STAT 505 Project

Daniel Girvitz, Additional authors redacted 2022-06-19

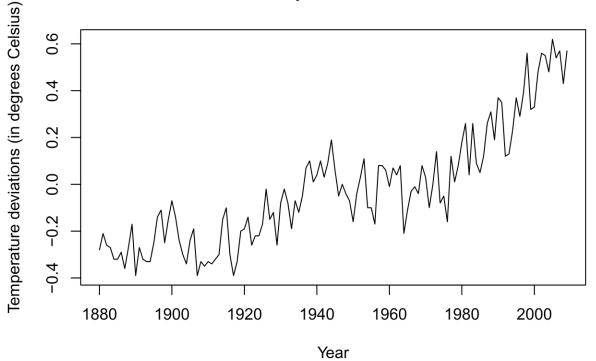
31/03/2022

Problem 1

In this problem, use the Box and Jenkins steps to model yearly data of Global Mean land-ocean temperature deviations (measured in degrees centigrade) from 1880 to 2009 (gtemp). The database is named gtemp.txt.

```
# Load data
rm(list=ls())
eData <- scan(file="gtemp.txt", what=double())</pre>
```

Global mean land-ocean temperature deviations from 1880 to 2009



```
temp.ts = ts(data=eData, start = 1880, end = 2009)
```

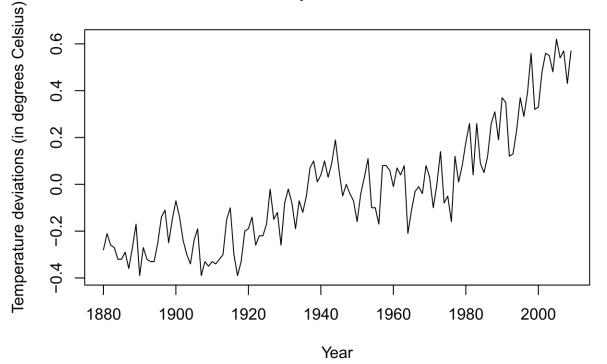
Problem 1: Identification

Should the time series be transformed? What is the choice of the degree of differencing? Use ACF and PACF plots, and unit root tests such as the ADF test.

Should the time series be transformed? Yes, To remove the trend. From the ADF test we see lag 1 is significant, so we difference by lag 1.

```
# Plot time series
year = 1880:2009
plot(year, eData,
    main = "Global mean land-ocean temperature deviations from 1880 to 2009",
    xlab = "Year",
    ylab = "Temperature deviations (in degrees Celsius)",
    type = "l")
```

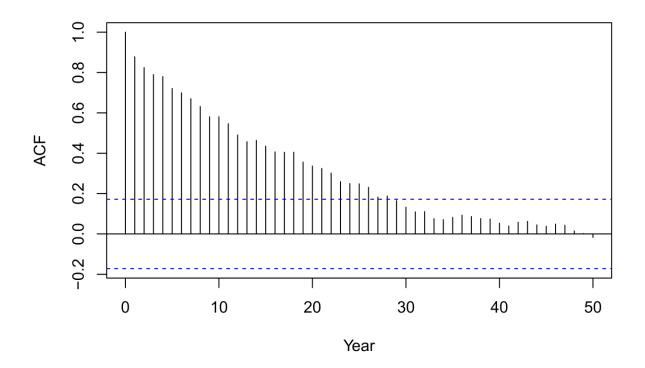
Global mean land-ocean temperature deviations from 1880 to 2009



```
temp.ts = ts(data=eData, start = 1880, end = 2009)
```

