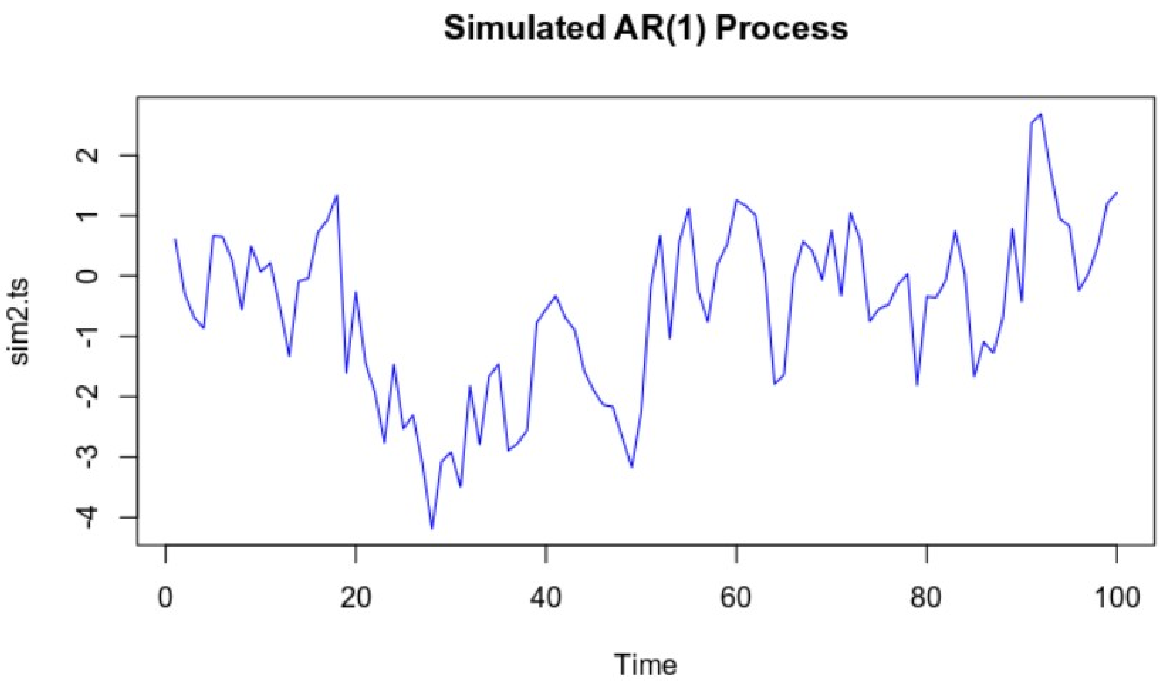
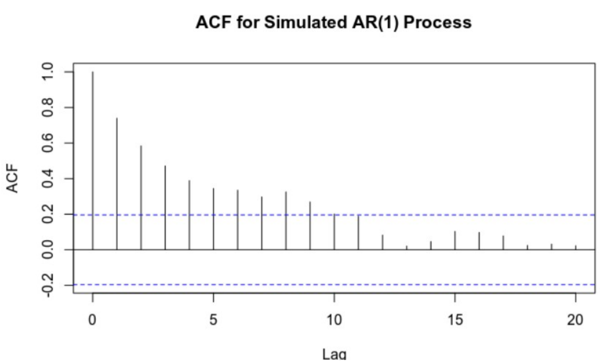
EC 513 Problem Set 2

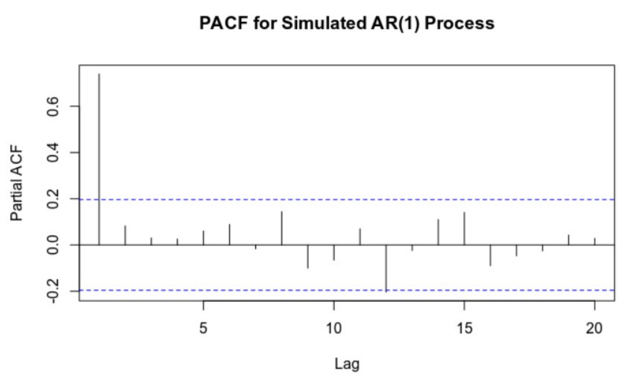
CARTER YANCEY

1a) The mean does not appear constant, so it is not stationary.



