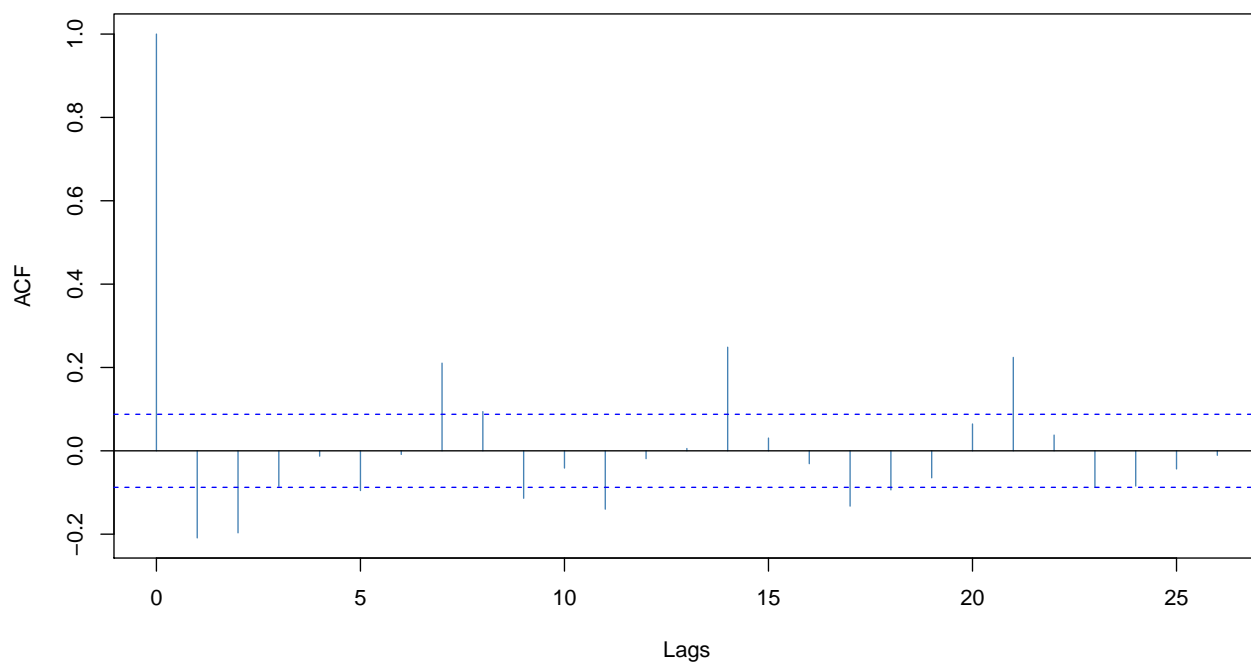
Conditional SD



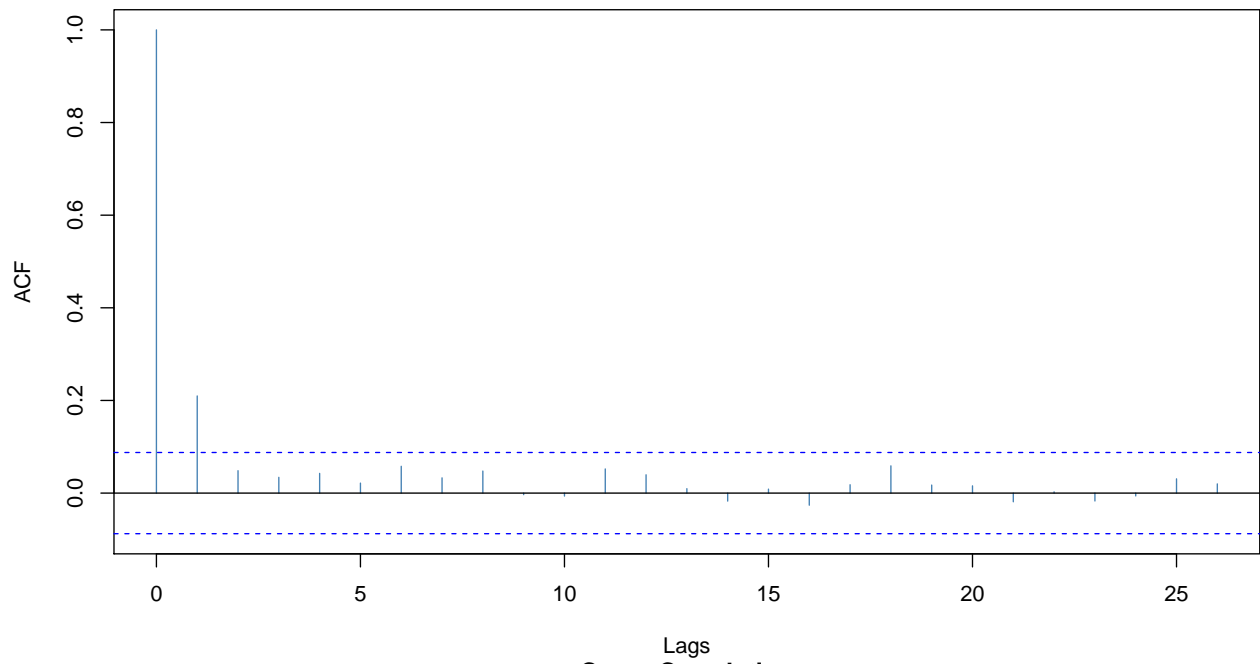
Series with 2 Conditional SD Superimposed