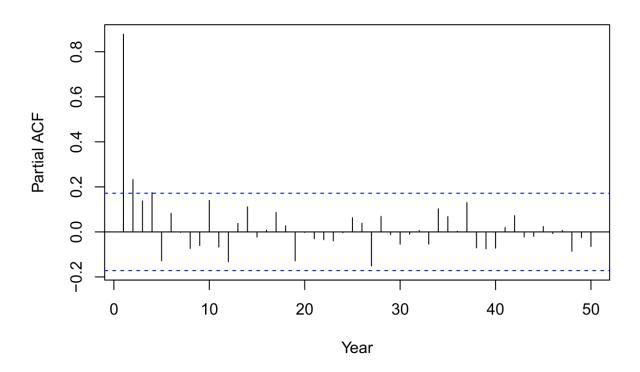
#ACF and PACF plots
acf(temp.ts,xlab="Year", lag.max =50)

Series temp.ts



pacf(temp.ts,xlab="Year",lag.max =50)

Series temp.ts



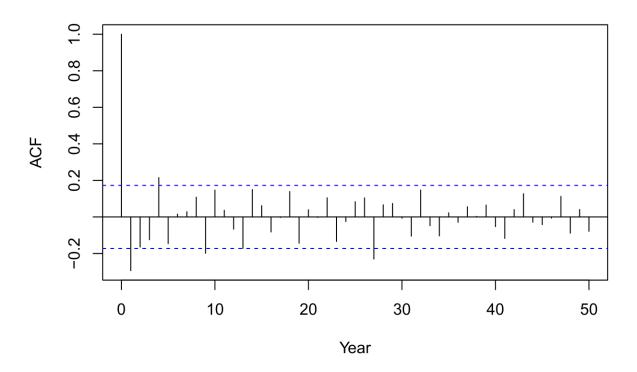
#Augmented Dickey Fuller aTSA::adf.test(temp.ts)

```
## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##
        lag
               ADF p.value
## [1,]
          0 -2.156 0.0322
  [2,]
          1 -1.378
                    0.1840
## [3,]
          2 -0.795
                    0.3940
##
  [4,]
          3 -0.166
                    0.5956
                    0.5629
## [5,]
          4 -0.280
## Type 2: with drift no trend
        lag
##
                ADF p.value
## [1,]
          0 -2.0881
                      0.295
##
  [2,]
          1 -1.2888
                      0.595
## [3,]
          2 -0.6567
                      0.817
                      0.959
##
   [4,]
          3 0.0555
##
  [5,]
          4 -0.0159
                      0.954
## Type 3: with drift and trend
##
              ADF p.value
        lag
          0 -5.39 0.0100
## [1,]
## [2,]
          1 -4.29 0.0100
## [3,]
          2 - 3.29
                  0.0761
## [4,]
          3 -2.29 0.4520
```

```
## [5,] 4 -2.29 0.4498
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01

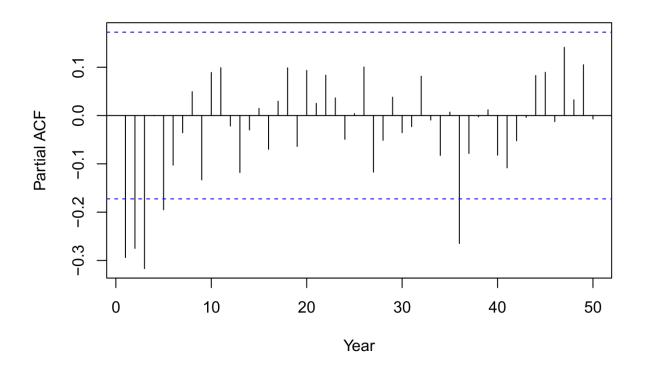
#Difference by 1
difftemp.ts = diff(temp.ts, lag = 1)
#ACF and PACF plots
acf(difftemp.ts,xlab="Year", lag.max =50)</pre>
```

