DaiglePredictionofSocialSecurity.R

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Sun Dec 9 13:45:23 2018

Chris Daigle Prediction of Social Security Awards

```
# Prepare workspace ####
rm(list = ls())
library(tseries)
library(quantmod)
```

```
## Loading required package: xts
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
## Loading required package: TTR
```

```
## Version 0.4-0 included new data defaults. See ?getSymbols.
```

```
library(data.table)
```

```
##
## Attaching package: 'data.table'
```

```
## The following objects are masked from 'package:xts':
##
##     first, last
```

```
library(leaps)
library(plm)
```

```
## Loading required package: Formula
```

```
##
## Attaching package: 'plm'
```

```
## The following object is masked from 'package:data.table':
##
##     between
```

```
library(class)
library(lmtest)
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
library(knitr)
library(pastecs)
```

```
##
## Attaching package: 'pastecs'

## The following objects are masked from 'package:data.table':
##
##     first, last

## The following objects are masked from 'package:xts':
##
##     first, last
```

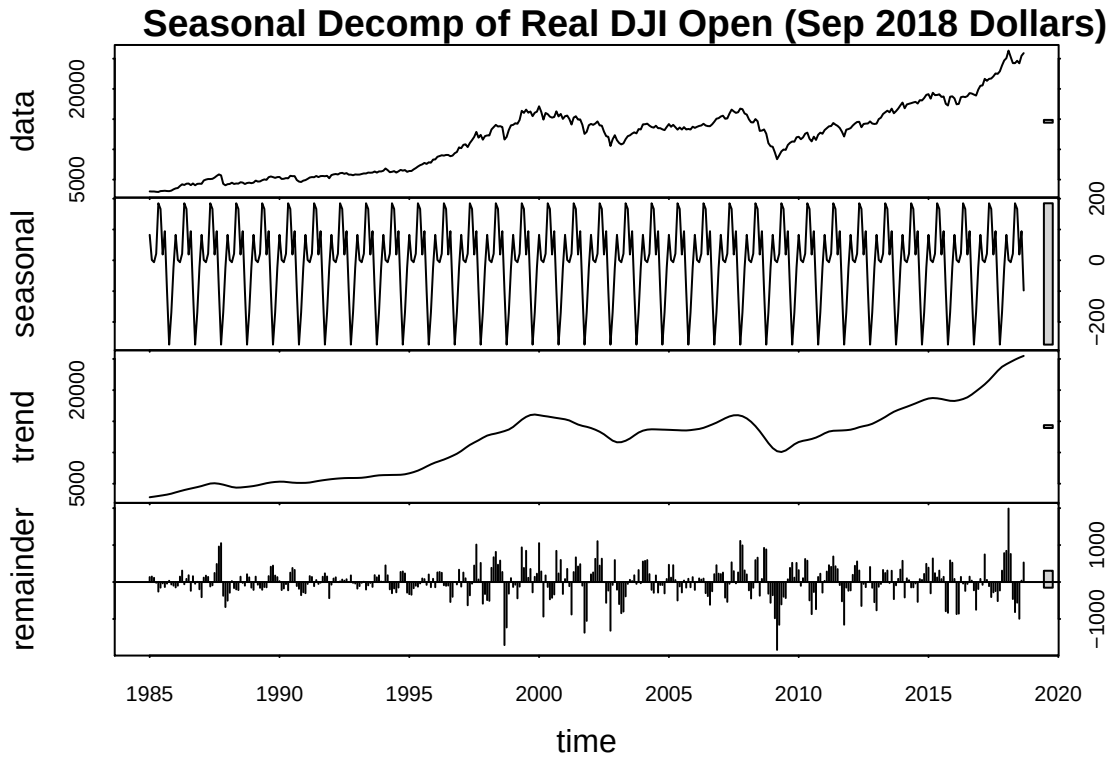
```
setwd('~/Git/MachineLearningAndBigDataWithR/Data')
dataName <- 'assembled.csv'
df <- read.csv(dataName, stringsAsFactors = FALSE)
# Summarize and clean data ####
# head(df)
df <- df[-1]
# head(df)
# str(df)

# Variable Manipulation ####
# Set dates
df$date <- as.Date(df$date, "%Y-%m-%d")
# Functions to clean data #
spaceless <- function(x) {
  x <- gsub(" ", ".", x)
  x
}

commaless <- function(x) {
  x <- gsub(",", "", x)
  x
}

dollarless <- function(x) {
  x <- gsub("\\$", "", x)
  x
}

# Loops to apply functions #
for (i in 15:20) {
  df[, i] <- commaless(df[, i])
}
for (i in 15:20) {
  df[, i] <- dollarless(df[, i])
}

# Loop to transform variable types #
for (i in 15:20) {
  df[, i] <- as.numeric(df[, i])
}
# Names with Index ####
# 1 date                    : Date
# 2 DJIopen                 : num
# 3 DJIhigh                 : num
```

```
# 4 DJIlow                    : num
# 5 DJIclose                  : num
# 6 DJIadjClose               : num
# 7 DJIvolume                 : num
# 8 SPopen                    : num
# 9 SPhigh                    : num
# 10 SPlow                     : num
# 11 SPclose                   : num
# 12 SPadjClose                : num
# 13 SPvolume                  : num
# 14 fedFundRate               : num
# 15 totalSSRetired            : num
# 16 averageSSRetiredPay       : num
# 17 totalMaleSSRetired        : num
# 18 averageMaleSSRetiredPay   : num
# 19 totalFemaleSSRetired      : num
# 20 averageFemaleSSRetiredPay: num
# 21 cpi                       : num
#
# Order Change #
df <- df[, c(1, 15, 17, 19, 21, 14, 7, 13, 2:6, 8:12, 16, 18, 20)]
# 1 date                      : Date
# 2 totalSSRetired            : num
# 3 totalMaleSSRetired        : num
# 4 totalFemaleSSRetired      : num
# 5 cpi                       : num
# 6 fedFundRate               : num
# 7 DJIvolume                 : num
# 8 SPvolume                  : num
# 9 DJIopen                   : num
# 10 DJIhigh                   : num
# 11 DJIlow                    : num
# 12 DJIclose                  : num
# 13 DJIadjClose               : num
# 14 SPopen                    : num
# 15 SPhigh                    : num
# 16 SPlow                     : num
# 17 SPclose                   : num
# 18 SPadjClose                : num
# 19 averageSSRetiredPay       : num
# 20 averageMaleSSRetiredPay   : num
# 21 averageFemaleSSRetiredPay: num
#
# Variable Creation ####
# CPI Inflator
latestDate <- tail(df$date, n = 1)

baseCpi <- df$cpi[df$date == latestDate]
df$inflator <- baseCpi / df$cpi

df <- df[, c(1:6, 22, 7:21)]

realNames <-
```

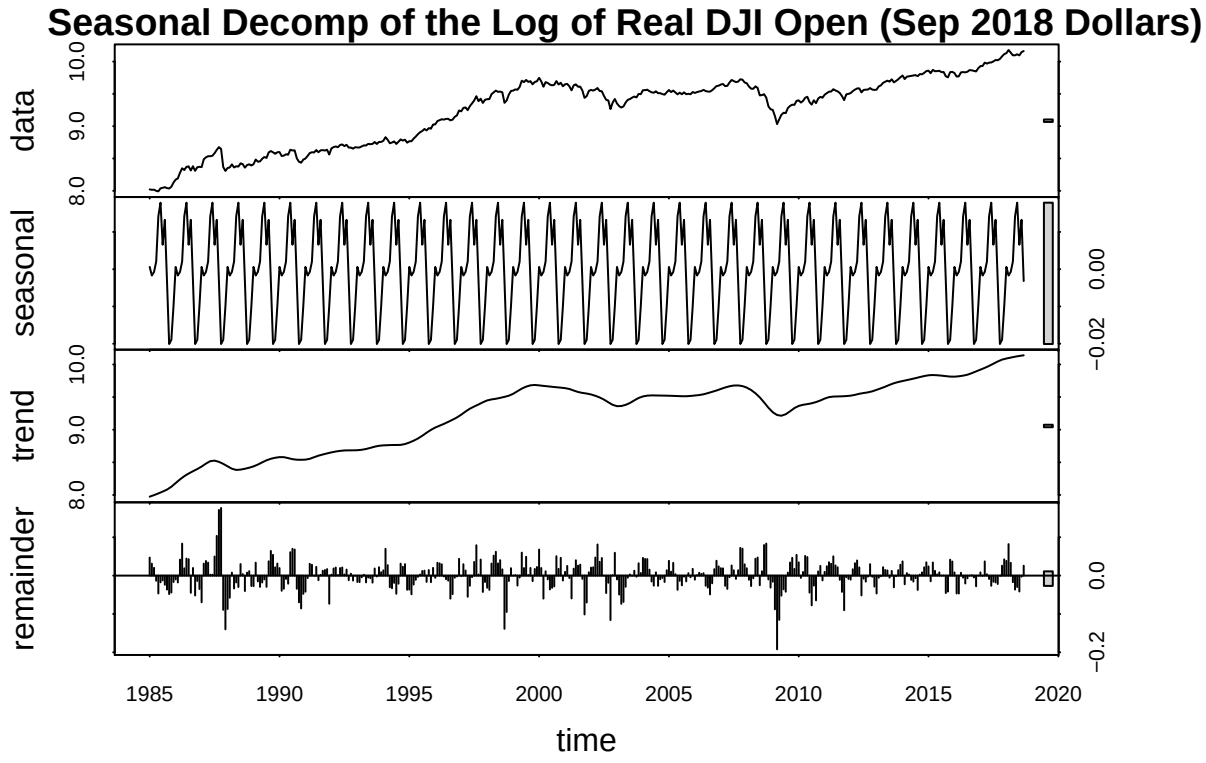
```
  paste('real',
        colnames(df[, 10:22]),
        sep = "")

df[, realNames] <- df$inflator * df[10:22]

# Differences #
diffNames <-
  paste('diff',
        c(colnames(df[10:22]),
          paste('Real',
                colnames(df[10:22]),
                sep = "")),
        sep = "")
df[, diffNames] <- rep(NA, nrow(df))
for (i in 36:61) {
  df[, i][2:nrow(df)] <- diff(df[, i - 26], lag = 1)
}
diffTargetNames <-
  paste('diff',
        c(colnames(df[2:4])),
        sep = "")
df[, diffTargetNames] <- rep(NA, nrow(df))
for (i in 62:64) {
  df[, i][2:nrow(df)] <- diff(df[, i - 60], lag = 1)
}

# Positive Indicator #
posNames <-
  paste('pos',
        c(colnames(df[10:22]),
          paste('Real',
                colnames(df[10:22]),
                sep = "")),
        sep = "")
df[, posNames] <- rep(0, nrow(df))
for (i in 65:90) {
  df[, i][df[, i - 20] > 0] <- 1
}

posTargetNames <-
  paste('pos',
        c(colnames(df[2:4])),
        sep = "")
df[, posTargetNames] <- rep(0, nrow(df))
for (i in 91:93) {
  df[, i][df[, i - 29] > 0] <- 1
}

# Percent Changes #
percChangeNames <-
  paste('percChange',
        c(colnames(df[10:22]),
```

```
          paste('Real', colnames(df[10:22]), sep = "")),
        sep = "")
df[, percChangeNames] <- rep(NA, nrow(df))

for (i in 94:119) {
  df[, i] <- Delt(df[, i - 84])
}
for (i in 94:119) {
  df[, i] <- as.numeric(df[, i])
}
percChangeTargetNames <-
  paste('percChange',
        c(colnames(df[2:4])),
        sep = "")
df[, percChangeTargetNames] <- rep(NA, nrow(df))
for (i in 120:122) {
  df[, i] <- Delt(df[, i - 118])
}
for (i in 120:122) {
  df[, i] <- as.numeric(df[, i])
}

# Place all target variables - totalRetired* - together
df <- df[, c(1:4, 62:64, 91:93, 120:122, 5:61, 65:90, 94:119)]
df1 <- df[complete.cases(df), ]

# Timeseries Evaluation ####
realDJIOpen <-
  ts(
    df$realDJIopen,
    start = c(1985, 1),
    end = c(2018, 9),
    frequency = 12
  )
percRealDJIOpen <-
  ts(
    df1$percChangeRealDJIopen,
    start = c(1985, 2),
    end = c(2018, 9),
    frequency = 12
  )
realSPOpen <-
  ts(
    df$realSPopen,
    start = c(1985, 1),
    end = c(2018, 9),
    frequency = 12
  )
percRealSPOpen <-
  ts(
    df1$percChangeRealSPopen,
    start = c(1985, 2),
    end = c(2018, 9),
```

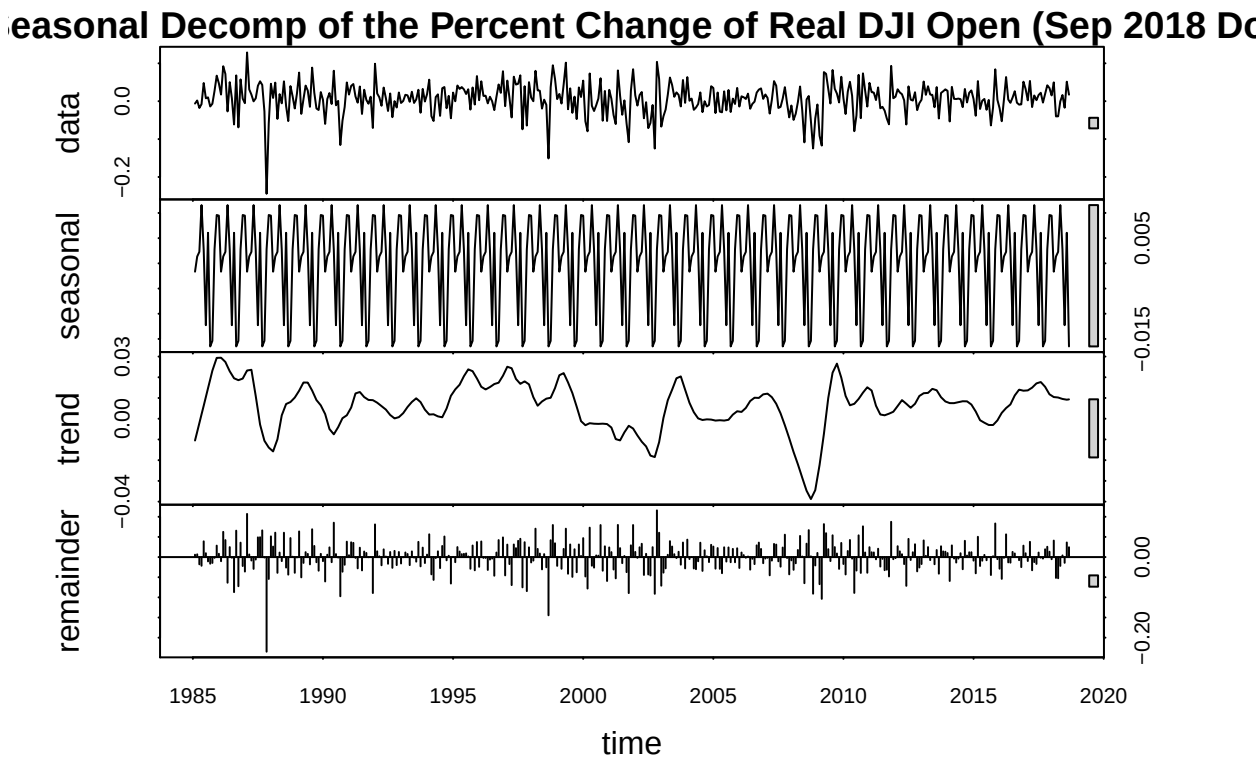
```
    frequency = 12
  )
fedFund <-
  ts(
    df$fedFundRate,
    start = c(1985, 1),
    end = c(2018, 9),
    frequency = 12
  )

totalRetired <-
  ts(
    df$totalSSRetired,
    start = c(1985, 1),
    end = c(2018, 9),
    frequency = 12
  )


plot(stl(realDJIOpen, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of Real DJI Open (Sep 2018 Dollars)')
```




```
plot(stl(log(realDJIOpen), s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of the Log of Real DJI Open (Sep 2018 Dollars)')
```

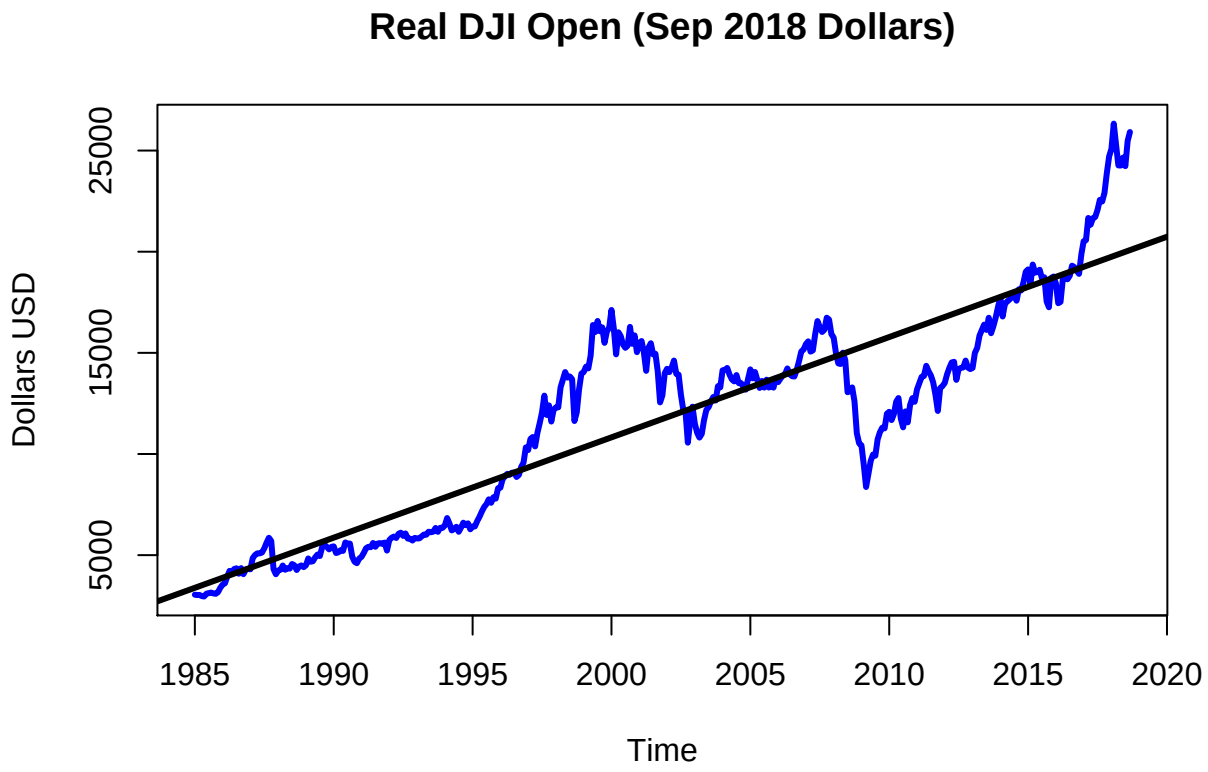



```
plot(stl(percRealDJIOpen, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of the Percent Change of Real DJI Open (Sep 2018 Dollars)')
```

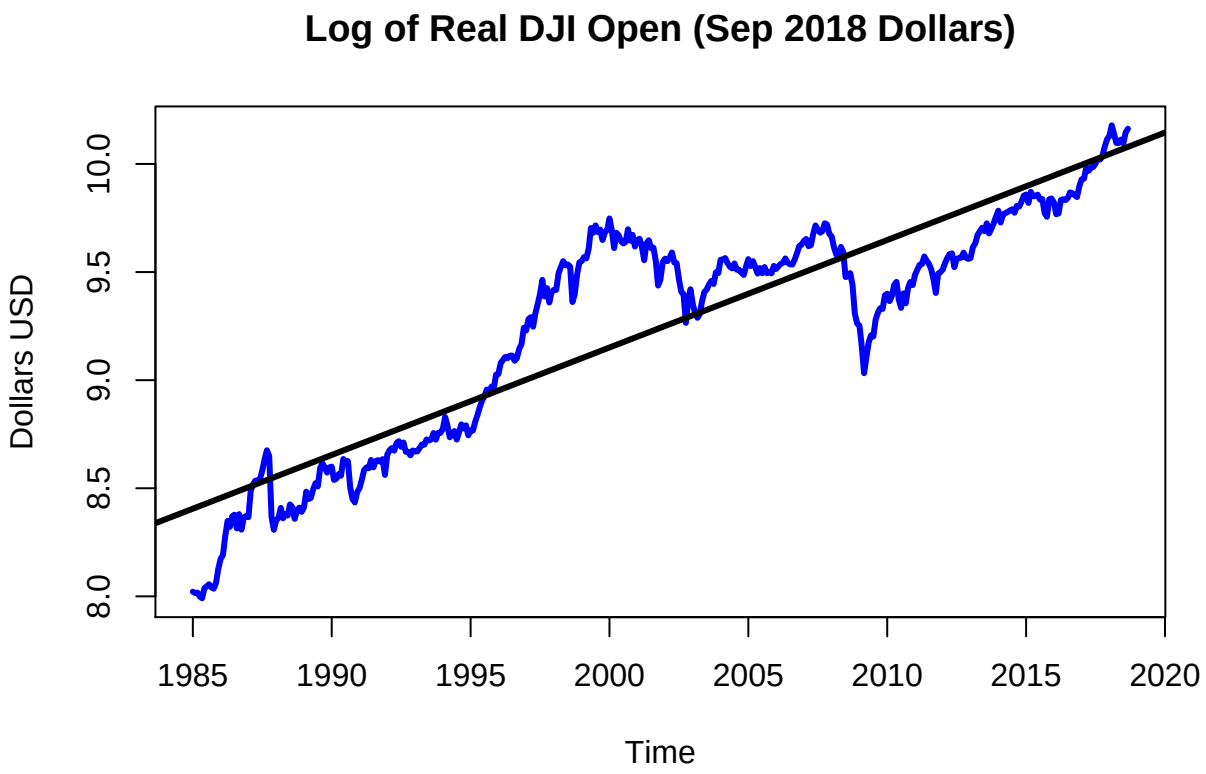



```
plot(realDJIOpen,
     col = 'blue',
     lwd = 3,
```