1b)





1c)

```
ARIMA(1,0,0) with non-zero mean
Coefficients:
          ar1     mean
       0.7545  -0.5586


ARIMA(2,0,0) with non-zero mean
Coefficients:
          ar1     ar2     mean
       0.6865  0.0888  -0.5530
```

```
ARIMA(1,0,1) with non-zero mean
Coefficients:
         ar1      ma1     mean
      0.8000  -0.1169  -0.5804
```

```
ARIMA(1,0,4) with non-zero mean
Coefficients:
         ar1      ma1      ma2      ma3      ma4     mean
      0.9078  -0.2372  -0.0813  -0.0756  -0.0840  -0.5739
```

```
ARIMA(2,0,1) with non-zero mean
Coefficients:
         ar1      ar2      ma1     mean
      1.1856  -0.2835  -0.5106  -0.5169
```

1d)

```
ARIMA(2,0,0) with zero mean
Coefficients:
         ar1     ar2
      0.7102  0.1051
```

```
ARIMA(1,0,1) with zero mean
Coefficients:
         ar1      ma1
      0.8432  -0.1467
```

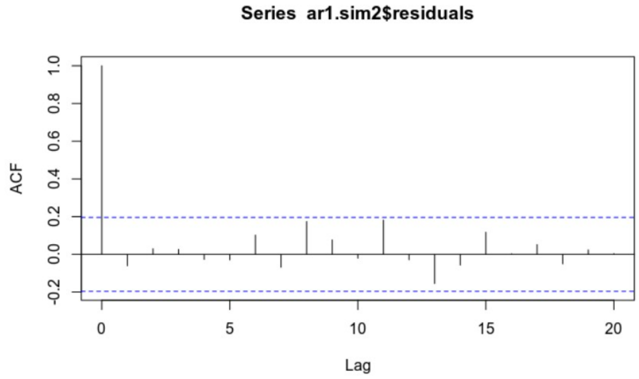
1e) AR(1) has the best overall goodness of fit

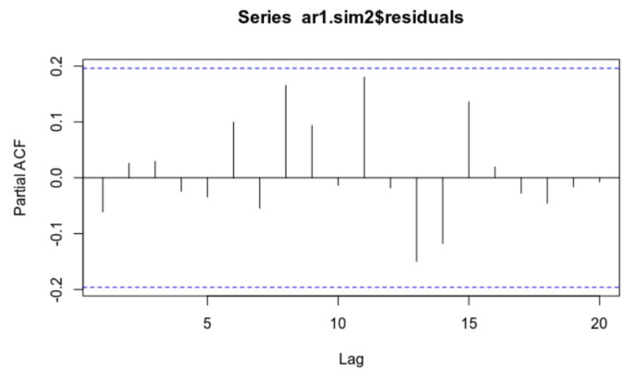
```
>    table
```

	r2	AIC	BIC
AR(1)	0.5708751	272.7899	280.6054
AR(2)	0.3683040	272.4685	282.8490
ARMA(1,1)	0.3649626	271.9522	282.3327
ARMA(1,4)	0.3994322	277.0626	295.2284
ARMA(2,1)	0.3745751	274.1471	287.1227
AR(2) [mean 0]	0.3694484	271.9214	279.7067
ARMA(1,1) [mean 0]	0.3661052	271.5617	279.3471

