Holt Winter and ARIMA on INR vs USD

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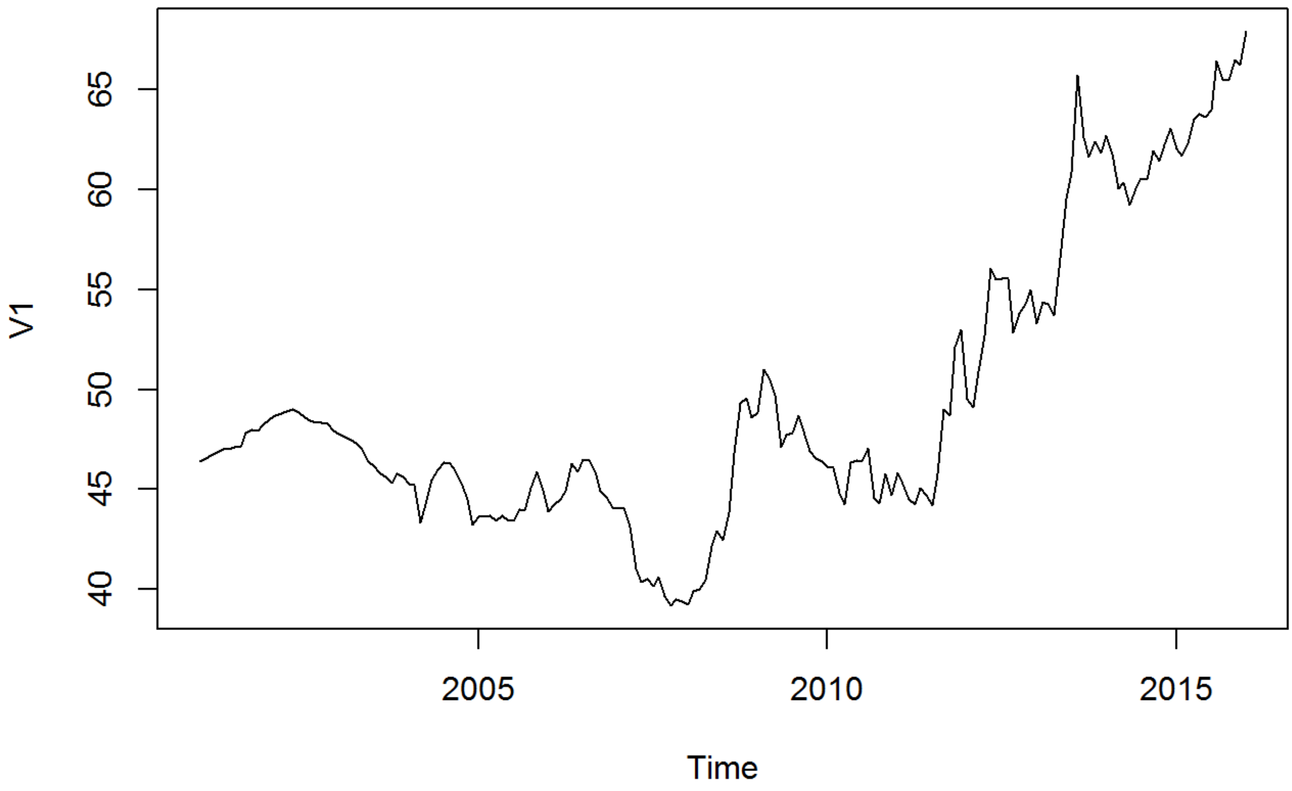
R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com (http://rmarkdown.rstudio.com).

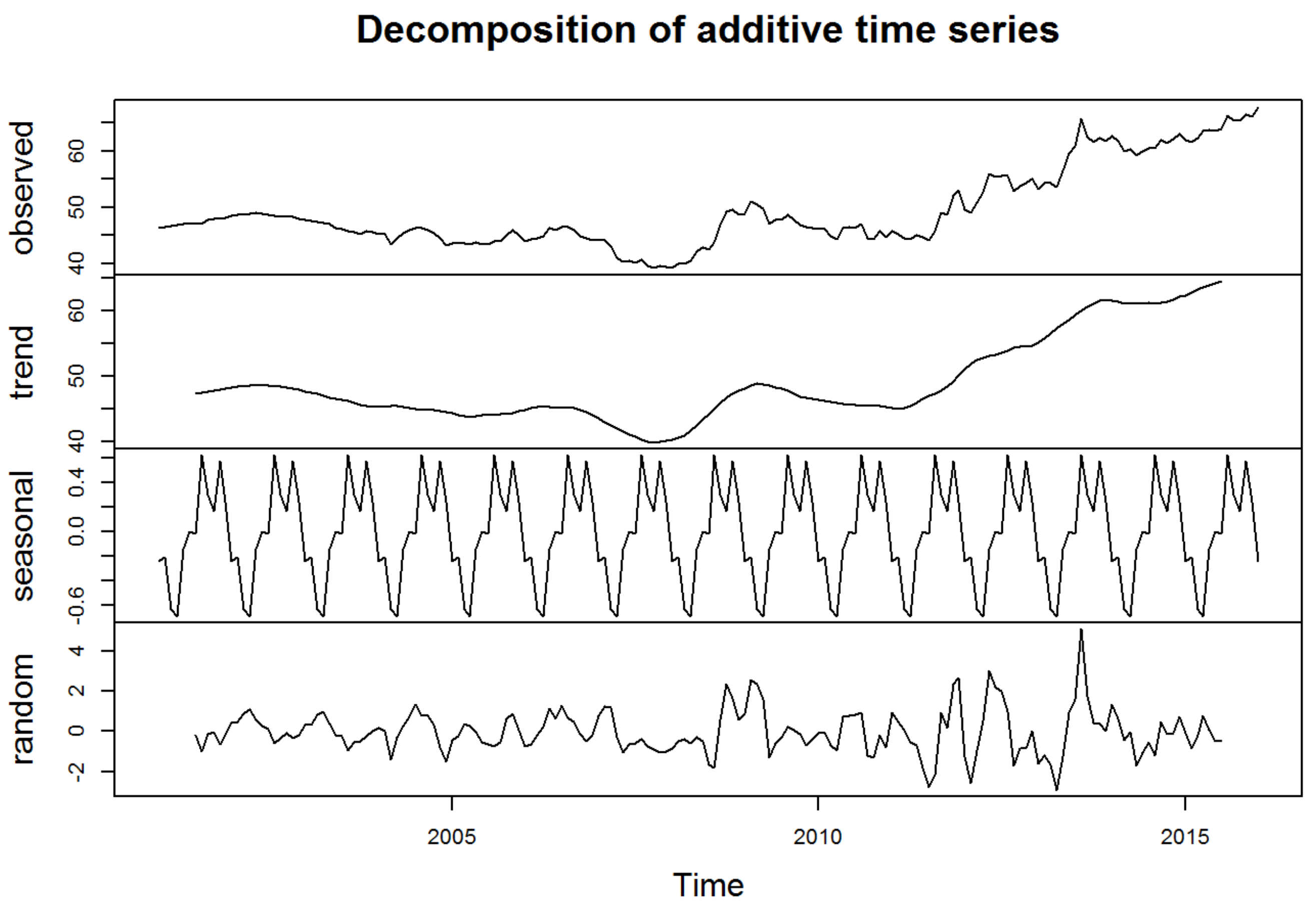
```
# Getting Data and plotting
setwd("C:/Users/coffee/Downloads/Software/R/Cowpertwait/IF")
data = read.csv("data.csv", header = FALSE)
data.ts = ts(data, start = 2001, frequency = 12)
head(data.ts)
```

```
## [1] 46.39 46.54 46.71 46.84 47.00 47.04
```