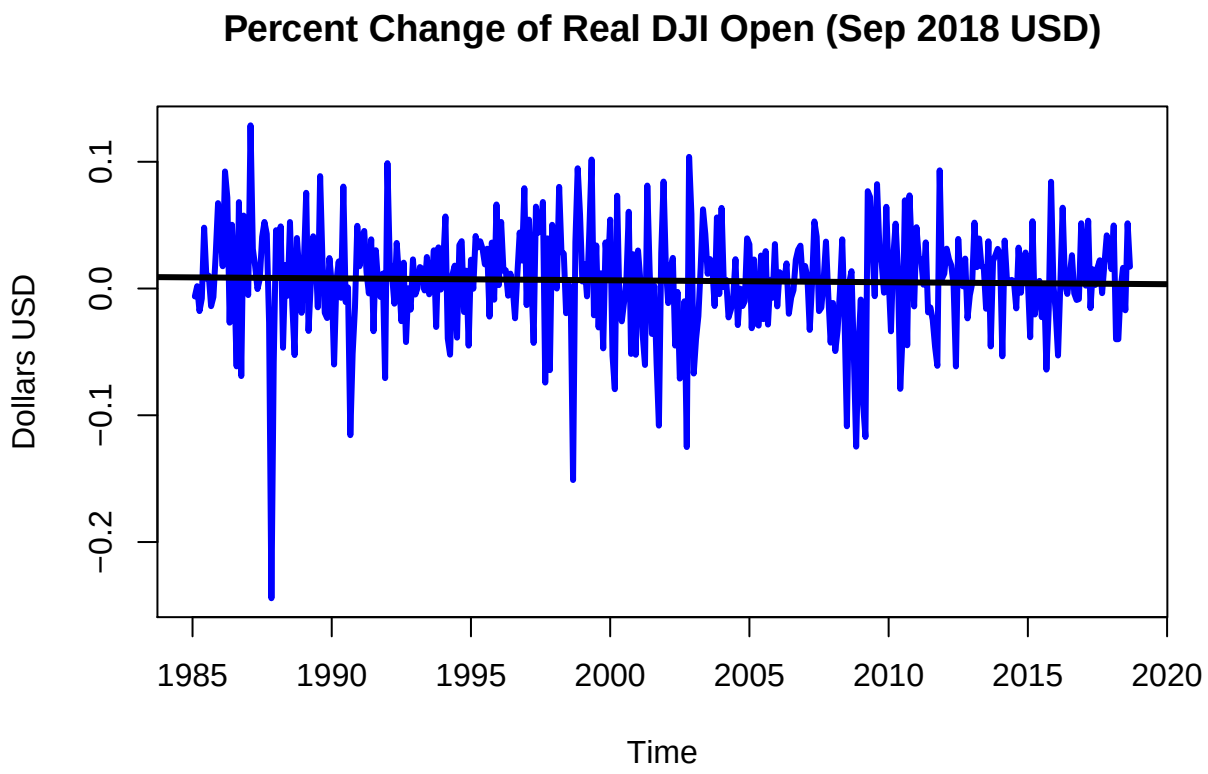
```
     ylab = 'Dollars USD')
abline(reg = lm(realDJIOpen ~ time(realDJIOpen)), lwd = 3)
title(main = 'Real DJI Open (Sep 2018 Dollars)')
```



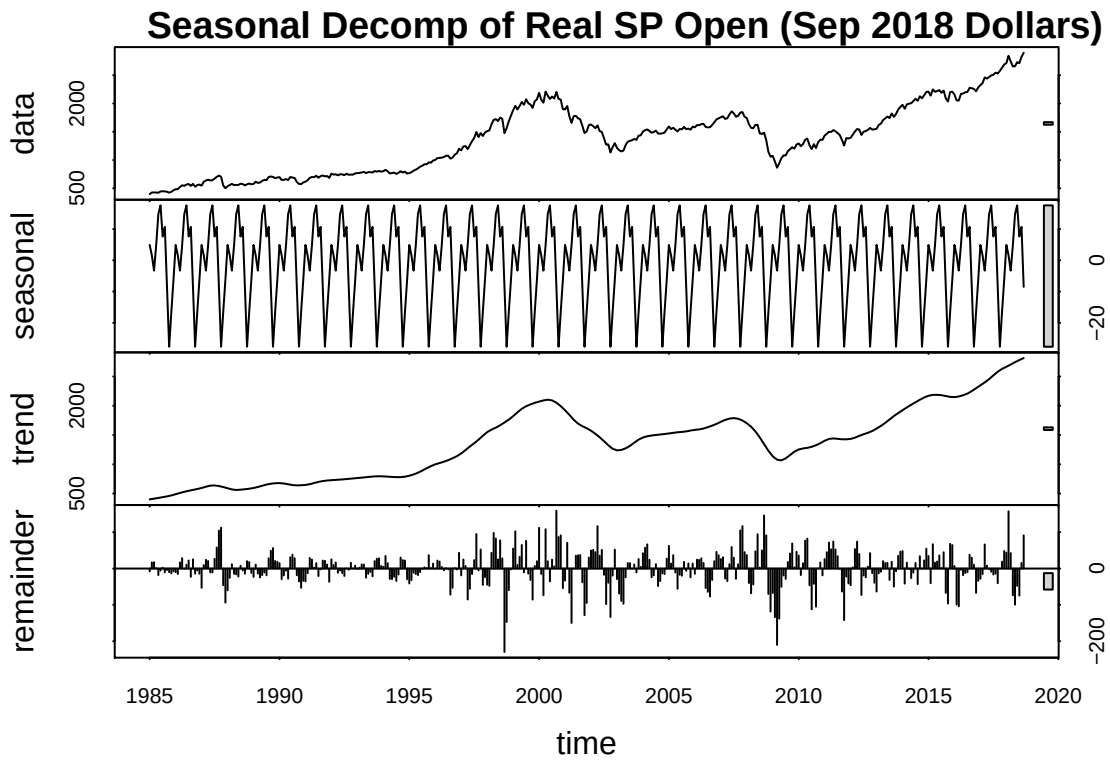

```
plot(log(realDJIOpen),
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(log(realDJIOpen) ~ time(log(realDJIOpen))), lwd = 3)
title(main = 'Log of Real DJI Open (Sep 2018 Dollars)')
```



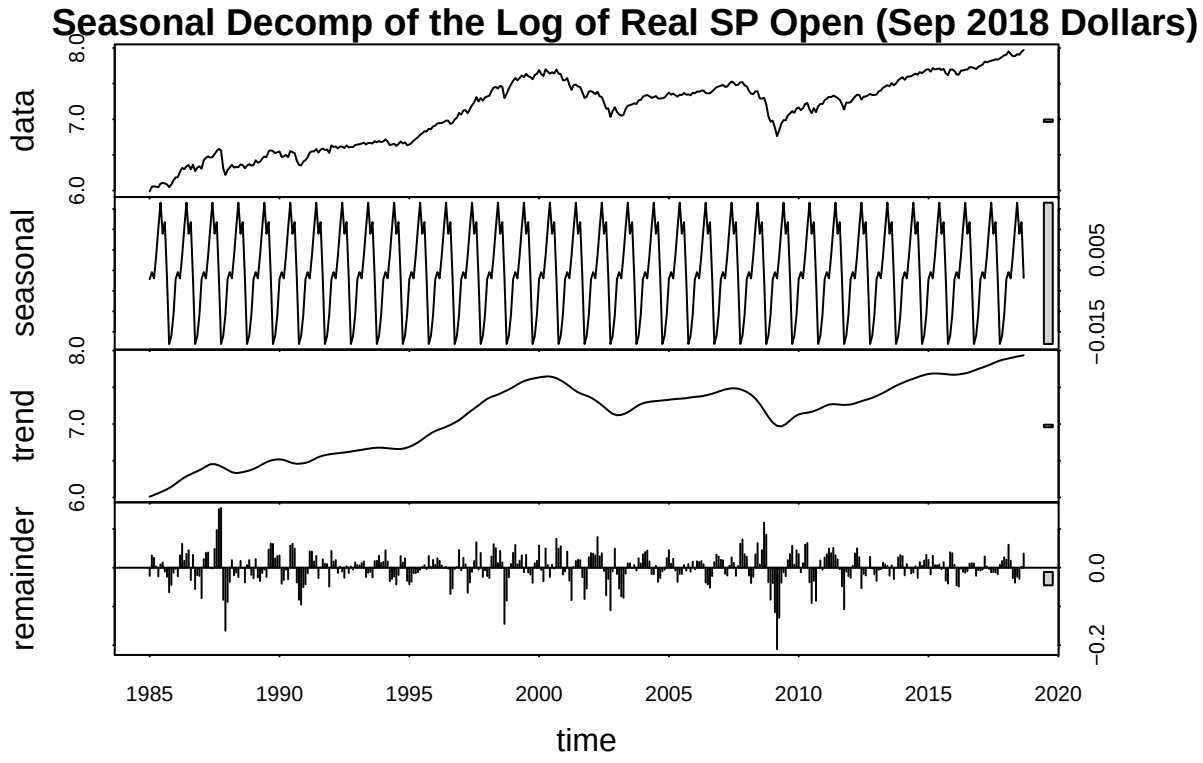

```
plot(percRealDJIOpen,
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(percRealDJIOpen ~ time(percRealDJIOpen)), lwd = 3)
title(main = 'Percent Change of Real DJI Open (Sep 2018 USD)')
```



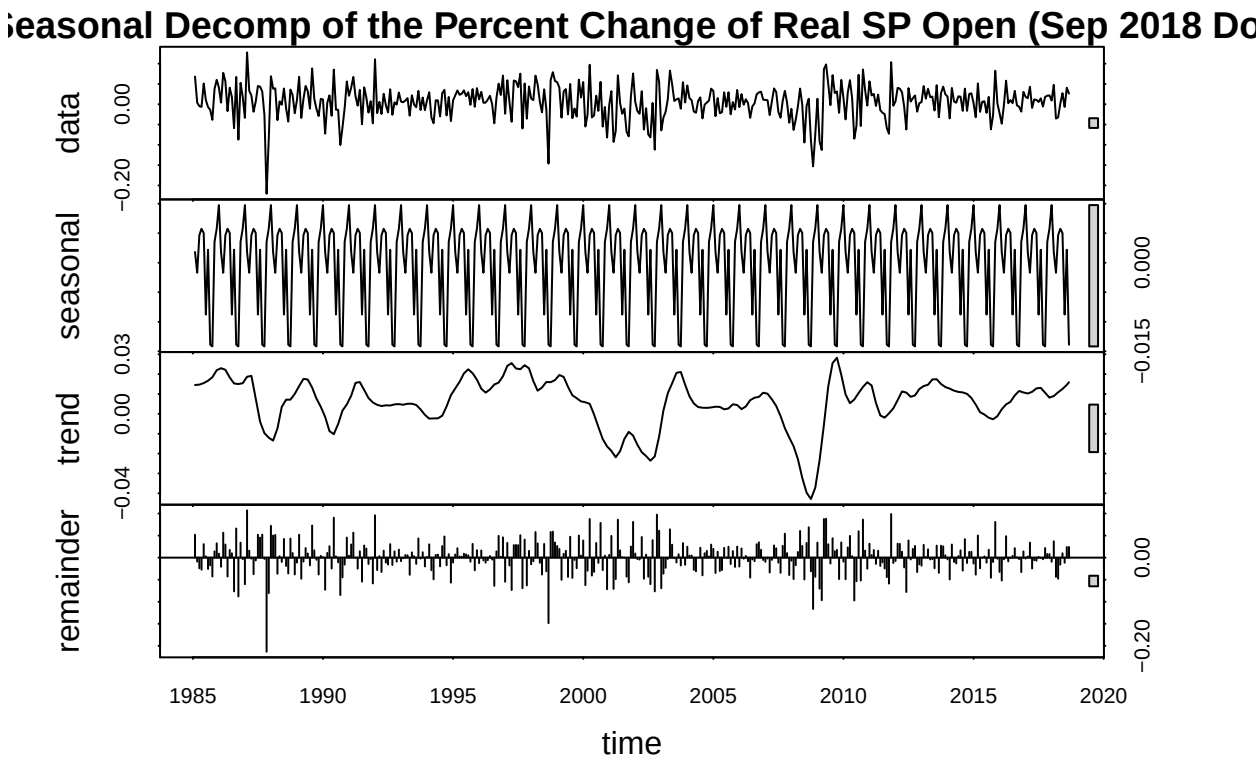

```
plot(stl(realSPOpen, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of Real SP Open (Sep 2018 Dollars)')
```




```
plot(stl(log(realSPOpen), s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of the Log of Real SP Open (Sep 2018 Dollars)')
```

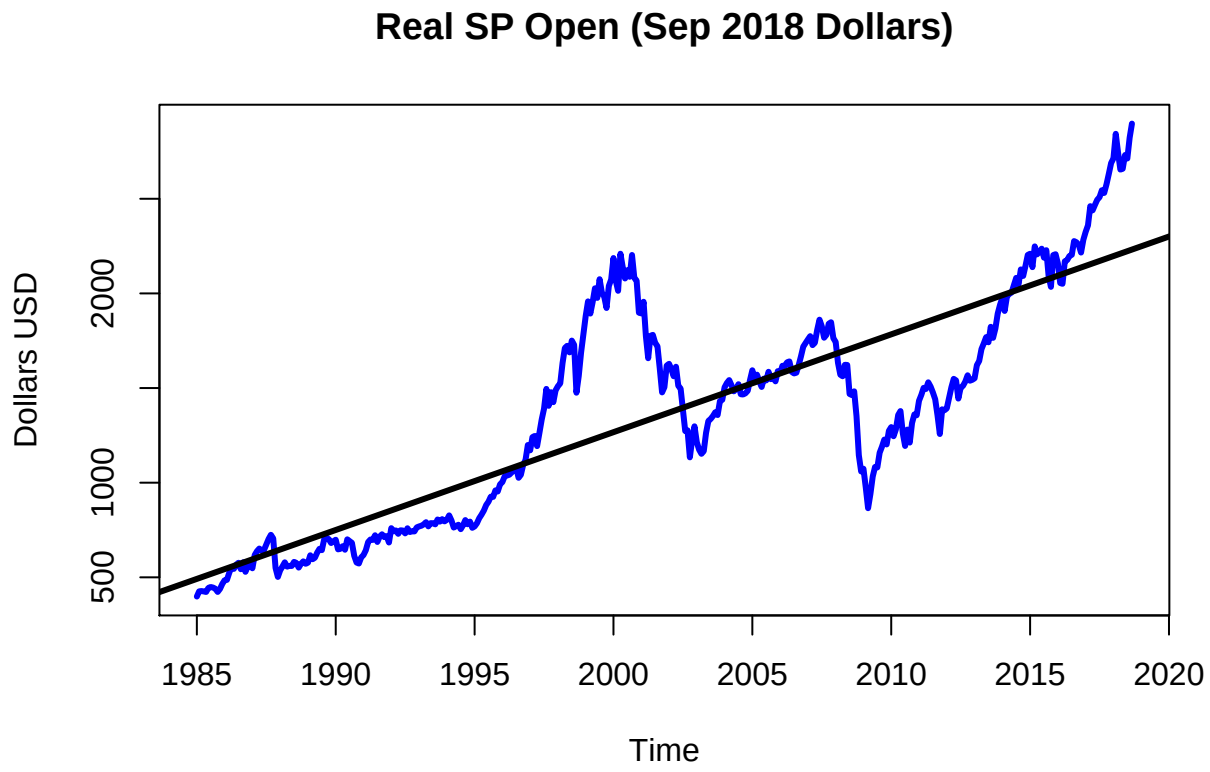



```
plot(stl(percRealSPOpen, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of the Percent Change of Real SP Open (Sep 2018 Dollars)')
```

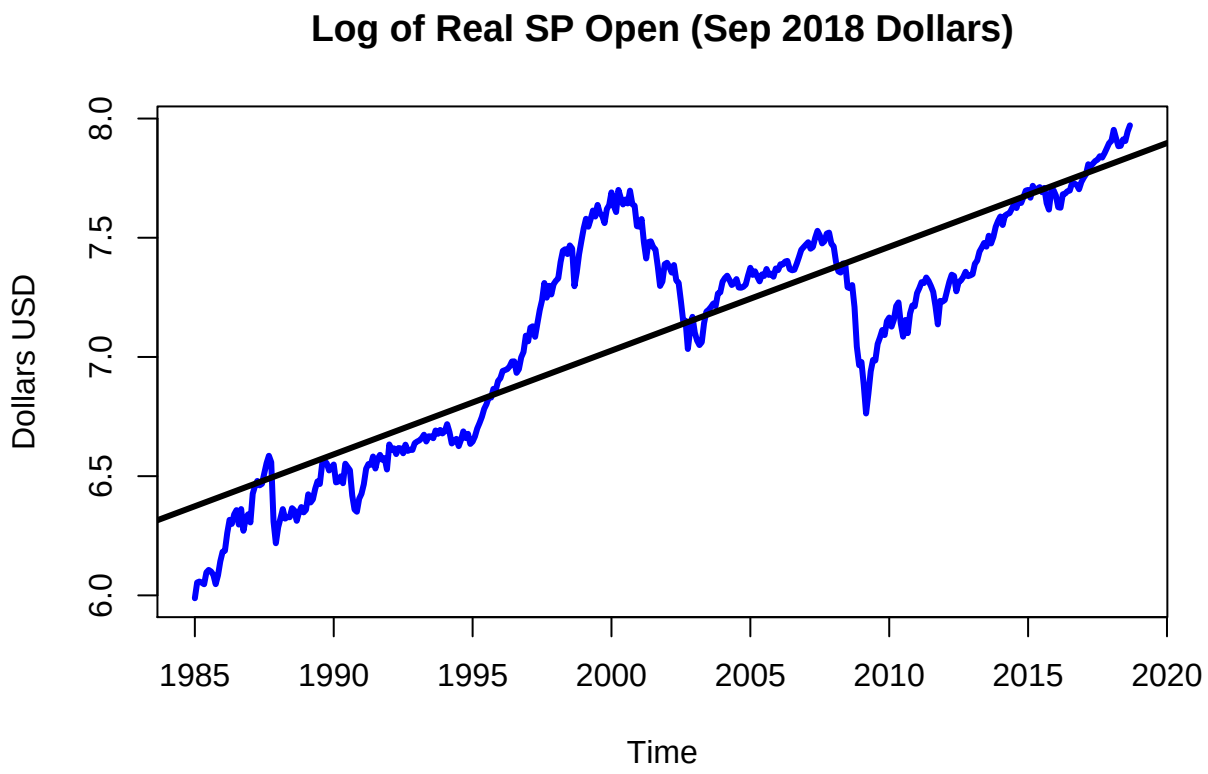



```
plot(realSPOpen,
     col = 'blue',
     lwd = 3,
```

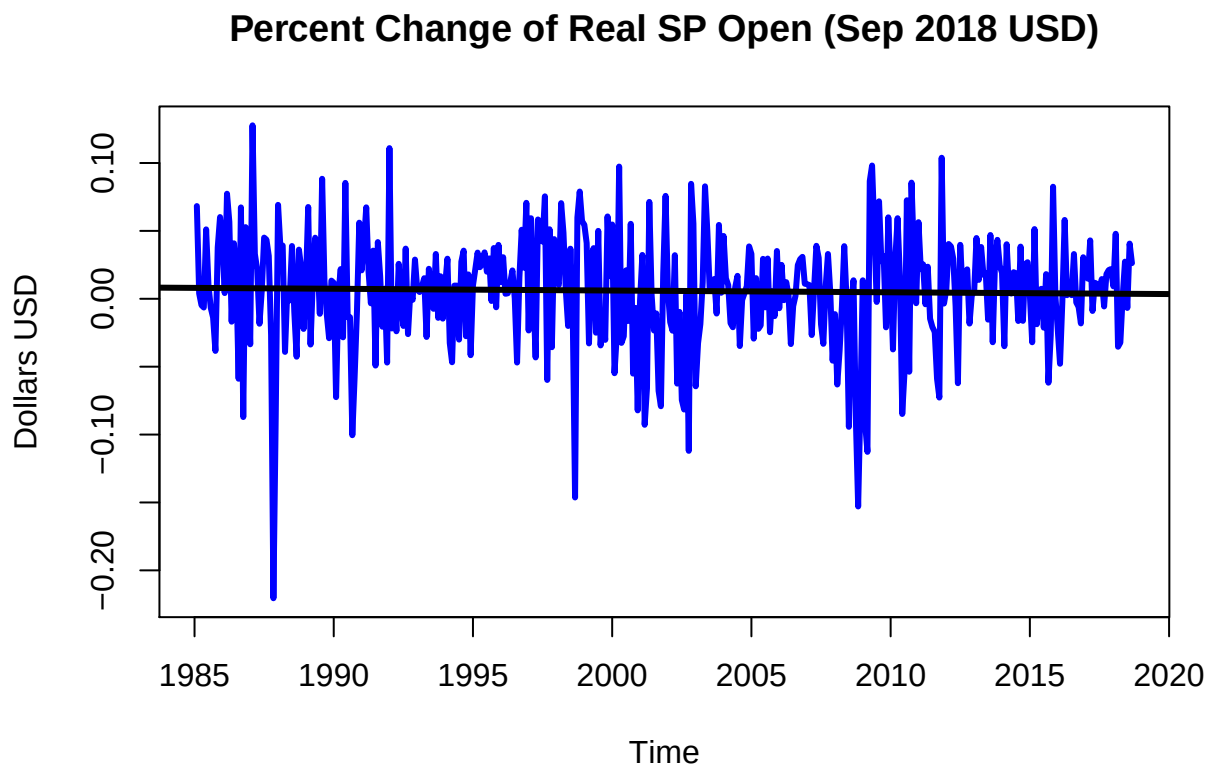
```
     ylab = 'Dollars USD')
abline(reg = lm(realSPOpen ~ time(realSPOpen)), lwd = 3)
title(main = 'Real SP Open (Sep 2018 Dollars)')
```