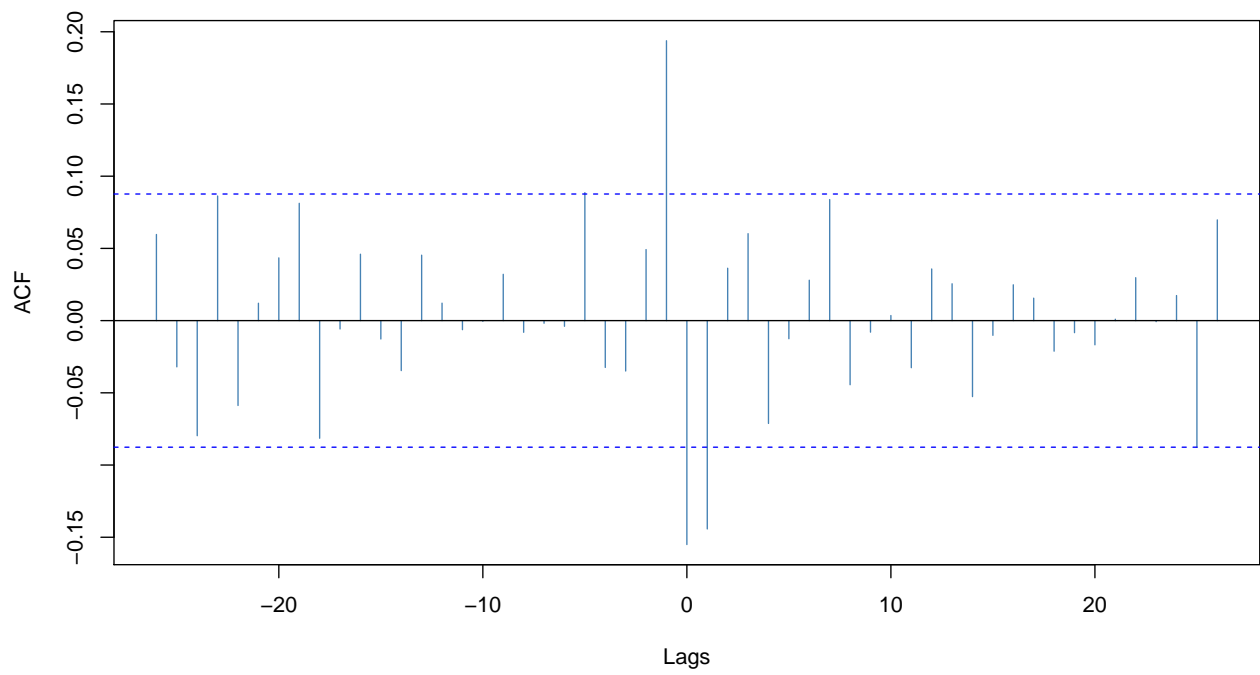
ACF of Observations