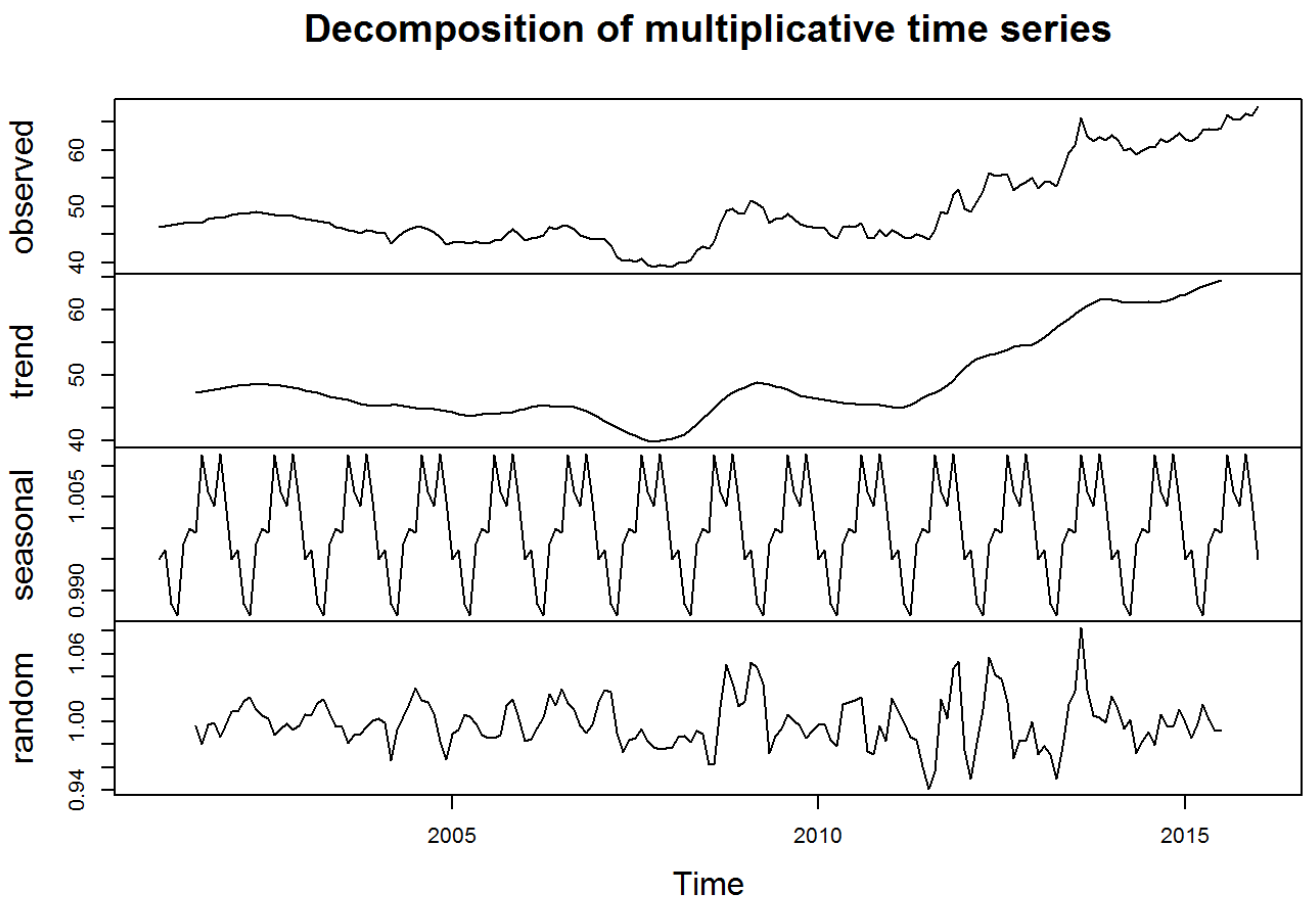
```
plot.ts(data.ts)
```



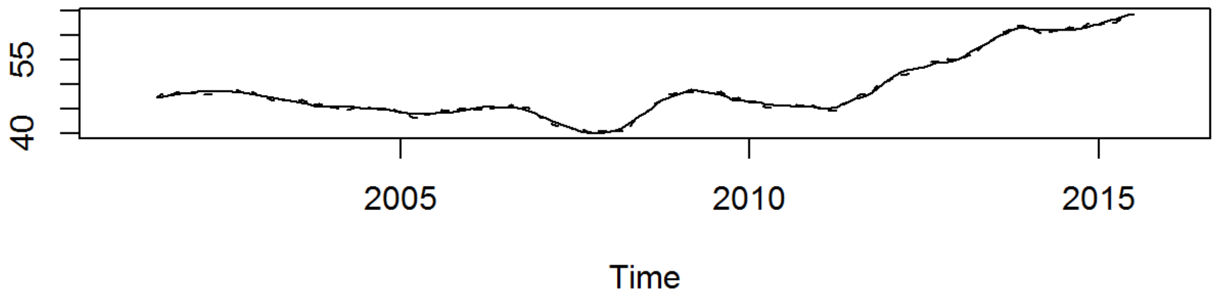
```
# time series decomposition (additive), into TREND, SEASON and RANDOM ERRORS
a = decompose(data.ts, type="additive")
plot(a)
```

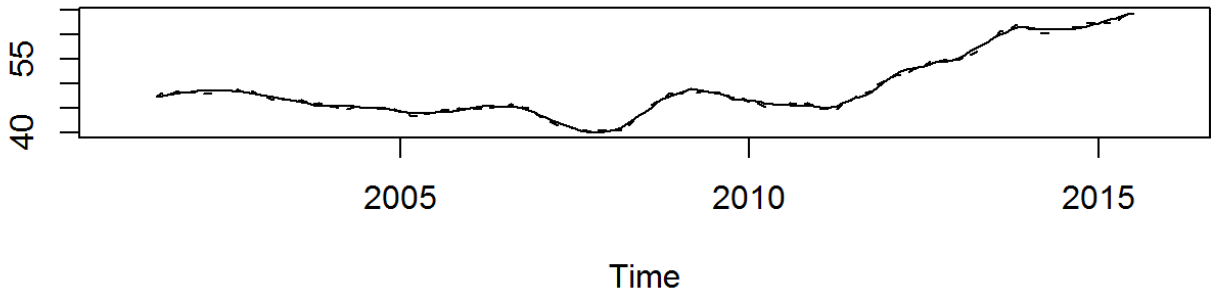



```
# time series decomposition (multiplicative), into TREND, SEASON and RANDOM ERRORS
b = decompose(data.ts, type="mult")
plot(b)
```




```
# Com#pare additive and multiplicative
par(mfrow = c(2,1))
ts.plot(cbind(a$trend, a$trend + a$seasonal), lty = 1:2)
ts.plot(cbind(b$trend, b$trend * b$seasonal), lty = 1:2)
```

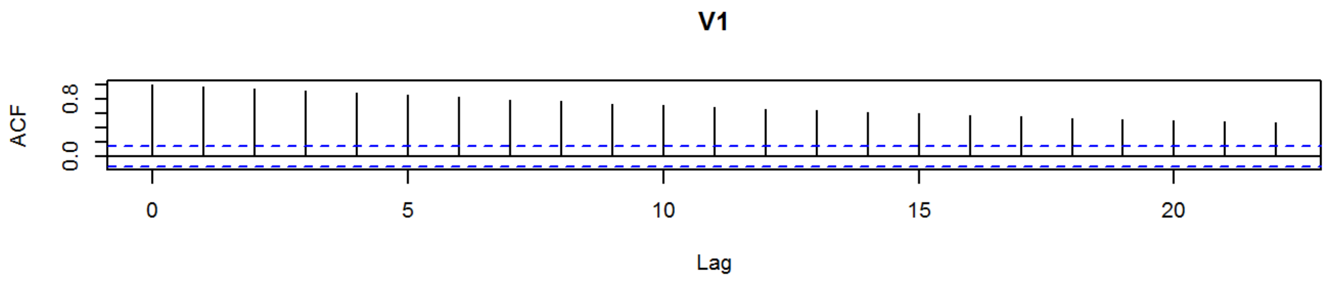


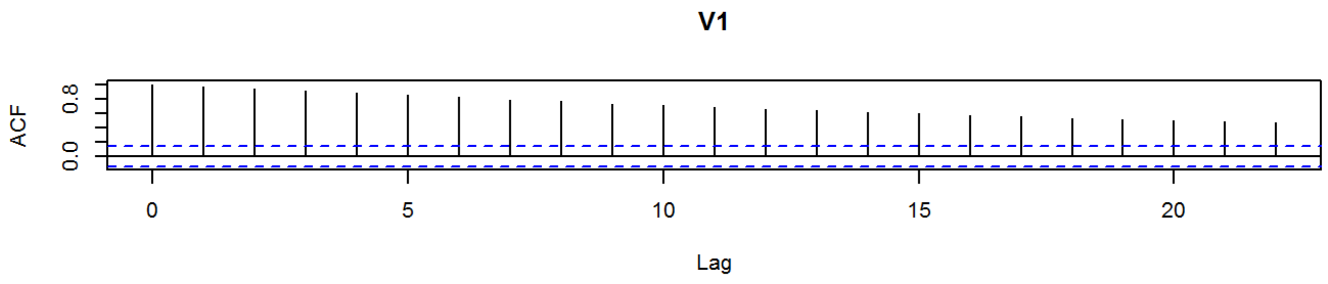


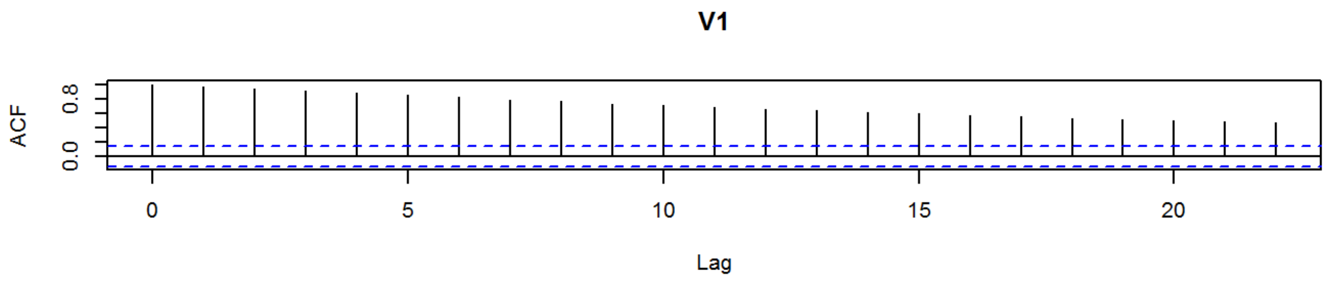

```
# AUTOCORRELATION with lag 1 and 2 of orignal data
par(mfrow = c(3,1))
acf(data)
acf(data)$acf[2]
```

```
## [1] 0.9677792
```

```
acf(data)$acf[3]
```








```
## [1] 0.936691
```