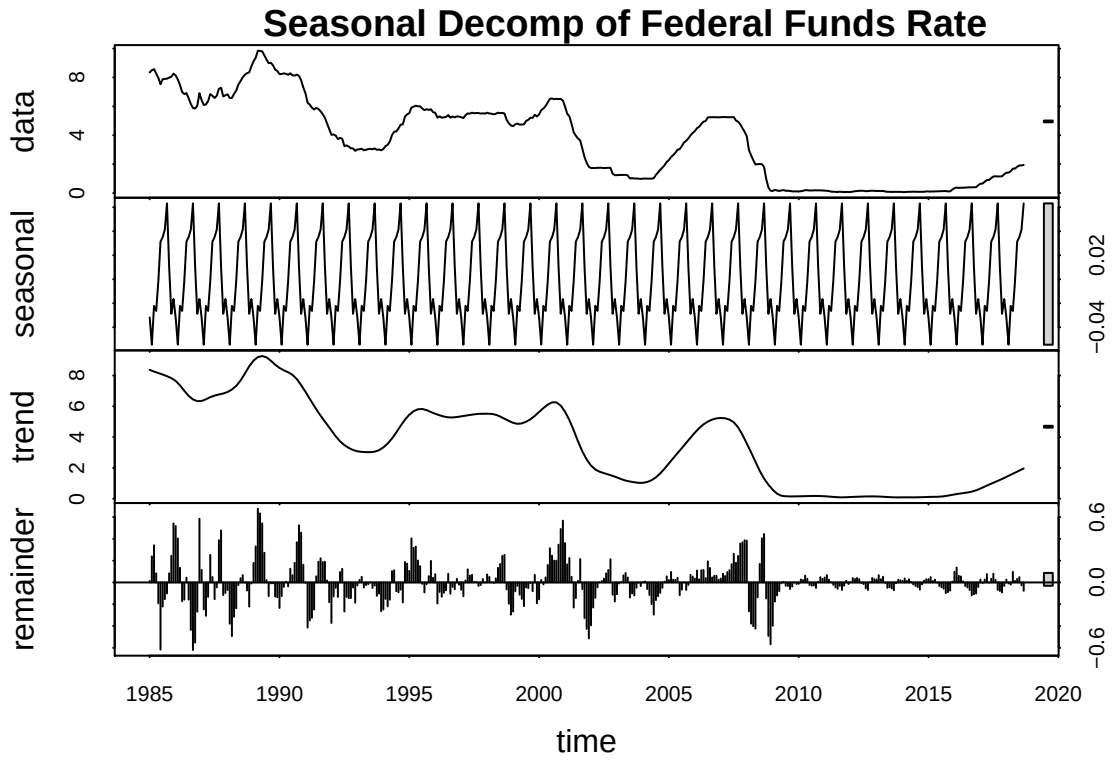

```
plot(log(realSPOpen),
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(log(realSPOpen) ~ time(log(realSPOpen))), lwd = 3)
title(main = 'Log of Real SP Open (Sep 2018 Dollars)')
```




```
plot(percRealSPOpen,
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(percRealSPOpen ~ time(percRealSPOpen)), lwd = 3)
title(main = 'Percent Change of Real SP Open (Sep 2018 USD)')
```

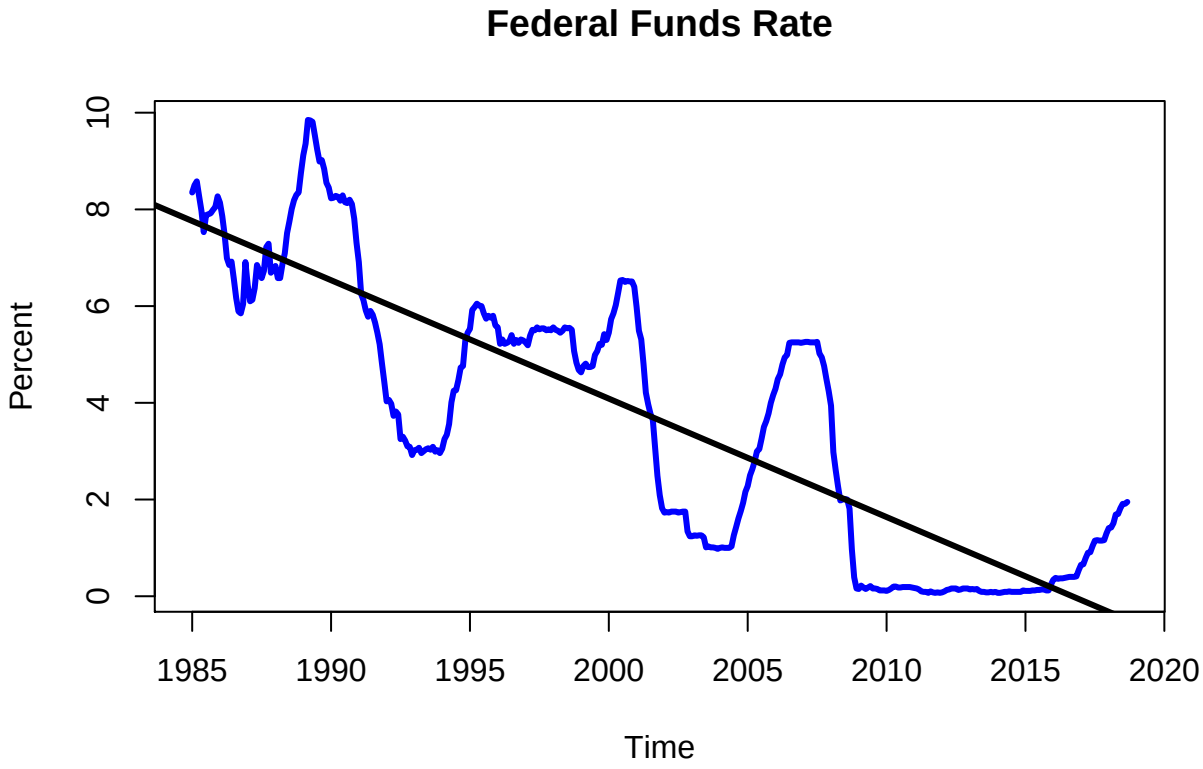



```
plot(stl(fedFund, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of Federal Funds Rate')
```

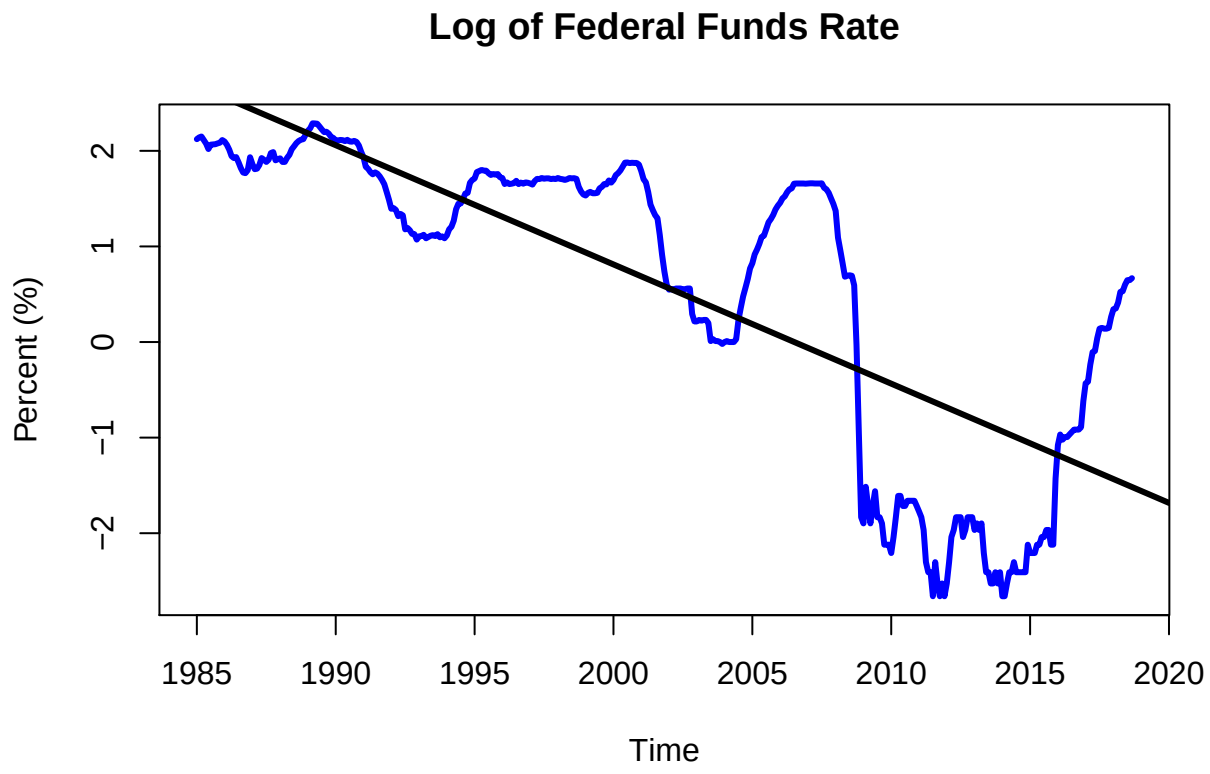



```
plot(fedFund,
     col = 'blue',
     lwd = 3,
```

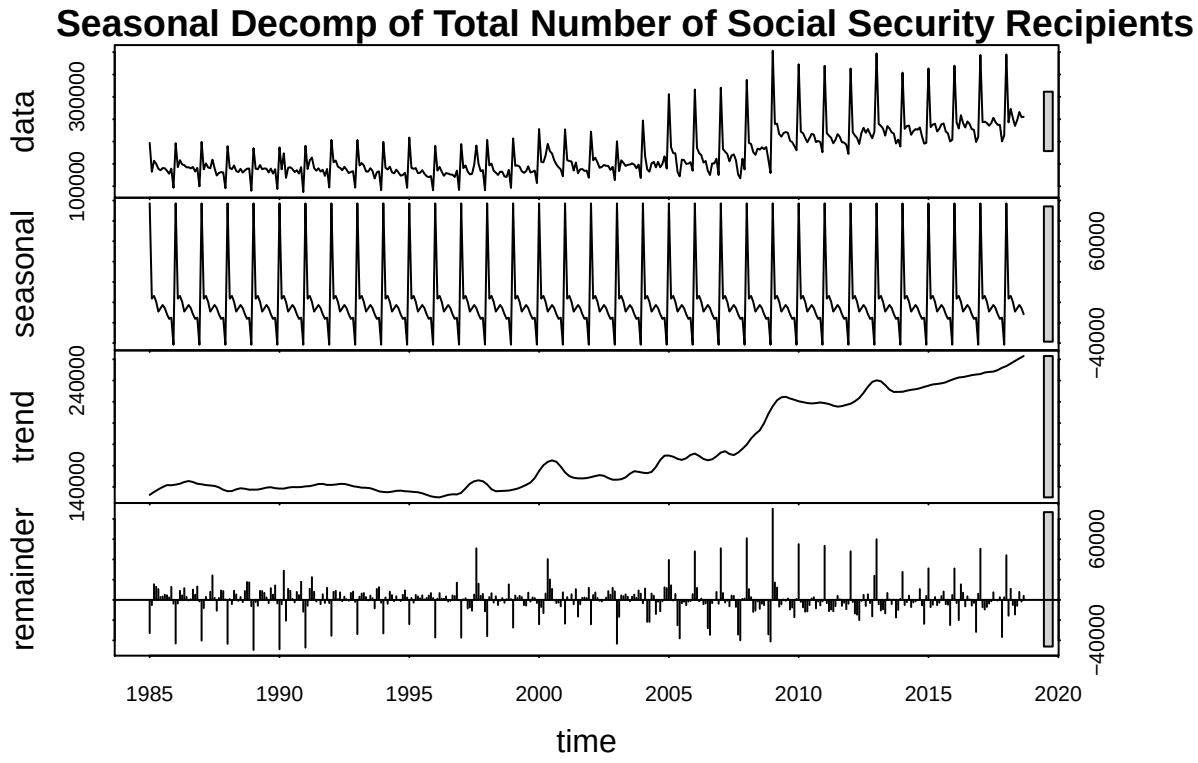
```
     ylab = 'Percent')
abline(reg = lm(fedFund ~ time(fedFund)), lwd = 3)
title(main = 'Federal Funds Rate')
```




```
plot(log(fedFund),
     col = 'blue',
     lwd = 3,
     ylab = 'Percent (%)')
abline(reg = lm(log(fedFund) ~ time(log(fedFund))), lwd = 3)
title(main = 'Log of Federal Funds Rate')
```

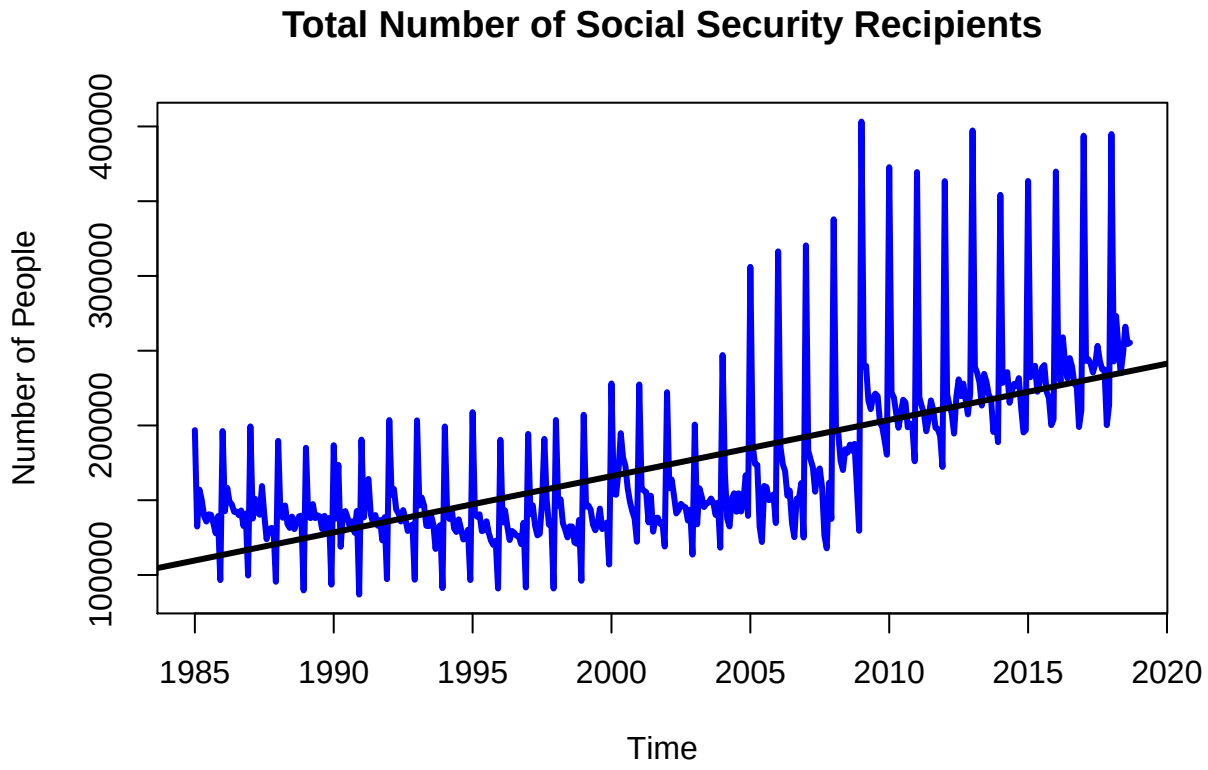



```
plot(stl(totalRetired, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of Total Number of Social Security Recipients')
```