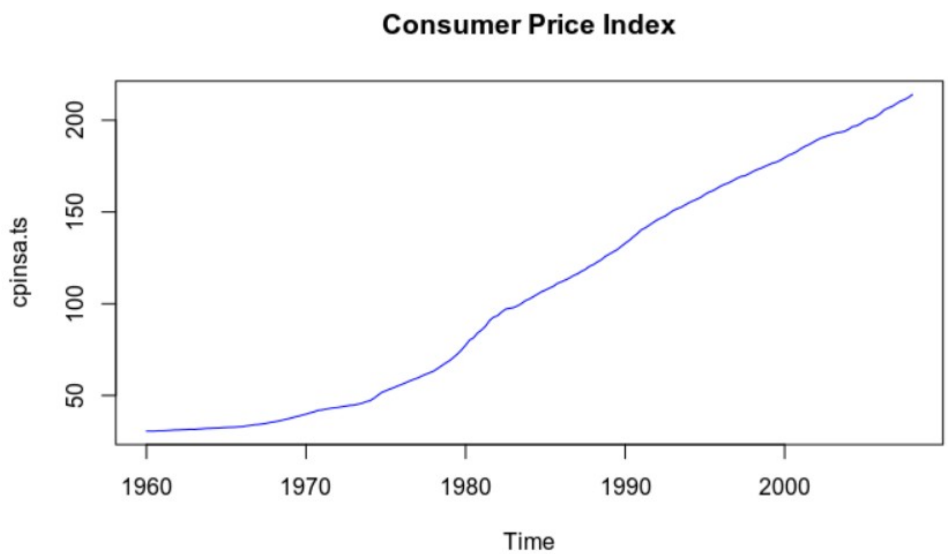
1f) The sample data being used is from a simulated AR(1); it is not surprising that AR(1) should be the best model for the data.

1g) Since the mean of the residuals is zero and there is no autocorrelation (as shown by the ACF and PACF), the residuals are white noise.

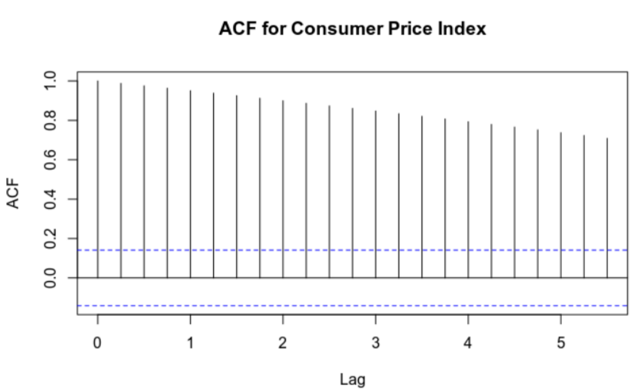


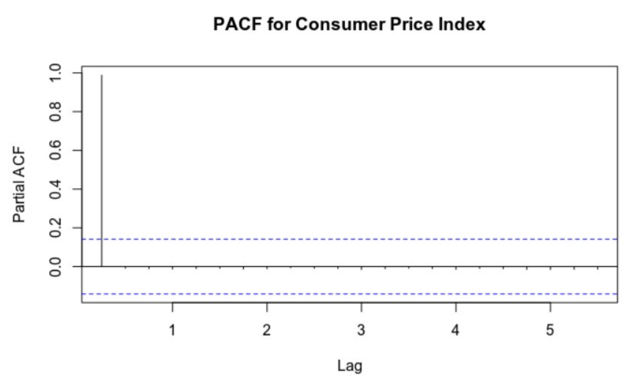


2a) The mean is not constant, so it is not stationary.