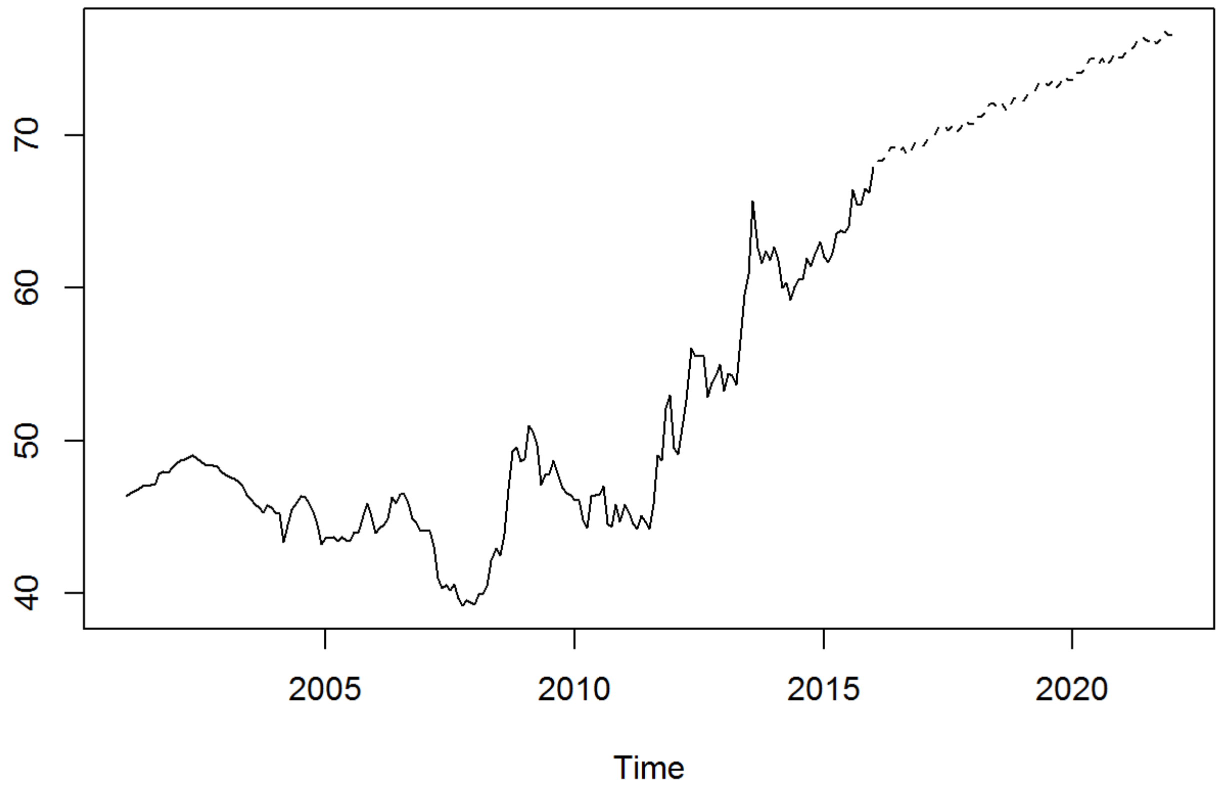
```
# HOLT WINTERS - including level, slope and seasonal effects - ADDITIVE
data.hw4 = HoltWinters(data.ts, seasonal = "additive")
data.hw4$coef
```

```
##           a           b          s1          s2          s3          s4
## 68.18042311  0.12055653 -0.01034713 -0.09673709  0.08736384  0.51218266
##          s5          s6          s7          s8          s9         s10
##  0.39137121 -0.01278056  0.15154959 -0.38206687 -0.21855667  0.14821692
##         s11         s12
## -0.24200736 -0.30242311
```

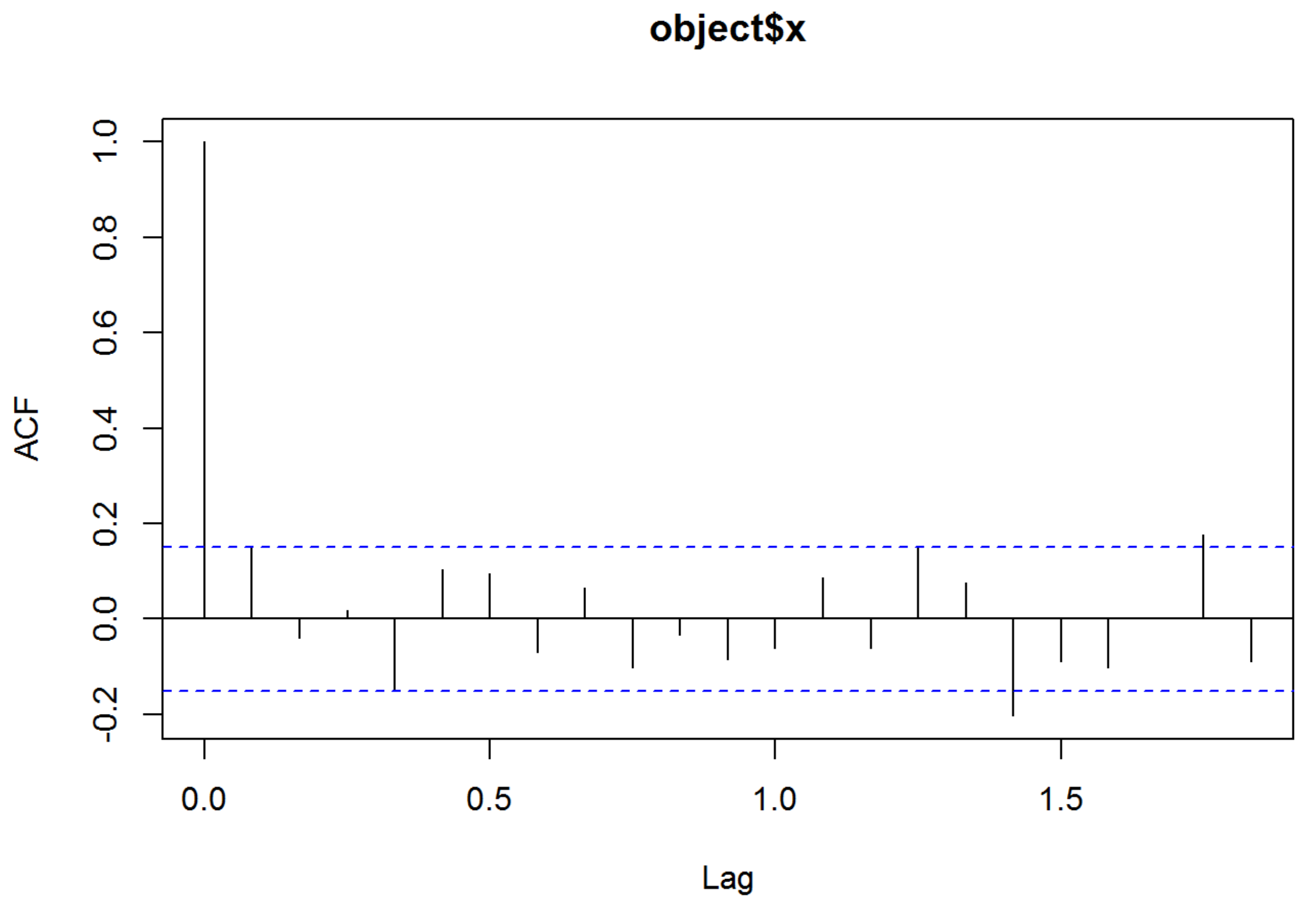
```
data.hw4$SSE
```

```
## [1] 250.0229
```

```
par(mfrow = c(1,1))
data.predict1 = predict(data.hw4, n.ahead = 6*12)
ts.plot(data.ts, data.predict1, lty = 1:2)
```




```
acf(residuals(data.hw4))
```