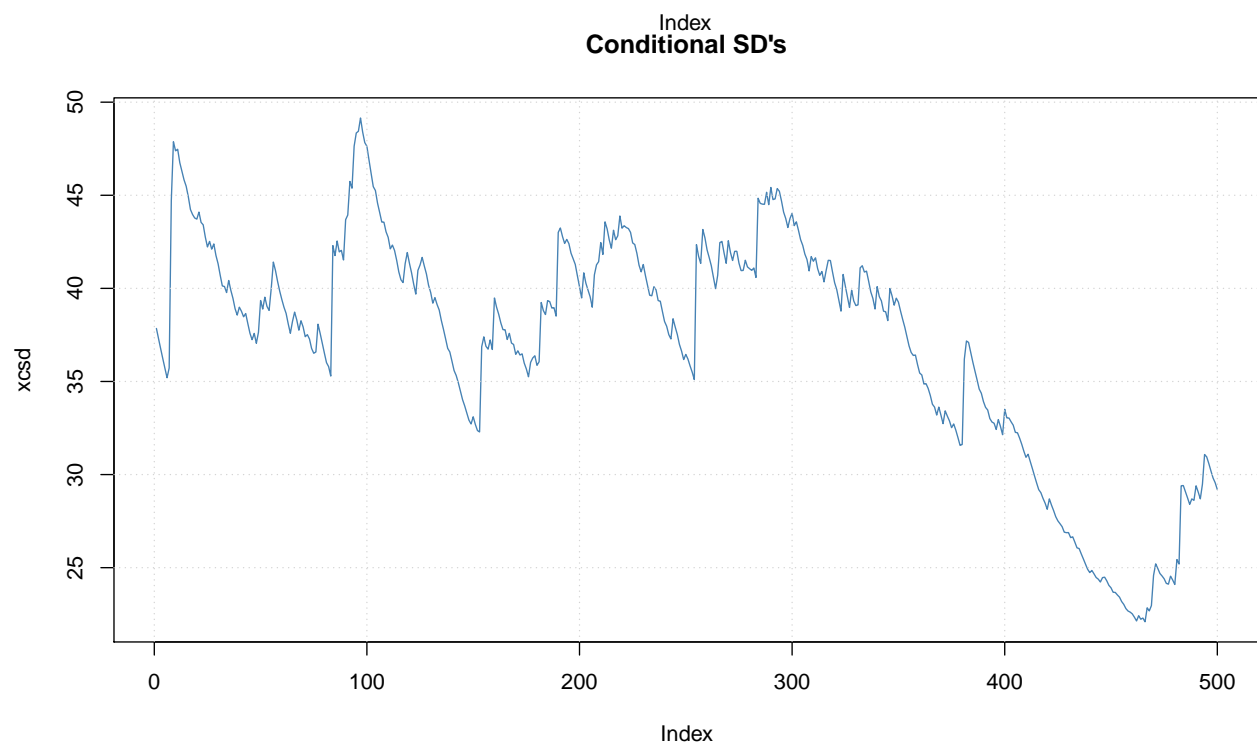
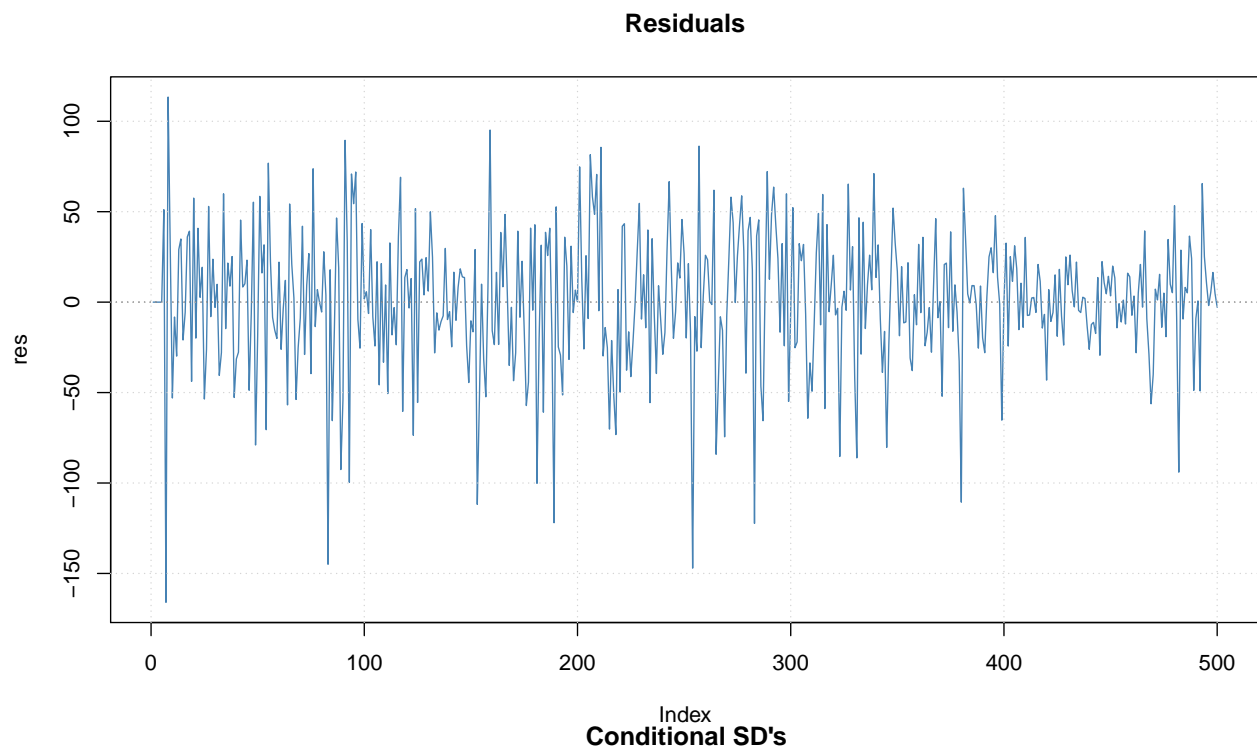


