DollarIndex

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```r
library(readxl)
Data <- read_excel("~/Desktop/FinalPaperR/UpdatedData.xls")
```

```
## New names:
## * `` -> `..11`
## * `` -> `..12`
```

```r
#View(Data)
library(forecast)
```

```r
DollarIndex <- Data[53:236,9]
DollarIndexts <- ts(data = DollarIndex, start = c(1973,1), frequency = 4, end = c(2018,4)) # data start

DollarIndex2 <- Data[57:236,9]
DollarIndex2ts <- ts(data = DollarIndex2, start = c(1974,1), frequency = 4, end = c(2018,4)) # data sta
```

ARIMA TESTING d = 0:

mean trend:

```r
R000mean <- Arima(DollarIndexts, order = c(0,0,0))
summary(R000mean)
```

```
## Series: DollarIndexts
## ARIMA(0,0,0) with non-zero mean
##
## Coefficients:
##          mean
##       95.9379
## s.e.   0.6679
##
## sigma^2 estimated as 82.54:  log likelihood=-666.6
## AIC=1337.21   AICc=1337.27   BIC=1343.64
##
## Training set error measures:
##                          ME     RMSE      MAE        MPE     MAPE     MASE
## Training set -1.814864e-14 9.060298 7.071943 -0.8348537 7.257095 1.633569
##                   ACF1
## Training set 0.9647064
```

```r
RES_mean = residuals(R000mean)
```

BIC = 1343.64

linear trend:

```r
R000lt <- Arima(DollarIndexts, order = c(0,0,0), include.drift = TRUE)
summary(R000lt)
```

```
## Series: DollarIndexts
## ARIMA(0,0,0) with drift
```

```
##
## Coefficients:
##       intercept    drift
##         98.8381  -0.0314
## s.e.     1.3185   0.0124
##
## sigma^2 estimated as 80.19:  log likelihood=-663.44
## AIC=1332.88   AICc=1333.01   BIC=1342.53
##
## Training set error measures:
##                         ME     RMSE      MAE        MPE    MAPE     MASE
## Training set -1.333272e-12 8.905925 7.303373 -0.8056882 7.49351 1.687028
##                  ACF1
## Training set 0.963065
```

BIC = 1342.53

trend + seasonal dummies:

```r
Sdum <- seasonaldummy(DollarIndexts)
R000sd <- Arima(DollarIndexts, order = c(0,0,0), include.drift = TRUE, xreg = Sdum)
summary(R000sd)
```

```
## Series: DollarIndexts
## Regression with ARIMA(0,0,0) errors
##
## Coefficients:
##       intercept    drift      Q1       Q2      Q3
##         98.8161  -0.0314  0.0887  -0.1051  0.1033
## s.e.     1.7535   0.0124  1.8573   1.8571  1.8570
##
## sigma^2 estimated as 81.52:  log likelihood=-663.43
## AIC=1338.87   AICc=1339.34   BIC=1358.15
##
## Training set error measures:
##                         ME     RMSE      MAE        MPE     MAPE     MASE
## Training set -1.168379e-12 8.905536 7.302618 -0.8056274 7.492816 1.686853
##                   ACF1
## Training set 0.9632563
```

BIC = 1358.15

trend + seasonal differences:

```r
R000sf <- Arima(DollarIndexts, order = c(0,0,0), seasonal = c(0,1,0), include.drift = TRUE)
summary(R000sf)
```

```
## Series: DollarIndexts
## ARIMA(0,0,0)(0,1,0)[4] with drift
##
## Coefficients:
##        drift
##       0.0004
## s.e.  0.1040
##
## sigma^2 estimated as 31.33:  log likelihood=-564.91
## AIC=1133.83   AICc=1133.9   BIC=1140.21
```

```
##
## Training set error measures:
##                       ME     RMSE     MAE        MPE     MAPE      MASE
## Training set 0.002151536 5.520607 4.23714 -0.1503283 4.329701 0.9787496
##                   ACF1
## Training set 0.8496842
```

BIC = 1140.21

compare w/ same sample size:

```
R0002 <- Arima(DollarIndex2ts, order = c(0,0,0), include.drift = TRUE)
summary(R0002)
```

```
## Series: DollarIndex2ts
## ARIMA(0,0,0) with drift
##
## Coefficients:
##       intercept    drift
##         98.6915  -0.0312
## s.e.     1.3464   0.0129
##
## sigma^2 estimated as 81.81:  log likelihood=-650.79
## AIC=1307.59   AICc=1307.72   BIC=1317.17
##
## Training set error measures:
##                         ME     RMSE      MAE        MPE     MAPE     MASE
## Training set -8.289834e-15 8.994243 7.412056 -0.8217289 7.605963 1.703259
##                   ACF1
## Training set 0.9648573
```

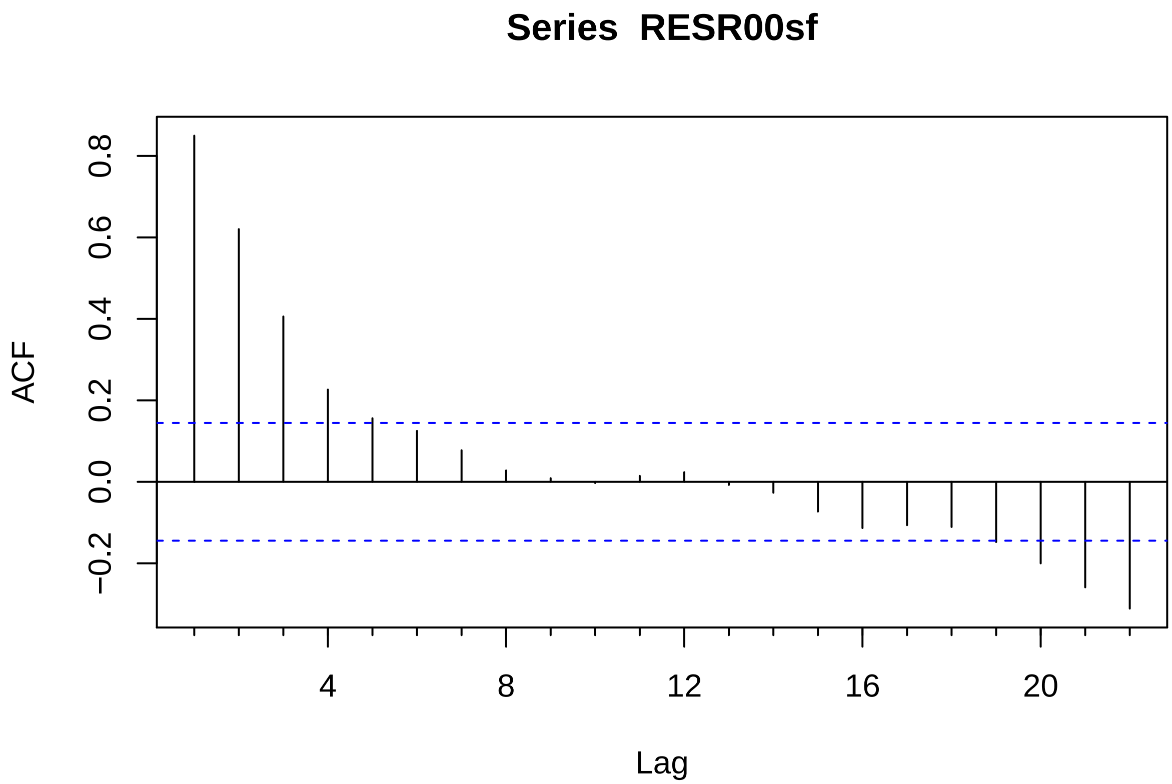
BIC = 1317.17

best model:

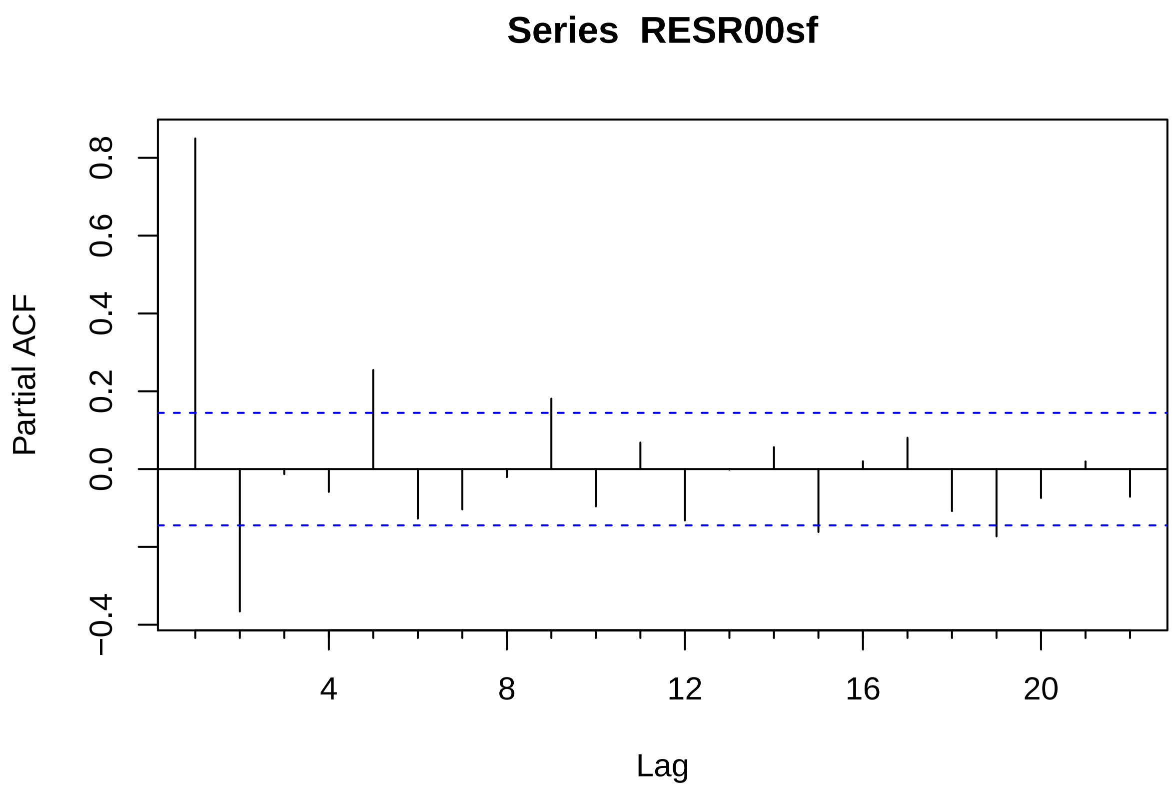
```
RESR00sf <- residuals(R000sf)
```

PAC's/ AC's:

```
Acf(RESR00sf)
```




```
Pacf(RESR00sf)
```



MA(4) or AR(4)

ARIMA testing:

```r
Rma4 <- Arima(DollarIndexts, order = c(0,0,4), seasonal = c(0,1,0), include.drift = TRUE)
summary(Rma4)
```

```
## Series: DollarIndexts
## ARIMA(0,0,4)(0,1,0)[4] with drift
##
## Coefficients:
##          ma1     ma2     ma3     ma4    drift
##       1.3294  1.3211  1.3446  0.3529  -0.0084
## s.e.  0.0706  0.0761  0.0834  0.0709   0.2142
##
## sigma^2 estimated as 4.846:  log likelihood=-401.69
## AIC=815.38   AICc=815.87   BIC=834.54
##
## Training set error measures:
##                      ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 0.02861031 2.146793 1.728893 0.01331864 1.792215 0.3993621
##                    ACF1
## Training set 0.00426291
```

BIC = 834.54

```r
Rar4 <- Arima(DollarIndexts, order = c(4,0,0), seasonal = c(0,1,0), include.drift = TRUE)
summary(Rar4)
```

```
## Series: DollarIndexts
## ARIMA(4,0,0)(0,1,0)[4] with drift
##
## Coefficients:
##          ar1      ar2     ar3      ar4   drift
##       1.1638  -0.3467  0.0122  -0.0458  0.0036
## s.e.  0.0741   0.1152  0.1162   0.0760  0.2279
##
## sigma^2 estimated as 7.323:  log likelihood=-432.89
## AIC=877.78   AICc=878.27   BIC=896.94
##
## Training set error measures:
##                      ME     RMSE      MAE         MPE     MAPE      MASE
## Training set 0.02180748 2.639181 2.064221 0.003394189 2.146652 0.4768206
##                    ACF1
## Training set 0.01383598
```

BIC = 896.94

```r
Rarma11 <- Arima(DollarIndexts, order = c(1,0,1), seasonal = c(0,1,0), include.drift = TRUE)
summary(Rarma11)
```

```
## Series: DollarIndexts
## ARIMA(1,0,1)(0,1,0)[4] with drift
##
## Coefficients:
##          ar1     ma1   drift
##       0.7512  0.4449  0.0013
## s.e.  0.0573  0.0917  0.2863
##
## sigma^2 estimated as 7.379:  log likelihood=-434.58
```

```
## AIC=877.16   AICc=877.39   BIC=889.93
##
## Training set error measures:
##                       ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 0.02840087 2.664196 2.079716 0.02062567 2.156987 0.4803999
##                     ACF1
## Training set 0.001224304
```

BIC = 889.93

```
Rma2 <- Arima(DollarIndexts, order = c(0,0,2), seasonal = c(0,1,0), include.drift = TRUE)
summary(Rma2)
```

```
## Series: DollarIndexts
## ARIMA(0,0,2)(0,1,0)[4] with drift
##
## Coefficients:
##          ma1     ma2   drift
##       1.0854  0.4047  0.0015
## s.e.  0.0720  0.0867  0.1425
##
## sigma^2 estimated as 9.677:  log likelihood=-458.81
## AIC=925.62   AICc=925.84   BIC=938.39
##
## Training set error measures:
##                     ME     RMSE      MAE         MPE     MAPE      MASE
## Training set 0.0105296 3.051086 2.354838 -0.03836274 2.427658 0.5439511
##                   ACF1
## Training set 0.1978423
```

BIC = 938.39

```
Rma3 <- Arima(DollarIndexts, order = c(0,0,3), seasonal = c(0,1,0), include.drift = TRUE)
summary(Rma3)
```

```
## Series: DollarIndexts
## ARIMA(0,0,3)(0,1,0)[4] with drift
##
## Coefficients:
##          ma1     ma2     ma3    drift
##       0.9923  0.9923  1.0000  -0.0042
## s.e.  0.0212  0.0559  0.0559   0.1696
##
## sigma^2 estimated as 5.425:  log likelihood=-412
## AIC=834   AICc=834.34   BIC=849.96
##
## Training set error measures:
##                       ME    RMSE      MAE         MPE     MAPE      MASE
## Training set 0.03106536 2.27798 1.833981 0.004903099 1.896429 0.4236368
##                   ACF1
## Training set 0.2997758
```

BIC = 849.96

```
Rarma14 <- Arima(DollarIndexts, order = c(1,0,4), seasonal = c(0,1,0), include.drift = TRUE)
summary(Rarma14)
```

```
## Series: DollarIndexts
```

```
## ARIMA(1,0,4)(0,1,0)[4] with drift
##
## Coefficients:
##          ar1     ma1     ma2     ma3     ma4    drift
##       0.0400  1.2949  1.2872  1.3113  0.3190  -0.0090
## s.e.  0.2017  0.1910  0.1901  0.1905  0.1885   0.2175
##
## sigma^2 estimated as 4.872:  log likelihood=-401.67
## AIC=817.34   AICc=817.99   BIC=839.69
##
## Training set error measures:
##                      ME     RMSE      MAE        MPE    MAPE     MASE
## Training set 0.02877304 2.146437 1.730403 0.01397242 1.79408 0.399711
##                      ACF1
## Training set -0.001134682
```

BIC = 839.69