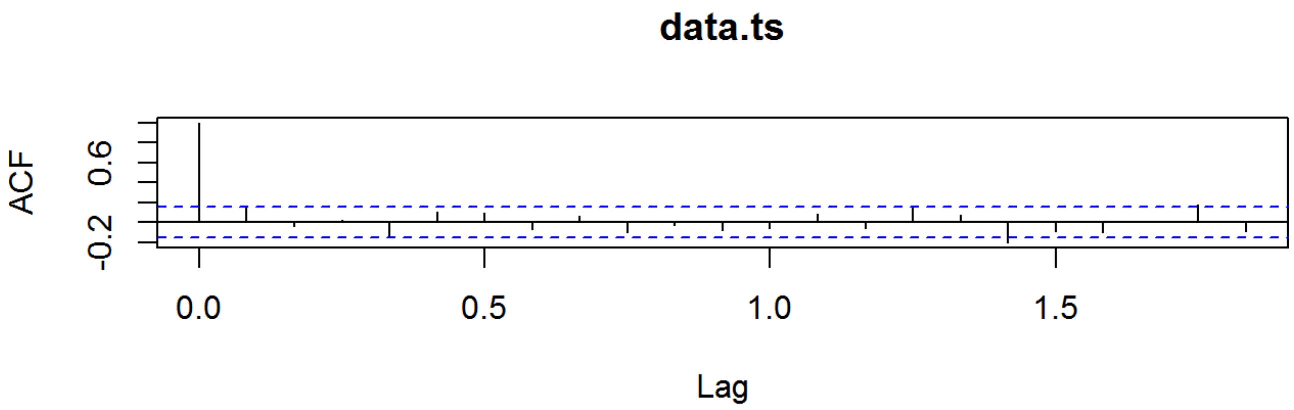
```
# Calculating if residual series (data.ts - data.hw4$fitted[,1]) is white noise or not
residual_series = data.ts - data.hw4$fitted[,1]
mean(residual_series)
```

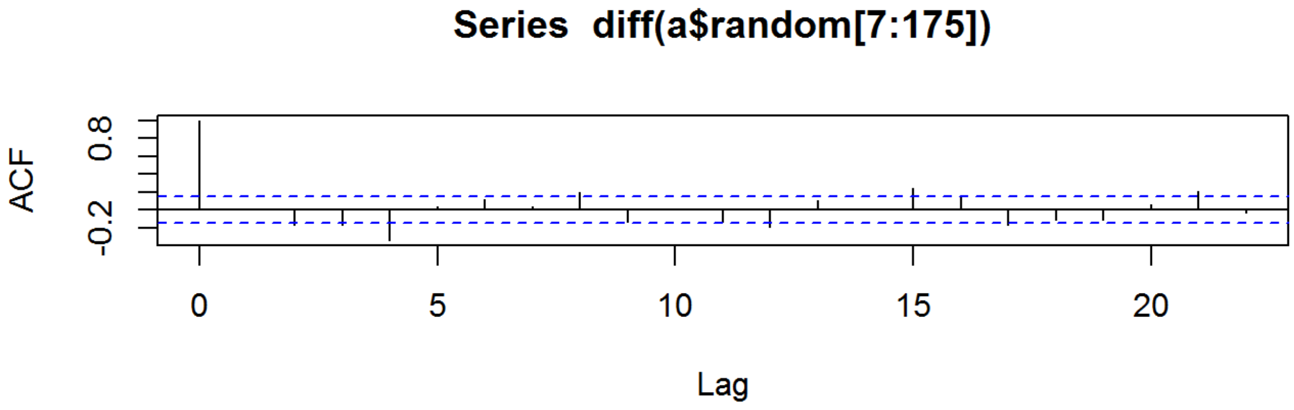
```
## [1] 0.002901398
```

```
var(residual_series)
```

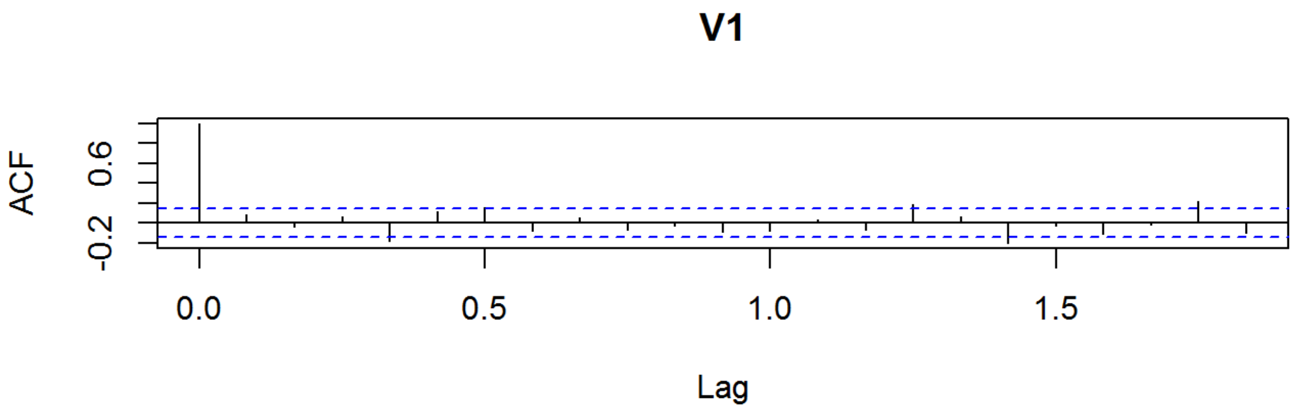
```
##          data.ts
## data.ts 1.488223
```

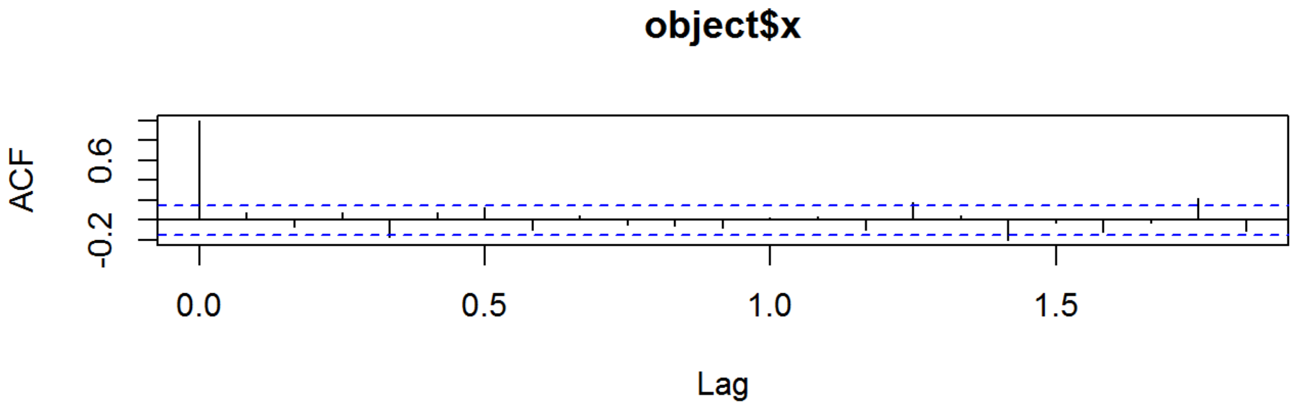
```
par(mfrow=c(2,1))
acf(residual_series)
# variance  = 1.5, mean = 0, and correlogram shows it resembles white noise.
acf(diff(a$random[7:175]))
```





```
# first order difference of random walk are white noise
# shows that random errors follows random walk
# head(a$random[7:175])
# head(diff(a$random[7:175]))
acf(diff(data.ts))
# first order differences also shows no significant value at lag 1 but other significan
t values shows the model needs some extension.
data.hw4_2 = HoltWinters(data.ts,  gamma=0)
acf(resid(data.hw4_2))
```






```
# better fit using gamma =0

# Fitted AR
layout(1:1)
data.ar = ar(data.ts)
mean(data.ts)
```

```
## [1] 49.4268
```

```
data.ar$order
```