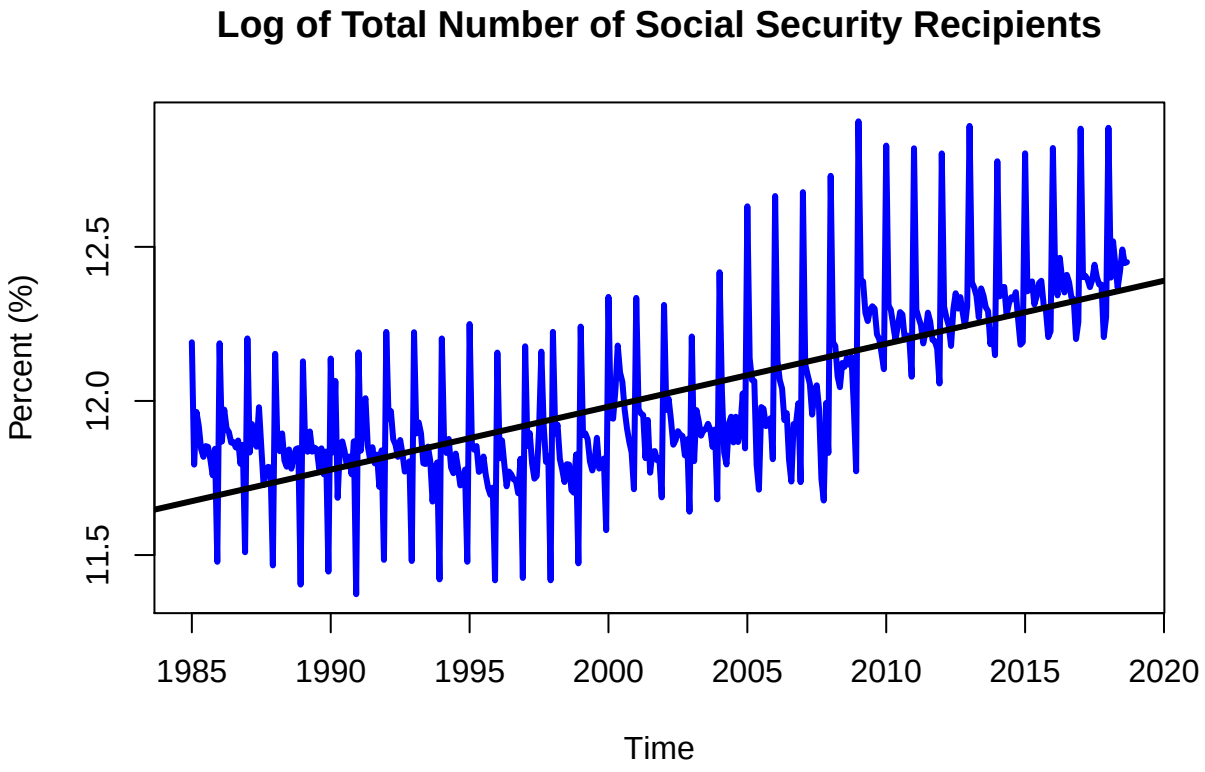



```
plot(totalRetired,
     col = 'blue',
     lwd = 3,
```

```
     ylab = 'Number of People')
abline(reg = lm(totalRetired ~ time(totalRetired)), lwd = 3)
title(main = 'Total Number of Social Security Recipients')
```




```
plot(log(totalRetired),
     col = 'blue',
     lwd = 3,
     ylab = 'Percent (%)')
abline(reg = lm(log(totalRetired) ~ time(log(totalRetired))), lwd = 3)
title(main = 'Log of Total Number of Social Security Recipients')
```




```
# Remove nominal values aside indicators of positive change
df2 <- df1[, c(1, 8:10, 11:18, 32:44, 58:96, 110:122)]
# remove components of the total SS Retirees (male + female = total) and percent increases and decrease
df3 <- df2[, c(1:2, 8:9, 13:77)]

# Hypothesis Tests ####
# Stationarity Loop Testing
statVars <- matrix(data = NA, nrow = 68, ncol = 2)
df3TS <- ts(
  df3,
  start = c(1985, 12),
  end = c(2018, 9),
  frequency = 12
)
for (i in c(1:68)) {
  statVars[i,1] <- i+1
  statVars[i,2] <- adf.test(df3TS[,i+1], alternative = 'stationary')[[4]]
}
```

```
## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
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## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

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## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value
```

```
## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
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## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

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## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
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## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
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## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value
```
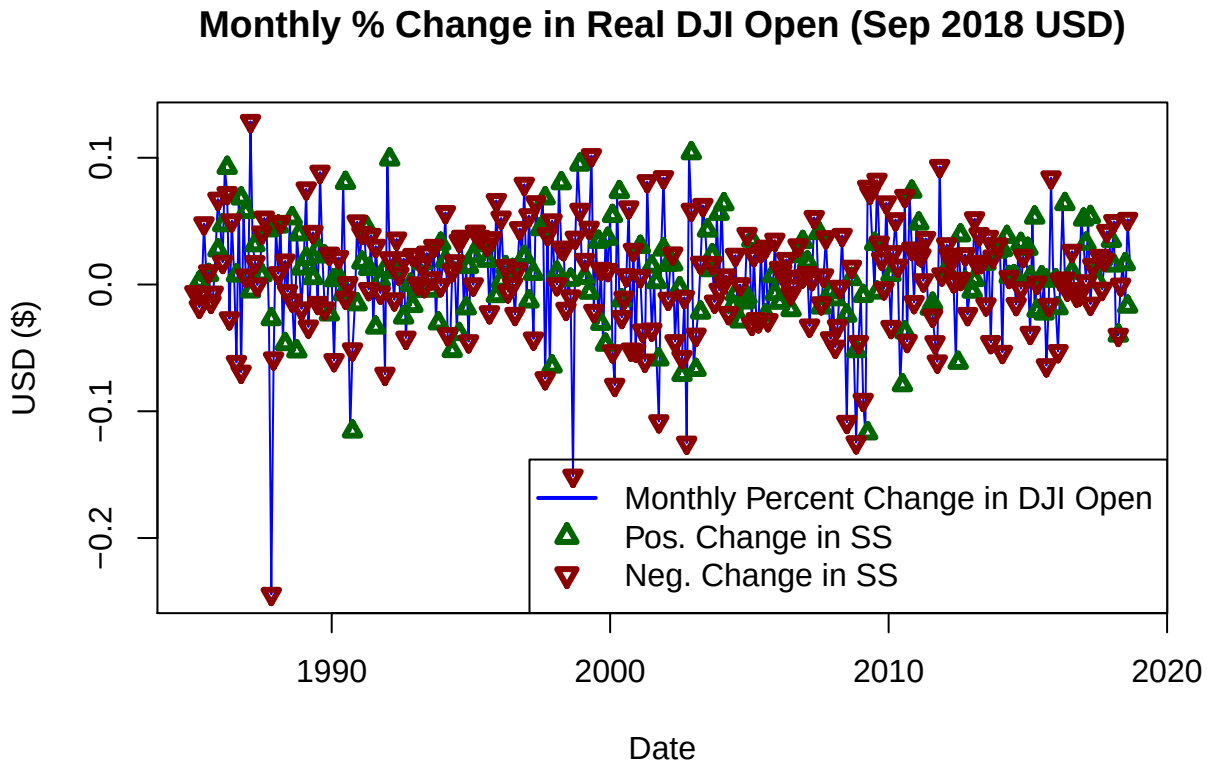
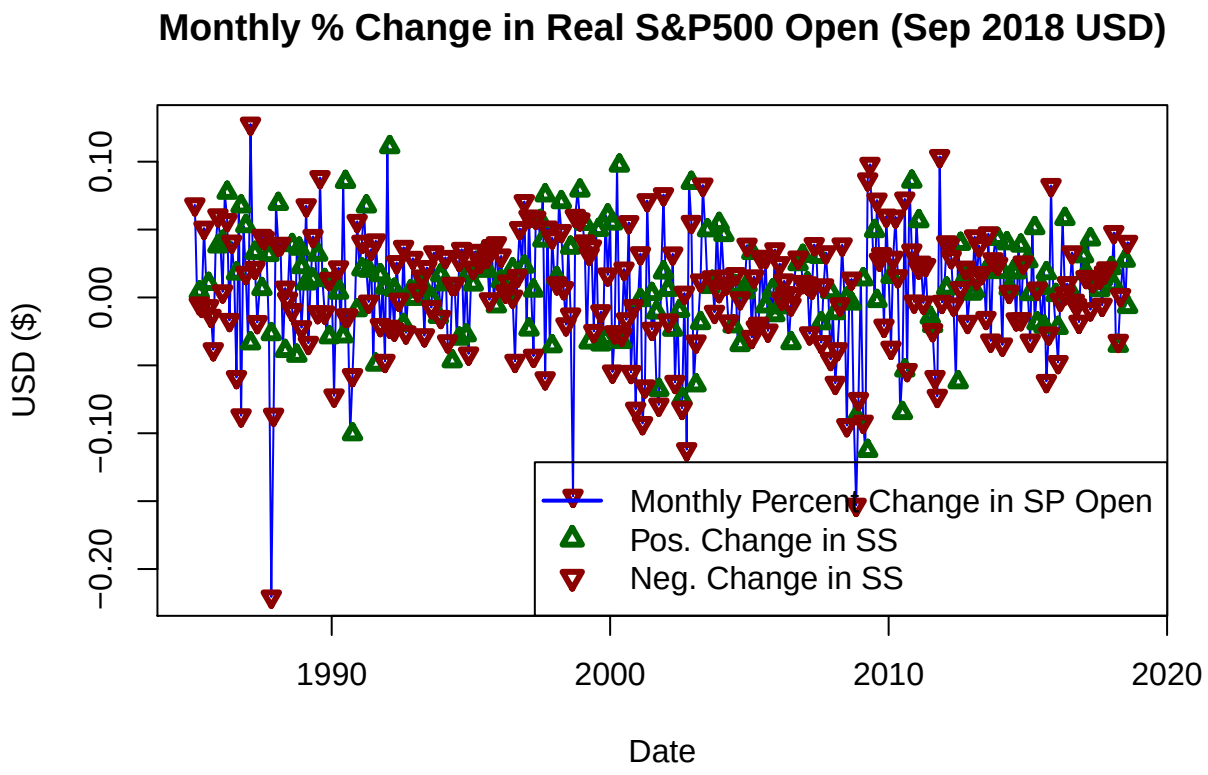

```r
# Reject the null when p < 0.05. So, the variables associated with this are
# likely stationary and useful for prediction of time series
dfStatSelect<- statVars[,1][statVars[,2] < 0.05]
dfStationary<- df3[,c(1,dfStatSelect)]
```

```r
# Visualizations ####
plot(
  x = dfStationary$date,
  y = dfStationary$percChangeRealDJIopen,
  col = 'blue',
  lwd = 1,
  type = 'l',
  ylab = 'USD ($)',
  xlab = 'Date'
)
points(
  x = dfStationary$date[df$postotalSSRetired == 1],
  y = dfStationary$percChangeRealDJIopen[dfStationary$postotalSSRetired == 1],
  pch = 24,
  col = 'darkgreen',
  cex = 0.8,
  lwd = 3
)
points(
  x = dfStationary$date[dfStationary$postotalSSRetired == 0],
  y = dfStationary$percChangeRealDJIopen[dfStationary$postotalSSRetired == 0],
  pch = 25,
  col = 'darkred',
  cex = 0.8,
  lwd = 3
)
legend(
  'bottomright',
  legend = c(
    'Monthly Percent Change in DJI Open',
    c('Pos. Change in SS', 'Neg. Change in SS')
  ),
  lty = c(1, c(NA, NA)),
  pch = c(NA, c(24, 25)),
  col = c('blue', c('darkgreen', 'darkred')),
  bg = c(NA, c('darkgreen', 'darkred')),
  lwd = c(2, c(3, 3))
)
title(main = 'Monthly % Change in Real DJI Open (Sep 2018 USD)')
```



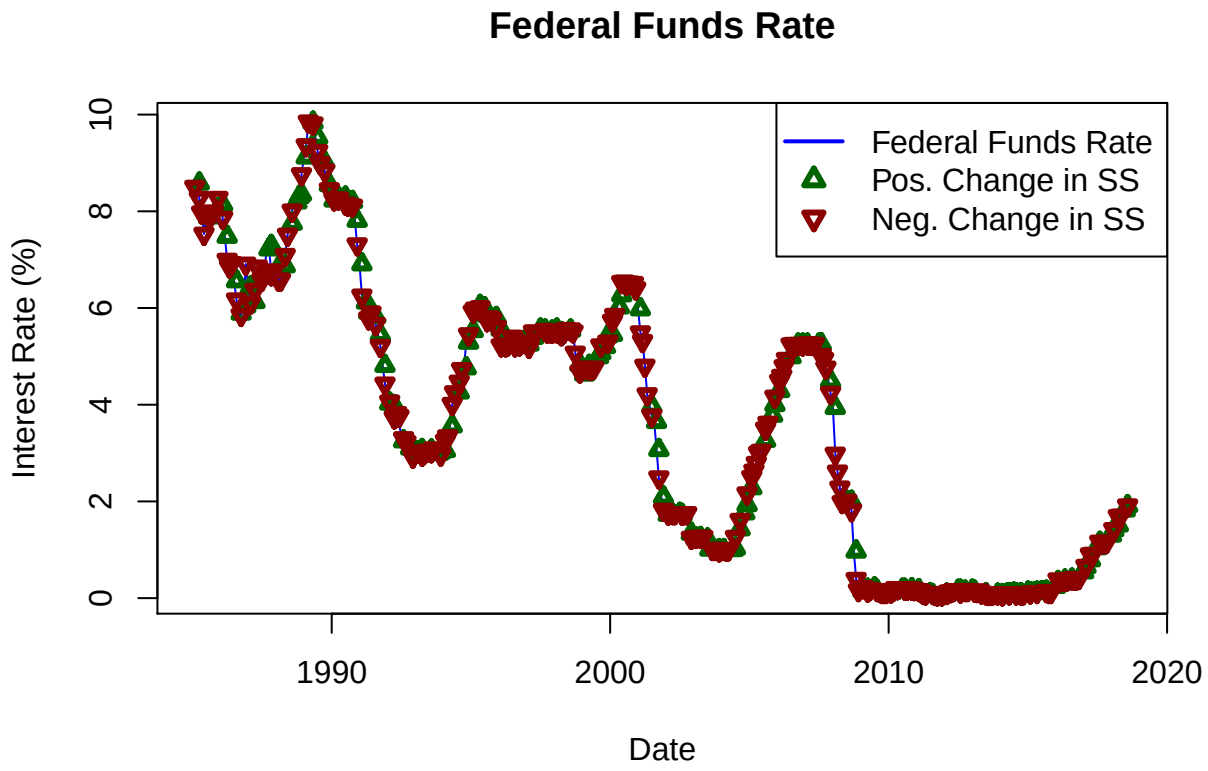

```
plot(
  x = dfStationary$date,
  y = dfStationary$percChangeRealSPopen,
  col = 'blue',
  lwd = 1,
  type = 'l',
  ylab = 'USD ($)',
  xlab = 'Date'
)
points(
  x = dfStationary$date[df$postotalSSRetired == 1],
  y = dfStationary$percChangeRealSPopen[dfStationary$postotalSSRetired == 1],
  pch = 24,
  col = 'darkgreen',
  cex = 0.8,
  lwd = 3
)
points(
  x = dfStationary$date[dfStationary$postotalSSRetired == 0],
  y = dfStationary$percChangeRealSPopen[dfStationary$postotalSSRetired == 0],
  pch = 25,
  col = 'darkred',
  cex = 0.8,
  lwd = 3
)
legend(
  'bottomright',
  legend = c(
    'Monthly Percent Change in SP Open',
    c('Pos. Change in SS', 'Neg. Change in SS')
```

```
  ),
  lty = c(1, c(NA, NA)),
  pch = c(NA, c(24, 25)),
  col = c('blue', c('darkgreen', 'darkred')),
  bg = c(NA, c('darkgreen', 'darkred')),
  lwd = c(2, c(3, 3))
)
title(main = 'Monthly % Change in Real S&P500 Open (Sep 2018 USD)')
```



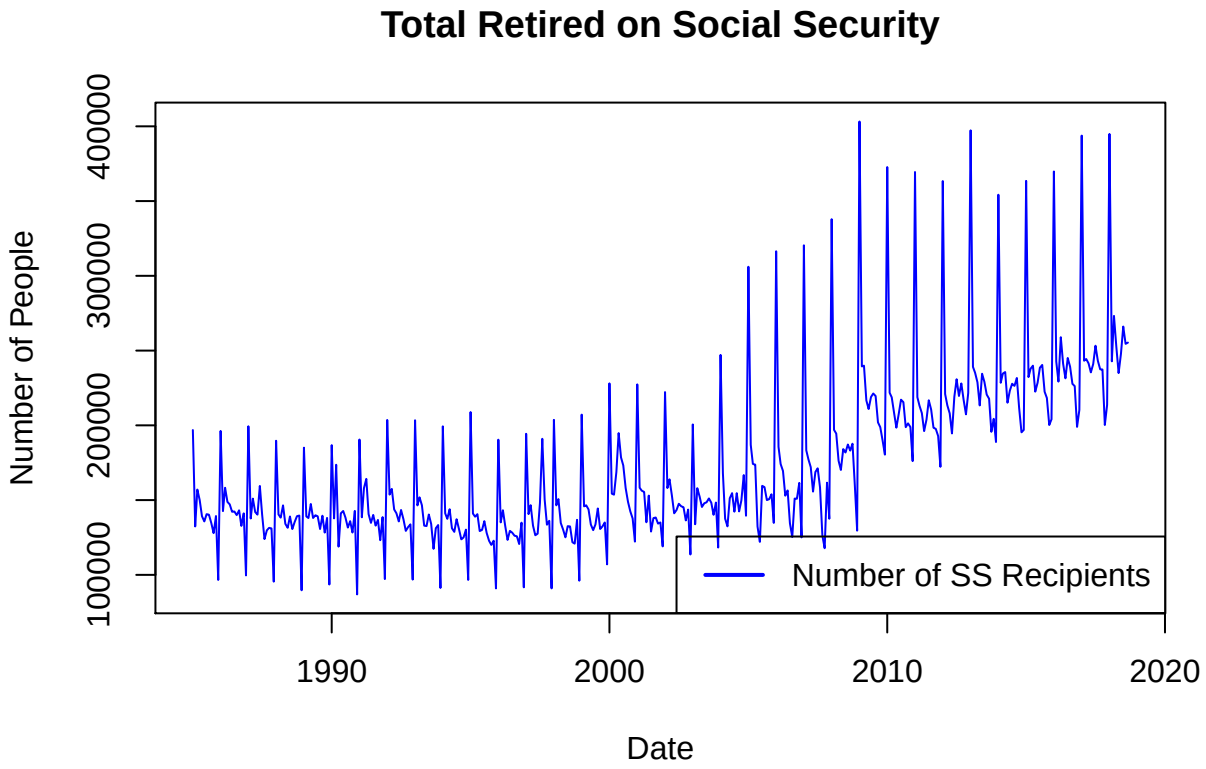

```
plot(
  x = dfStationary$date,
  y = dfStationary$fedFundRate,
  col = 'blue',
  lwd = 1,
  type = 'l',
  ylab = 'Interest Rate (%)',
  xlab = 'Date'
)
points(
  x = dfStationary$date[df$postotalSSRetired == 1],
  y = dfStationary$fedFundRate[dfStationary$postotalSSRetired == 1],
  pch = 24,
  col = 'darkgreen',
  cex = 0.8,
  lwd = 3
)
points(
  x = dfStationary$date[dfStationary$postotalSSRetired == 0],
  y = dfStationary$fedFundRate[dfStationary$postotalSSRetired == 0],
```

```
  pch = 25,
  col = 'darkred',
  cex = 0.8,
  lwd = 3
)
legend(
  'topright',
  legend = c('Federal Funds Rate',
             c('Pos. Change in SS', 'Neg. Change in SS')),
  lty = c(1, c(NA, NA)),
  pch = c(NA, c(24, 25)),
  col = c('blue', c('darkgreen', 'darkred')),
  bg = c(NA, c('darkgreen', 'darkred')),
  lwd = c(2, c(3, 3))
)
title(main = 'Federal Funds Rate')
```




```
plot(
  x = df$date,
  y = df$totalSSRetired,
  col = 'blue',
  lwd = 1,
  type = 'l',
  ylab = 'Number of People',
  xlab = 'Date'
)
legend(
  'bottomright',
  legend = c('Number of SS Recipients'),
  lty = c(1),
```

```
  col = c('blue'),
  lwd = c(2)
)
title(main = 'Total Retired on Social Security')
```




```
# Selection ####
# Set a few dataframes for different variables
dfDiff <- dfStationary[,c(2:5,7:19)]
dfPosChange <- dfStationary[,c(2:5, 20:45)]
dfPerc <- dfStationary[,c(2:5, 46:58)]
# Run the selections
# Differences ####
# SeqRep
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfDiff,
  method= 'seqrep',
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

```
##  [1] 0.1731698 0.1779456 0.1839180 0.2391592 0.2410517 0.2463118 0.2466627
```

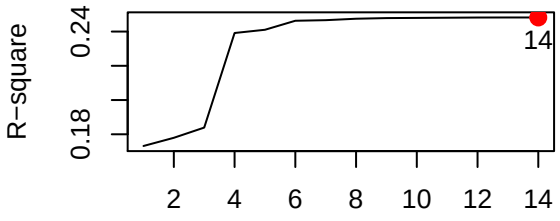
```
##  [8] 0.2474956 0.2478743 0.2479814 0.2480829 0.2481942 0.2482266 0.2482272
```

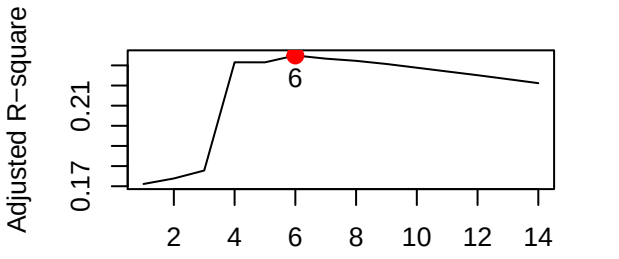
```
regSummary$adjr2
```

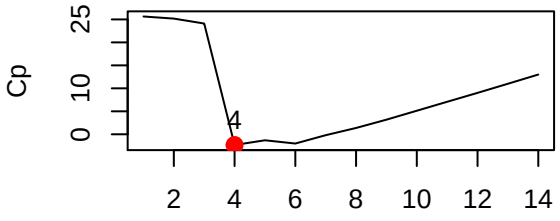
```
##  [1] 0.1711130 0.1738456 0.1777974 0.2315317 0.2315172 0.2349210 0.2333461
##  [8] 0.2322550 0.2306938 0.2288461 0.2269832 0.2251209 0.2231675 0.2211711
```

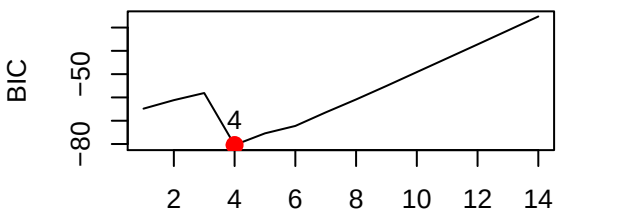
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - SeqRep - Differences",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - SeqRep - Differences",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - SeqRep - Differences",
     ylab = "Cp",
```

```
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - SeqRep - Differences",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

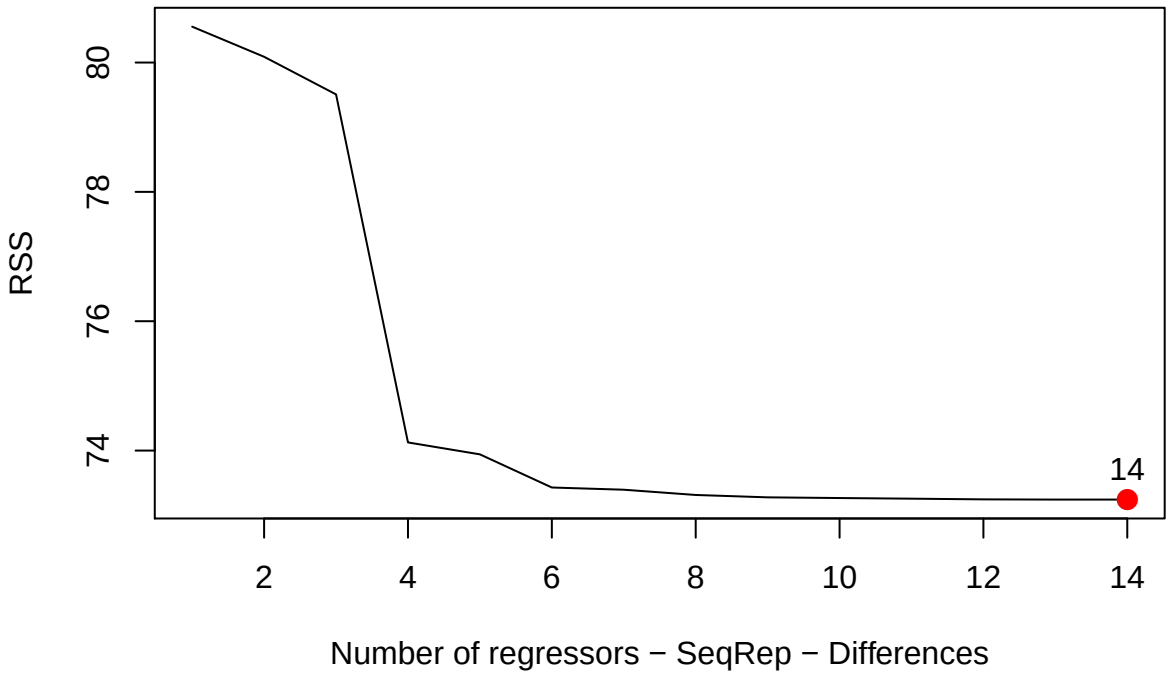




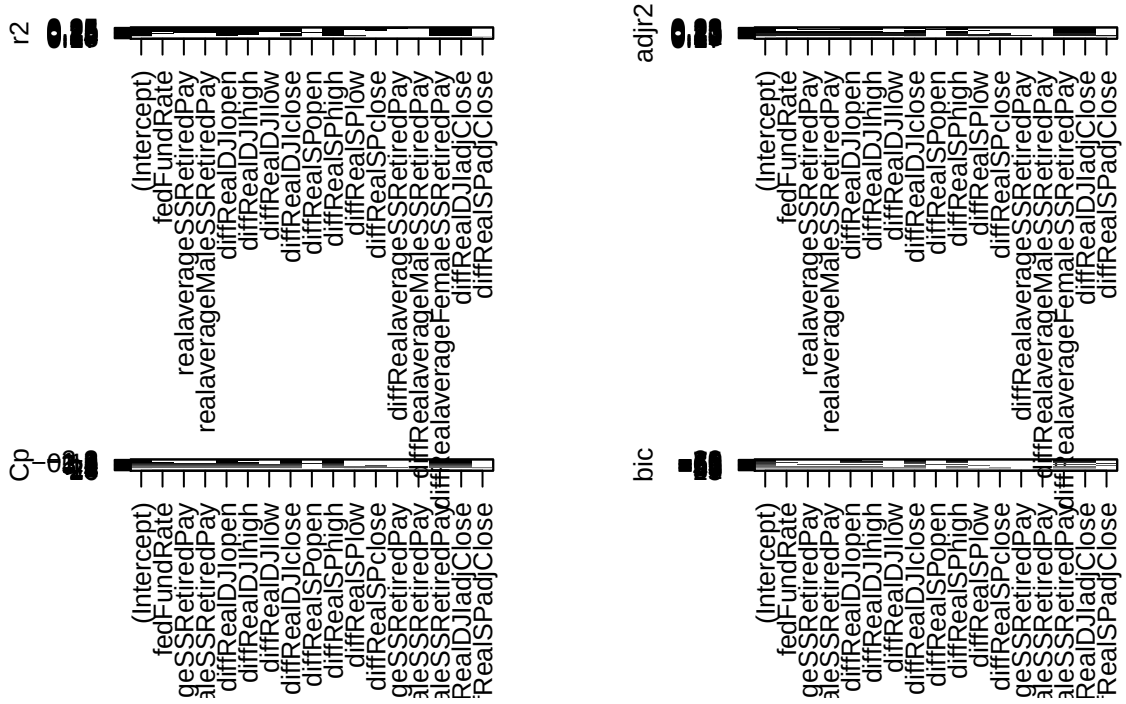