```r
Rma5 <- Arima(DollarIndexts, order = c(0,0,5), seasonal = c(0,1,0), include.drift = TRUE)
summary(Rma5)
```

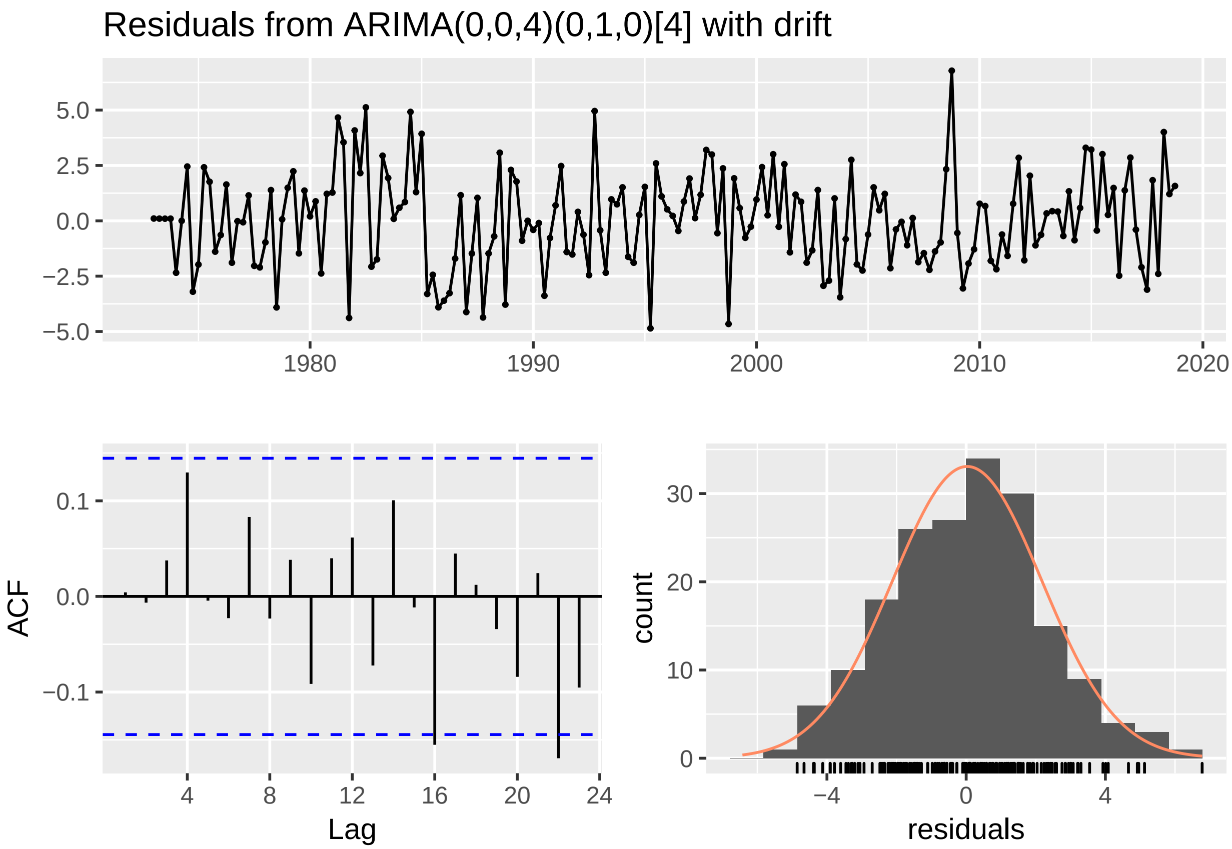
```
## Series: DollarIndexts
## ARIMA(0,0,5)(0,1,0)[4] with drift
##
## Coefficients:
##          ma1     ma2     ma3     ma4     ma5    drift
##       1.3350  1.3405  1.3643  0.3730  0.0142  -0.0089
## s.e.  0.0768  0.1245  0.1306  0.1244  0.0715   0.2174
##
## sigma^2 estimated as 4.872:  log likelihood=-401.67
## AIC=817.34   AICc=817.99   BIC=839.69
##
## Training set error measures:
##                      ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 0.02871899 2.146464 1.730401 0.01390263 1.794078 0.3997106
##                     ACF1
## Training set -0.00116923
```

BIC = 839.69

So, MA(4) is our best model.

White noise?

```r
checkresiduals(Rma4)
```

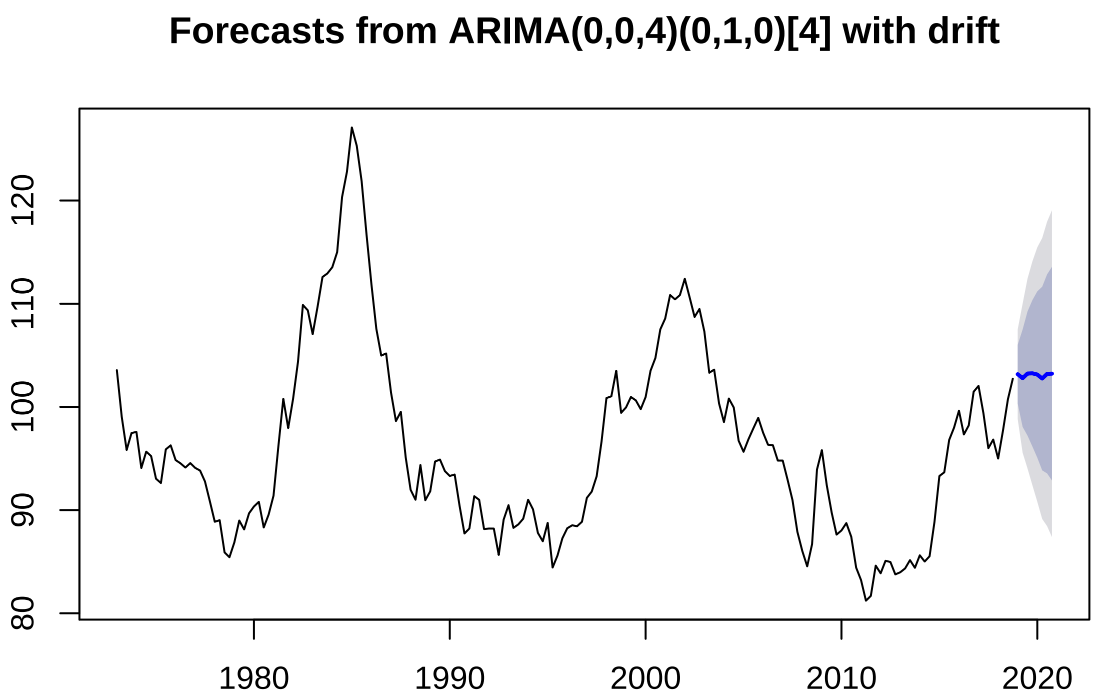



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,4)(0,1,0)[4] with drift
## Q* = 5.0168, df = 3, p-value = 0.1706
##
## Model df: 5.   Total lags used: 8
```

White noise!

Forecast: QUESTION (what to forecast on)?

```
plot(forecast(Rma4,h=8))
```




```r
for011 <- forecast(Rma4, h = 8)
print(for011)
```

```
##         Point Forecast      Lo 80    Hi 80    Lo 95    Hi 95
## 2019 Q1       103.1661 100.32198 106.0103 98.81638 107.5159
## 2019 Q2       102.7802  98.06091 107.4995 95.56265 109.9978
## 2019 Q3       103.2285  97.21795 109.2390 94.03617 112.4208
## 2019 Q4       103.2515  96.15785 110.3451 92.40270 114.1003
## 2020 Q1       103.1326  95.07028 111.1949 90.80234 115.4628
## 2020 Q2       102.7467  93.84817 111.6452 89.13757 116.3558
## 2020 Q3       103.1949  93.54931 112.8406 88.44322 117.9467
## 2020 Q4       103.2179  92.86269 113.5732 87.38095 119.0550
```

ARIMA TESTING d = 1:

Test for a unit root just to see

Let's run the KPSS and ADF tests:

```r
Rmean <- Arima(DollarIndexts, order = c(0,0,0))
ndiffs(RES_mean,test="kpss")
```

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

```r
ndiffs(RES_mean,test="adf")
```

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

This implies that there is a unit root, so lets see how taking it out changes the BIC:

mean trend:

```r
R010mean <- Arima(DollarIndexts, order = c(0,1,0))
summary(R010mean)
```

```
## Series: DollarIndexts
## ARIMA(0,1,0)
```

```
##
## sigma^2 estimated as 5.257:  log likelihood=-411.51
## AIC=825.02   AICc=825.04   BIC=828.23
##
## Training set error measures:
##                        ME     RMSE      MAE         MPE     MAPE      MASE
## Training set -0.003891554 2.286517 1.827156 -0.03121957 1.888098 0.4220601
##                   ACF1
## Training set 0.2934896
```

BIC = 828.23

linear trend:

```
R010lt <- Arima(DollarIndexts, order = c(0,1,0), include.drift = TRUE)
summary(R010lt)
```

```
## Series: DollarIndexts
## ARIMA(0,1,0) with drift
##
## Coefficients:
##         drift
##       -0.0045
## s.e.   0.1695
##
## sigma^2 estimated as 5.286:  log likelihood=-411.51
## AIC=827.02   AICc=827.09   BIC=833.44
##
## Training set error measures:
##                        ME     RMSE      MAE         MPE     MAPE      MASE
## Training set 0.0005628186 2.286513 1.827513 -0.02653575 1.888425 0.4221426
##                   ACF1
## Training set 0.2935108
```

BIC = 833.44

trend + seasonal dummies:

```
Sdum2 <- seasonaldummy(DollarIndexts)
R010sd <- Arima(DollarIndexts, order = c(0,1,0), xreg = Sdum2)
summary(R010sd)
```

```
## Series: DollarIndexts
## Regression with ARIMA(0,1,0) errors
##
## Coefficients:
##           Q1       Q2      Q3
##       0.1722  -0.0495  0.1312
## s.e.  0.2943   0.3379  0.2921
##
## sigma^2 estimated as 5.312:  log likelihood=-410.95
## AIC=829.9   AICc=830.12   BIC=842.73
##
## Training set error measures:
##                        ME     RMSE     MAE         MPE     MAPE      MASE
## Training set -0.002956422 2.279508 1.82469 -0.03016412 1.885264 0.4214907
##                   ACF1
```

```
## Training set 0.3008621
```