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

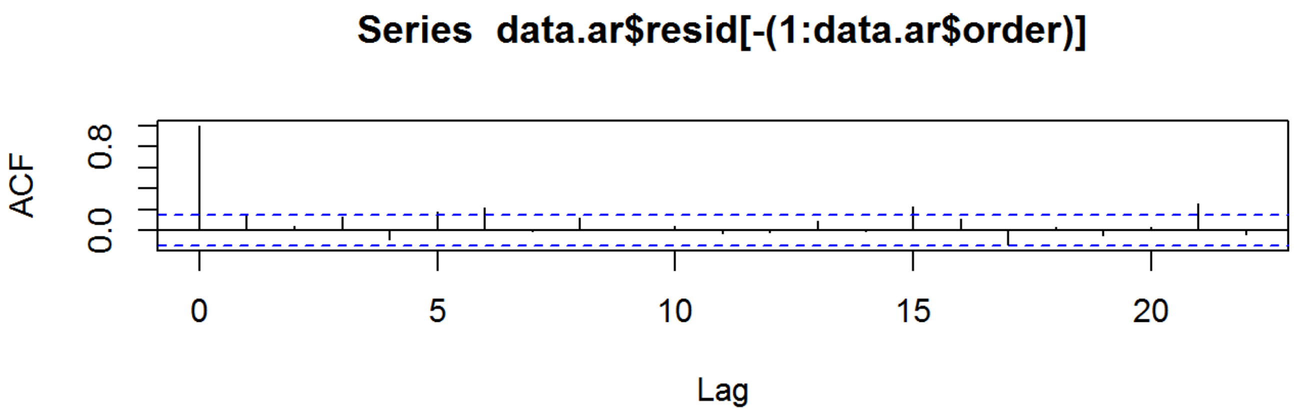
```
data.ar$ar
```

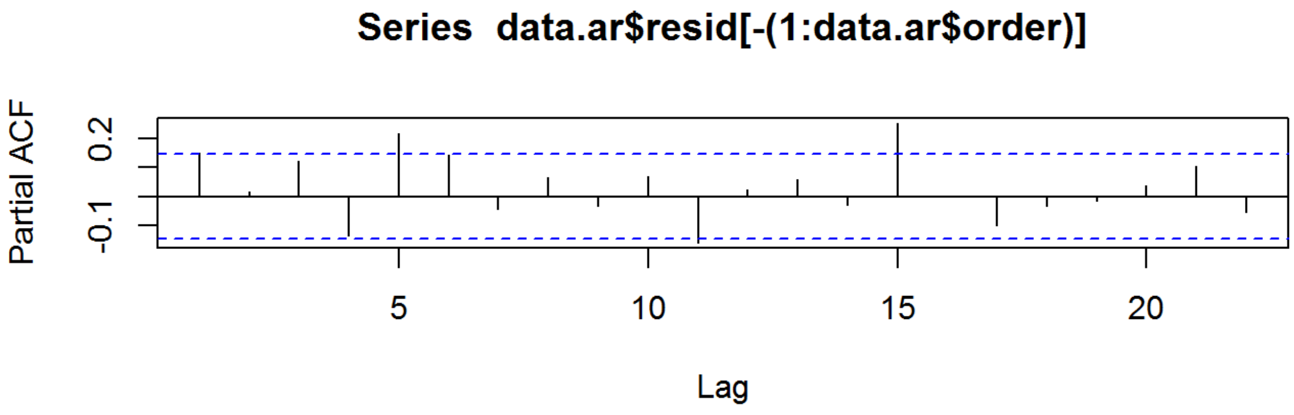
```
## [1] 0.9677792
```

```
data.ar$ar + c(-1.96,1.96)*sqrt(data.ar$asy.var)
```

```
## [1] 0.9308912 1.0046673
```

```
par(mfrow=c(2,1))
acf(data.ar$resid[-(1:data.ar$order)])
pacf(data.ar$resid[-(1:data.ar$order)])
```






```
#method = MLE, only take vector i.e first column
data.ar2 = ar(data.ts[,1], method = "mle")
```

```
## Warning in arima0(x, order = c(i, 0L, 0L), include.mean = demean): possible
## convergence problem: optim gave code = 1

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## Warning in arima0(x, order = c(i, 0L, 0L), include.mean = demean): possible
## convergence problem: optim gave code = 1
```

```
mean(data.ts)
```

```
## [1] 49.4268
```

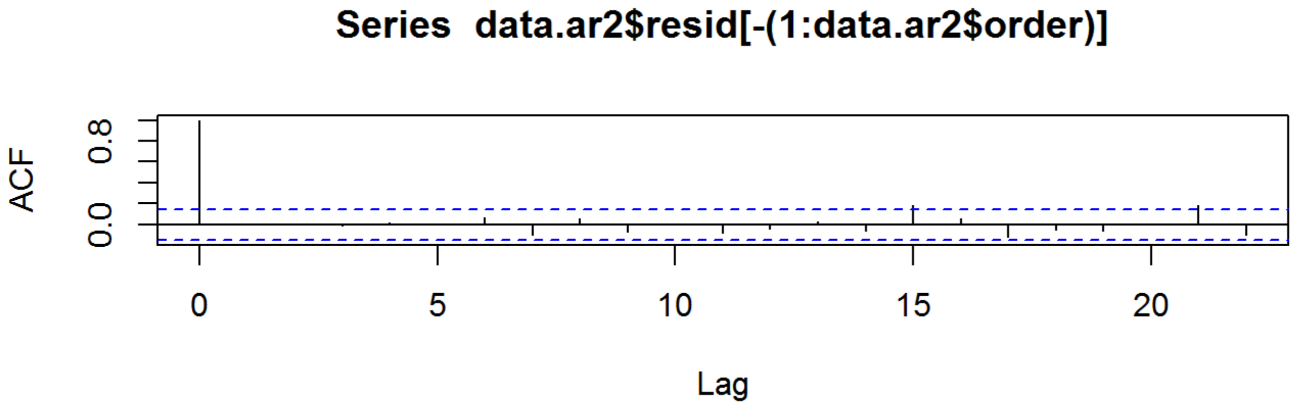
```
data.ar2$order
```

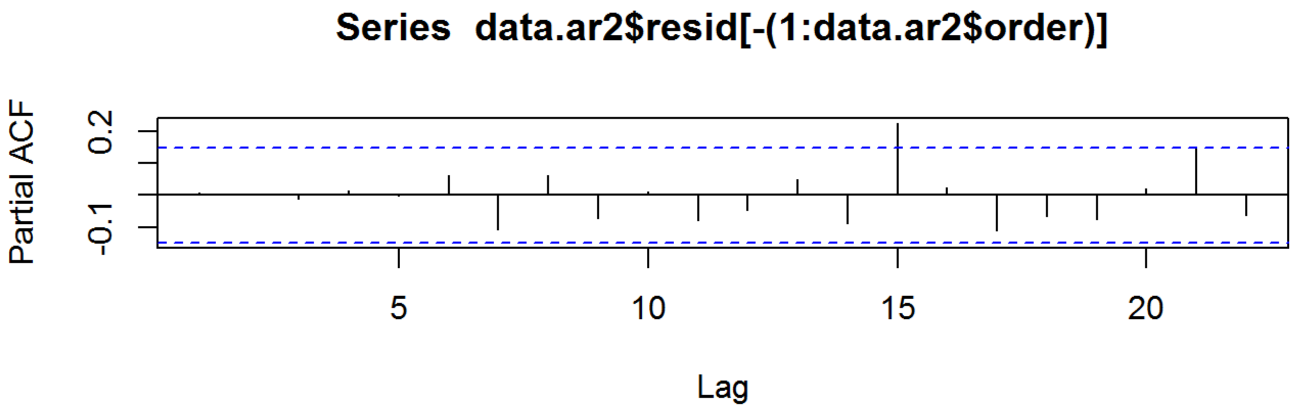
```
## [1] 7
```

```
data.ar2$ar
```

```
## [1]  1.12327492 -0.17770508  0.14730567 -0.29403681  0.35168902 -0.03855551
## [7] -0.12122875
```

```
acf(data.ar2$resid[-(1:data.ar2$order)])
pacf(data.ar2$resid[-(1:data.ar2$order)])
```






```
# fitting moving aveergae
data.ma = arima(data.ts, order = c(0,0,1))
data.ma
```

```
##
## Call:
## arima(x = data.ts, order = c(0, 0, 1))
##
## Coefficients:
##          ma1  intercept
##       0.9426    49.4671
## s.e.  0.0235     0.5548
##
## sigma^2 estimated as 14.84:  log likelihood = -502.05,  aic = 1010.09
```

```
par(mfrow=c(2,1))
acf(data.ma$res[-1])
# not a satisfactory fit
# com#parison of ARMA, AR, and MA

data.ARvsARMA = arima(data.ts, order = c(1,0,0))
data.MAvsARMA = arima(data.ts, order = c(0,0,1))
data.ARMA = arima(data.ts, order = c(1,0,1))
AIC(data.ARvsARMA)
```

```
## [1] 569.9773
```

