1)

a) The properties of MA don't depend on time: E[Yt] is constant over time and Cov(Yt, Yt-k) only depends on k, not time. So, it is stationary.

b)

$$E[Y_t]=0$$

$$Var(Y_t)=Var(E_t) + Var(w_1 * E_{t-1}) + Var(w_2 * E_{t-2}) = \sigma^2(1+w_1^2+w_2^2)$$

c)

$$E[Y_t Y_t] = \sigma^2(1+w^2_1+w^2_2)$$

$$E[Y_t Y_{t-1}] = \sigma^2(w_1 + w_1 w_2)$$

$$E[Y_t Y_{t-2}] = \sigma^{2*} W_2$$

$$E[Y_t Y_{t-k}] = 0$$
 , k=3,4,5....

Corr
$$(Y_t, Y_{t+1}) = E[Y_t Y_{t+1}] / E[Y_t Y_t] = (W_1 + W_{1*} W_2) / (1 + W_{1*}^2 + W_{2}^2)$$

Corr
$$(Y_t, Y_{t+2}) = E[Y_t Y_{t+2}] / E[Y_t Y_t] = W_2 / (1 + W_1^2 + W_2^2)$$

Corr
$$(Y_t, Y_{t+k}) = 0$$
, k=3,4,5...

2)

a)

AR(1):
$$Y_t = \mu + \varphi^* Y_{t-1} + \varepsilon_t$$

= 10 + 0.7* $Y_{t-1} + \varepsilon_t$

$$Y_{20} = 12.5$$

$$Y_{21|20} = E[Y_{21} | Y_{20}] = E[10 + 0.7* Y_{20} + \varepsilon_{21} | Y_{20}] = 10 + 0.7*E[Y_{20} | Y_{20}] + E[\varepsilon_{21} | Y_{20}]$$

=10 + 0.7*12.5 = 18.75

$$Y_{22|20} = E[Y_{22} \mid Y_{20}] = E[10 + 0.7* Y_{21} + \varepsilon_{22} \mid Y_{20}] = 10 + 0.7* E[Y_{21} \mid Y_{20}] + E[\varepsilon_{22} \mid Y_{20}]$$

=10+0.7*18.75 = 23.125

$$Y_{23|20} = E[Y_{23} \mid Y_{20}] = E[10 + 0.7* Y_{22} + \varepsilon_{23} \mid Y_{20}] = 10 + 0.7* E[Y_{22} \mid Y_{20}] + E[\varepsilon_{23} \mid Y_{20}]$$

=10+0.7*23.125 = 26.1875

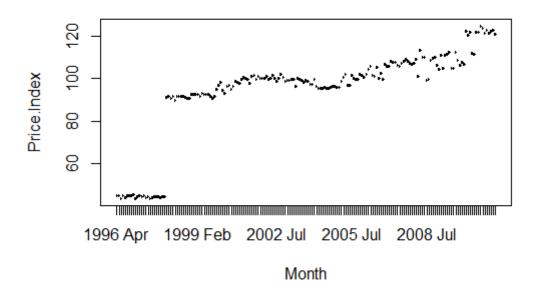
b)
$$Y_{21}-Y_{21|20}=10+0.7*\ Y_{20}+\ \epsilon_{21}-10-0.7*\ Y_{20}=\ \epsilon_{21}$$

$$Y_{22}-Y_{22|20}=10+0.7*\ Y_{21}+\ \epsilon_{22}-10-0.7*\ Y_{21|20}=\ \epsilon_{22}+0.7*\ \epsilon_{21}$$

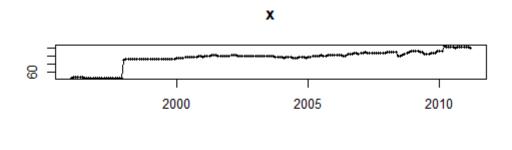
$$Y_{23}-Y_{23|20}=10+0.7*\ Y_{22}+\ \epsilon_{23}-10-0.7*\ Y_{22|20}=\ \epsilon_{23}+0.7*\ \epsilon_{22}+0.49*\ \epsilon_{22}$$
 3) a)
$$setwd("C:/Users/g\"ulce/Desktop/3-2/IE360/assignment3")$$