Series difftemp.ts

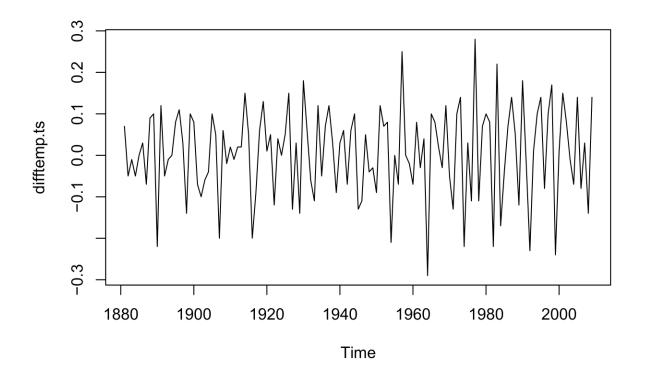


```
pacf(difftemp.ts,xlab="Year", lag.max =50)
```

Series difftemp.ts



plot.ts(difftemp.ts)



aTSA::adf.test(difftemp.ts)

```
## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##
        lag
               ADF p.value
## [1,]
          0 - 15.18
                      0.01
## [2,]
          1 -11.80
                      0.01
                       0.01
## [3,]
          2 -11.02
          3 -7.56
                       0.01
## [4,]
## [5,]
          4 -7.39
                       0.01
  Type 2: with drift no trend
##
               ADF p.value
        lag
                      0.01
## [1,]
          0 -15.18
## [2,]
          1 -11.87
                       0.01
## [3,]
          2 -11.20
                      0.01
## [4,]
          3 -7.77
                       0.01
## [5,]
          4 -7.72
                       0.01
## Type 3: with drift and trend
##
        lag
               ADF p.value
## [1,]
          0 -15.16
                       0.01
## [2,]
                       0.01
          1 -11.88
## [3,]
          2 -11.27
                      0.01
## [4,]
          3 -7.84
                      0.01
```

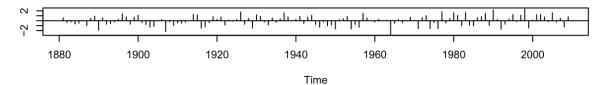
```
4 -7.83
## [5,]
                      0.01
## ----
## Note: in fact, p.value = 0.01 means p.value <= 0.01
AIC1=BIC1=matrix(0,4,4)
for (i in 1:4){ for (j in 1:4){
        fit=arima(difftemp.ts, order = c(i-1, 0, j-1))
        AIC1[i,j]=AIC(fit);
        BIC1[i,j]=BIC(fit);
}}
AIC1
##
             [,1]
                       [,2]
                                 [,3]
## [1,] -201.0879 -228.0342 -231.4121 -229.4476
## [2,] -210.8328 -230.6761 -229.4253 -232.3445
## [3,] -218.8417 -230.2359 -228.6083 -232.1489
## [4,] -230.2707 -229.2290 -231.8402 -229.9940
BIC1
##
             [,1]
                       [,2]
                                 [,3]
## [1,] -195.3683 -219.4548 -219.9729 -215.1485
## [2,] -202.2533 -219.2368 -215.1262 -215.1856
## [3,] -207.4024 -215.9368 -211.4495 -212.1303
## [4,] -215.9716 -212.0702 -211.8216 -207.1155
idxminA=which(AIC1 == min(AIC1), arr.ind = TRUE)
idxminA
##
       row col
## [1,]
         2
idxminB=which(BIC1 == min(BIC1), arr.ind = TRUE)
idxminB
##
        row col
## [1,] 1 3
```

Problem 1: Parameter Estimation

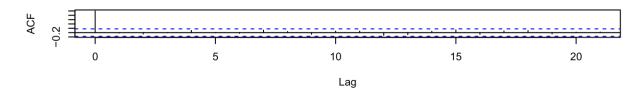
[Use Maximum Likelihood approach] The AIC and BIC minimizing models are tested. We find that only the ARMA(1,3) model achieves significance on all the coefficients.

```
#Test for ARMA(1,3)
fit1 = arima(difftemp.ts, order = c(1,0,3))
tsdiag(fit1)
```