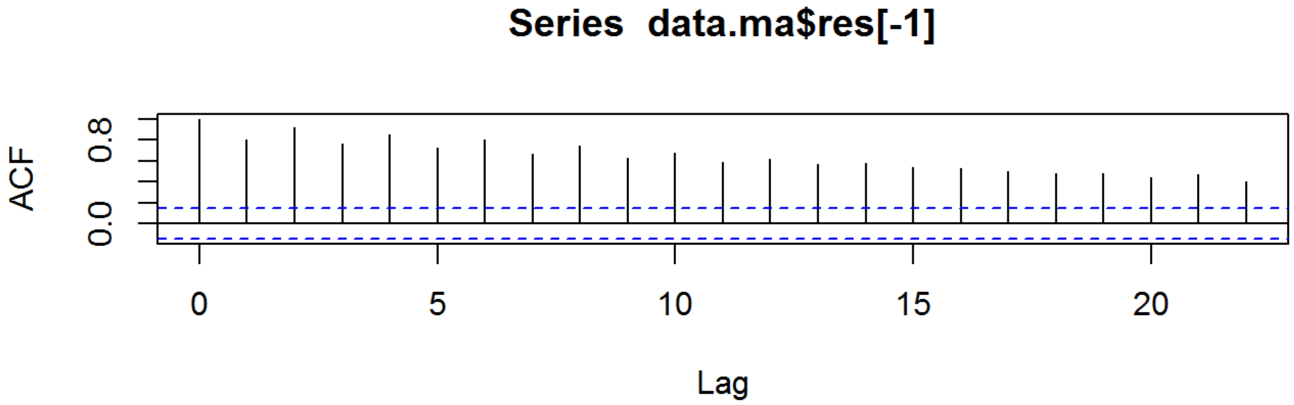
```
AIC(data.MAvsARMA)
```

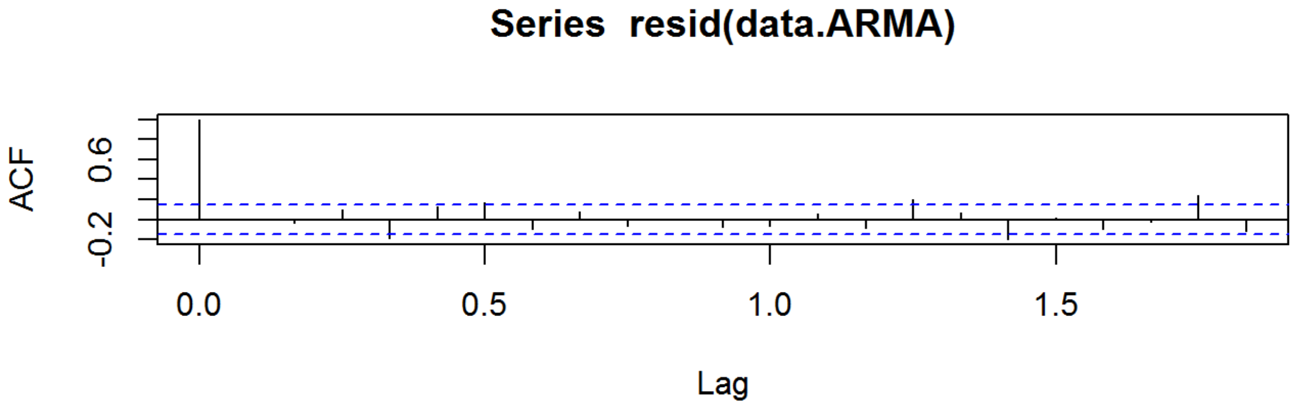
```
## [1] 1010.094
```

```
AIC(data.ARMA)
```

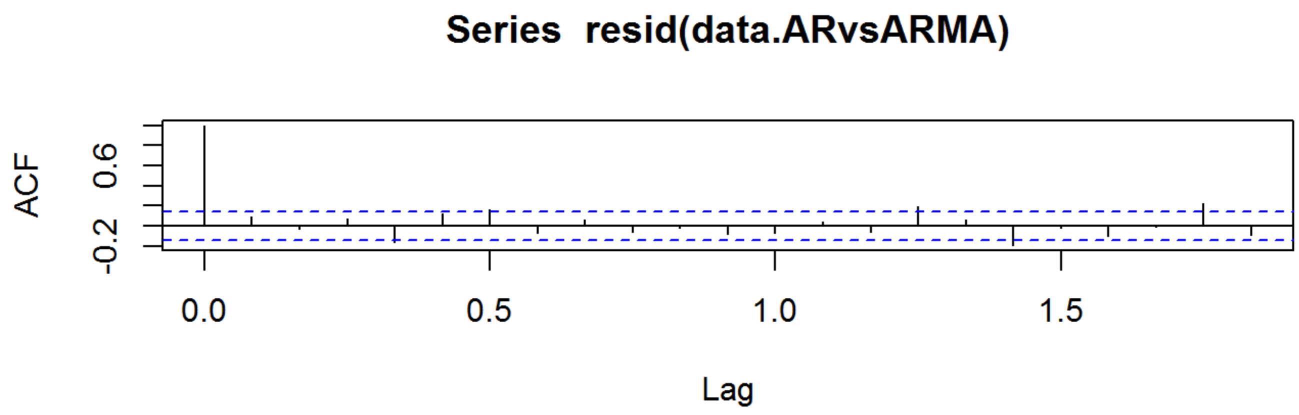
```
## [1] 570.2117
```

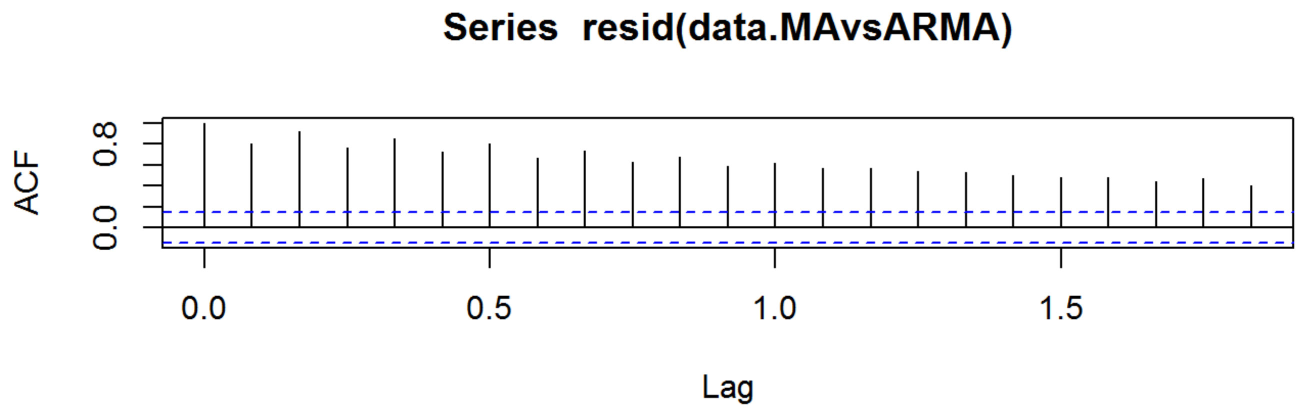
```
acf(resid(data.ARMA))
```



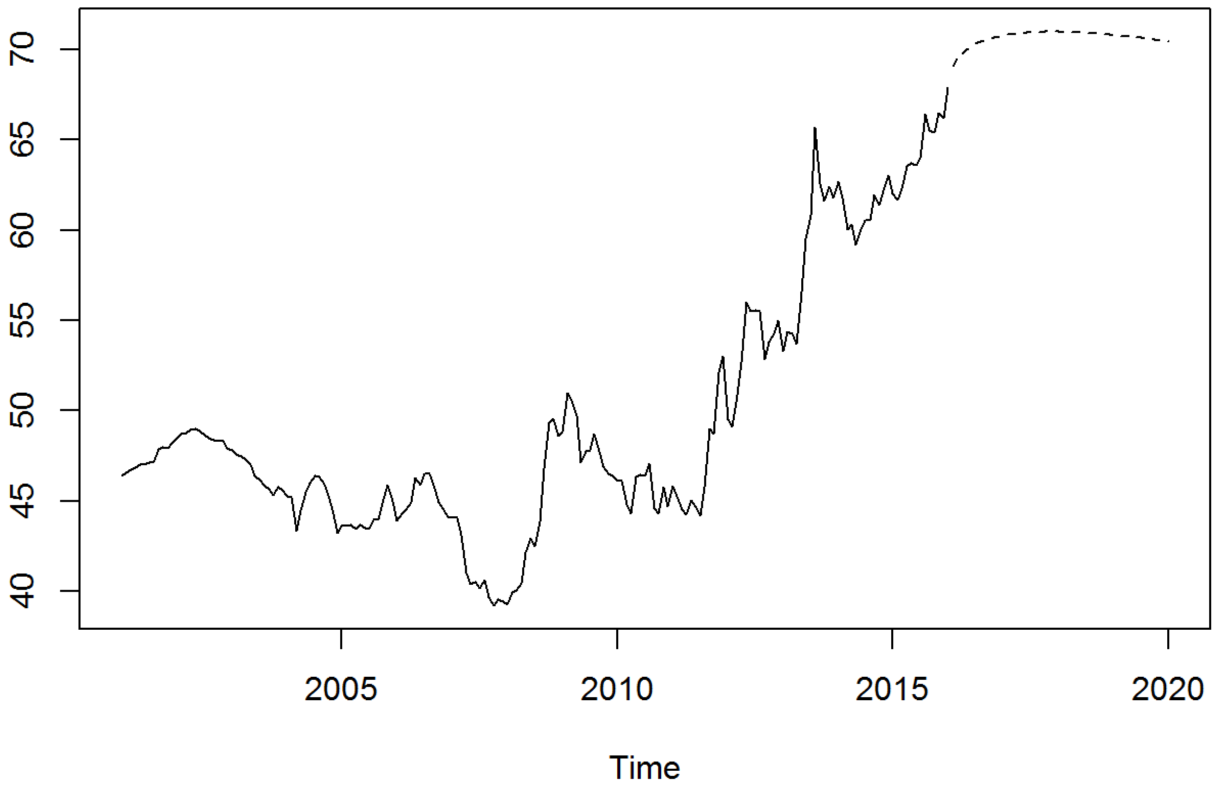



```
acf(resid(data.ARvsARMA))
acf(resid(data.MAvsARMA))
```