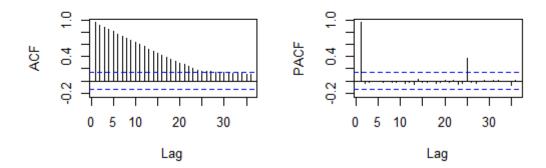
$$res<-read.csv("UKPlasticPrices.csv",skip=1,header=T)$$

$$plot(res)$$



x<-ts(res\$Price.Index,freq=12,start=1996)
library(forecast)
tsdisplay(x)</pre>

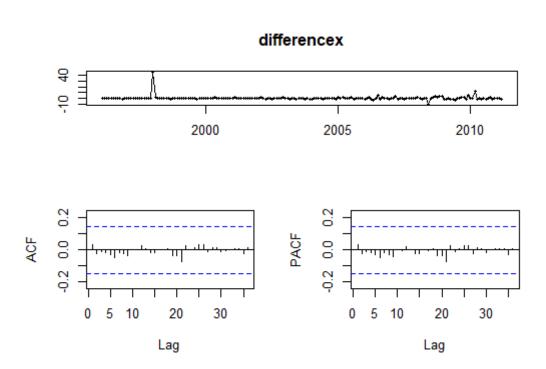




As it can be seen from the linear decrease in ACF, there is a trend in data which we should get rid of.

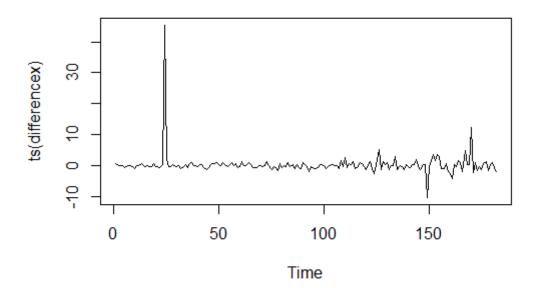
differencex<-diff(x)

tsdisplay(differencex)



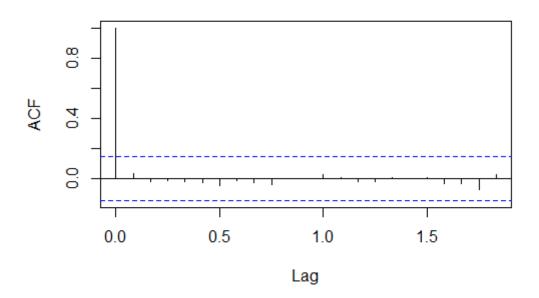
#Graphs seem ok.

plot(ts(differencex))



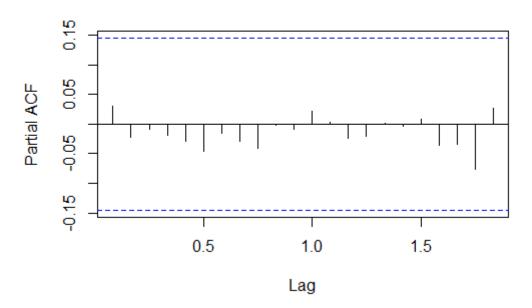
acf(differencex)

Series differencex



#As it can be seen from ACF, MA(1) is suitable for the data. pacf(differencex)

Series differencex



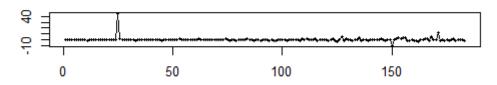
#As it can be seen from PartialACF, AR seems to be zero.

```
fit1<-Arima(ts(x),c(0,1,1),include.drift=T)
fit1
 #Series: ts(x)
#ARIMA(0,1,1) with drift
 #Coefficients:
             ma1
                     drift
                   0.4189
0.2841
          0.0309
 #s.e.
         0.0755
                                       log likelihood=-497.27
BIC=1010.14
 #sigma^2 estimated as 13.98:
#AIC=1000.53 AICc=1000.67
fit2<-Arima(ts(x),c(0,1,0),include.drift=T)
fit2
#Series: ts(x)
\#ARIMA(0,1,0) with drift
#Coefficients:
          drift
         0.4192
#s.e.
        0.2758
#sigma^2 estimated as 13.92: log likelihood=-497.35
                AICc=998.77
                                  BIC=1005.11
#AIC=998.7
```