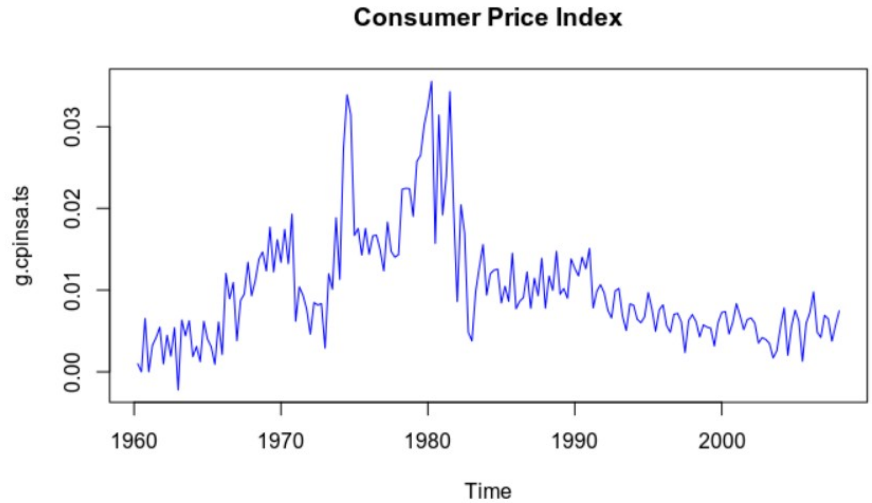


2b)

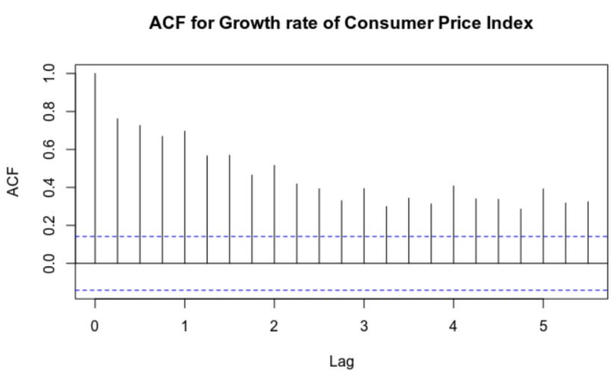


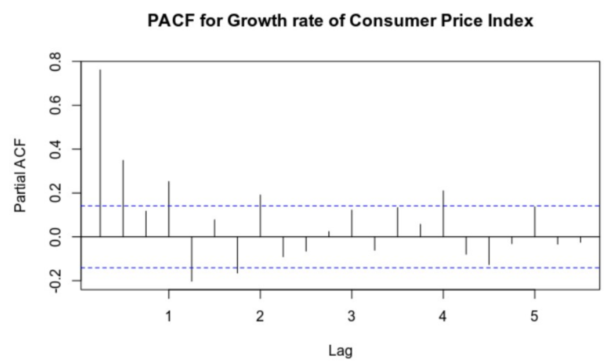


2c) Definitely not stationary.



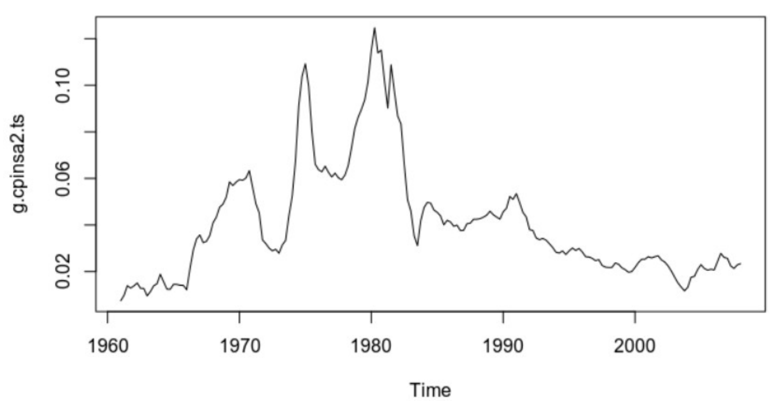
2d)