ACF of Squared Observations

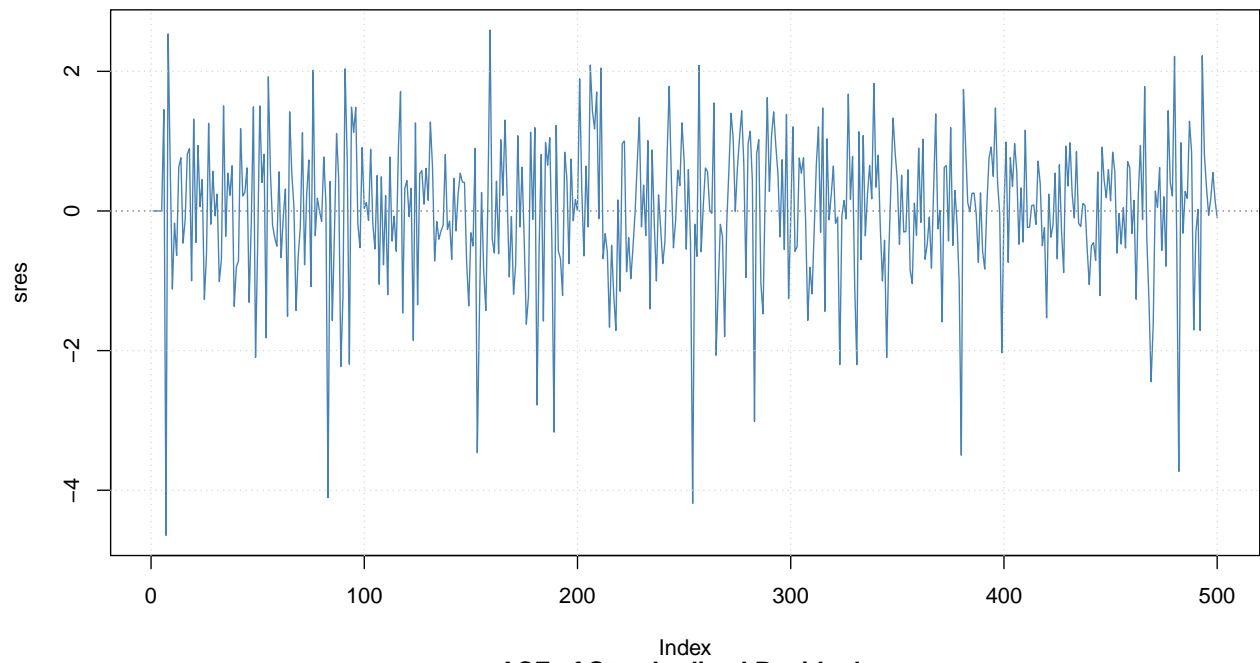