```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - SeqRep - Differences",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesSeqRep <- c(names(coef(regFitSelect, id = 4))[-1])
# Forward
regFitSelect <- regsubsets(
  postotalSSRetired~.,
```

```
  data=dfDiff,
  method= 'forward',
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in rval$lopt[] <- rval$vorder[rval$lopt]: number of items to
## replace is not a multiple of replacement length
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

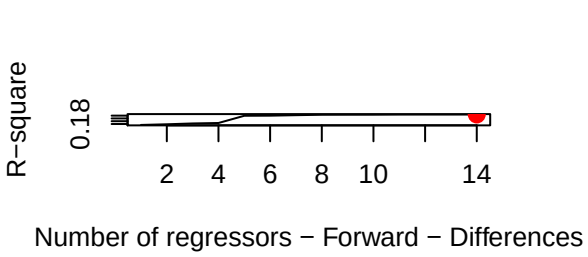
```
##  [1] 0.1731698 0.1779456 0.1839180 0.1871817 0.2391704 0.2399022 0.2433283
##  [8] 0.2463473 0.2466978 0.2469470 0.2479080 0.2480453 0.2481380 0.2482272
```

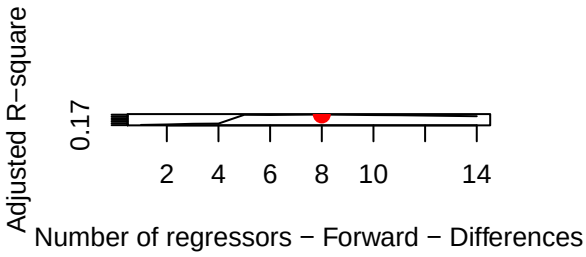
```
regSummary$adjr2
```

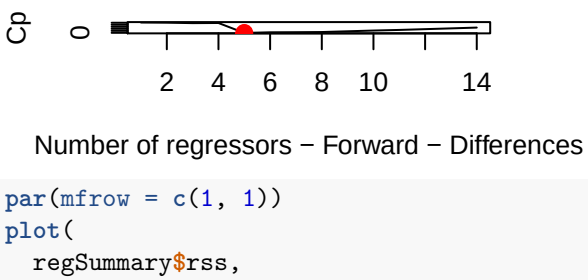
```
##  [1] 0.1711130 0.1738456 0.1777974 0.1790331 0.2296123 0.2284146 0.2299528
##  [8] 0.2310835 0.2294904 0.2277853 0.2268034 0.2249674 0.2230759 0.2211711
```

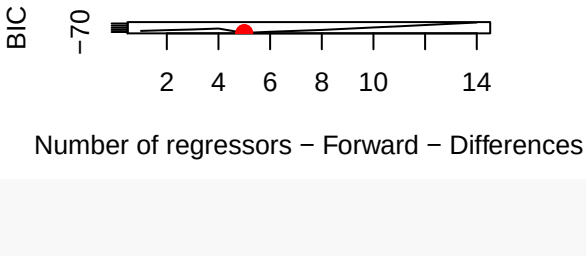
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Forward - Differences",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Forward - Differences",
```

```
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Forward - Differences",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Forward - Differences",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

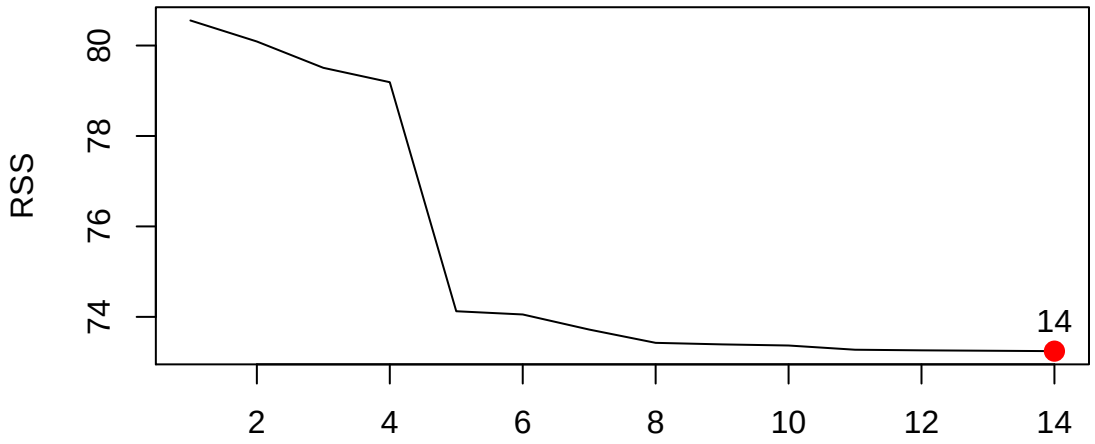




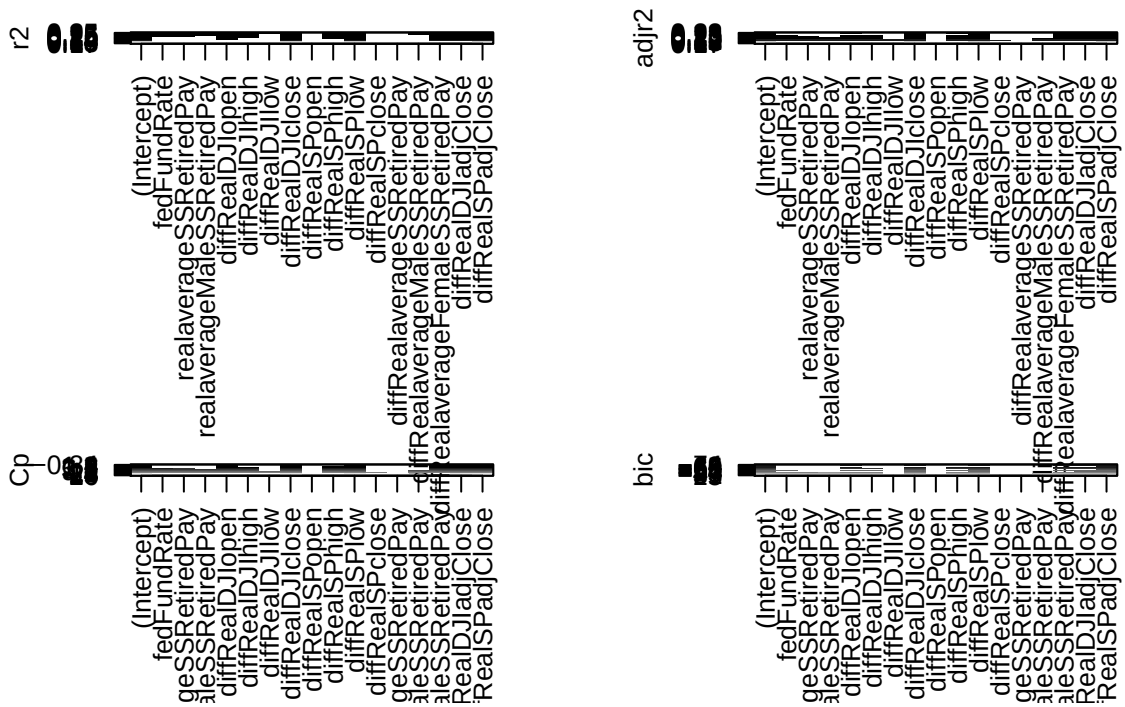





```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Forward - Differences",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesForward <- c(names(coef(regFitSelect, id = 5))[-1])
# Backward
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfDiff,
  method= 'backward',
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
```

```
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in rval$lopt[] <- rval$vorder[rval$lopt]: number of items to
## replace is not a multiple of replacement length
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

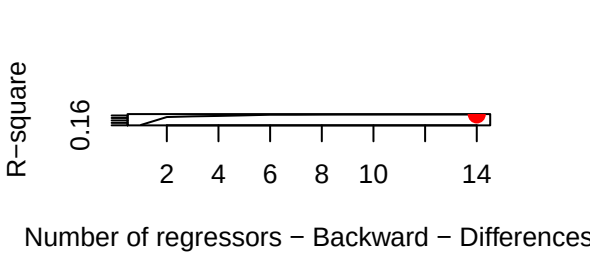
```
##  [1] 0.1630296 0.2273926 0.2330672 0.2364933 0.2410517 0.2463118 0.2464133
##  [8] 0.2474956 0.2478743 0.2479814 0.2480829 0.2481942 0.2482266 0.2482272
```

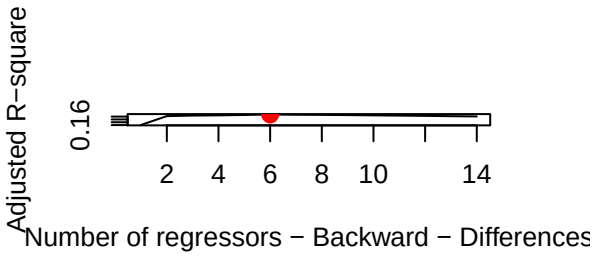
```
regSummary$adjr2
```

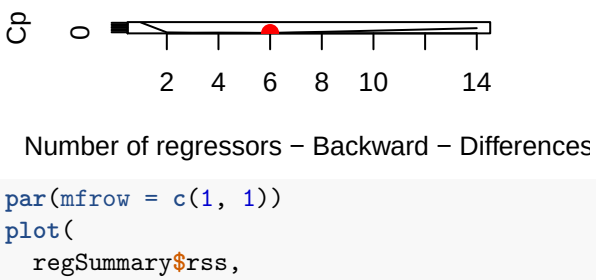
```
##  [1] 0.1609476 0.2235392 0.2273153 0.2288391 0.2315172 0.2349210 0.2330923
##  [8] 0.2322550 0.2306938 0.2288461 0.2269832 0.2251209 0.2231675 0.2211711
```

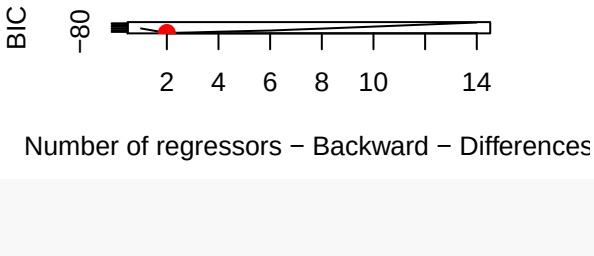
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Backward - Differences",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Backward - Differences",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
```

```
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Backward - Differences",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Backward - Differences",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

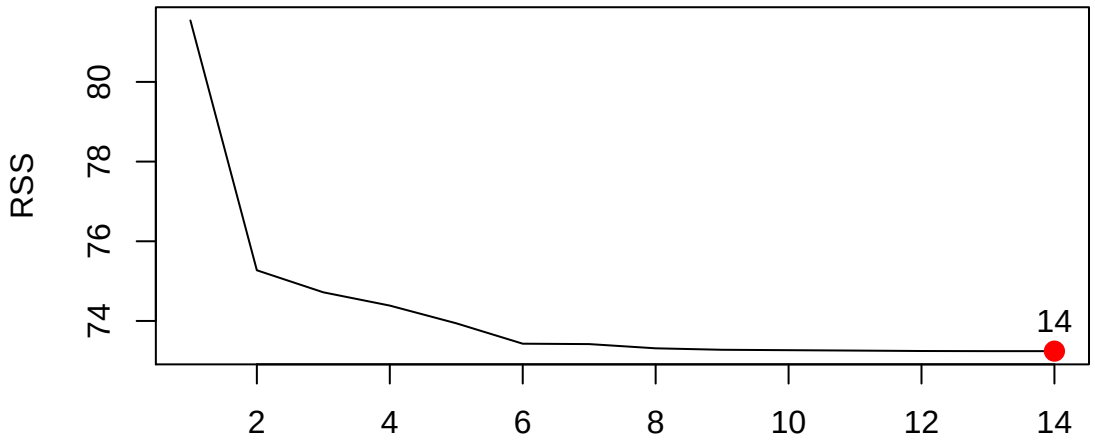




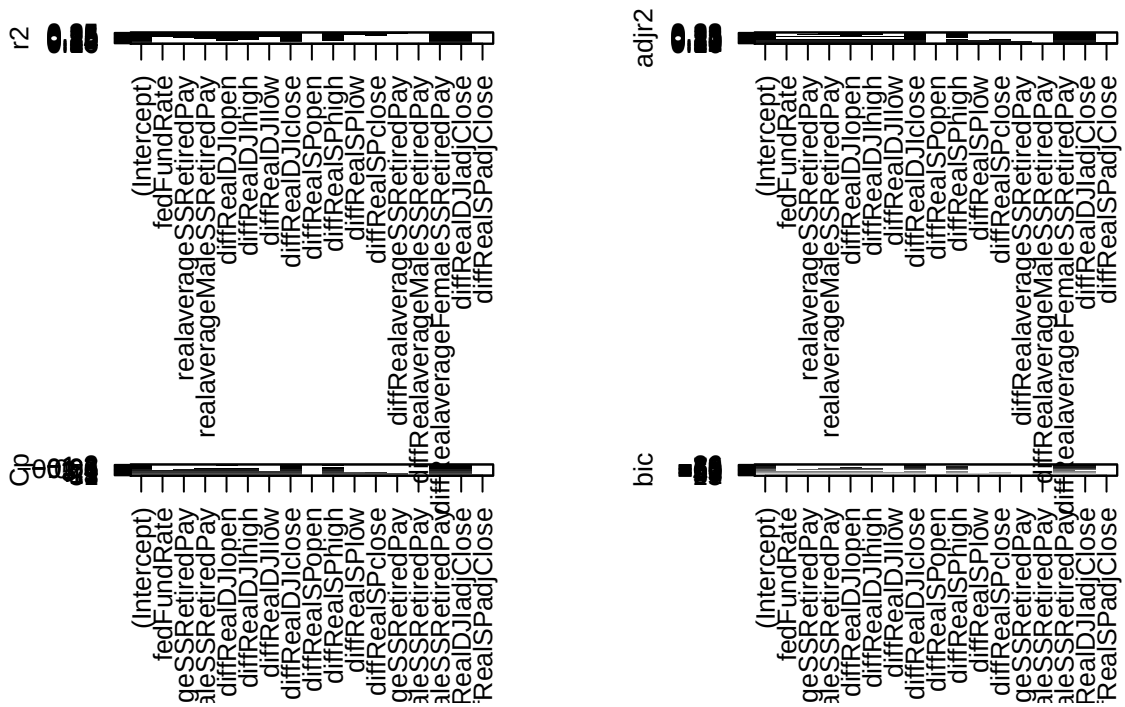





```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Backward - Differences",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesBackward <- c(names(coef(regFitSelect, id = 6))[-1])
# Exhaustive
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfDiff,
  method= 'exhaustive',
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
```

```
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

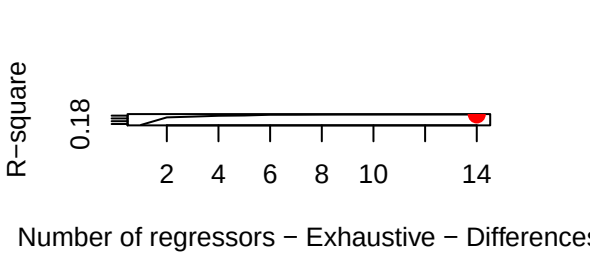
```
##  [1] 0.1731698 0.2273926 0.2330672 0.2391592 0.2410517 0.2463118 0.2466627
##  [8] 0.2474956 0.2478743 0.2479814 0.2480829 0.2481942 0.2482266 0.2482272
```

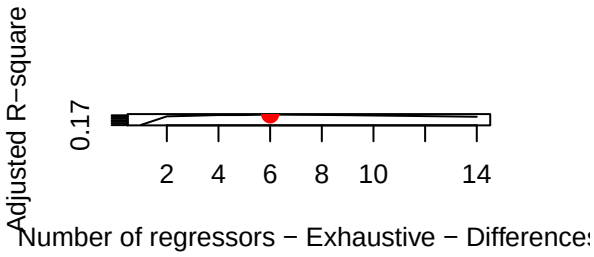
```
regSummary$adjr2
```

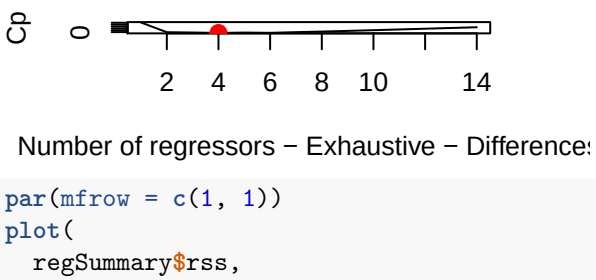
```
##  [1] 0.1711130 0.2235392 0.2273153 0.2315317 0.2315172 0.2349210 0.2333461
##  [8] 0.2322550 0.2306938 0.2288461 0.2269832 0.2251209 0.2231675 0.2211711
```

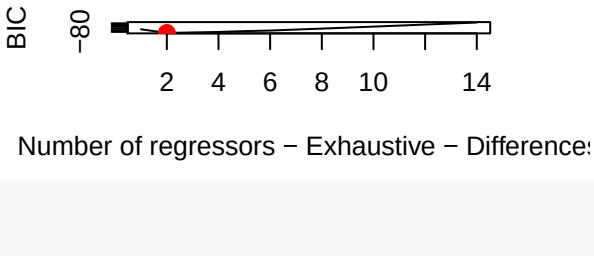
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Exhaustive - Differences",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Exhaustive - Differences",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
```

```
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Exhaustive - Differences",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Exhaustive - Differences",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