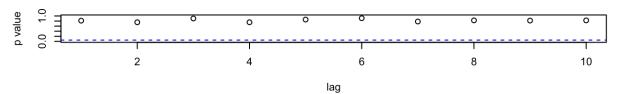
Standardized Residuals



ACF of Residuals



p values for Ljung-Box statistic

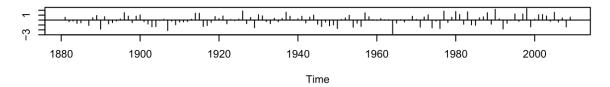


library(lmtest)

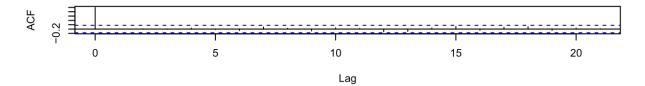
```
## Warning: package 'lmtest' was built under R version 4.1.3
## Loading required package: zoo
## Warning: package 'zoo' was built under R version 4.1.2
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
## as.Date, as.Date.numeric
```

coeftest(fit1)

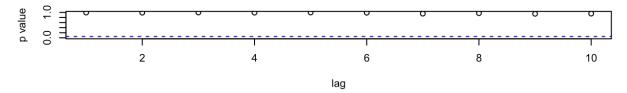
Standardized Residuals



ACF of Residuals



p values for Ljung-Box statistic



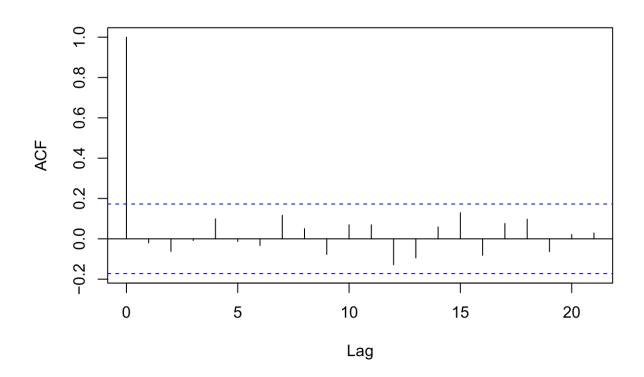
coeftest(fit2)

```
##
## z test of coefficients:
##
             Estimate Std. Error z value Pr(>|z|)
##
           -0.4316585 0.5157592 -0.8369 0.402627
## ar1
            0.4022230
                      0.5130463 0.7840 0.433046
## ma1
           ## ma2
           -0.8532493
                      0.3063676 -2.7851 0.005352 **
                      0.3405038 0.0800 0.936222
## ma3
            0.0272467
## ma4
            0.2224738
                      0.1432431
                                1.5531 0.120394
## intercept 0.0064689 0.0028137 2.2991 0.021498 *
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
```

Problem 1: Validation of the model

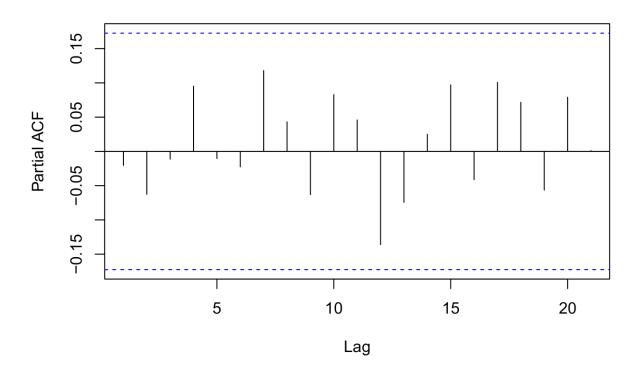
```
#Analyze Residuals
resid=fit1$residuals
acf(resid,main="Residuals")
```

Residuals



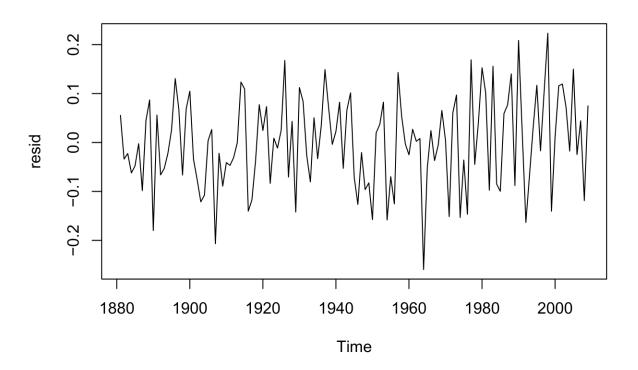
pacf(resid,main="Residuals")

Residuals



plot(resid, main="Residuals") # The residuals look like white noise with O mean and constant variance.