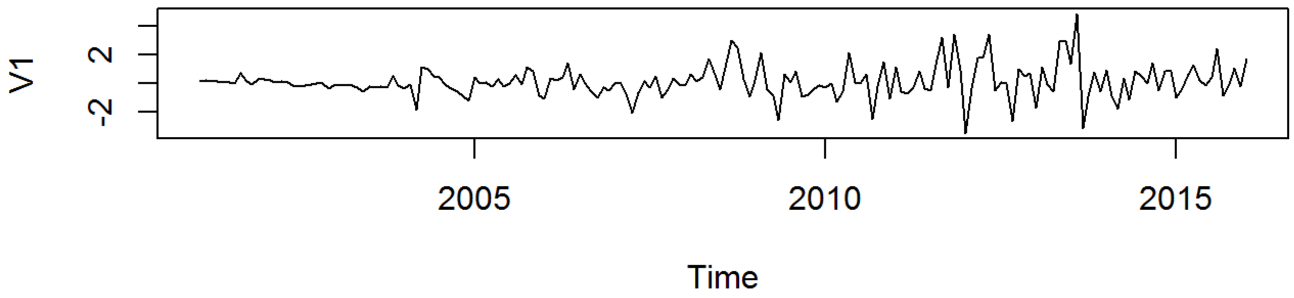


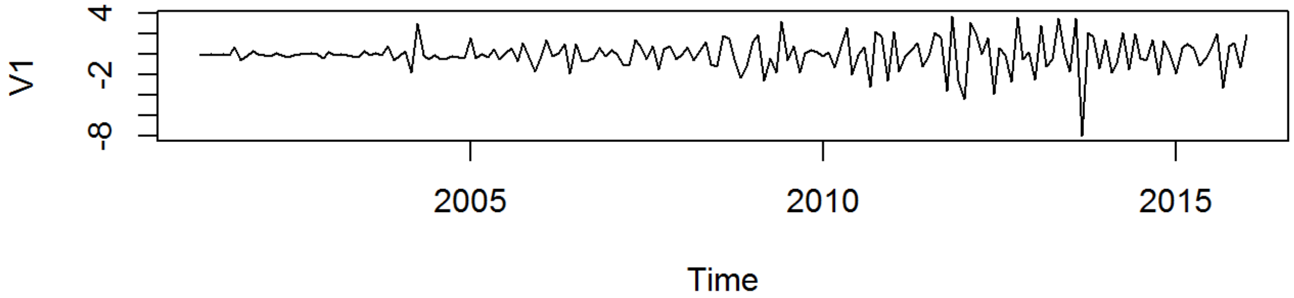



```
# both AR and ARMA are good approximate
predict.arma = predict(data.ARMA, n.ahead = 48)
par(mfrow=c(1,1))
ts.plot(cbind(data.ts, predict.arma$pred+predict.arma$se), lty = 1:2)
```

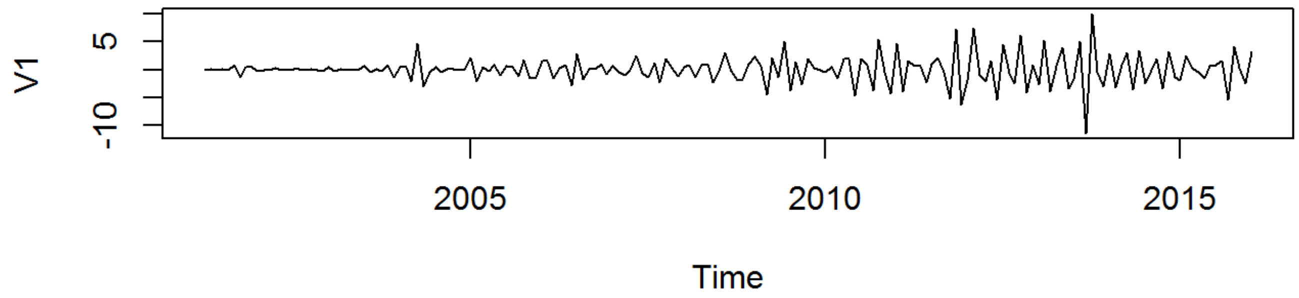


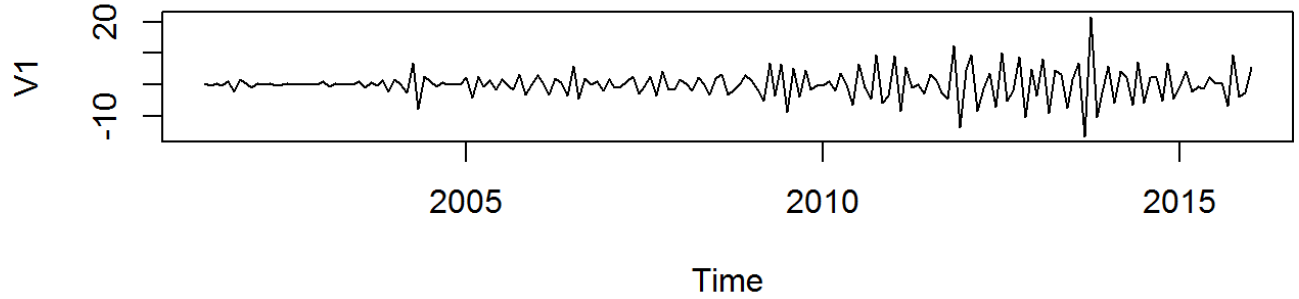

```
# difference
par(mfrow=c(2,1))

plot(diff(data.ts))
plot(diff(data.ts, d = 2))
```






```
plot(diff(data.ts, d = 3))

plot(diff(data.ts, d = 4))
```

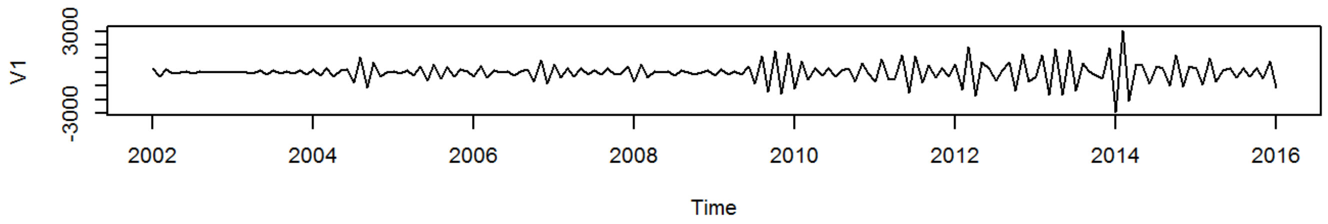




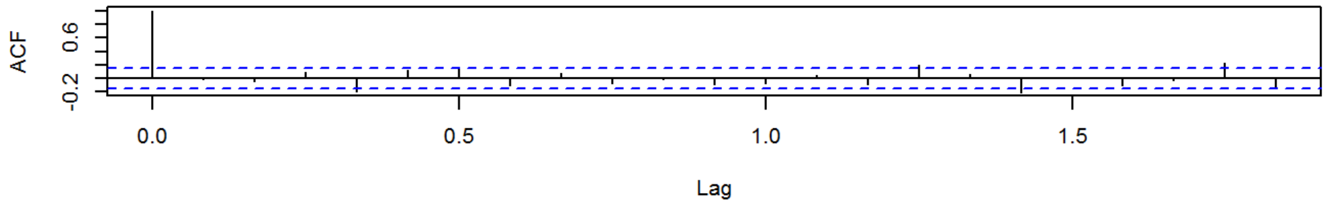

```
par(mfrow=c(3,1))

plot(diff(data.ts, d = 12))

#ARIMA
data.ima =  arima(data.ts, order = c(0,1,1))
data.ima
```

```
##
## Call:
## arima(x = data.ts, order = c(0, 1, 1))
##
## Coefficients:
##          ma1
##       0.1012
## s.e.  0.0798
##
## sigma^2 estimated as 1.281:  log likelihood = -277.7,  aic = 559.41
```

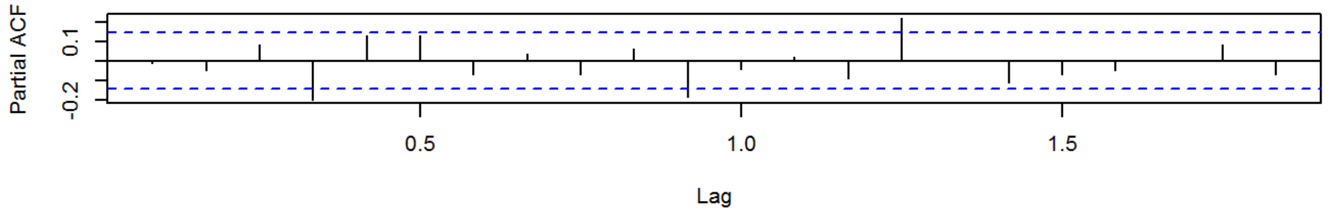
```
acf(resid(data.ima))
pacf(resid(data.ima))
```



Series resid(data.ima)