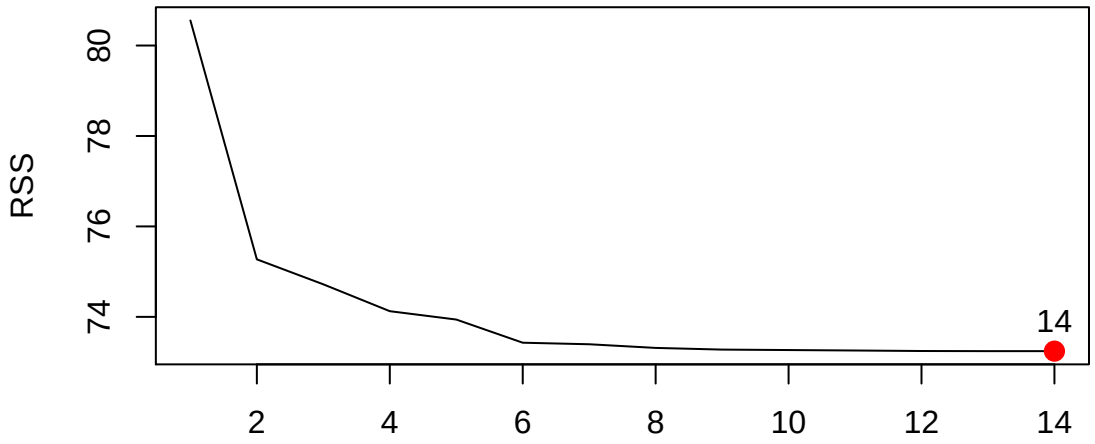




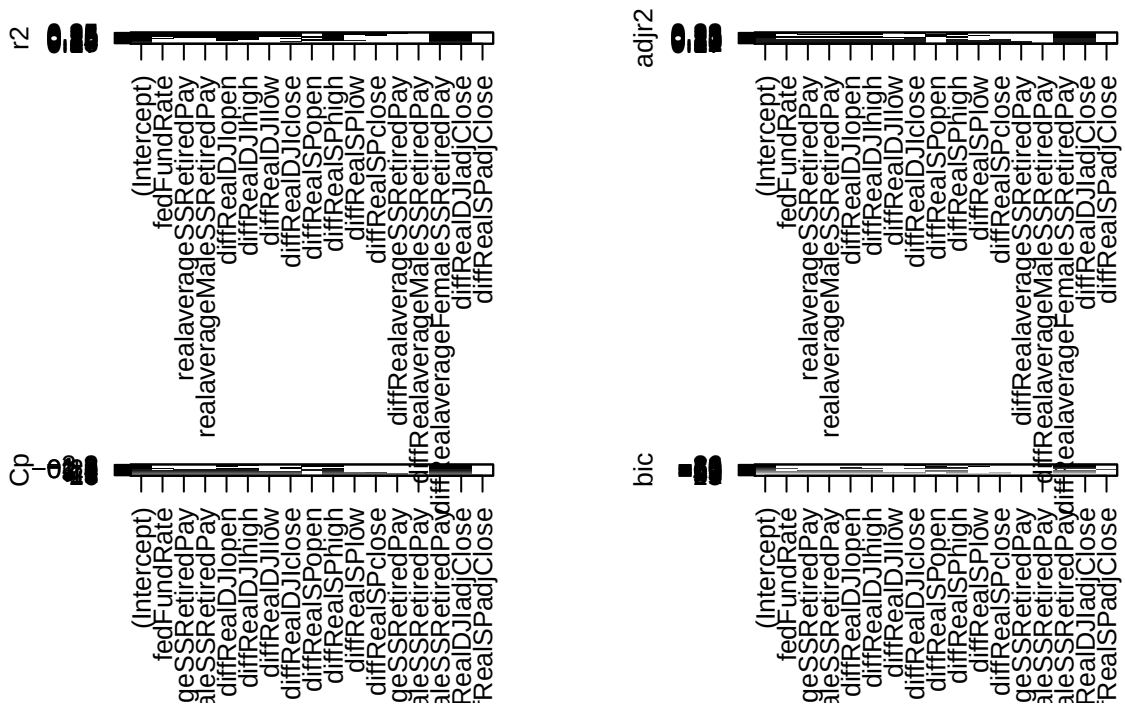





```
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Exhaustive - Differences",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesExhaustive <- c(names(coef(regFitSelect, id = 4))[-1])

# Percentages - Fairly low value, not going to use ####
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfPerc,
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
```

```
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

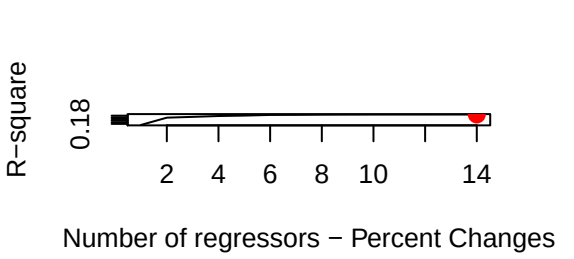
```
##  [1] 0.1734833 0.2178484 0.2228415 0.2279842 0.2305041 0.2344034 0.2348847
##  [8] 0.2361503 0.2366112 0.2368900 0.2370863 0.2371085 0.2371529 0.2371530
```

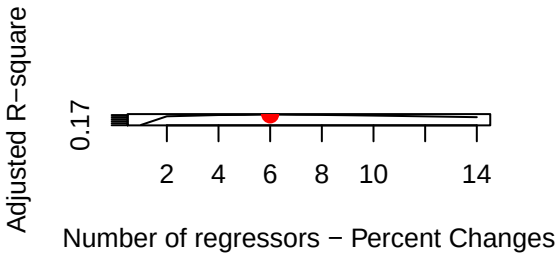
```
regSummary$adjr2
```

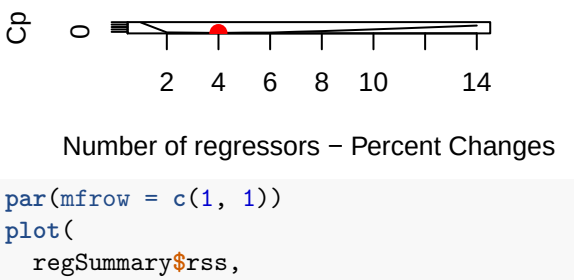
```
##  [1] 0.1714273 0.2139474 0.2170129 0.2202447 0.2208371 0.2228327 0.2213599
##  [8] 0.2206799 0.2191734 0.2174725 0.2156780 0.2136949 0.2117246 0.2096984
```

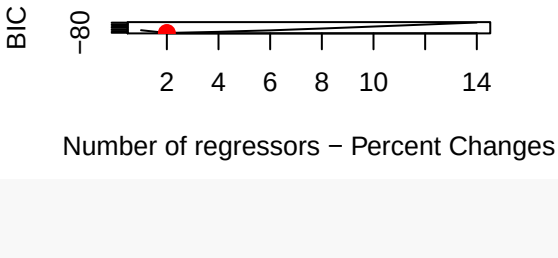
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Percent Changes",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Percent Changes",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
```

```
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Percent Changes",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Percent Changes",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

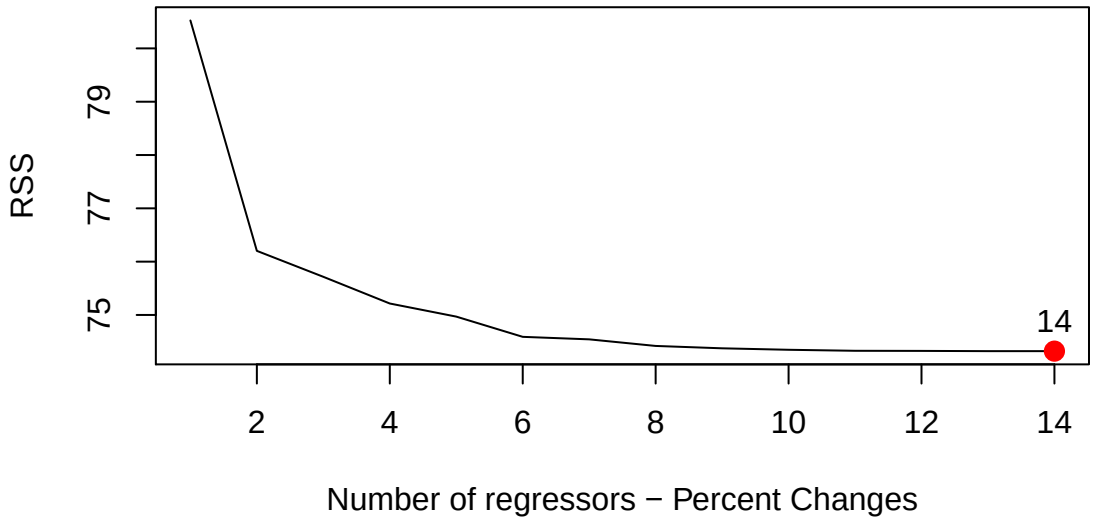




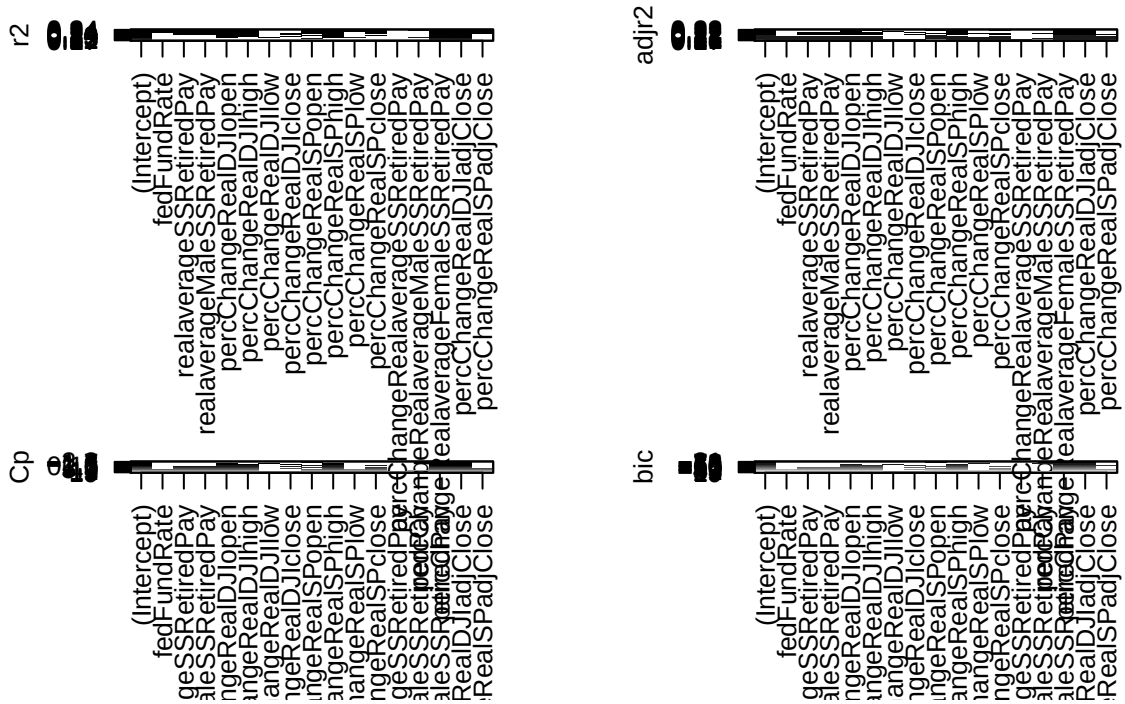





```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Percent Changes",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
# All Data Selection ####
# Exhaustive - All Data
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfStationary[-1],
  method= 'exhaustive',
  really.big = TRUE,
  nvmax=56)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 12 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
regSummary <- summary(regFitSelect)
```

```
## Warning in log(vr): NaNs produced
```

```
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

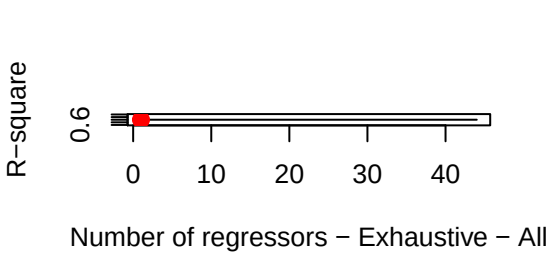
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

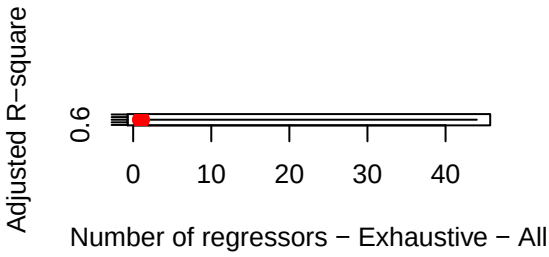
```
regSummary$adjr2
```

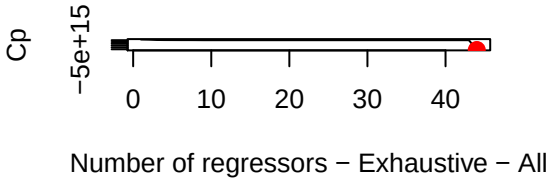
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

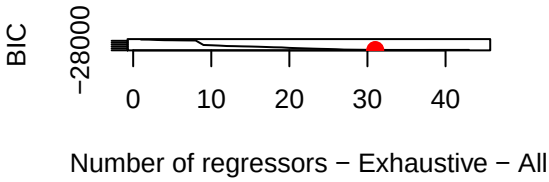
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Exhaustive - All",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Exhaustive - All",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
```

```
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Exhaustive - All",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Exhaustive - All",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

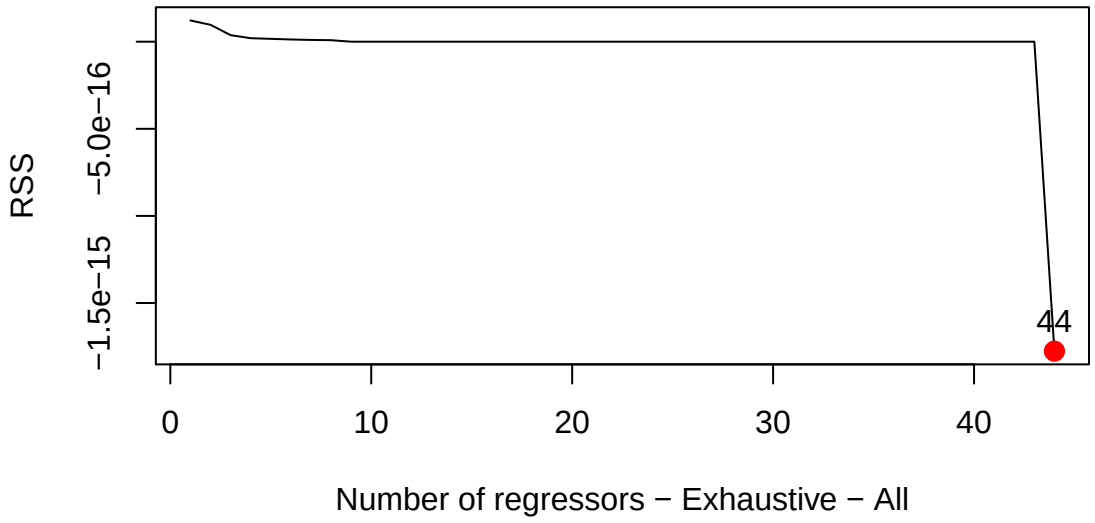









```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Exhaustive - All",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
```

```
## Warning in log(vr): NaNs produced
```

```
plot(regFitSelect, scale = "adjr2")
```

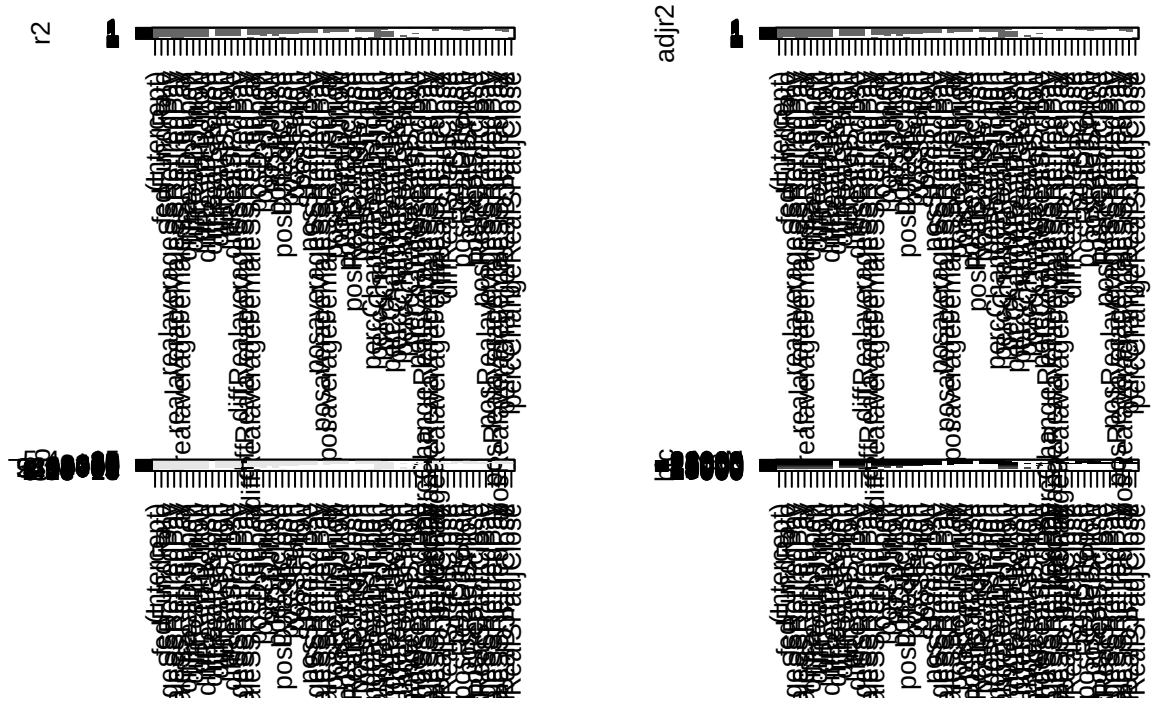
```
## Warning in log(vr): NaNs produced
```

```
plot(regFitSelect, scale = "Cp")
```

```
## Warning in log(vr): NaNs produced
```

```
plot(regFitSelect, scale = "bic")
```

```
## Warning in log(vr): NaNs produced
```



```
valuesStatExhaustive <- c(names(coef(regFitSelect, id = 31))[-1])
```

```
## Warning in log(vr): NaNs produced
```

```
# Backward
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfStationary[-1],
  method= 'backward',
  really.big = TRUE,
  nvmax=55)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 12 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in rval$lopt[] <- rval$vorder[rval$lopt]: number of items to
## replace is not a multiple of replacement length
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

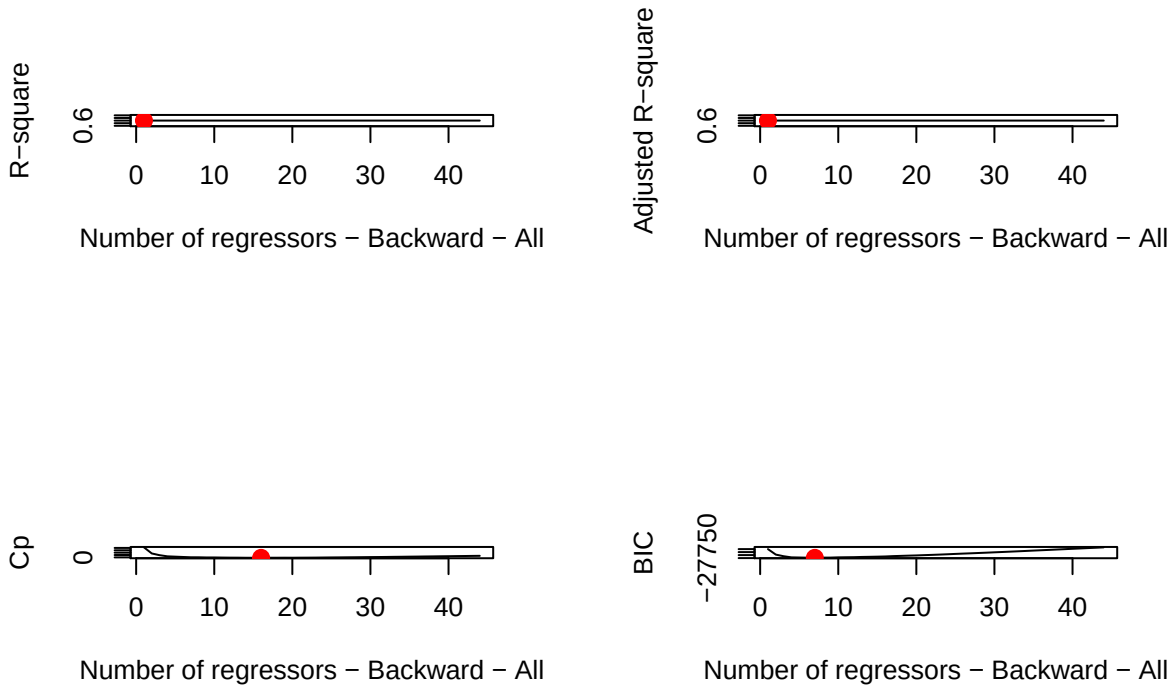
```
regSummary$adjr2
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

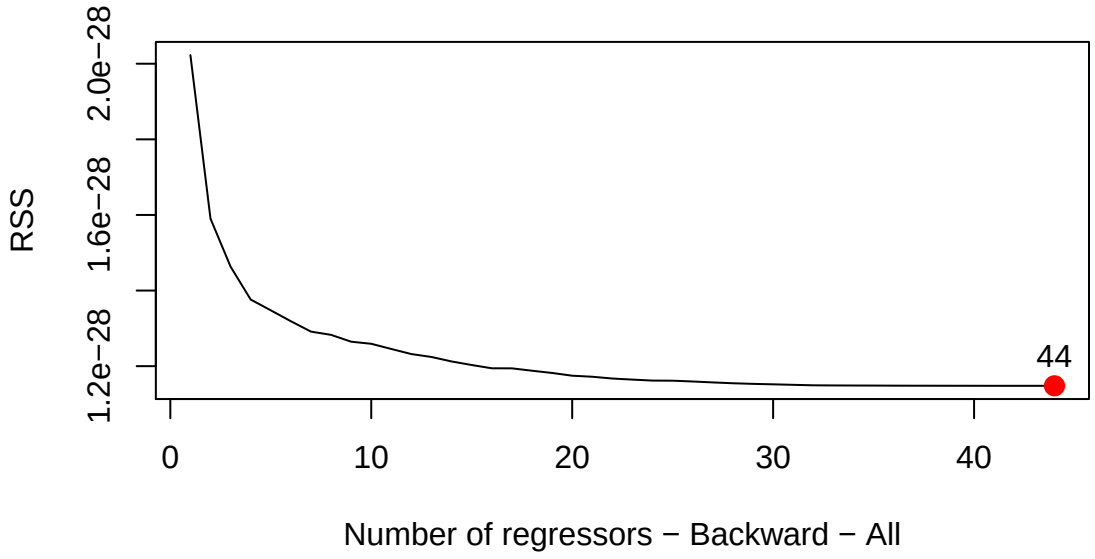
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Backward - All",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
```