Cross Correlation

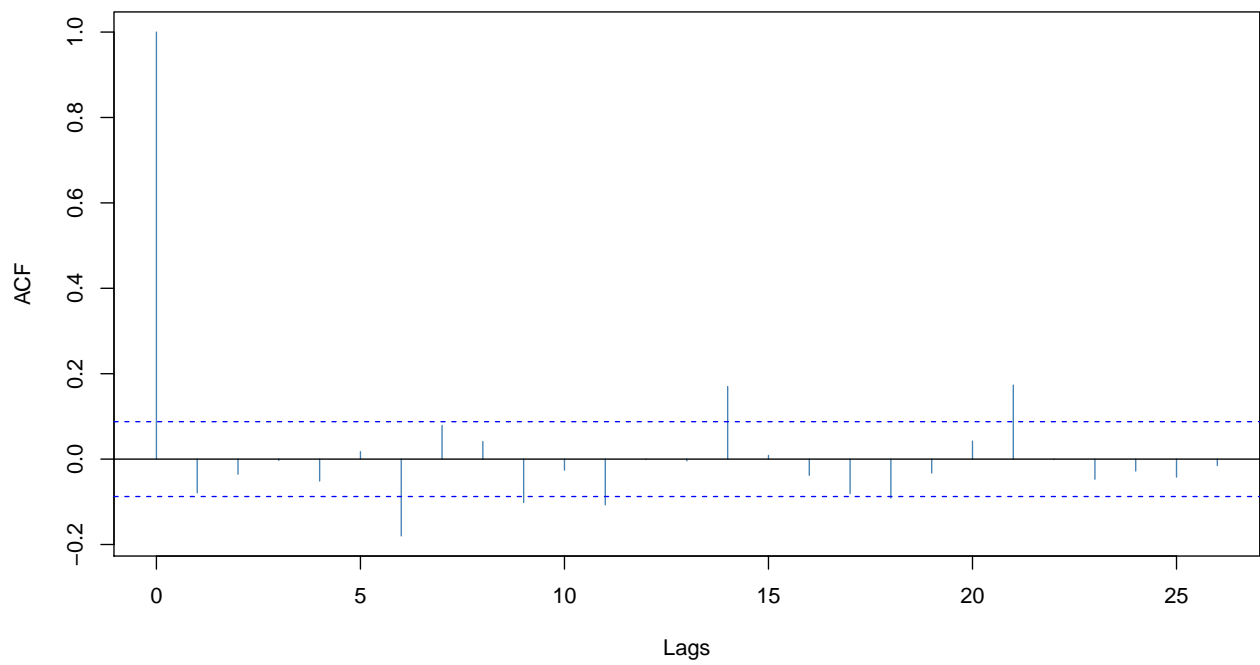




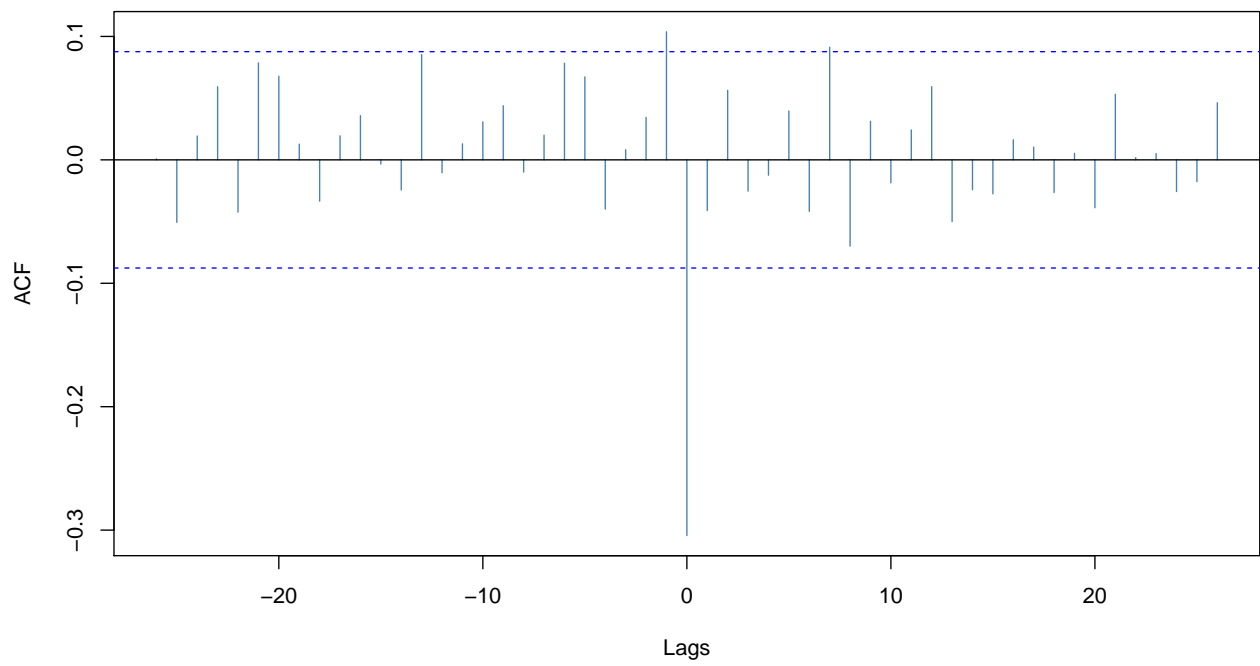