BIC = 842.73

trend + seasonal differences:

```r
R010sf <- Arima(DollarIndexts, order = c(0,1,0), seasonal = c(0,1,0))
summary(R010sf)
```

```
## Series: DollarIndexts
## ARIMA(0,1,0)(0,1,0)[4]
##
## sigma^2 estimated as 9.017:  log likelihood=-450.81
## AIC=903.62   AICc=903.65   BIC=906.81
##
## Training set error measures:
##                     ME     RMSE      MAE        MPE     MAPE     MASE
## Training set 0.0637363 2.961828 2.270991 0.08956863 2.361058 0.524583
##                   ACF1
## Training set 0.2825227
```

BIC = 906.81

compare w/ same sample size:

```r
R0102 <- Arima(DollarIndex2ts, order = c(0,1,0))
summary(R0102)
```

```
## Series: DollarIndex2ts
## ARIMA(0,1,0)
##
## sigma^2 estimated as 5.188:  log likelihood=-401.33
## AIC=804.66   AICc=804.68   BIC=807.85
##
## Training set error measures:
##                      ME     RMSE      MAE         MPE     MAPE      MASE
## Training set 0.02924704 2.271282 1.815111 0.002114955 1.876169 0.4171049
##                   ACF1
## Training set 0.2944004
```

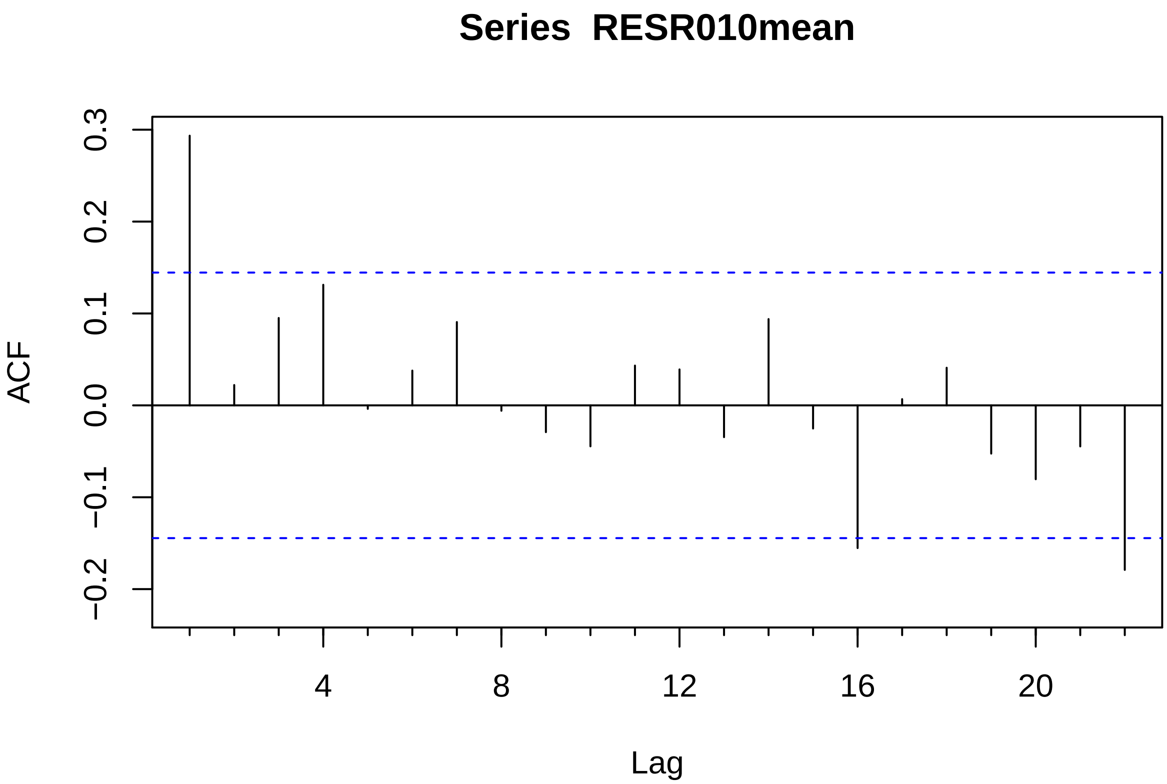
BIC = 807.85

best model:

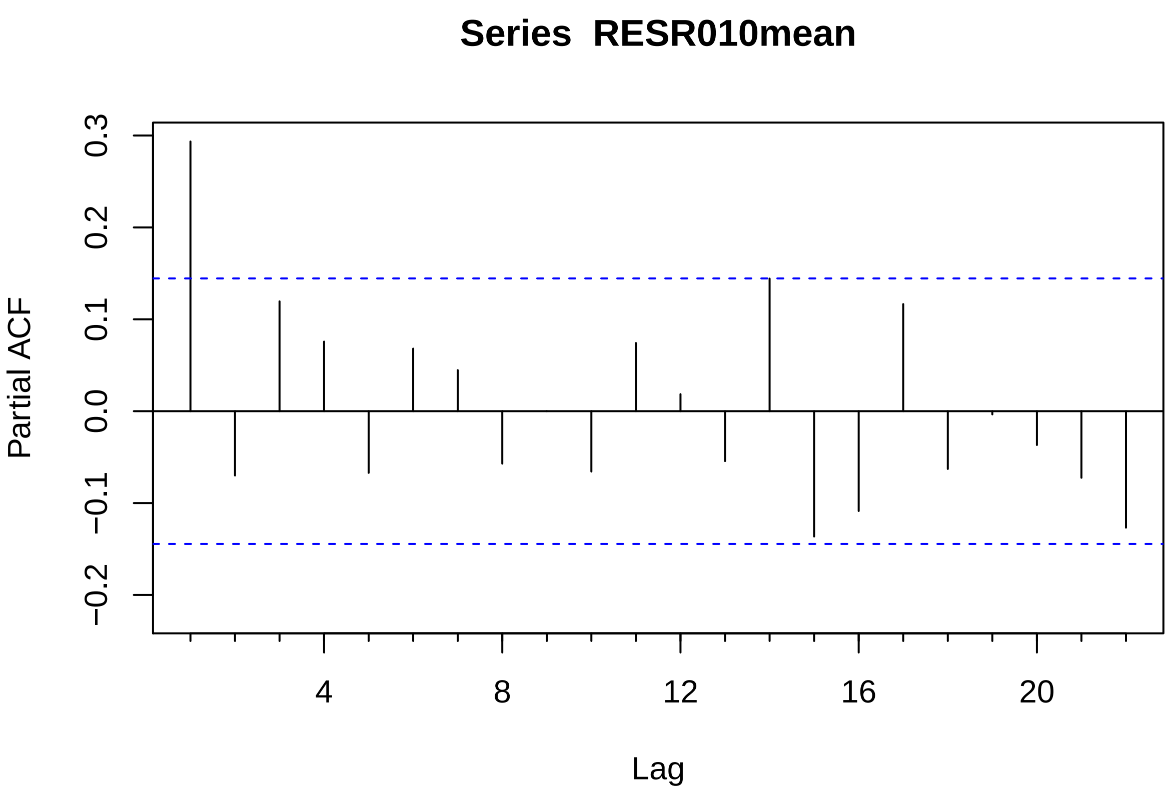
```r
RESR010mean <- residuals(R010mean)
```

PAC's/ AC's:

```r
Acf(RESR010mean)
```




```r
Pacf(RESR010mean)
```



ARIMA testing:

```r
Rima11 <- Arima(DollarIndexts, order = c(0,1,1))
summary(Rima11)
```

```
## Series: DollarIndexts
## ARIMA(0,1,1)
##
## Coefficients:
##          ma1
##       0.3236
## s.e.  0.0688
##
## sigma^2 estimated as 4.779:  log likelihood=-402.35
## AIC=808.7   AICc=808.76   BIC=815.12
##
## Training set error measures:
##                         ME     RMSE      MAE         MPE     MAPE
## Training set -0.0003146226 2.174219 1.759237 -0.01734548 1.824451
##                   MASE         ACF1
## Training set 0.4063714 -0.001025563
```

BIC = 815.12

```r
Rari11 <- Arima(DollarIndexts, order = c(1,1,0))
summary(Rari11)
```

```
## Series: DollarIndexts
## ARIMA(1,1,0)
##
## Coefficients:
##          ar1
##       0.2999
## s.e.  0.0712
##
## sigma^2 estimated as 4.817:  log likelihood=-403.06
## AIC=810.12   AICc=810.19   BIC=816.54
##
## Training set error measures:
##                       ME     RMSE      MAE         MPE     MAPE      MASE
## Training set 0.001827526 2.182791 1.780609 -0.01297951 1.846864 0.4113081
##                     ACF1
## Training set 0.01487932
```