```
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Backward - All",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Backward - All",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Backward - All",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
```

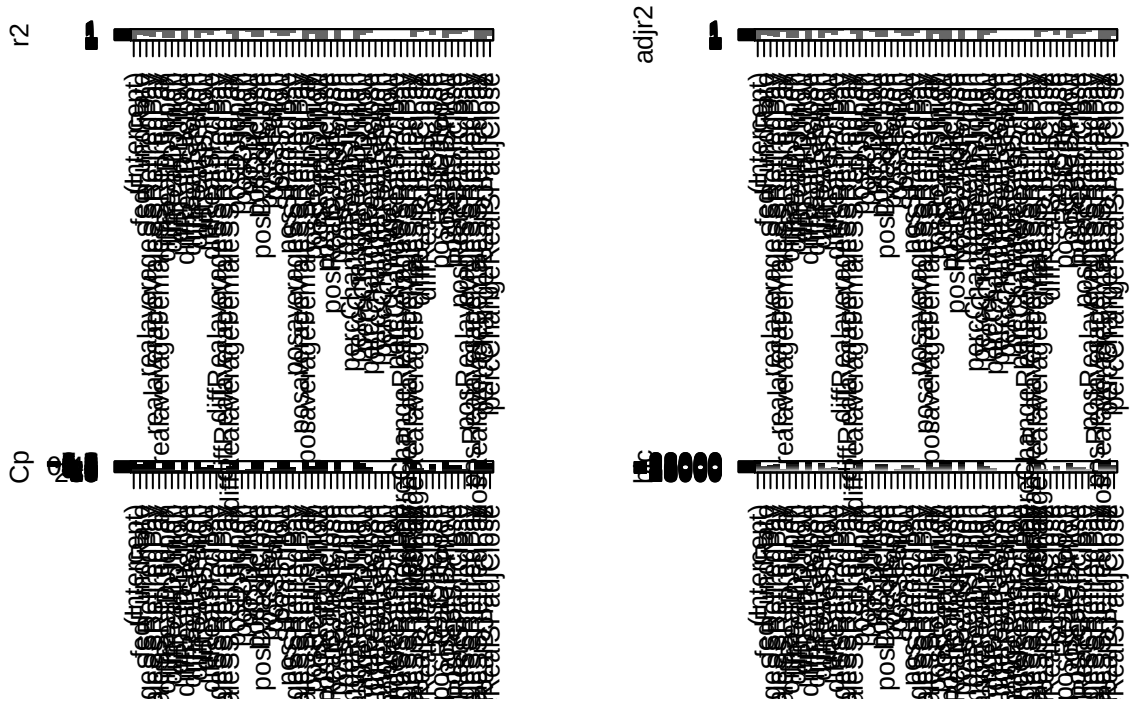
```
     labels = aBIC,
     pos = 3)
```




```
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Backward - All",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesStatBackward <- c(names(coef(regFitSelect, id = 7))[-1])

# Forward
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfStationary[-1],
  method= 'forward',
  really.big = TRUE,
```

```
  nvmax=55)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 12 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in rval$lopt[] <- rval$vorder[rval$lopt]: number of items to
## replace is not a multiple of replacement length
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

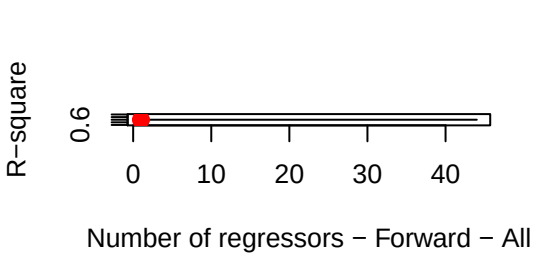
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

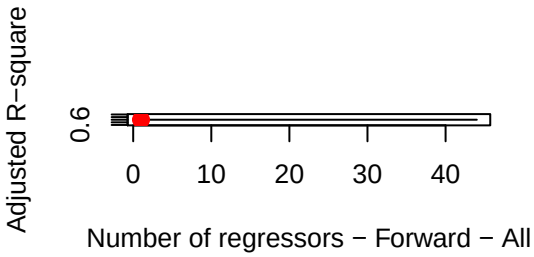
```
regSummary$adjr2
```

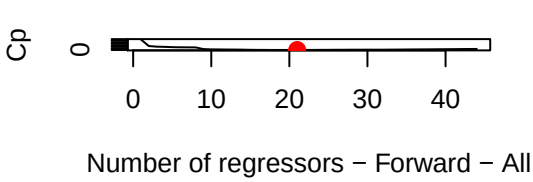
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

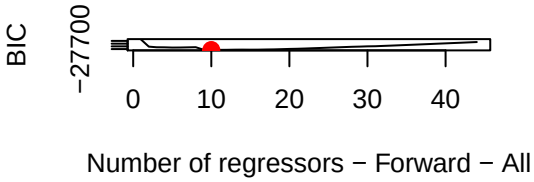
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Forward - All",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Forward - All",
  ylab = "Adjusted R-square",
  type = "l"
```

```
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Forward - All",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Forward - All",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

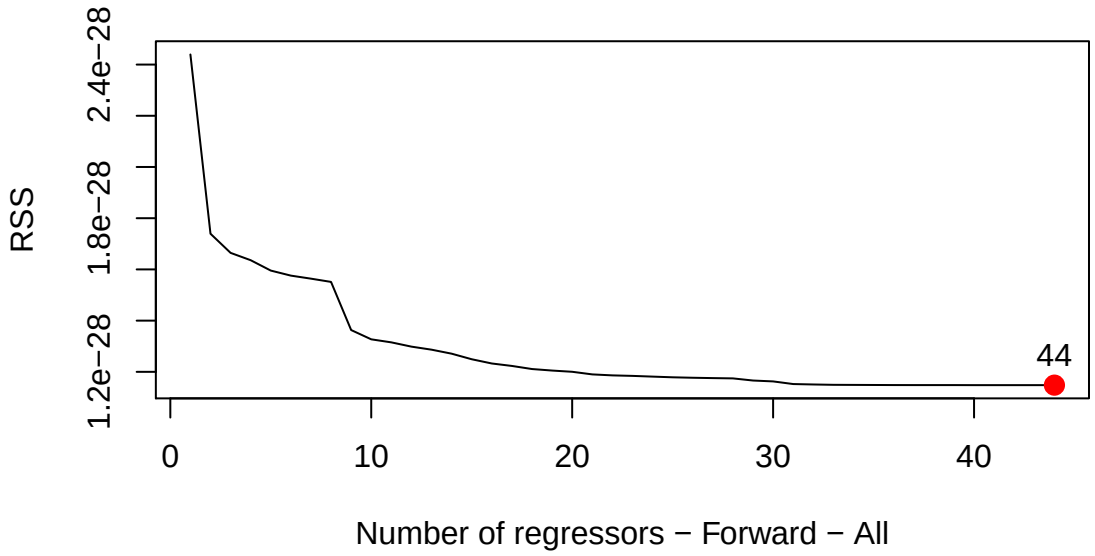




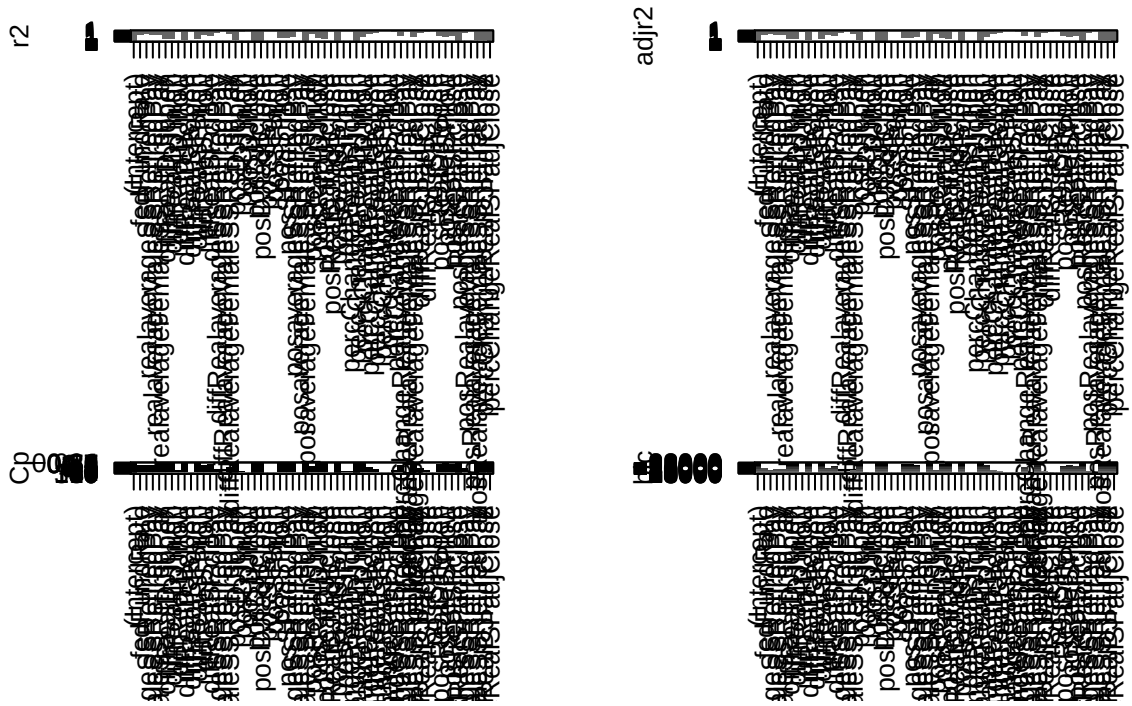





```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Forward - All",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesStatForward <- c(names(coef(regFitSelect, id = 10))[-1])

fmlaForward <- as.formula(paste("postotalSSRetired ~ ", paste(valuesStatForward, collapse= "+")))
fmlaBackward <- as.formula(paste("postotalSSRetired ~ ", paste(valuesStatBackward, collapse= "+")))
fmlaExhaust <- as.formula(paste("postotalSSRetired ~ ", paste(valuesStatExhaustive, collapse= "+")))

# Model ####
# Setting train/test split
```

```r
set.seed(1)
trainSample <- sample(1:nrow(dfStationary), round(nrow(dfStationary)/2), replace = F)
trainData <- dfStationary[trainSample,]
testData <- dfStationary[-trainSample,]

trainX <- trainData[,c(1, 3:58)]
trainY <- trainData[,c(1:2)]
testX <- testData[,c(1, 3:58)]
trainY <- testData[,c(1:2)]

# Logistic ####

# Exhaustive Selected model
logFit <- glm(fmlaExhaust,
              family = binomial,
              data = dfStationary)
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = fmlaExhaust, family = binomial, data = dfStationary)
##
## Deviance Residuals:
##       Min          1Q      Median          3Q         Max
## -6.65e-05  -2.10e-08  -2.10e-08   2.10e-08   7.67e-05
##
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      -3.740e+02  2.429e+06   0.000    1.000
## fedFundRate                      -1.826e+00  5.610e+04   0.000    1.000
## realaverageSSRetiredPay           4.457e-01  3.568e+03   0.000    1.000
## realaverageMaleSSRetiredPay       3.177e-01  1.549e+03   0.000    1.000
## realaverageFemaleSSRetiredPay    -7.487e-01  1.798e+03   0.000    1.000
## diffRealDJIopen                   8.708e-02  2.692e+02   0.000    1.000
## diffRealDJIhigh                  -9.536e-02  3.648e+02   0.000    1.000
## diffRealDJIlow                   -9.996e-02  2.308e+02   0.000    1.000
## diffRealDJIclose                  1.026e-01  2.825e+02   0.000    1.000
## diffRealSPhigh                   -5.578e-02  9.441e+02   0.000    1.000
## diffRealSPlow                     9.387e-01  2.054e+03   0.000    1.000
## diffRealSPclose                  -8.024e-01  1.307e+03  -0.001    1.000
## diffRealaverageSSRetiredPay      -2.077e+00  1.769e+03  -0.001    0.999
## diffRealaverageFemaleSSRetiredPay  2.315e+00  2.784e+03   0.001    0.999
## posDJIopen                       -8.073e+00  3.913e+05   0.000    1.000
## posDJIhigh                        8.907e+01  1.074e+05   0.001    0.999
## posDJIlow                        -7.844e+00  1.396e+05   0.000    1.000
## posDJIclose                      -8.014e+01  1.063e+05  -0.001    0.999
## posDJIadjClose                    4.842e+01  8.540e+04   0.001    1.000
## posSPopen                        -9.421e+00  1.519e+05   0.000    1.000
## posSPhigh                        -5.175e+00  7.073e+04   0.000    1.000
## posSPlow                          1.310e+01  3.304e+05   0.000    1.000
```

```
## posSPadjClose                     -5.501e+01  8.350e+04  -0.001    0.999
## posaverageSSRetiredPay             1.374e+01  1.007e+05   0.000    1.000
## posaverageFemaleSSRetiredPay      -6.536e+01  2.678e+05   0.000    1.000
## posRealDJIhigh                    -1.473e+00  8.302e+04   0.000    1.000
## posRealDJIlow                     -1.582e+01  1.677e+05   0.000    1.000
## posRealDJIclose                    4.006e+01  6.266e+04   0.001    0.999
## posRealSPopen                      1.578e+02  5.881e+04   0.003    0.998
## posRealSPhigh                      9.575e+01  3.884e+04   0.002    0.998
## percChangeRealDJIopen             -1.179e+03  4.426e+06   0.000    1.000
## percChangeRealDJIhigh              1.768e+03  5.401e+06   0.000    1.000
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5.4568e+02  on 403  degrees of freedom
## Residual deviance: 4.0544e-08  on 372  degrees of freedom
## AIC: 64
##
## Number of Fisher Scoring iterations: 25
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##                                          2.5 %       97.5 %
## (Intercept)                                 NA 252002.49723
## fedFundRate                       -3.983147e+03   4703.37124
## realaverageSSRetiredPay           -2.546648e+02    268.77575
## realaverageMaleSSRetiredPay       -8.577694e+01     77.87345
## realaverageFemaleSSRetiredPay     -9.572672e+01     76.17133
## diffRealDJIopen                   -9.242949e+00      8.84281
## diffRealDJIhigh                   -1.829923e+01     16.61109
## diffRealDJIlow                    -1.504885e+01     16.18882
## diffRealDJIclose                  -1.549278e+01     15.26941
## diffRealSPhigh                    -8.653673e+01     94.17654
## diffRealSPlow                     -9.404891e+01     84.85045
## diffRealSPclose                   -5.913237e+01     52.72950
## diffRealaverageSSRetiredPay       -6.627266e+01     70.74603
## diffRealaverageFemaleSSRetiredPay -1.311546e+02    162.12368
## posDJIopen                        -2.341307e+04  26188.87448
## posDJIhigh                        -3.817369e+03   4672.39169
## posDJIlow                         -6.241243e+03   5712.80741
## posDJIclose                       -8.751598e+03   8591.31205
## posDJIadjClose                    -4.072687e+03   4000.15889
## posSPopen                         -6.995852e+03   8452.16400
## posSPhigh                         -3.335126e+03   3324.77570
## posSPlow                          -1.239607e+04  15042.40911
## posSPadjClose                     -3.586792e+03   3898.06575
## posaverageSSRetiredPay            -3.065634e+03   3148.67282
## posaverageFemaleSSRetiredPay      -1.515226e+04  16011.10232
## posRealDJIhigh                    -6.244430e+03   5933.91934
## posRealDJIlow                     -8.292697e+03   6536.94787
## posRealDJIclose                   -5.699962e+03   6294.56015
## posRealSPopen                     -1.457712e+03   1784.94750
## posRealSPhigh                     -1.023044e+03   1260.88953
## percChangeRealDJIopen             -1.509047e+05 150183.97188
## percChangeRealDJIhigh             -2.276793e+05 227418.56595
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##            2            3            4            5            6
## 2.220446e-16 1.000000e+00 2.220446e-16 2.220446e-16 2.220446e-16
##            7            8            9           10           11
## 1.000000e+00 4.891675e-10 2.220446e-16 2.220446e-16 1.000000e+00
```

```
logPred <- rep(NA, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
logPred[logProbs < 0.5] = 0

table(logPred)
```

```
## logPred
##   0   1
## 240 164
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0 240   0
##       1   0 164
```

```
mean(logPred == dfStationary[,2])
```

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

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(fmlaExhaust,
               family = binomial,
               data = train)
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 58  5
##        1  1 37
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9405941
```

Predicition accuracy is approximately 94% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 37/5; 88% Negative Class prediction: 58/1; 98.3%

```
# Backard Selected model
logFit <- glm(fmlaBackward,
              family = binomial,
              data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = fmlaBackward, family = binomial, data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.87722  -0.16582  -0.06502   0.14678   2.93502
##
## Coefficients:
```

```
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                       -3.9626     0.8825  -4.490 7.12e-06 ***
## posDJIopen                         1.0262     1.2013   0.854 0.392953
## posaverageFemaleSSRetiredPay      -2.3635     1.2734  -1.856 0.063449 .
## posRealDJIlow                      2.6609     0.7858   3.386 0.000708 ***
## posRealSPopen                      7.6607     0.8839   8.667  < 2e-16 ***
## percChangeRealDJIhigh             31.9746    16.1912   1.975 0.048290 *
## posRealaverageFemaleSSRetiredPay  -1.3853     0.8903  -1.556 0.119728
## percChangeRealDJIadjClose         -1.6774    11.0572  -0.152 0.879418
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 109.01  on 396  degrees of freedom
## AIC: 125.01
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                      2.5 %     97.5 %
## (Intercept)                       -6.017531 -2.4528686
## posDJIopen                        -1.605622  3.2647653
## posaverageFemaleSSRetiredPay      -4.803546  0.3041155
## posRealDJIlow                      1.316928  4.5526627
## posRealSPopen                      6.175544  9.7417619
## percChangeRealDJIhigh              1.004724 64.9354675
## posRealaverageFemaleSSRetiredPay  -3.220072  0.3118396
## percChangeRealDJIadjClose        -23.719774 19.5259955
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##           2           3           4           5           6           7
## 0.004460318 0.974363975 0.011132525 0.002320106 0.001827138 0.996462622
##           8           9          10          11
## 0.014180239 0.012967488 0.002486971 0.955606920
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs >= 0.5] <- 1
logPred[logProbs < 0.5] <- 0

table(logPred)
```

```
## logPred
##   0   1
## 235 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0 229   6
```

```
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] 0.9579208
```

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(fmlaBackward,
               family = binomial,
               data = train)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 53  3
##        1  6 39
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9108911
```

Predicition accuracy is approximately 91% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 39/3; 92.8% Negative Class prediction: 53/6; 89.8%

```
# Forward Selected model - Best Model
logFitForwardAll <- glm(fmlaForward,
               family = binomial,
               data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = fmlaBackward, family = binomial, data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.87722  -0.16582  -0.06502   0.14678   2.93502
##
## Coefficients:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      -3.9626     0.8825  -4.490 7.12e-06 ***
## posDJIopen                        1.0262     1.2013   0.854 0.392953
## posaverageFemaleSSRetiredPay     -2.3635     1.2734  -1.856 0.063449 .
## posRealDJIlow                     2.6609     0.7858   3.386 0.000708 ***
## posRealSPopen                     7.6607     0.8839   8.667  < 2e-16 ***
## percChangeRealDJIhigh            31.9746    16.1912   1.975 0.048290 *
```

```
## posRealaverageFemaleSSRetiredPay  -1.3853     0.8903  -1.556 0.119728
## percChangeRealDJIadjClose         -1.6774    11.0572  -0.152 0.879418
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 109.01  on 396  degrees of freedom
## AIC: 125.01
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                       2.5 %     97.5 %
## (Intercept)                      -6.017531 -2.4528686
## posDJIopen                       -1.605622  3.2647653
## posaverageFemaleSSRetiredPay     -4.803546  0.3041155
## posRealDJIlow                     1.316928  4.5526627
## posRealSPopen                     6.175544  9.7417619
## percChangeRealDJIhigh             1.004724 64.9354675
## posRealaverageFemaleSSRetiredPay  -3.220072  0.3118396
## percChangeRealDJIadjClose        -23.719774 19.5259955
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##           2           3           4           5           6           7
## 0.004460318 0.974363975 0.011132525 0.002320106 0.001827138 0.996462622
##           8           9          10          11
## 0.014180239 0.012967488 0.002486971 0.955606920
```

```
logPred <- rep(NA, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
logPred[logProbs < 0.5] = 0


table(logPred)
```

```
## logPred
##   0   1
## 235 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0 229   6
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] 0.9579208
```

```r
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(fmlaForward,
               family = binomial,
               data = train)
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 54  2
##        1  5 40
```

```r
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95% Negative Class prediction: 54/5; 91.5% This is the best model.