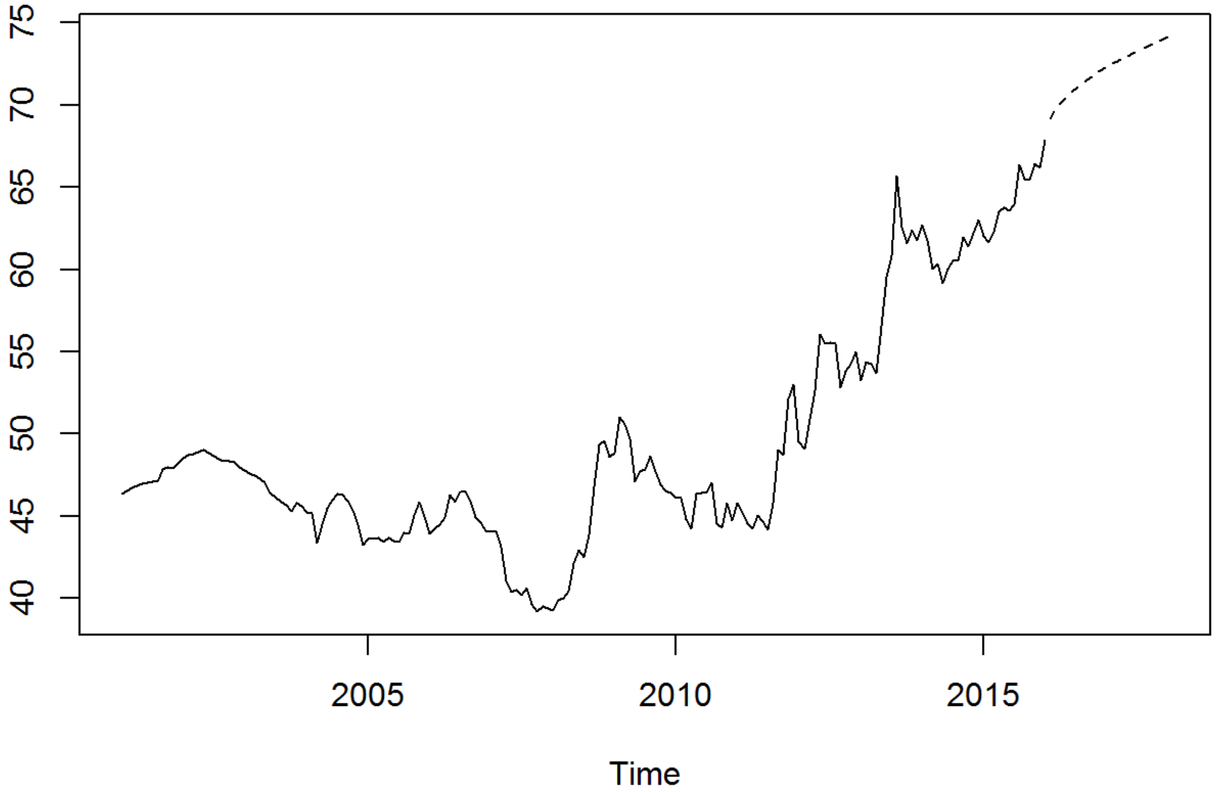
Series resid(data.ima)




```
par(mfrow=c(1,1))
data.ima_predict = predict(data.ima, n.ahead = 24)
data.ima_predict
```

```
## $pred
##           Jan      Feb      Mar      Apr      May      Jun      Jul
## 2016          68.05066 68.05066 68.05066 68.05066 68.05066 68.05066
## 2017 68.05066 68.05066 68.05066 68.05066 68.05066 68.05066 68.05066
## 2018 68.05066
##           Aug      Sep      Oct      Nov      Dec
## 2016 68.05066 68.05066 68.05066 68.05066 68.05066
## 2017 68.05066 68.05066 68.05066 68.05066 68.05066
## 2018
##
## $se
##           Jan      Feb      Mar      Apr      May      Jun      Jul
## 2016          1.131821 1.683567 2.094702 2.437449 2.737615 3.007975
## 2017 4.285812 4.463358 4.634107 4.798784 4.957994 5.112248 5.261983
## 2018 6.083481
##           Aug      Sep      Oct      Nov      Dec
## 2016 3.255963 3.486355 3.702439 3.906588 4.100586
## 2017 5.407573 5.549344 5.687583 5.822540 5.954440
## 2018
```

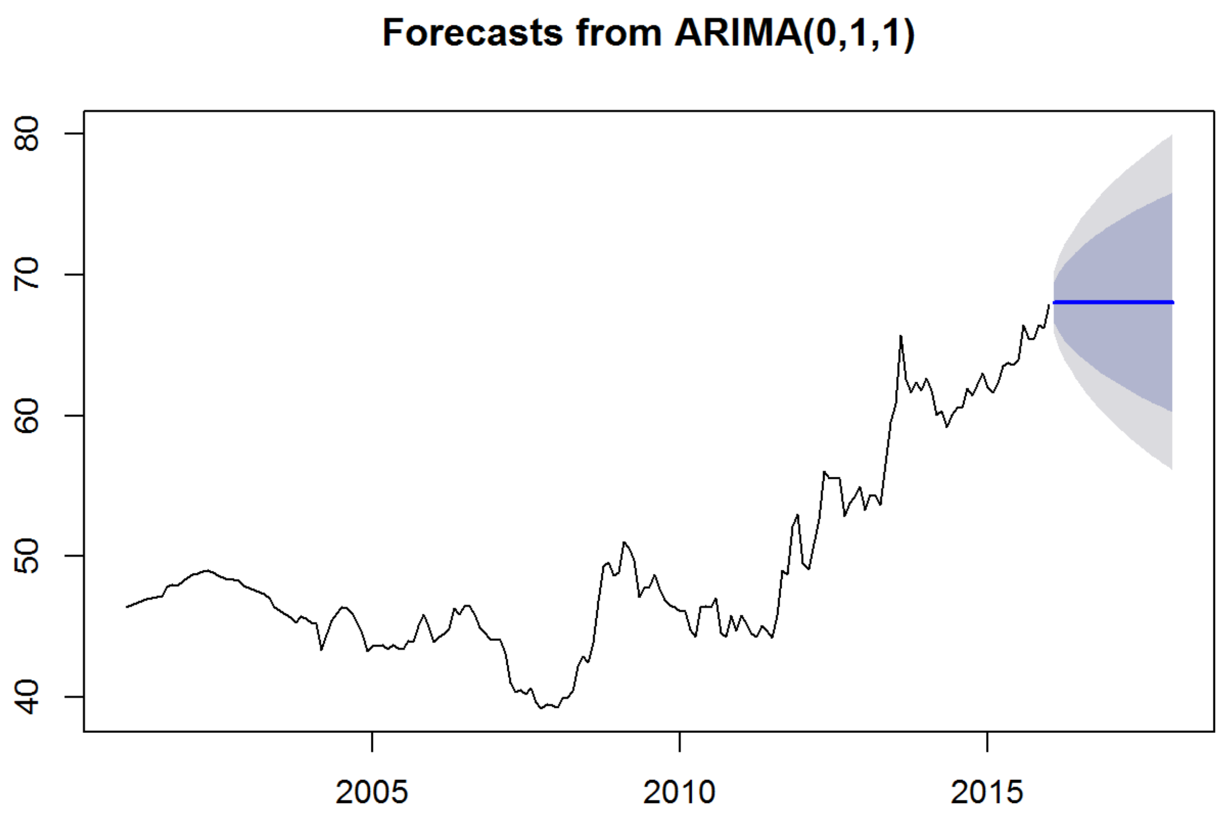
```
ts.plot(cbind(data.ts, data.ima_predict$pred+data.ima_predict$se), lty = 1:2)
```




```
data.ima_forecast = forecast(data.ima)
data.ima_forecast
```

```
##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Feb 2016       68.05066 66.60017 69.50114 65.83233 70.26899
## Mar 2016       68.05066 65.89308 70.20823 64.75093 71.35039
## Apr 2016       68.05066 65.36619 70.73513 63.94512 72.15620
## May 2016       68.05066 64.92694 71.17437 63.27334 72.82797
## Jun 2016       68.05066 64.54226 71.55905 62.68503 73.41628
## Jul 2016       68.05066 64.19578 71.90553 62.15513 73.94618
## Aug 2016       68.05066 63.87797 72.22334 61.66909 74.43223
## Sep 2016       68.05066 63.58271 72.51860 61.21753 74.88379
## Oct 2016       68.05066 63.30579 72.79552 60.79401 75.30730
## Nov 2016       68.05066 63.04416 73.05715 60.39388 75.70743
## Dec 2016       68.05066 62.79554 73.30577 60.01365 76.08766
## Jan 2017       68.05066 62.55817 73.54315 59.65062 76.45069
## Feb 2017       68.05066 62.33063 73.77068 59.30263 76.79868
## Mar 2017       68.05066 62.11181 73.98950 58.96797 77.13334
## Apr 2017       68.05066 61.90077 74.20055 58.64521 77.45610
## May 2017       68.05066 61.69673 74.40458 58.33317 77.76815
## Jun 2017       68.05066 61.49905 74.60227 58.03083 78.07048
## Jul 2017       68.05066 61.30715 74.79416 57.73736 78.36395
## Aug 2017       68.05066 61.12057 74.98074 57.45201 78.64930
## Sep 2017       68.05066 60.93889 75.16243 57.17414 78.92717
## Oct 2017       68.05066 60.76173 75.33959 56.90320 79.19811
## Nov 2017       68.05066 60.58877 75.51254 56.63869 79.46263
## Dec 2017       68.05066 60.41973 75.68158 56.38017 79.72114
## Jan 2018       68.05066 60.25436 75.84695 56.12725 79.97406
```

```
plot(data.ima_forecast)
```


Forecasts from ARIMA(0,1,1)
80
70
60
50
40
2005
2010
2015