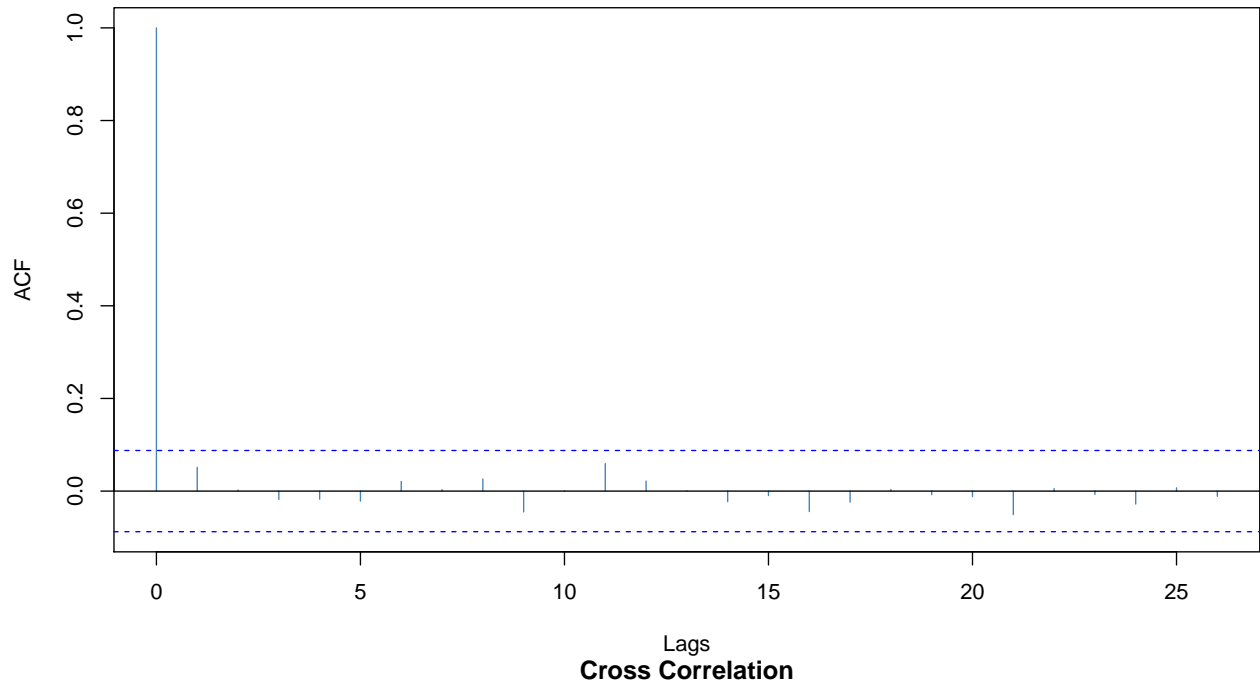
Standardized Residuals