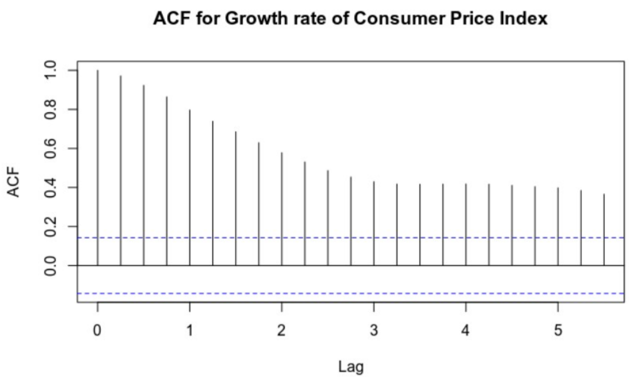


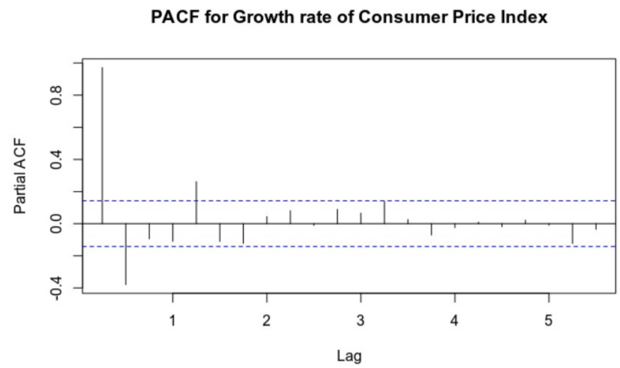
2e) This time series still is not stationary.

Seasonally Differenced CPI



f) The PACF indicates lags at times 1,2, and 5.





2g)

```
ARIMA(1,0,0) with non-zero mean
Coefficients:
          ar1    mean
       0.9741  0.0439


ARIMA(2,0,0) with non-zero mean
Coefficients:
          ar1      ar2    mean
       1.4481  -0.4829  0.0422

ARIMA(5,0,0) with non-zero mean
Coefficients:
          ar1      ar2     ar3      ar4     ar5    mean
       1.4432  -0.4340  0.2176  -0.6344  0.3808  0.0434
```

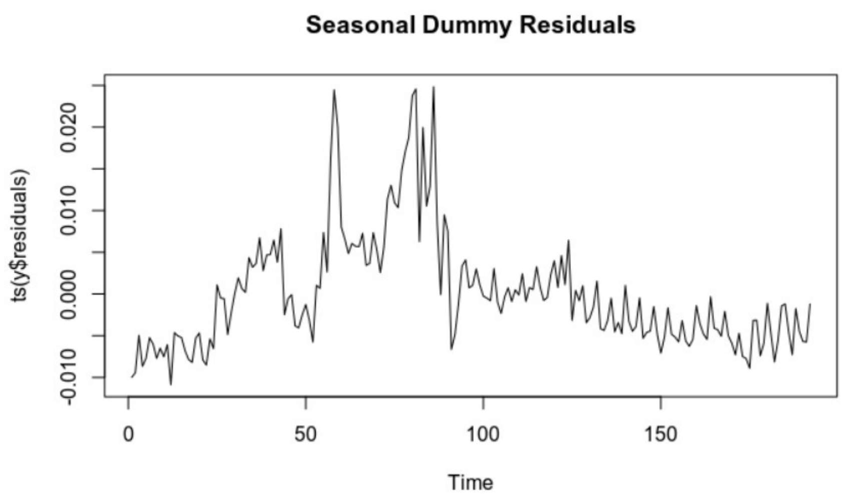
2h) Of the AR models, AR(5) has the best fit. Testing other models, ARMA(2,5) had an even better fit.

```
>   table
                  AIC       BIC        r2
AR(1)     -1436.731 -1427.006 0.9557229
AR(2)     -1484.806 -1471.839 0.9660894
AR(5)     -1510.859 -1488.167 0.9715190
ARMA(5,2) -1539.913 -1510.737 0.9764233
ARMA(2,5) -1559.647 -1530.471 0.9789113
```