```r
# Check only those with good statistical significance
logFit <- glm(postotalSSRetired ~ posDJIclose + posDJIadjClose + posRealSPopen  + posRealSPadjClose + po
               family = binomial,
               data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = postotalSSRetired ~ posDJIclose + posDJIadjClose +
##     posRealSPopen + posRealSPadjClose + posRealaverageFemaleSSRetiredPay,
##     family = binomial, data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -3.06535  -0.13360  -0.05683   0.13530   2.48559
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                       -6.4278     1.0182  -6.313 2.74e-10 ***
## posDJIclose                        1.5484     0.9552   1.621  0.10501
## posDJIadjClose                     1.7133     0.6531   2.623  0.00871 **
## posRealSPopen                      7.7315     0.9048   8.545  < 2e-16 ***
## posRealSPadjClose                  1.8369     0.9750   1.884  0.05956 .
## posRealaverageFemaleSSRetiredPay  -1.0678     0.6117  -1.746  0.08090 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 104.59  on 398  degrees of freedom
## AIC: 116.59
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                      2.5 %     97.5 %
## (Intercept)                     -8.7614151 -4.6808299
## posDJIclose                     -0.1244147  3.6921985
## posDJIadjClose                   0.4920897  3.0838235
## posRealSPopen                    6.2167780  9.8785185
## posRealSPadjClose                0.1224186  4.0102672
## posRealaverageFemaleSSRetiredPay -2.3042923  0.1182437
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##            2            3            4            5            6
## 0.0016134028 0.9897014801 0.0016134028 0.0005552172 0.0834023010
##            7            8            9           10           11
## 0.9952008178 0.0088844333 0.0016134028 0.0034749324 0.9952008178
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
table(logPred)
```

```
## logPred
##   0   1
##  34 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0  33   1
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

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

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(postotalSSRetired ~ posDJIclose + posDJIadjClose + posRealSPopen  + posRealSPadjClose + p
               family = binomial,
               data = train)
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 54  2
##        1  5 40
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95% Negative Class prediction: 54/5; 91.5% There is no change, but we have reduced the number of regressors by half, from 10 to 5.

```
# Subset this further by selecting only those with statistical significance from this model
logFit <- glm(postotalSSRetired ~  posDJIadjClose + posRealSPopen  + posRealSPadjClose + posRealaverageF
              family = binomial,
              data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = postotalSSRetired ~ posDJIadjClose + posRealSPopen +
##     posRealSPadjClose + posRealaverageFemaleSSRetiredPay, family = binomial,
##     data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.95006  -0.14982  -0.06188   0.16107   2.60136
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                       -6.2573     0.9852  -6.351 2.14e-10 ***
## posDJIadjClose                     1.9282     0.6514   2.960 0.003077 **
## posRealSPopen                      7.6875     0.8767   8.768  < 2e-16 ***
## posRealSPadjClose                  2.9082     0.7852   3.704 0.000212 ***
## posRealaverageFemaleSSRetiredPay  -1.1351     0.6097  -1.862 0.062626 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 107.82  on 399  degrees of freedom
## AIC: 117.82
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                      2.5 %      97.5 %
## (Intercept)                     -8.4911635 -4.55434311
## posDJIadjClose                   0.7088555  3.29449737
## posRealSPopen                    6.2092825  9.74742204
## posRealSPadjClose                1.5701719  4.80067290
```

```
## posRealaverageFemaleSSRetiredPay -2.3670651  0.04756246
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##            2            3            4            5            6
## 0.0019128306 0.9663798429 0.0019128306 0.0006155424 0.0720274306
##            7            8            9           10           11
## 0.9941271498 0.0130086210 0.0019128306 0.0111603749 0.9941271498
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
table(logPred)
```

```
## logPred
##   0   1
##  34 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0  33   1
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

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

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(postotalSSRetired ~ posDJIadjClose + posRealSPopen  + posRealSPadjClose + posRealaverageF
               family = binomial,
               data = train)
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 54  2
##        1  5 40
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95% Negative Class prediction: 54/5; 91.5% There is no change, but we have reduced the number of regressors from 5 to 4.

```
# Subset once more based on those with statistical significance better than 0.05
logFitForwardMinimal <- glm(postotalSSRetired ~  posDJIadjClose + posRealSPopen  + posRealSPadjClose,
```

```
             family = binomial,
             data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = postotalSSRetired ~ posDJIadjClose + posRealSPopen +
##     posRealSPadjClose + posRealaverageFemaleSSRetiredPay, family = binomial,
##     data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.95006  -0.14982  -0.06188   0.16107   2.60136
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                       -6.2573     0.9852  -6.351 2.14e-10 ***
## posDJIadjClose                     1.9282     0.6514   2.960 0.003077 **
## posRealSPopen                      7.6875     0.8767   8.768  < 2e-16 ***
## posRealSPadjClose                  2.9082     0.7852   3.704 0.000212 ***
## posRealaverageFemaleSSRetiredPay  -1.1351     0.6097  -1.862 0.062626 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 107.82  on 399  degrees of freedom
## AIC: 117.82
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                       2.5 %      97.5 %
## (Intercept)                      -8.4911635 -4.55434311
## posDJIadjClose                    0.7088555  3.29449737
## posRealSPopen                     6.2092825  9.74742204
## posRealSPadjClose                 1.5701719  4.80067290
## posRealaverageFemaleSSRetiredPay -2.3670651  0.04756246
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##            2            3            4            5            6
## 0.0019128306 0.9663798429 0.0019128306 0.0006155424 0.0720274306
##            7            8            9           10           11
## 0.9941271498 0.0130086210 0.0019128306 0.0111603749 0.9941271498
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
table(logPred)
```

```
## logPred
```

```
##   0   1
##  34 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0  33   1
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

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

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(postotalSSRetired ~ posDJIadjClose + posRealSPopen  + posRealSPadjClose,
               family = binomial,
               data = train)
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 54  2
##        1  5 40
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95% Negative Class prediction: 54/5; 91.5% There is no change, but we have reduced the number of regressors from 4 to 3. All factors are statisticall siginificant.

```
predForm <- as.formula(postotalSSRetired ~ posDJIadjClose + posRealSPopen  + posRealSPadjClose)
```

Switch up the train/test split to account for about 80% of the data

```
train80 <- subset(dfStationary, dfStationary$date < as.Date(dfStationary$date[round(nrow(dfStationary)
test20 <- subset(dfStationary, dfStationary$date >= as.Date(dfStationary$date[round(nrow(dfStationary)

logFit <- glm(predForm,
              family = binomial,
              data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = predForm, family = binomial, data = dfStationary)
##
## Deviance Residuals:
```

```
##     Min       1Q   Median       3Q      Max
## -2.7339  -0.1139  -0.0556   0.2196   2.7439
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -6.4717     0.9659  -6.700 2.08e-11 ***
## posDJIadjClose      1.4368     0.5820   2.469 0.013560 *
## posRealSPopen       7.4540     0.8341   8.936  < 2e-16 ***
## posRealSPadjClose   2.7306     0.7696   3.548 0.000388 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 111.36  on 400  degrees of freedom
## AIC: 119.36
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                       2.5 %    97.5 %
## (Intercept)       -8.6700560 -4.804306
## posDJIadjClose     0.3477433  2.669307
## posRealSPopen      6.0508612  9.436552
## posRealSPadjClose  1.4244555  4.600410
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##           2           3           4           5           6           7
## 0.001544224 0.918271072 0.001544224 0.001544224 0.090771223 0.994232497
##           8           9          10          11
## 0.006464772 0.001544224 0.023179357 0.994232497
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
table(logPred)
```

```
## logPred
##   0   1
##  34 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0  33   1
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

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

```
# Testing Prediction ####
logFit1 <- glm(predForm,
               family = binomial,
               data = train80)
logProbs1 <- predict(logFit1, test20, type = 'response') # setting prediction for the testing set FROM

logPred1 <- rep(NA, dim(train80)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test20$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 43  1
##        1  3 35
```

```
mean(logPred1 == test20$postotalSSRetired)
```

```
## [1] 0.9512195
```

Predicition accuracy is approximately 95% with a train/test split of 80/20. Positive class prediction: 43/3; 93.4% Negative Class prediction: 35/36; 97.2%.

```
# Test the models with all features and reduced (minimal) features
lrtest(logFitForwardAll, logFitForwardMinimal)
```

```
## Likelihood ratio test
##
## Model 1: postotalSSRetired ~ posDJIopen + posDJIclose + posDJIadjClose +
##     posaverageFemaleSSRetiredPay + posRealSPopen + percChangeRealDJIhigh +
##     posRealSPadjClose + posRealaverageFemaleSSRetiredPay + percChangeRealDJIadjClose +
##     percChangeRealSPadjClose
## Model 2: postotalSSRetired ~ posDJIadjClose + posRealSPopen + posRealSPadjClose
##   #Df  LogLik Df  Chisq Pr(>Chisq)
## 1  11 -50.117
## 2   4 -55.679 -7 11.124     0.1333
```

```
lrtest(logFitForwardMinimal, logFitForwardAll)
```

```
## Likelihood ratio test
##
## Model 1: postotalSSRetired ~ posDJIadjClose + posRealSPopen + posRealSPadjClose
## Model 2: postotalSSRetired ~ posDJIopen + posDJIclose + posDJIadjClose +
##     posaverageFemaleSSRetiredPay + posRealSPopen + percChangeRealDJIhigh +
##     posRealSPadjClose + posRealaverageFemaleSSRetiredPay + percChangeRealDJIadjClose +
##     percChangeRealSPadjClose
##   #Df  LogLik Df  Chisq Pr(>Chisq)
## 1   4 -55.679
## 2  11 -50.117  7 11.124     0.1333
```

Testing the null hypothesis that the restricted model (3 predictors) fits the data BETTER than the unrestricted model (10 predictors) results in a p-value greater than 0.05 (p-value = 0.1333), and thus we fail to reject the null hypothesis. The restricted model is at least as good as the unrestricted.

```
# Given that H0 holds that the reduced model is true, a p-value for the overall model fit statistic tha
anova(logFitForwardAll, logFitForwardMinimal, test ="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: postotalSSRetired ~ posDJIopen + posDJIclose + posDJIadjClose +
##     posaverageFemaleSSRetiredPay + posRealSPopen + percChangeRealDJIhigh +
##     posRealSPadjClose + posRealaverageFemaleSSRetiredPay + percChangeRealDJIadjClose +
##     percChangeRealSPadjClose
## Model 2: postotalSSRetired ~ posDJIadjClose + posRealSPopen + posRealSPadjClose
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       393     100.23
## 2       400     111.36 -7  -11.124   0.1333
```

```
anova(logFitForwardMinimal, logFitForwardAll, test ="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: postotalSSRetired ~ posDJIadjClose + posRealSPopen + posRealSPadjClose
## Model 2: postotalSSRetired ~ posDJIopen + posDJIclose + posDJIadjClose +
##     posaverageFemaleSSRetiredPay + posRealSPopen + percChangeRealDJIhigh +
##     posRealSPadjClose + posRealaverageFemaleSSRetiredPay + percChangeRealDJIadjClose +
##     percChangeRealSPadjClose
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1       400     111.36
## 2       393     100.23  7   11.124   0.1333
```

```
varImp(logFitForwardAll)
```

```
##                                   Overall
## posDJIopen                      0.7975565
## posDJIclose                     1.7542048
## posDJIadjClose                  2.1449539
## posaverageFemaleSSRetiredPay    1.5956928
## posRealSPopen                   8.0411833
## percChangeRealDJIhigh           0.9670385
## posRealSPadjClose               1.8205001
## posRealaverageFemaleSSRetiredPay 1.9270498
## percChangeRealDJIadjClose       0.5928742
## percChangeRealSPadjClose        0.3598276
```

```
varImp(logFitForwardMinimal)
```

```
##                    Overall
## posDJIadjClose    2.468723
## posRealSPopen     8.936028
## posRealSPadjClose 3.547970
```

Let's check how probit fits the data

```
# Probit ####
```

As the variable of interest is generated from the differences in Total SS Recipients, which appears about normally distributed, a probit model may be more appropriate.

```
probFit <- glm(predForm,
               family = binomial(link = "probit"),
               data = dfStationary)
summary(probFit, diagnostics=TRUE)
```

```
##
```

```
## Call:
## glm(formula = predForm, family = binomial(link = "probit"), data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.67493  -0.09598  -0.02853   0.23807   2.79822
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -3.3480     0.4453  -7.519 5.50e-14 ***
## posDJIadjClose      0.7431     0.2886   2.575     0.01 *
## posRealSPopen       3.9669     0.3551  11.170  < 2e-16 ***
## posRealSPadjClose   1.2930     0.3300   3.918 8.91e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 110.30  on 400  degrees of freedom
## AIC: 118.3
##
## Number of Fisher Scoring iterations: 8
```

```
confint(probFit)
```

```
## Waiting for profiling to be done...
```

```
##                        2.5 %    97.5 %
## (Intercept)       -4.3500091 -2.558896
## posDJIadjClose     0.1993879  1.337637
## posRealSPopen      3.3429631  4.773703
## posRealSPadjClose  0.7017883  2.036072
```

```
probProbs <- predict(probFit, type = 'response')
probProbs[1:10]
```

```
##            2            3            4            5            6
## 0.0004069635 0.9134087643 0.0004069635 0.0004069635 0.0947859691
##            7            8            9           10           11
## 0.9960355244 0.0045953487 0.0004069635 0.0199403179 0.9960355244
```

```
probPred <- rep(NA, dim(dfStationary)[2])
probPred[probProbs >= 0.5] <- 1
probPred[probProbs < 0.5] <- 0

table(probPred)
```

```
## probPred
##   0   1
## 235 169
```

```
table(probPred, dfStationary$postotalSSRetired)
```

```
##
## probPred   0   1
##        0 229   6
```

```
##        1  11 158
```

```
mean(probPred == dfStationary$postotalSSRetired)
```

```
## [1] 0.9579208
```

```
# Testing Prediction
probFit1 <- glm(predForm,
                family = binomial(link = "probit"),
                data = train)
probProbs1 <- predict(probFit1, test3rdQuart, type = 'response') # setting prediction for the testing s

probPred1 <- rep(0, dim(train)[2])
probPred1[probProbs1 >= 0.5] <- 1
probPred1[probProbs1 < 0.5] <- 0

table(probPred1, test3rdQuart$postotalSSRetired)
```

```
##
## probPred1  0  1
##         0 54  2
##         1  5 40
```

```
mean(probPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95.2% Negative Class prediction: 54/5; 91.5%.

```
# Test it at the 80/20 split
train80 <- subset(dfStationary, dfStationary$date < as.Date(dfStationary$date[round(nrow(dfStationary) =
test20 <- subset(dfStationary, dfStationary$date >= as.Date(dfStationary$date[round(nrow(dfStationary) =

probFit1 <- glm(predForm,
                family = binomial(link = "probit"),
                data = train)
probProbs1 <- predict(probFit1, test20, type = 'response') # setting prediction for the testing set FRO

probPred1 <- rep(0, dim(train80)[2])
probPred1[probProbs1 >= 0.5] <- 1
probPred1[probProbs1 < 0.5] <- 0

table(probPred1, test20$postotalSSRetired)
```

```
##
## probPred1  0  1
##         0 43  1
##         1  3 35
```

```
mean(probPred1 == test20$postotalSSRetired)
```

```
## [1] 0.9512195
```

Predicition accuracy is approximately 95% with a train/test split of 80/20. Positive class prediction: 43/3; 93.4% Negative Class prediction: 35/1; 97.2% This prediction accuracy is the same as the logit model

```
# Descriptive Statistics ####
stat.desc(dfStationary[, valuesStatForward])
```

```
##                posDJIopen  posDJIclose posDJIadjClose
## nbr.val      404.00000000 404.00000000   404.00000000
## nbr.null     146.00000000 206.00000000   159.00000000
## nbr.na         0.00000000   0.00000000     0.00000000
## min            0.00000000   0.00000000     0.00000000
## max            1.00000000   1.00000000     1.00000000
## range          1.00000000   1.00000000     1.00000000
## sum          258.00000000 198.00000000   245.00000000
## median         1.00000000   0.00000000     1.00000000
## mean           0.63861386   0.49009901     0.60643564
## SE.mean        0.02393053   0.02490189     0.02433592
## CI.mean.0.95   0.04704427   0.04895383     0.04784120
## var            0.23135887   0.25052207     0.23926369
## std.dev        0.48099778   0.50052180     0.48914588
## coef.var       0.75319033   1.02126671     0.80659157
##              posaverageFemaleSSRetiredPay posRealSPopen
## nbr.val                     404.00000000  404.00000000
## nbr.null                    159.00000000  235.00000000
## nbr.na                        0.00000000    0.00000000
## min                           0.00000000    0.00000000
## max                           1.00000000    1.00000000
## range                         1.00000000    1.00000000
## sum                         245.00000000  169.00000000
## median                        1.00000000    0.00000000
## mean                          0.60643564    0.41831683
## SE.mean                       0.02433592    0.02457216
## CI.mean.0.95                  0.04784120    0.04830563
## var                           0.23926369    0.24393165
## std.dev                       0.48914588    0.49389437
## coef.var                      0.80659157    1.18067057
##              percChangeRealDJIhigh posRealSPadjClose
## nbr.val              404.000000000      404.00000000
## nbr.null               0.000000000      215.00000000
## nbr.na                 0.000000000        0.00000000
## min                   -0.241092661        0.00000000
## max                    0.117105913        1.00000000
## range                  0.358198574        1.00000000
## sum                    2.369177169      189.00000000
## median                 0.006099073        0.00000000
## mean                   0.005864300        0.46782178
## SE.mean                0.001588591        0.02485514
## CI.mean.0.95           0.003122961        0.04886193
## var                    0.001019544        0.24958234
## std.dev                0.031930293        0.49958217
## coef.var               5.444860179        1.06788992
##              posRealaverageFemaleSSRetiredPay percChangeRealDJIadjClose
## nbr.val                          404.00000000              404.000000000
## nbr.null                         157.00000000                0.000000000
## nbr.na                             0.00000000                0.000000000
## min                                0.00000000               -0.234162150
## max                                1.00000000                0.132106278
## range                              1.00000000                0.366268428
## sum                              247.00000000                2.529224083
## median                             1.00000000                0.008433098
```

```
## mean                                0.61138614              0.006260456
## SE.mean                             0.02428088              0.002105521
## CI.mean.0.95                        0.04773300              0.004139177
## var                                 0.23818269              0.001791021
## std.dev                             0.48803964              0.042320456
## coef.var                            0.79825107              6.759964196
##              percChangeRealSPadjClose
## nbr.val                  404.000000000
## nbr.null                   0.000000000
## nbr.na                     0.000000000
## min                       -0.219671380
## max                        0.125671204
## range                      0.345342584
## sum                        2.290283887
## median                     0.008526646
## mean                       0.005669020
## SE.mean                    0.002104440
## CI.mean.0.95               0.004137051
## var                        0.001789182
## std.dev                    0.042298718
## coef.var                   7.461381574
```

```
kable(stat.desc(dfStationary[, valuesStatForward[c(1, 2, 3, 5)]], norm=TRUE, p=0.95), digits=3, align='
      "Summary Statistics of Relevant Variables 1")
```

Table 1: Summary Statistics of Relevant Variables 1

	posDJIopen	posDJIclose	posDJIadjClose	posRealSPopen
nbr.val	404.000	404.000	404.000	404.000
nbr.null	146.000	206.000	159.000	235.000
nbr.na	0.000	0.000	0.000	0.000
min	0.000	0.000	0.000	0.000
max	1.000	1.000	1.000	1.000
range	1.000	1.000	1.000	1.000
sum	258.000	198.000	245.000	169.000
median	1.000	0.000	1.000	0.000
mean	0.639	0.490	0.606	0.418
SE.mean	0.024	0.025	0.024	0.025
CI.mean.0.95	0.047	0.049	0.048	0.048
var	0.231	0.251	0.239	0.244
std.dev	0.481	0.501	0.489	0.494
coef.var	0.753	1.021	0.807	1.181
skewness	-0.575	0.039	-0.434	0.330
skew.2SE	-2.368	0.163	-1.788	1.359
kurtosis	-1.674	-2.003	-1.816	-1.896
kurt.2SE	-3.454	-4.135	-3.748	-3.913
normtest.W	0.608	0.636	0.620	0.627
normtest.p	0.000	0.000	0.000	0.000

```
kable(stat.desc(dfStationary[, valuesStatForward[c(4,7,8)]], norm=TRUE, p=0.95), digits=3, align='c',ca
      "Summary Statistics of Relevant Variables 2")
```

Table 2: Summary Statistics of Relevant Variables 2

	posaverageFemaleSSRetiredPay	posRealSPadjClose	posRealaverageFemaleSSRetiredPay
nbr.val	404.000	404.000	404.000
nbr.null	159.000	215.000	157.000
nbr.na	0.000	0.000	0.000
min	0.000	0.000	0.000
max	1.000	1.000	1.000
range	1.000	1.000	1.000
sum	245.000	189.000	247.000
median	1.000	0.000	1.000
mean	0.606	0.468	0.611
SE.mean	0.024	0.025	0.024
CI.mean.0.95	0.048	0.049	0.048
var	0.239	0.250	0.238
std.dev	0.489	0.500	0.488
coef.var	0.807	1.068	0.798
skewness	-0.434	0.129	-0.455
skew.2SE	-1.788	0.529	-1.875
kurtosis	-1.816	-1.988	-1.797
kurt.2SE	-3.748	-4.104	-3.709
normtest.W	0.620	0.635	0.618
normtest.p	0.000	0.000	0.000

```
kable(stat.desc(dfStationary[, valuesStatForward[c(6, 9, 10)]], norm=TRUE, p=0.95), digits=3, align='c'
        "Summary Statistics of Relevant Variables 3")
```

Table 3: Summary Statistics of Relevant Variables 3

	percChangeRealDJIhigh	percChangeRealDJIadjClose	percChangeRealSPadjClose
nbr.val	404.000	404.000	404.000
nbr.null	0.000	0.000	0.000
nbr.na	0.000	0.000	0.000
min	-0.241	-0.234	-0.220
max	0.117	0.132	0.126
range	0.358	0.366	0.345
sum	2.369	2.529	2.290
median	0.006	0.008	0.009
mean	0.006	0.006	0.006
SE.mean	0.002	0.002	0.002
CI.mean.0.95	0.003	0.004	0.004
var	0.001	0.002	0.002
std.dev	0.032	0.042	0.042
coef.var	5.445	6.760	7.461
skewness	-1.295	-0.813	-0.781
skew.2SE	-5.331	-3.347	-3.217
kurtosis	8.998	3.002	2.509
kurt.2SE	18.571	6.197	5.178
normtest.W	0.924	0.963	0.966
normtest.p	0.000	0.000	0.000