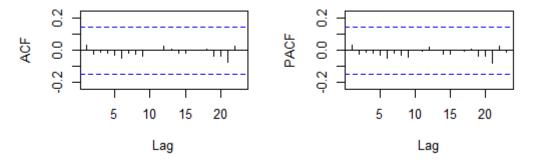
fit3<-Arima(ts(x),c(1,1,0),include.drift=T)

```
#Series: ts(x)
\#ARIMA(1,1,0) with drift
#Coefficients:
#
          ar1
                drift
       0.0296
               0.4189
#s.e.
       0.0740
               0.2840
#sigma^2 estimated as 13.98:
                               log likelihood=-497.27
#AIC=1000.54
                               BIC=1010.15
               AICc=1000.68
fit4<-Arima(ts(x),c(0,0,1),include.drift=T)</pre>
fit4
#Series: ts(x)
\#ARIMA(0,0,1) with drift
#Coefficients:
#
                intercept
                            drift
          ma1
                           0.3179
       0.8207
                  65.1318
                   2.0209
#s.e.
       0.0303
                           0.0190
                               log likelihood=-629.52
#sigma^2 estimated as 57.54:
               AICc=1267.26
#AIC=1267.03
                               BIC=1279.87
#It can be seen that taking the difference is important!
```

residuals(fit2)



#Since the lowest AIC and BIC values are in fit2, fit2 is chosen.



#Graphs seem ok.

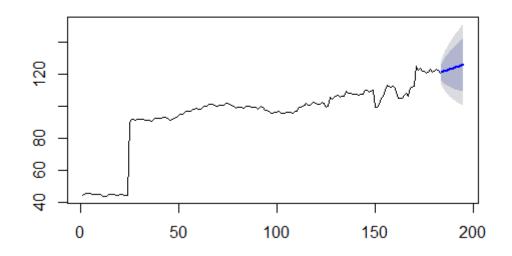
tsdisplay(residuals(fit2))

b)
forecastfit2<-(forecast(fit2, h=12))</pre>

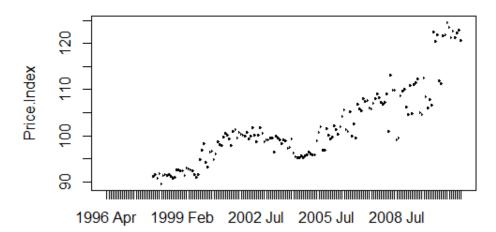
forecastfit2 Lo 95 Lo 80 Hi 80 Point Forecast #184 121.0192 116.2386 125.7999 113.7078 128.3306 #185 121.4385 114.6776 128.1994 111.0986 131.7784 #186 121.8577 113.5773 130.1381 109.1940 134.5214 122.2769 112.7156 131.8383 107.6541 136.8997 #187 #188 122.6962 112.0062 133.3861 106.3474 139.0450 #189 123.1154 111.4052 134.8256 105.2062 141.0246 #190 123.5346 110.8861 136.1831 104.1905 142.8788 #191 123.9538 110.4321 137.4756 103.2741 144.6336 #192 124.3731 110.0311 138.7151 102.4389 146.3073 #193 124.7923 109.6745 139.9101 101.6716 147.9130 #194 125.2115 109.3558 141.0672 100.9623 149.4607 125.6308 109.0700 142.1915 100.3033 150.9582 #195

plot(forecastfit2)

Forecasts from ARIMA(0,1,0) with drift

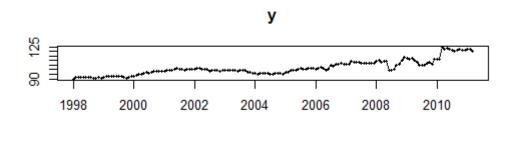


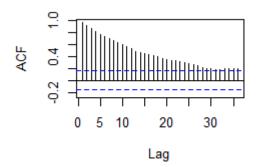
c) res2<-res[c(-1:-24),] plot(res2)