Residuals



```
print(AIC(fit1))

## [1] -232.3445

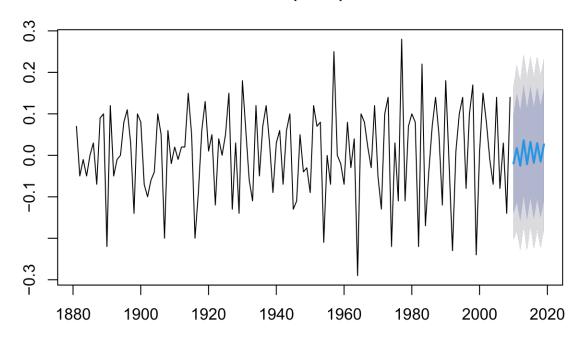
print(BIC(fit1))

## [1] -215.1856
```

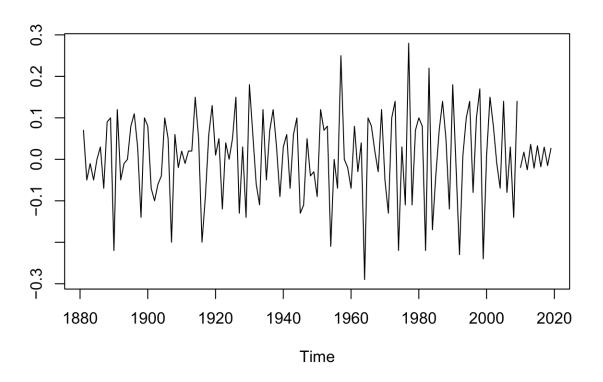
Problem 1: Forecast

```
library(forecast)
pm <- forecast(fit1, h = 10)
plot(pm)</pre>
```

Forecasts from ARIMA(1,0,3) with non-zero mean



```
pred = predict(fit1, n.ahead = 10)
ts.plot(difftemp.ts, pred$pred)
```



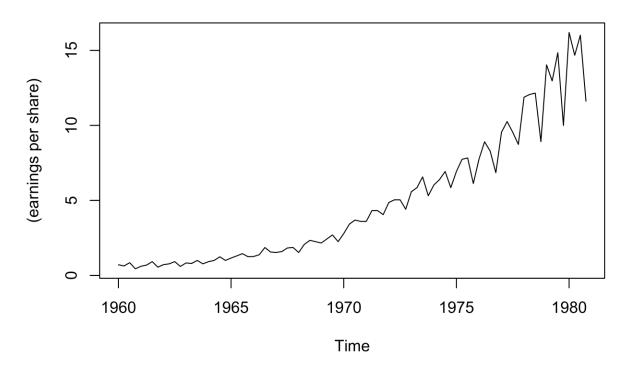
Problem 2

```
library(aTSA)
##
## Attaching package: 'aTSA'
## The following object is masked from 'package:forecast':
##
##
       forecast
## The following object is masked from 'package:graphics':
##
##
       identify
library(lmtest)
library(forecast)
library(uroot)
# Load data
rm(list=ls())
nonlogeData <- scan(file="jj.txt", what=double())</pre>
```

```
eData<-log(nonlogeData)
time = (seq(1960,1980.75,by=0.25))
# Note:
# .00 - first quarter
# .25 - second "
# .50 - third "
# .75 - fourth quarter</pre>
# Plot time series
```