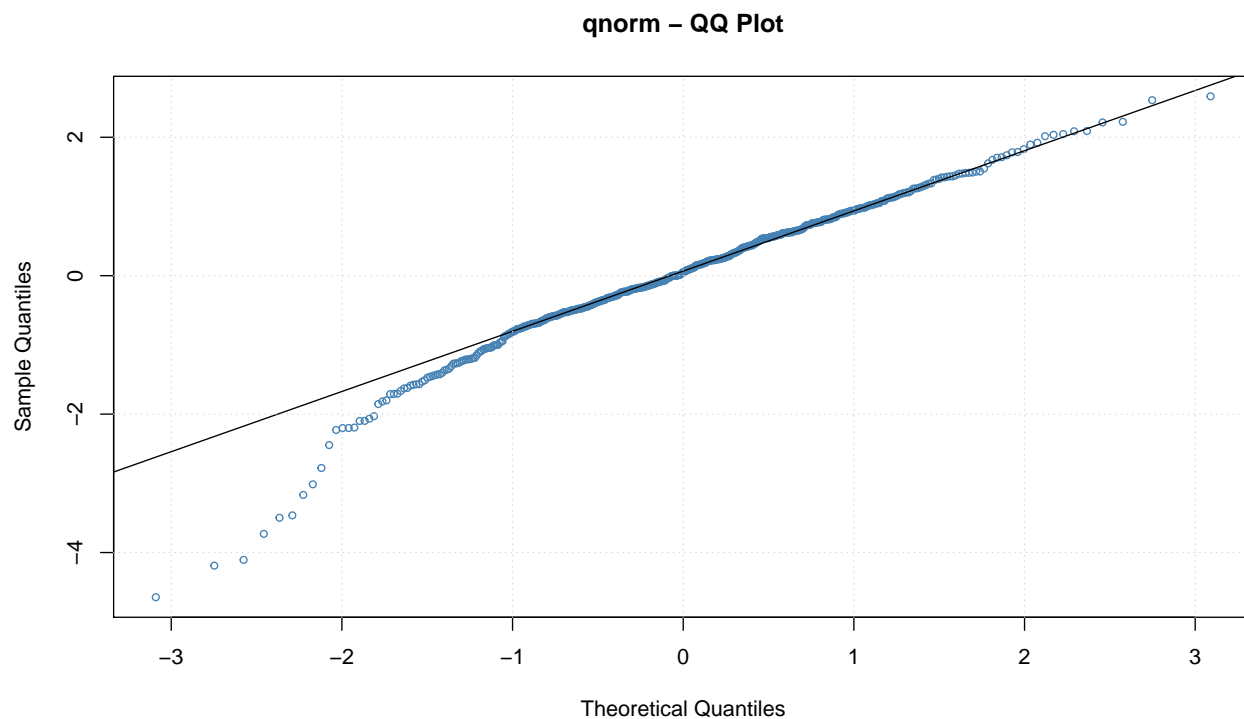


ACF of Standardized Residuals



ACF of Squared Standardized Residuals





16 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      -0.000933    0.001843  -0.50626 0.612671
## ar1      0.438936    0.040808  10.75611 0.000000
## ma1     -0.907031    0.018217 -49.79115 0.000000
## omega    0.001547    0.000794   1.94779 0.051441
## alpha1   0.059765    0.016525   3.61666 0.000298
## beta1    0.929694    0.017588  52.86031 0.000000
##
## Robust Standard Errors:
```