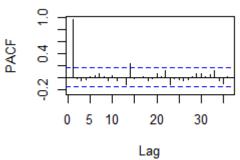


Month

y<-ts(res2\$Price.Index,freq=12,start=1998)
tsdisplay(y)





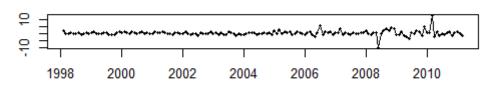


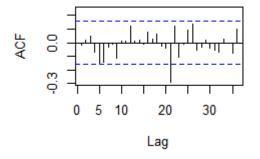
As it can be seen from the linear decrease in ACF, there is a trend in data which we should get rid of.

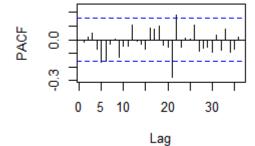
differencey<-diff(y)

tsdisplay(differencey)

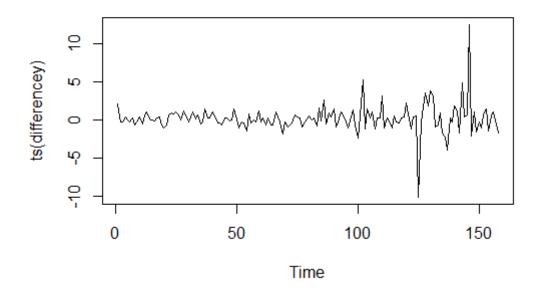






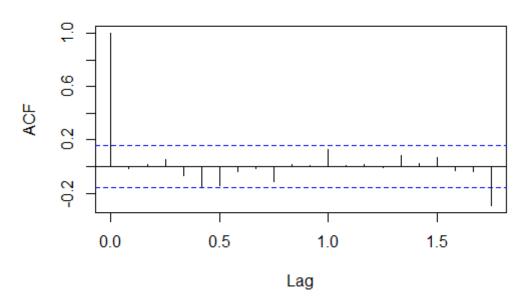


plot(ts(differencey))



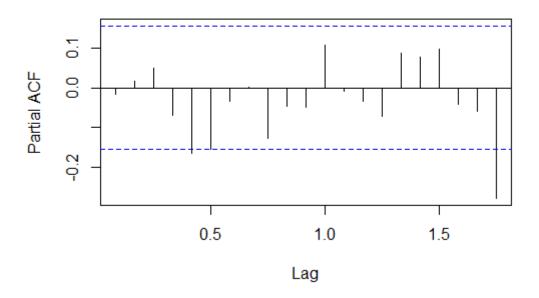
acf(differencey)

Series differencey



#As it can be seen from ACF, MA(1) is suitable for the data. pacf(differencey)

Series differencey



```
auto.arima(ts(y), seasonal=FALSE)
#Series: ts(y)
\#ARIMA(0,1,0)
#sigma^2 estimated as 3.134: log likelihood=-314.44
#AIC=630.87
             AICc=630.9
                           BIC=633.93
fity<- auto.arima(ts(y), seasonal=FALSE)</pre>
forecastfity<-(forecast(fity, h=12))</pre>
forecastfity
                                                 Hi 95
# Point Forecast
                     Lo 80
                               Hi 80
                                        Lo 95
              120.6 118.3312 122.8688 117.1302 124.0698
#160
#161
              120.6 117.3915 123.8085 115.6930 125.5070
#162
              120.6 116.6704 124.5296 114.5901 126.6099
#163
              120.6 116.0624 125.1376 113.6604 127.5396
#164
              120.6 115.5269 125.6731 112.8413 128.3587
#165
              120.6 115.0426 126.1574 112.1008 129.0992
#166
              120.6 114.5974 126.6026 111.4198 129.7802
              120.6 114.1829 127.0171 110.7859 130.4141
#167
              120.6 113.7937 127.4063 110.1906 131.0094
#168
#169
              120.6 113.4255 127.7745 109.6275 131.5725
#170
              120.6 113.0753 128.1247 109.0920 132.1080
              120.6 112.7407 128.4593 108.5803 132.6197
#171
```

plot(forecastfity)

Forecasts from ARIMA(0,1,0)