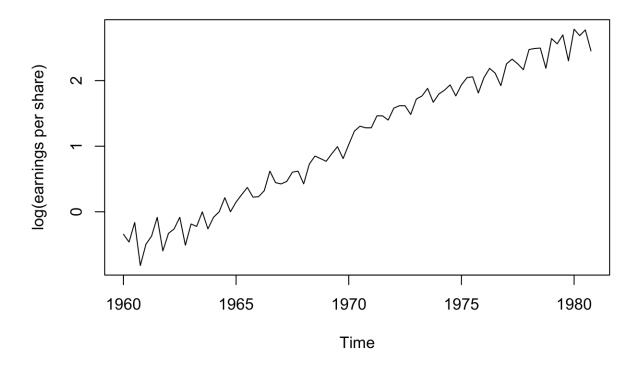
```
# Plot time series
plot(time, nonlogeData,
    main = "U.S. Johnson and Johnson earnings series",
    xlab = "Time",
    ylab = "(earnings per share)",
    type = "l")
```

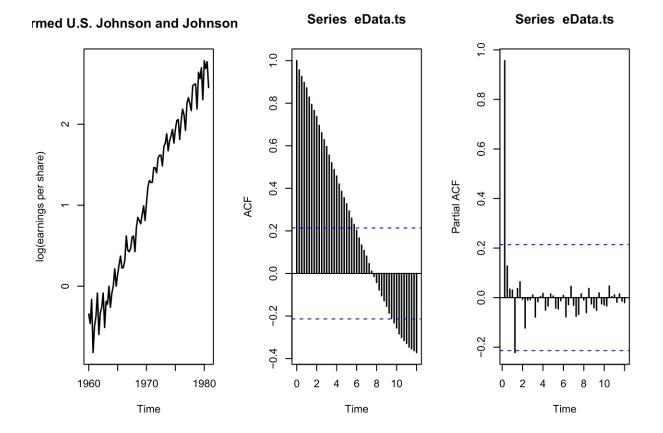
U.S. Johnson and Johnson earnings series



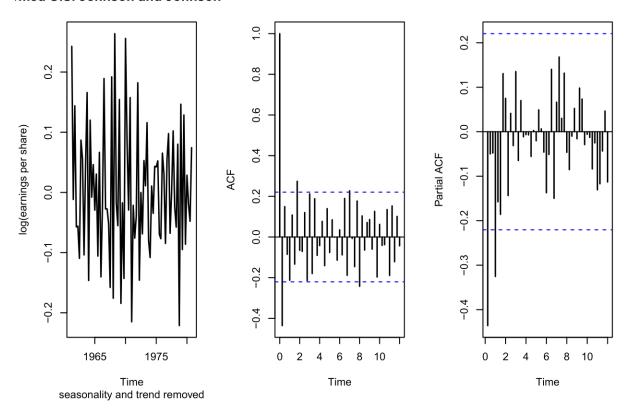
```
plot(time, eData,
    main = "log-transformed U.S. Johnson and Johnson earnings series",
    xlab = "Time",
    ylab = "log(earnings per share)",
    type = "l")
```

log-transformed U.S. Johnson and Johnson earnings series





rmed U.S. Johnson and Johnson Series NoTrend.NoSeaso.eDat Series NoTrend.NoSeaso.eDat