BIC = 816.54

```r
Rarima111 <- Arima(DollarIndexts, order = c(1,1,1))
summary(Rarima111)
```

```
## Series: DollarIndexts
## ARIMA(1,1,1)
##
## Coefficients:
##          ar1     ma1
##       0.0220  0.3043
## s.e.  0.2161  0.2035
##
## sigma^2 estimated as 4.805:  log likelihood=-402.34
```

```
## AIC=810.69   AICc=810.82   BIC=820.32
##
## Training set error measures:
##                          ME     RMSE      MAE         MPE     MAPE
## Training set -0.0001980127 2.174156 1.760857 -0.01699674 1.826232
##                    MASE         ACF1
## Training set 0.4067456 -0.003743528
```

BIC = 820.32

```
Rima12 <- Arima(DollarIndexts, order = c(0,1,2))
summary(Rima12)
```

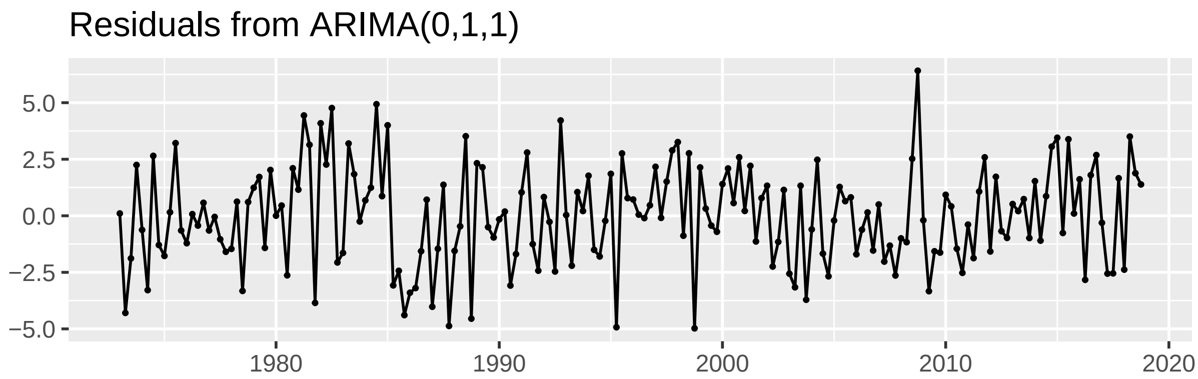
```
## Series: DollarIndexts
## ARIMA(0,1,2)
##
## Coefficients:
##          ma1     ma2
##       0.3262  0.0065
## s.e.  0.0741  0.0668
##
## sigma^2 estimated as 4.805:  log likelihood=-402.34
## AIC=810.69   AICc=810.82   BIC=820.32
##
## Training set error measures:
##                         ME    RMSE      MAE         MPE     MAPE      MASE
## Training set -0.000212206 2.17416 1.760718 -0.01703091 1.826081 0.4067134
##                      ACF1
## Training set -0.003641006
```

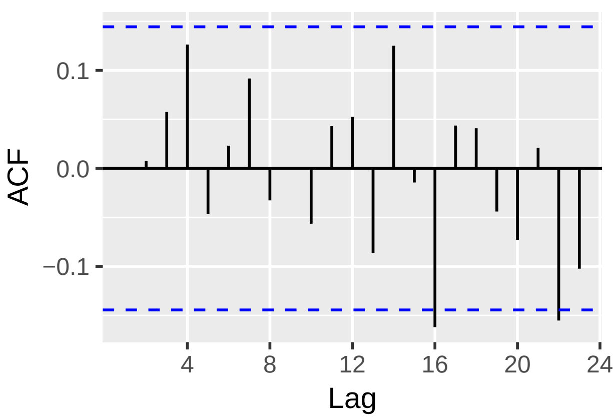
BIC = 820.32

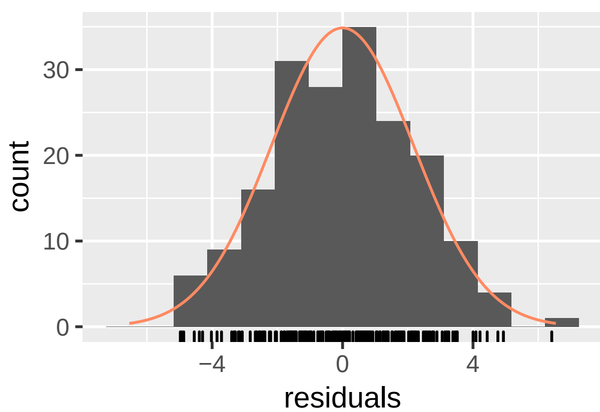
So, MA(1) is our best model.

White noise?

```
checkresiduals(Rima11)
```





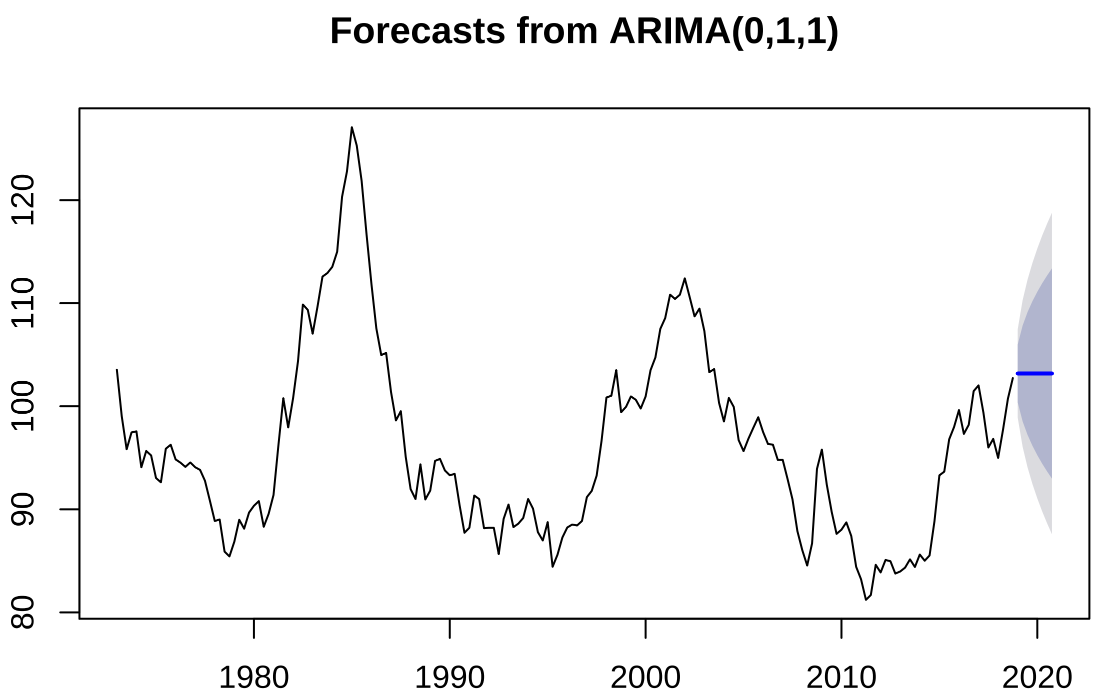



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,1)
## Q* = 6.0286, df = 7, p-value = 0.5364
##
## Model df: 1.   Total lags used: 8
```

White noise!

Forecast: QUESTION (what to forecast on and how many quarters out)?