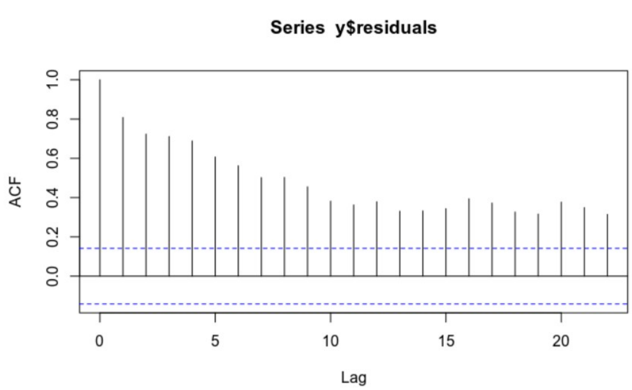
2i)

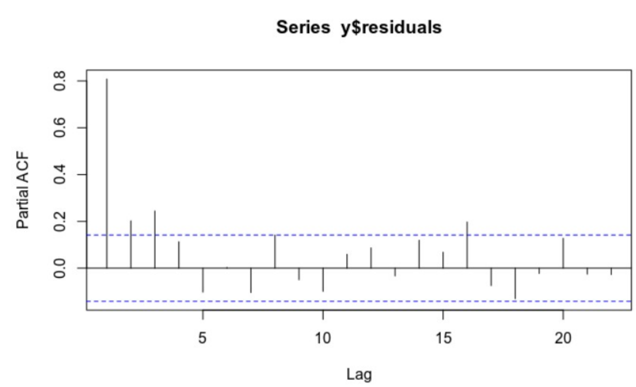
```
Call:
lm(formula = g.cpinsa.ts ~ dummies)

Coefficients:
(Intercept)    dummiesQ1    dummiesQ2    dummiesQ3
  0.0114750   -0.0028078   -0.0005135   -0.0020420
```

2j) Not stationary.