```

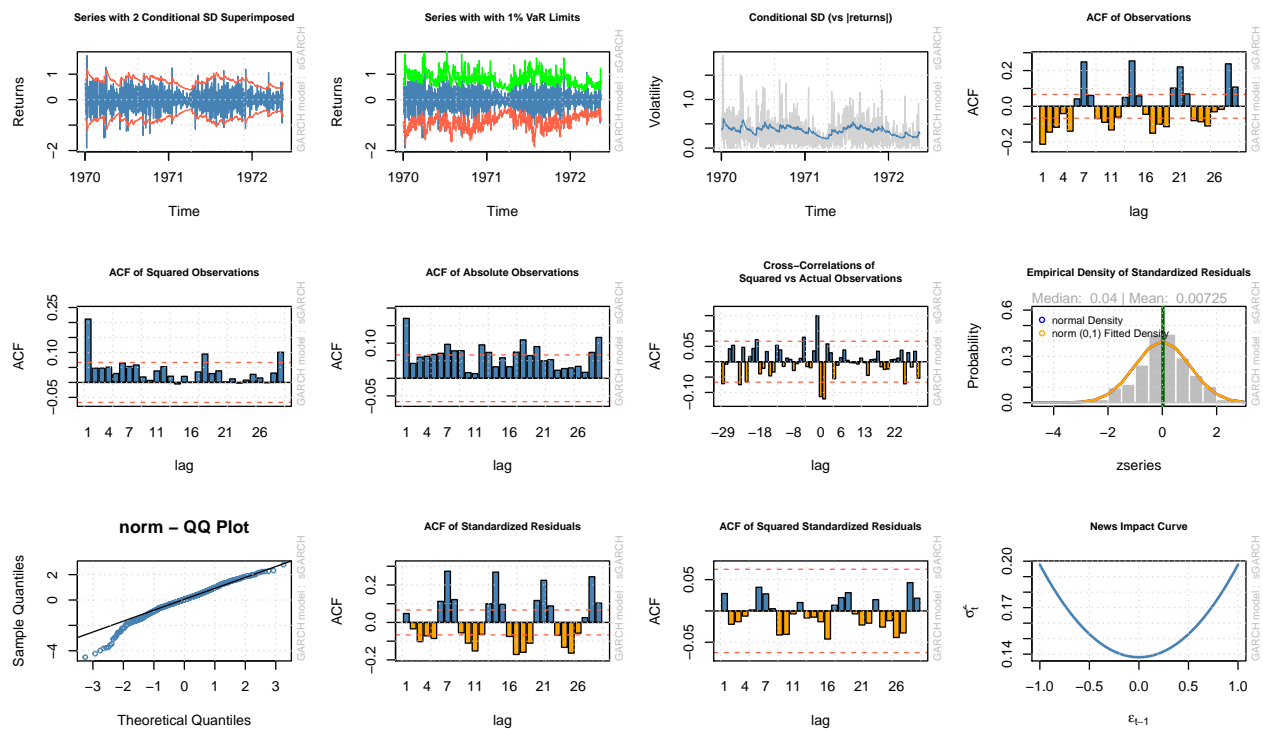
##          Estimate Std. Error   t value Pr(>|t|)
## mu      -0.000933   0.001691  -0.55159 0.581231
## ar1      0.438936   0.045003   9.75347 0.000000
## ma1     -0.907031   0.017634 -51.43736 0.000000
## omega    0.001547   0.001155   1.34011 0.180209
## alpha1   0.059765   0.021319   2.80331 0.005058
## beta1    0.929694   0.022554  41.22121 0.000000
##
## LogLikelihood : -328.4232
##
## Information Criteria
## -----
##
## Akaike          0.77145
## Bayes           0.80443
## Shibata         0.77135
## Hannan-Quinn    0.78407
##
## Weighted Ljung-Box Test on Standardized Residuals
## -----
##
##                statistic   p-value
## Lag[1]                1.983 1.591e-01
## Lag[2*(p+q)+(p+q)-1] [5] 11.366 2.220e-16
## Lag[4*(p+q)+(p+q)-1] [9] 46.554 0.000e+00
## d.o.f=2
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## -----
##
##                statistic p-value
## Lag[1]                0.674 0.4117
## Lag[2*(p+q)+(p+q)-1] [5] 1.168 0.8205
## Lag[4*(p+q)+(p+q)-1] [9] 2.186 0.8816
## d.o.f=2
##
## Weighted ARCH LM Tests
## -----
##
##          Statistic Shape Scale P-Value
## ARCH Lag[3]    0.2559 0.500 2.000 0.6129
## ARCH Lag[5]    0.3045 1.440 1.667 0.9391
## ARCH Lag[7]    1.2944 2.315 1.543 0.8615
##
## Nyblom stability test
## -----
## Joint Statistic: 0.8492

```

```

## Individual Statistics:
## mu      0.09902
## ar1     0.34588
## ma1     0.05834
## omega   0.18420
## alpha1  0.12554
## beta1   0.16573
##
## 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      0.84614 0.3977
## Negative Sign Bias 0.27514 0.7833
## Positive Sign Bias 0.02865 0.9772
## Joint Effect    2.21671 0.5287
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## -----
##   group statistic p-value(g-1)
## 1    20      31.94    0.03175
## 2    30      44.52    0.03272
## 3    40      48.66    0.13806
## 4    50      53.70    0.29888
##
##
## Elapsed time : 0.136488
##
## please wait...calculating quantiles...

```



17 Conclusions

It was really interesting!

18 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