#ADF test
adf.test(NoTrend.NoSeaso.eData)

```
## Augmented Dickey-Fuller Test
## alternative: stationary
##
## Type 1: no drift no trend
##
        lag
               ADF p.value
          0 - 14.57
                       0.01
## [1,]
   [2,]
          1
            -8.11
                       0.01
##
   [3,]
          2
             -6.70
                       0.01
          3
             -7.59
                       0.01
##
   [4,]
##
   Type 2: with drift no trend
##
        lag
               ADF p.value
## [1,]
          0 - 14.47
                       0.01
          1 -8.05
                       0.01
##
   [2,]
  [3,]
          2 -6.65
                       0.01
##
## [4,]
          3 -7.53
                       0.01
   Type 3: with drift and trend
##
        lag
               ADF p.value
## [1,]
          0 - 14.40
                       0.01
## [2,]
          1 -8.01
                       0.01
## [3,]
          2
             -6.59
                       0.01
## [4,]
          3 -7.50
                       0.01
## Note: in fact, p.value = 0.01 means p.value <= 0.01
```

```
#trial and error
#All Sarima model
\#model\ 1\ p\ =\ q=\ P\ =\ Q\ =\ 1
sarfit1 = arima(NoTrend.NoSeaso.eData, order = c(1,0,1), seasonal = list(order = c(1,0,1)))
coeftest(sarfit1)
## z test of coefficients:
##
##
              Estimate Std. Error z value Pr(>|z|)
## ar1
            0.17429464 0.16473226
                                   1.0580
                                             0.2900
            -0.84075361 0.10982979 -7.6551 1.932e-14 ***
## ma1
## sar1
            0.81721593 0.11644742
                                   7.0179 2.252e-12 ***
## sma1
            -0.99999271 0.09987851 -10.0121 < 2.2e-16 ***
## intercept 0.00057063 0.00120763
                                  0.4725
                                             0.6366
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
\#model\ 2\ p\ =\ 2,\ P\ =\ q\ =\ 1
sarfit2 = arima(NoTrend.NoSeaso.eData, order = c(2,0,1), seasonal = list(order = c(1,0,1)))
coeftest(sarfit2)
##
## z test of coefficients:
##
##
              Estimate Std. Error z value Pr(>|z|)
            0.18811464 0.20539448 0.9159
                                            0.3597
## ar1
            0.1833
## ar2
## ma1
            ## sar1
            -0.18445186  0.34061696  -0.5415
                                          0.5881
## sma1
            -0.10854701 0.34460064 -0.3150
                                            0.7528
## intercept 0.00079263 0.00187944 0.4217
                                            0.6732
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
\#model\ 3\ p\ =\ 0,\ q\ =\ P\ =\ Q\ =\ 1
sarfit3 = arima(NoTrend.NoSeaso.eData, order = c(0,0,1), seasonal = list(order = c(1,0,1)))
coeftest(sarfit3)
##
## z test of coefficients:
##
##
              Estimate Std. Error z value Pr(>|z|)
            -0.6761976  0.0968571  -6.9814  2.923e-12 ***
## ma1
## sar1
            0.5050
            -0.1398545 0.2982684 -0.4689
## sma1
                                           0.6391
## intercept 0.0010614 0.0024370 0.4355
                                           0.6632
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

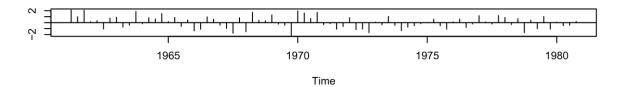
```
\#model\ 4\ p\ =\ P\ =\ q\ =\ 1,\ Q\ =\ 0
sarfit4 = arima(NoTrend.NoSeaso.eData, order = c(1,0,1), seasonal = list(order = c(1,0,0)))
coeftest(sarfit4)
##
## z test of coefficients:
##
            Estimate Std. Error z value Pr(>|z|)
           -0.0117778 0.2224559 -0.0529 0.957776
## ar1
          ## ma1
## sar1
           ## intercept 0.0010963 0.0025525 0.4295 0.667540
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
\#model\ 5\ p\ =\ Q\ =\ 0,\ P\ =\ q\ =\ 1
sarfit5 = arima(NoTrend.NoSeaso.eData, order = c(0,0,1), seasonal = list(order = c(1,0,0)))
coeftest(sarfit5)
##
## z test of coefficients:
##
##
             Estimate Std. Error z value Pr(>|z|)
           -0.6810164  0.0968857  -7.0291  2.079e-12 ***
## ma1
           ## intercept 0.0010894 0.0025251 0.4314 0.666161
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
# both Significant
\#model\ 6\ p\ =\ q\ =\ 0,\ P\ =\ Q\ =1
sarfit6 = arima(NoTrend.NoSeaso.eData, order = c(0,0,0), seasonal = list(order = c(1,0,1)))
coeftest(sarfit6)
## z test of coefficients:
##
             Estimate Std. Error z value Pr(>|z|)
## sar1
          -0.0407396  0.3170231  -0.1285  0.8977
           -0.2022336  0.3007672  -0.6724
## sma1
                                         0.5013
## intercept 0.0028567 0.0092753 0.3080 0.7581
#model 7 p = q = 1, P = Q = 0
sarfit7 = arima(NoTrend.NoSeaso.eData, order = c(1,0,1), seasonal = list(order = c(0,0,0)))
coeftest(sarfit7)
##
## z test of coefficients:
##
              Estimate Std. Error z value Pr(>|z|)
##
```