2k) The residuals do not have mean zero, and the ACF and PACF show autocorrelation. Therefore, they are not white noise. If the residuals are not white noise, then we need a different model.





```
## PS 2

  ## clear memory
  rm(list=ls())

  ## set seed
  set.seed(123456)

  #Question 1
  sim2<- read.csv("~/Downloads/1608.csv") # use read.csv if reading a csv file
  sim2.ts = ts(data=sim2$Y1)
  plot(sim2.ts, col="blue", main="Simulated AR(1) Process")
  acf(sim2.ts, main="ACF for Simulated AR(1) Process")
  pacf(sim2.ts, main="PACF for Simulated AR(1) Process")

  g.sim2.ts = ts(data=sim2.ts, start=2, end=100)
  plot(g.sim2.ts,col="blue", main="Log sim2", xlab="Time")

  ar1.sim2 <- Arima(sim2.ts, order=c(1,0,0), method = "CSS")
  ar1.sim2.r2 <- (cor(fitted(ar1.sim2), sim2.ts)^2)*(99/98)
  ar1.sim2.aic <- -2*ar1.sim2$loglik + 2*(3)
  ar1.sim2.bic <- -2*ar1.sim2$loglik + 3*log(ar1.sim2$nobs)
  ar2.sim2 <- Arima(g.sim2.ts, order=c(2,0,0), method = "CSS")
  ar2.sim2.r2 <- cor(fitted(ar2.sim2), sim2.ts[-1])^2*(99/97)
  ar2.sim2.aic <- -2*ar2.sim2$loglik + 2*(4)
  ar2.sim2.bic <- -2*ar2.sim2$loglik + 4*log(ar2.sim2$nobs)
  arma11.sim2 <- Arima(g.sim2.ts, order=c(1,0,1), method = "CSS")
  arma11.sim2.r2 <- cor(fitted(arma11.sim2), sim2.ts[-1])^2*(99/97)
  arma11.sim2.aic <- -2*arma11.sim2$loglik + 2*(4)
  arma11.sim2.bic <- -2*arma11.sim2$loglik + 4*log(arma11.sim2$nobs)
  arma14.sim2 <- Arima(g.sim2.ts, order=c(1,0,4), method = "CSS")
  arma14.sim2.r2 <- cor(fitted(arma14.sim2), sim2.ts[-4])^2*(99/94)
  arma14.sim2.aic <- -2*arma14.sim2$loglik + 2*(7)
  arma14.sim2.bic <- -2*arma14.sim2$loglik + 7*log(arma14.sim2$nobs)
  arma21.sim2 <- Arima(g.sim2.ts, order=c(2,0,1), method = "CSS")
  arma21.sim2.r2 <- cor(fitted(arma21.sim2), sim2.ts[-1])^2*(99/96)
  arma21.sim2.aic <- -2*arma21.sim2$loglik + 2*(5)
  arma21.sim2.bic <- -2*arma21.sim2$loglik + 5*log(arma21.sim2$nobs)
  ar1.sim2 #-.559 0.754
  ar2.sim2  #-.522 0.694 0.087
  arma11.sim2   #-0.549 0.805 -0.116
  arma14.sim2   #-0.520 +0.919 -0.245 -0.089 -0.084 -0.09
  arma21.sim2   #-0.539 - 0.031 0.617 0.762

  ar2.sim2.ni <- Arima(g.sim2.ts, order=c(2,0,0), method = "CSS", include.mean = FALSE)
  ar2.sim2.ni.r2 <- cor(fitted(ar2.sim2.ni), sim2.ts[-1])^2*(99/97)
  ar2.sim2.ni.aic <- -2*ar2.sim2.ni$loglik + 2*(3)
  ar2.sim2.ni.bic <- -2*ar2.sim2.ni$loglik + 3*log(ar2.sim2.ni$nobs)
  ar2.sim2.ni #.710 .105
```

```
  arma11.sim2.ni <- Arima(g.sim2.ts, order=c(1,0,1), method = "CSS", include.mean = FALSE)
  arma11.sim2.ni.r2 <- cor(fitted(arma11.sim2.ni), sim2.ts[-1])^2*(99/97)
  arma11.sim2.ni.aic <- -2*arma11.sim2.ni$loglik + 2*(3)
  arma11.sim2.ni.bic <- -2*arma11.sim2.ni$loglik + 3*log(arma11.sim2.ni$nobs)
  arma11.sim2.ni #846 147

  table <- matrix(c(ar1.sim2.r2, ar1.sim2.aic, ar1.sim2.bic,ar2.sim2.r2, ar2.sim2.aic, ar2.sim2.bic,
                   arma11.sim2.r2, arma11.sim2.aic, arma11.sim2.bic,arma14.sim2.r2, arma14.sim2.aic,
                   arma14.sim2.bic,arma21.sim2.r2,arma21.sim2.aic, arma21.sim2.bic, ar2.sim2.ni.r2,
                   ar2.sim2.ni.aic, ar2.sim2.ni.bic,arma11.sim2.ni.r2,arma11.sim2.ni.aic,arma11.sim2.ni.bic),