```
plot(forecast(Rima11,h=8))
```




```
for0112 <- forecast(Rima11, h = 8)
print(for0112)
```

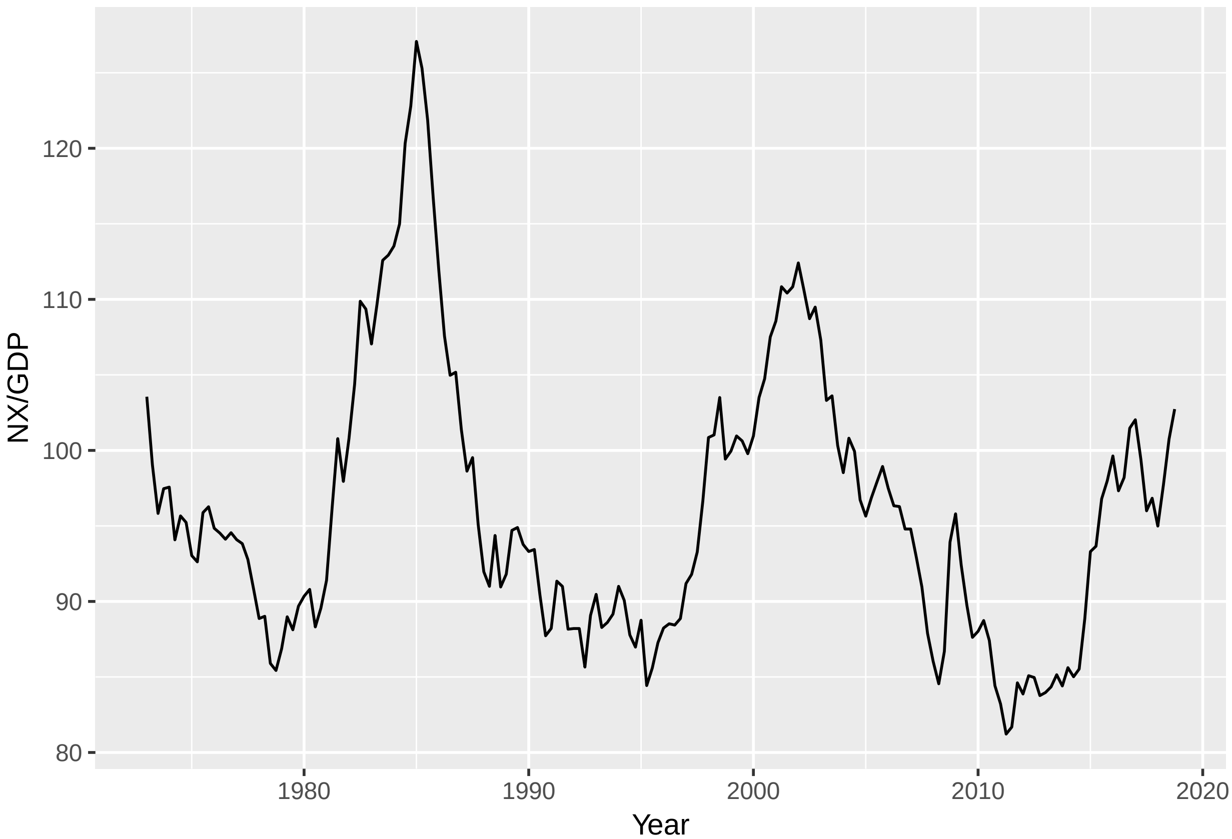
```
##         Point Forecast      Lo 80    Hi 80    Lo 95    Hi 95
## 2019 Q1       103.1832 100.38157 105.9849 98.89847 107.4680
## 2019 Q2       103.1832  98.53555 107.8309 96.07522 110.2912
## 2019 Q3       103.1832  97.23742 109.1290 94.08992 112.2765
## 2019 Q4       103.1832  96.17579 110.1906 92.46628 113.9001
## 2020 Q1       103.1832  95.25506 111.1114 91.05815 115.3083
## 2020 Q2       103.1832  94.43066 111.9358 89.79734 116.5691
## 2020 Q3       103.1832  93.67749 112.6889 88.64547 117.7210
## 2020 Q4       103.1832  92.97976 113.3867 87.57839 118.7880
```

- forecasts 2 years out?

SMOOTHING MODELS:

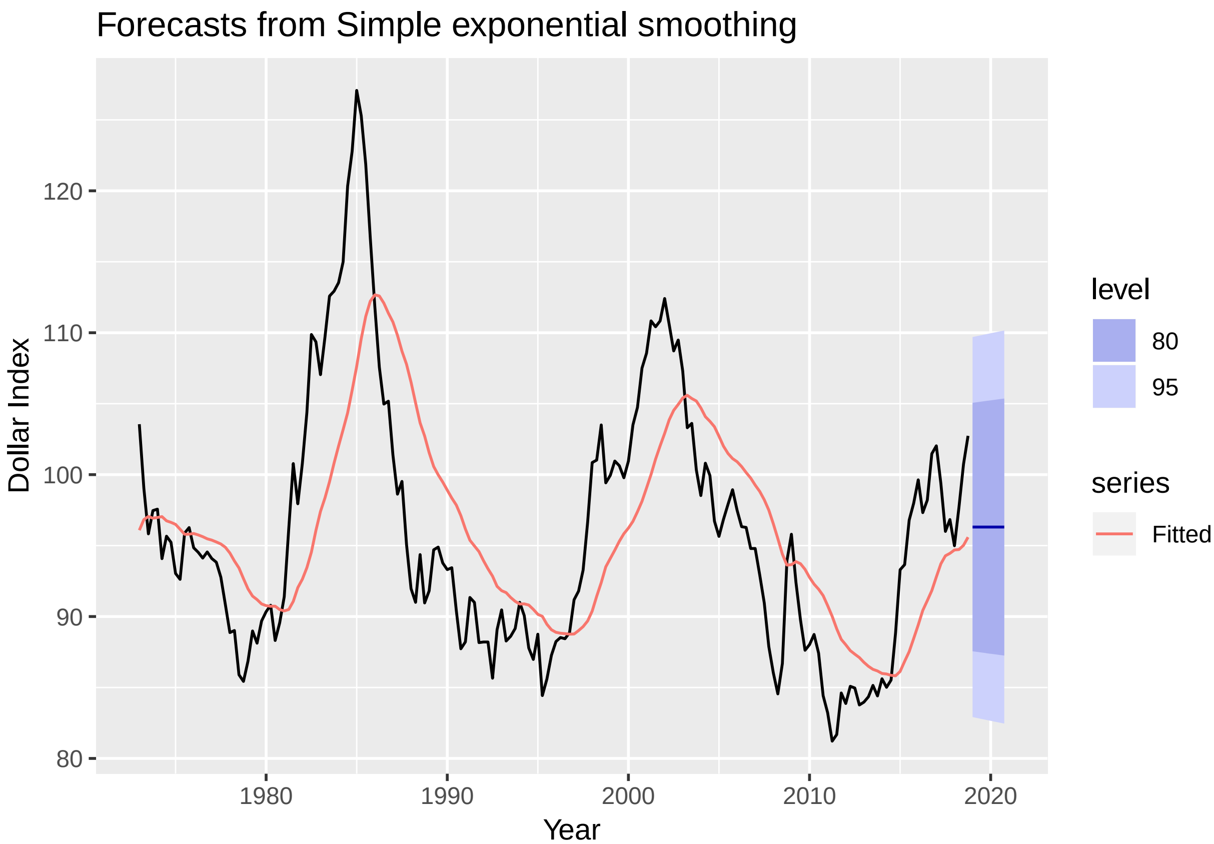
Plot:

```
library(ggplot2)
autoplot(DollarIndexts) +
ylab("NX/GDP") + xlab("Year")
```

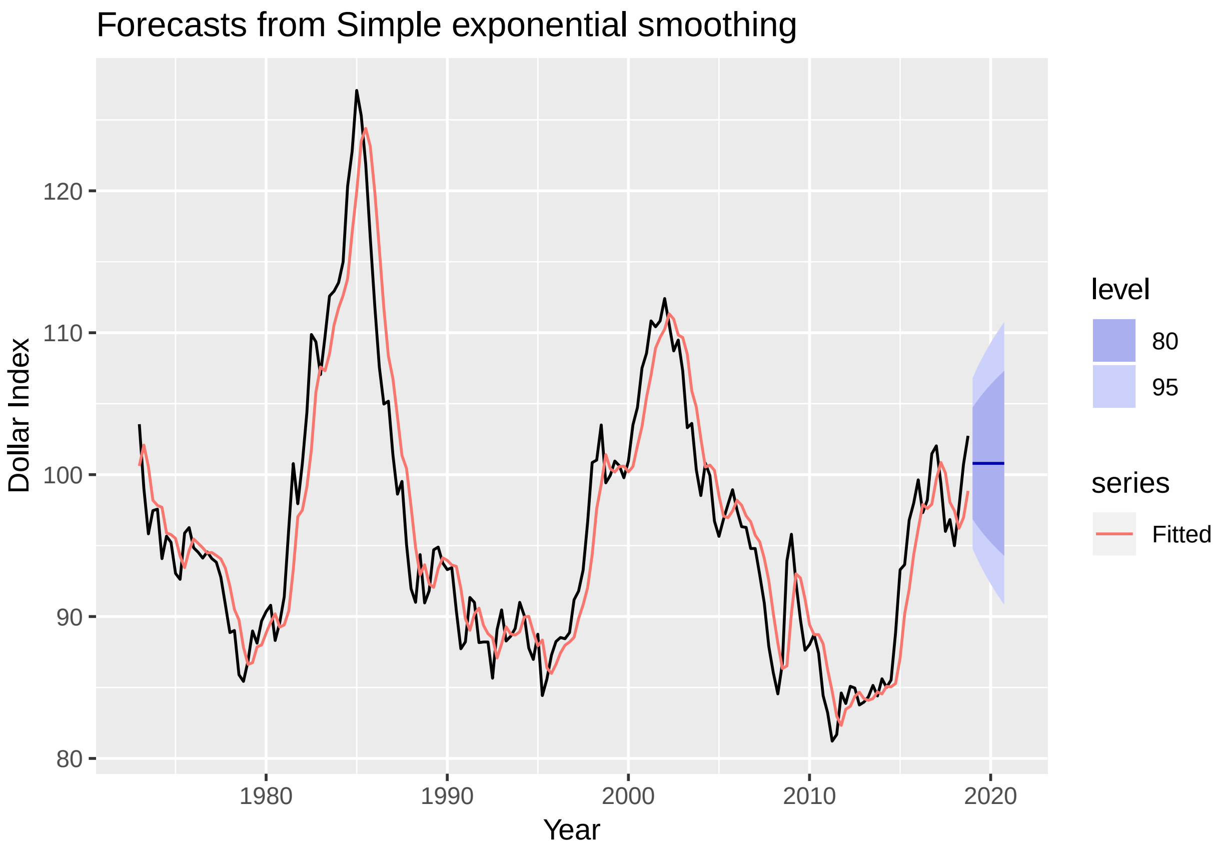


Simple Smoothing:

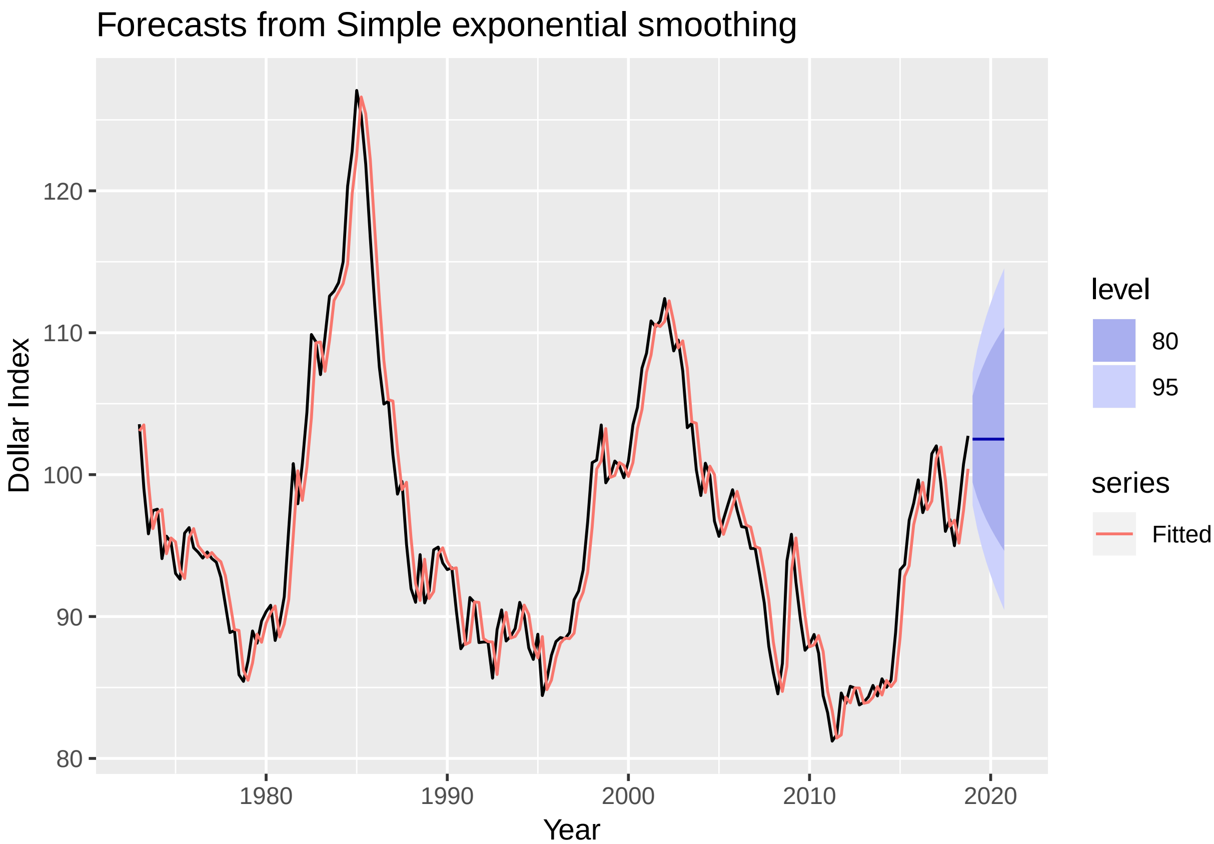
```r
s1 <- ses(DollarIndexts, h = 8, level = c(80, 95), alpha = 0.1)
autoplot(s1) +
autolayer(fitted(s1), series="Fitted") +
ylab("Dollar Index") + xlab("Year")
```




```
s2 <- ses(DollarIndexts, h = 8, level = c(80, 95), alpha = 0.5)
autoplot(s2) +
autolayer(fitted(s2), series="Fitted") +
ylab("Dollar Index") + xlab("Year")
```




```
s3 <- ses(DollarIndexts, h = 8, level = c(80, 95), alpha = 0.9)
autoplot(s3) +
autolayer(fitted(s3), series="Fitted") +
ylab("Dollar Index") + xlab("Year")
```



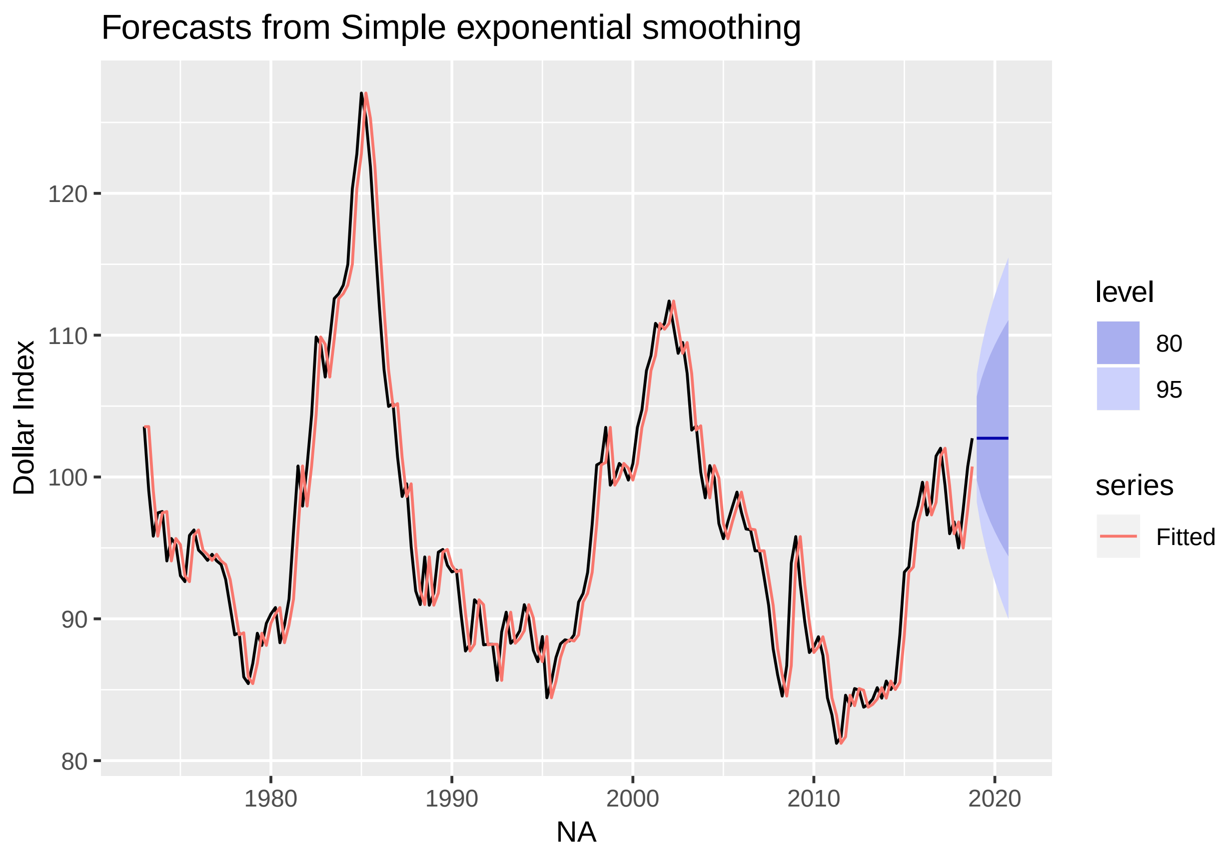