```
0.23693974 0.15031508 1.5763
                                            0.1150
## ar1
## ma1
            -0.88789693 0.09325722 -9.5209
                                            <2e-16 ***
## intercept 0.00071103 0.00175999 0.4040
                                            0.6862
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
\#model\ 8\ p\ =\ Q\ =\ 1,\ q\ =\ P\ =\ 0
sarfit8 = arima(NoTrend.NoSeaso.eData, order = c(1,0,0), seasonal = list(order = c(0,0,1)))
coeftest(sarfit8)
##
## z test of coefficients:
##
              Estimate Std. Error z value Pr(>|z|)
##
## ar1
            -0.3244254 0.1044776 -3.1052 0.001901 **
## sma1
## intercept 0.0017536 0.0047829 0.3666 0.713890
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
#both significant
#model 5 is the best fit by comparing autos
```

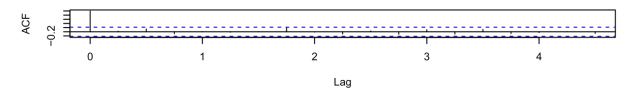
Standardized Residuals

#Residuals of the process

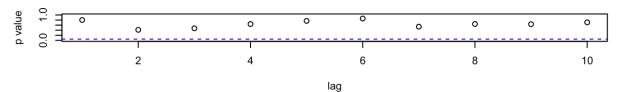
tsdiag(sarfit5)



ACF of Residuals



p values for Ljung-Box statistic



Our apologies for the use of .png image files: R Markdown failed to run the last two chunks, but the code runs in the console... Must be a bug?

```
# #forecast
# plot(forecast(arima(eData.ts, order=c(0,0,1),

# seasonal = list(order=c(1,0,0),period=12)),h=12),
# xlab="Year", ylab="log(earning per share)",
# main="Forecast of U.S. Johnson and Johnson earnings series.")
```

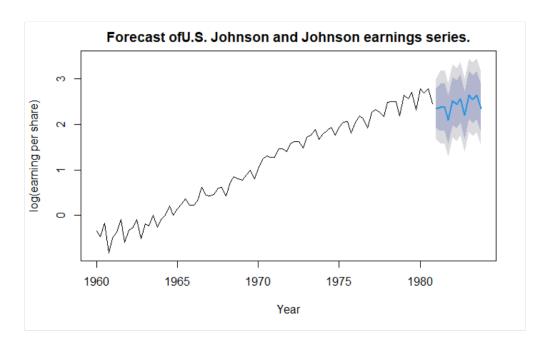


Figure 1: Forecast of U.S. Johnson and Johnson earnings series

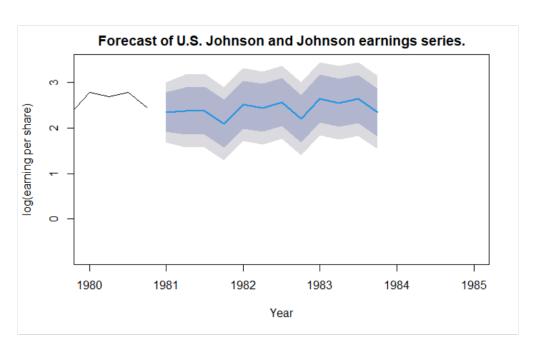


Figure 2: Forecast of U.S. Johnson and Johnson earnings series