                 ncol=3, byrow =TRUE)
  colnames(table) <- c("r2", "AIC", "BIC")
  rownames(table) <- c("AR(1)", "AR(2)", "ARMA(1,1)", "ARMA(1,4)", "ARMA(2,1)", "AR(2)
[mean 0]", "ARMA(1,1) [mean 0]")


   table

  acf(ar1.sim2$residuals)
  pacf(ar1.sim2$residuals)

  #Question2
  quarterly<- read.csv("~/Downloads/1607.csv") # use read.csv if reading a csv file
  names(quarterly)                  # lis the variables in mydata
  cpinsa <- quarterly$CPINSA
#a
  cpinsa.ts = ts(data=cpinsa, frequency = 4, start=c(1960,1), end=c(2008,1))
  plot(cpinsa.ts,col="blue", main="Consumer Price Index", xlab="Time")
#b
  acf(cpinsa.ts, main="ACF for Consumer Price Index")
  pacf(cpinsa.ts, main="PACF for Consumer Price Index")

  ## the code below cuts off the first observation off of one series
  ## and the last off of the other - this works for a first difference, but is not elegant
#c
  g.cpinsa<-log(cpinsa.ts[-1]/cpinsa.ts[-193])
  g.cpinsa.ts = ts(data=g.cpinsa, frequency = 4, start=c(1960,2), end=c(2008,1))
  plot(g.cpinsa.ts,col="blue", main="Consumer Price Index", xlab="Time")
#d
  acf(g.cpinsa.ts, main="ACF for Growth rate of Consumer Price Index")
  pacf(g.cpinsa.ts, main="PACF for Growth rate of Consumer Price Index")
#e
  g.cpinsa2<-log(cpinsa.ts[5:193]/cpinsa.ts[1:189])
  g.cpinsa2.ts = ts(data=g.cpinsa2, frequency = 4, start=c(1961,1), end=c(2008,1))
  plot(g.cpinsa2.ts, main="Logged, Seasonally Lagged CPI")
#f
  acf(g.cpinsa2.ts, main="ACF for Growth rate of Consumer Price Index")
  pacf(g.cpinsa2.ts, main="PACF for Growth rate of Consumer Price Index")
#g
```

```
  ar1.gcpinsa2 <-  Arima(g.cpinsa2.ts, order=c(1,0,0), method="CSS")
  ar1.gcpinsa2.r2 <- cor(fitted(ar1.gcpinsa2), g.cpinsa2.ts)^2
  arma25.gcpinsa2 <-  Arima(g.cpinsa2.ts, order=c(2,0,5), method="CSS")
  arma25.gcpinsa2.r2 <- cor(fitted(arma25.gcpinsa2), g.cpinsa2.ts)^2
  arma52.gcpinsa2 <-  Arima(g.cpinsa2.ts, order=c(5,0,2), method="CSS")
  arma52.gcpinsa2.r2 <- cor(fitted(arma52.gcpinsa2), g.cpinsa2.ts)^2
  ar2.gcpinsa2 <-  Arima(g.cpinsa2.ts, order=c(2,0,0), method="CSS")
  ar2.gcpinsa2.r2 <- cor(fitted(ar2.gcpinsa2), g.cpinsa2.ts)^2
  ar5.gcpinsa2 <-  Arima(g.cpinsa2.ts, order=c(5,0,0), method="CSS")
  ar5.gcpinsa2.r2 <- cor(fitted(ar5.gcpinsa2), g.cpinsa2.ts)^2

  ar1.gcpinsa2
  ar1.gcpinsa2.r2
  ar2.gcpinsa2
  ar2.gcpinsa2.r2
  arma25.gcpinsa2
  arma25.gcpinsa2.r2
  arma52.gcpinsa2
  arma52.gcpinsa2.r2
  ar5.gcpinsa2
  ar5.gcpinsa2.r2
#h
  table <- matrix(c(ar1.gcpinsa$aic, ar1.gcpinsa$bic, ar1.gcpinsa.r2,
                    ar2.gcpinsa$aic, ar2.gcpinsa$bic, ar2.gcpinsa.r2,
                    ar5.gcpinsa$aic, ar5.gcpinsa$bic, ar5.gcpinsa.r2,
                    arma52.gcpinsa$aic, arma52.gcpinsa$bic, arma52.gcpinsa.r2,
                    arma25.gcpinsa$aic, arma25.gcpinsa$bic, arma25.gcpinsa.r2),
                  ncol=3, byrow =TRUE)
  colnames(table) <- c("AIC", "BIC", "r2")
  rownames(table) <- c("AR(1)", "AR(2)", "AR(5)", "ARMA(5,2)","ARMA(2,5)")
  table
#i
  dummies = seasonaldummy(g.cpinsa.ts)
  y<- lm(g.cpinsa.ts ~ dummies)
  y
#j
  plot(ts(y$residuals), main="Seasonal Dummy Residuals")
#k
  acf(y$residuals)
  pacf(y$residuals)
```