```
ss4 <- ses(DollarIndexts)
 summary(ss4)
```

```
##
## Forecast method: Simple exponential smoothing
##
## Model Information:
## Simple exponential smoothing
##
## Call:
##  ses(y = DollarIndexts)
##
##   Smoothing parameters:
##     alpha = 0.9999
##
##   Initial states:
##     l = 103.547
##
##   sigma:  2.2991
##
##      AIC     AICc      BIC
## 1269.904 1270.037 1279.549
##
## Error measures:
##                        ME     RMSE      MAE         MPE     MAPE      MASE
## Training set -0.004416794 2.286572 1.826669 -0.03173101 1.887629 0.4219478
##                   ACF1
```

```
## Training set 0.2940282
##
## Forecasts:
##         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2019 Q1       102.7344 99.78798 105.6808 98.22825 107.2406
## 2019 Q2       102.7344 98.56775 106.9011 96.36205 109.1067
## 2019 Q3       102.7344 97.63140 107.8374 94.93003 110.5388
## 2019 Q4       102.7344 96.84201 108.6268 93.72277 111.7460
## 2020 Q1       102.7344 96.14654 109.3223 92.65914 112.8097
## 2020 Q2       102.7344 95.51779 109.9510 91.69754 113.7713
## 2020 Q3       102.7344 94.93958 110.5292 90.81326 114.6555
## 2020 Q4       102.7344 94.40141 111.0674 89.99019 115.4786
## 2021 Q1       102.7344 93.89594 111.5729 89.21714 116.2517
## 2021 Q2       102.7344 93.41785 112.0509 88.48597 116.9828
```

BIC = 1279.549 Alpha = 0.9999

```
s4 <- ses(DollarIndexts, h = 8, level = c(80, 95))
autoplot(s4) +
autolayer(fitted(s4), series="Fitted") +
ylab("Dollar Index")
```



Holt method:

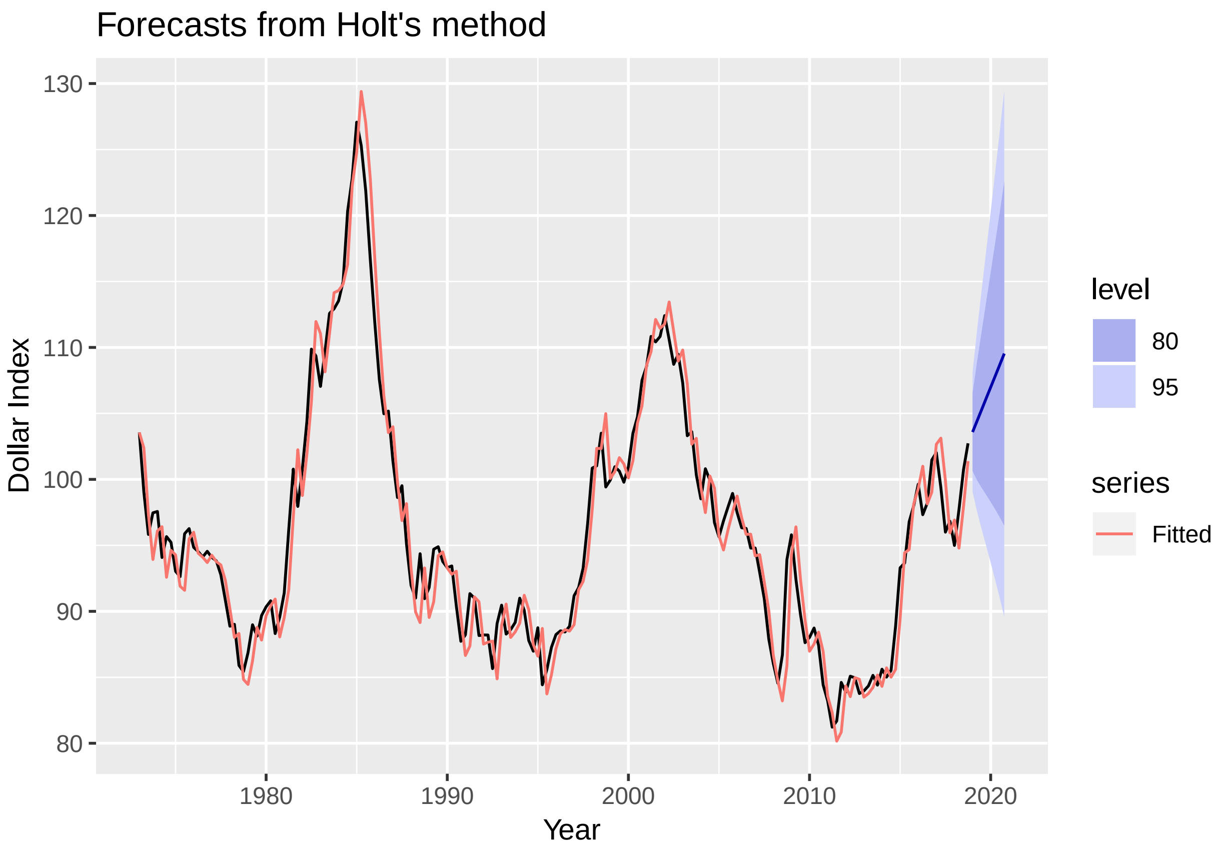
```
hr1 <- holt(DollarIndexts)
summary(hr1)
```

```
##
## Forecast method: Holt's method
```

```
##
## Model Information:
## Holt's method
##
## Call:
##  holt(y = DollarIndexts)
##
##   Smoothing parameters:
##     alpha = 0.9999
##     beta  = 0.149
##
##   Initial states:
##     l = 104.7268
##     b = -1.1723
##
##   sigma:  2.3079
##
##      AIC     AICc      BIC
## 1273.269 1273.606 1289.344
##
## Error measures:
##                      ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 0.07379101 2.282629 1.798997 0.09816736 1.863318 0.4155557
##                  ACF1
## Training set 0.187212
##
## Forecasts:
##         Point Forecast     Lo 80    Hi 80    Lo 95    Hi 95
## 2019 Q1       103.5845 100.62692 106.5422 99.06124 108.1079
## 2019 Q2       104.4346  99.92983 108.9394 97.54514 111.3241
## 2019 Q3       105.2847  99.36637 111.2031 96.23339 114.3360
## 2019 Q4       106.1348  98.83162 113.4380 94.96554 117.3041
## 2020 Q1       106.9849  98.28945 115.6803 93.68637 120.2834
## 2020 Q2       107.8350  97.72374 117.9462 92.37117 123.2988
## 2020 Q3       108.6851  97.12633 120.2438 91.00750 126.3626
## 2020 Q4       109.5351  96.49289 122.5774 89.58875 129.4815
## 2021 Q1       110.3852  95.82112 124.9493 88.11135 132.6591
## 2021 Q2       111.2353  95.10983 127.3608 86.57351 135.8971
```

BIC = 1289.344

```r
hr1f <- holt(DollarIndexts, h = 8, level = c(80, 95))
autoplot(hr1f) +
autolayer(fitted(hr1f), series="Fitted") +
ylab("Dollar Index") + xlab("Year")
```



Holt-Winters method:

```
hrw1 <- hw(DollarIndexts)
summary(hrw1)
```

```
##
## Forecast method: Holt-Winters' additive method
##
## Model Information:
## Holt-Winters' additive method
##
## Call:
##  hw(y = DollarIndexts)
##
##   Smoothing parameters:
##     alpha = 0.9999
##     beta  = 0.147
##     gamma = 1e-04
##
##   Initial states:
##     l = 101.9593
##     b = -1.2156
##     s = -0.0596 0.0721 -0.1204 0.1079
##
##   sigma:  2.3352
##
##      AIC     AICc      BIC
## 1281.465 1282.500 1310.400
```

```
##
## Error measures:
##                      ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 0.07653868 2.283849 1.818393 0.09995134 1.882382 0.4200361
##                   ACF1
## Training set 0.1843337
##
## Forecasts:
##         Point Forecast     Lo 80    Hi 80    Lo 95    Hi 95
## 2019 Q1       103.7567 100.76408 106.7494 99.17987 108.3336
## 2019 Q2       104.3824  99.82877 108.9361 97.41820 111.3467
## 2019 Q3       105.4290  99.45165 111.4063 96.28744 114.5705
## 2019 Q4       106.1515  98.78125 113.5218 94.87966 117.4234
## 2020 Q1       107.1736  98.40424 115.9430 93.76200 120.5853
## 2020 Q2       107.7993  97.60844 117.9903 92.21369 123.3850
## 2020 Q3       108.8459  97.20256 120.4892 91.03895 126.6528
## 2020 Q4       109.5684  96.43726 122.6996 89.48605 129.6508
```

BIC $= 1310.400$

```
hrw1f <- hw(DollarIndexts, h = 8, level = c(80, 95))
autoplot(hrw1f) +
autolayer(fitted(hrw1f), series="Fitted") +
ylab("Dollar Index") + xlab("Year")
```