ENV 790.30 - Time Series Analysis for Energy Data | Spring 2022

Assignment 3 - Due date 02/08/22

Yared S. Asfaw

Directions

You should open the .rmd file corresponding to this assignment on RStudio. The file is available on our class repository on Github.

Once you have the project open the first thing you will do is change "Student Name" on line 3 with your name. Then you will start working through the assignment by **creating code and output** that answer each question. Be sure to use this assignment document. Your report should contain the answer to each question and any plots/tables you obtained (when applicable).

Please keep this R code chunk options for the report. It is easier for us to grade when we can see code and output together. And the tidy.opts will make sure that line breaks on your code chunks are automatically added for better visualization.

When you have completed the assignment, **Knit** the text and code into a single PDF file. Rename the pdf file such that it includes your first and last name (e.g., "LuanaLima_TSA_A03_Sp22.Rmd"). Submit this pdf using Sakai.

Questions

Consider the same data you used for A2 from the spreadsheet "Table_10.1_Renewable_Energy_Production_and_Consumpti
The data comes from the US Energy Information and Administration and corresponds to the January 2022 **Monthly** Energy Review. Once again you will work only with the following columns: Total Biomass Energy Production, Total Renewable Energy Production, Hydroelectric Power Consumption. Create a data frame structure with these three time series only.

R packages needed for this assignment:"forecast","tseries", and "Kendall". Install these packages, if you haven't done yet. Do not forget to load them before running your script, since they are NOT default packages.\

Loading packages

```
#Load/install required package here
library(lubridate)
library(ggplot2)
library(forecast)
library(Kendall)
library(tseries)
library(openxlsx)
```

```r
# Importing the data set
library(openxlsx)
us_energy.data <- read.xlsx("./Data/Raw/Table_10.1_Ren._Energy_PC._by_Source.xlsx", startRow=11)
head(us_energy.data) # Looking at the nature of the dataset
```

```
##   Month Wood.Energy.Production Biofuels.Production
## 1    NA         (Trillion Btu)      (Trillion Btu)
## 2 26665                 129.63       Not Available
## 3 26696                117.194       Not Available
## 4 26724                129.763       Not Available
## 5 26755                125.462       Not Available
## 6 26785                129.624       Not Available
##   Total.Biomass.Energy.Production Total.Renewable.Energy.Production
## 1                  (Trillion Btu)                    (Trillion Btu)
## 2                         129.787                           403.981
## 3                         117.338                             360.9
## 4                         129.938                           400.161
## 5                         125.636                            380.47
## 6                         129.834                           392.141
##   Hydroelectric.Power.Consumption Geothermal.Energy.Consumption
## 1                  (Trillion Btu)                (Trillion Btu)
## 2                         272.703                         1.491
## 3                         242.199                         1.363
## 4                          268.81                         1.412
## 5                         253.185                         1.649
## 6                          260.77                         1.537
##   Solar.Energy.Consumption Wind.Energy.Consumption Wood.Energy.Consumption
## 1           (Trillion Btu)          (Trillion Btu)          (Trillion Btu)
## 2            Not Available           Not Available                  129.63
## 3            Not Available           Not Available                 117.194
## 4            Not Available           Not Available                 129.763
## 5            Not Available           Not Available                 125.462
## 6            Not Available           Not Available                 129.624
##   Waste.Energy.Consumption Biofuels.Consumption
## 1           (Trillion Btu)       (Trillion Btu)
## 2                    0.157        Not Available
## 3                    0.144        Not Available
## 4                    0.176        Not Available
## 5                    0.174        Not Available
## 6                     0.21        Not Available
##   Total.Biomass.Energy.Consumption Total.Renewable.Energy.Consumption
## 1                   (Trillion Btu)                     (Trillion Btu)
## 2                          129.787                            403.981
## 3                          117.338                              360.9
## 4                          129.938                            400.161
## 5                          125.636                             380.47
## 6                          129.834                            392.141
```

```r
# Select the three variables
#(Total Biomass Energy Production (TEBP),
#Total Renewable Energy Production (TREP) and
#Hydroelectric Power Consumption (HEPC);
#and Remove the row that has the unit of measurement
```

```r
us_energy.df <- data.frame(us_energy.data[-1,c(1,4:6)])
head(us_energy.df) # Looking at the newly created dataset with the selected variables
```

```
##   Month Total.Biomass.Energy.Production Total.Renewable.Energy.Production
## 2 26665                         129.787                           403.981
## 3 26696                         117.338                             360.9
## 4 26724                         129.938                           400.161
## 5 26755                         125.636                            380.47
## 6 26785                         129.834                           392.141
## 7 26816                         125.611                           377.232
##   Hydroelectric.Power.Consumption
## 2                         272.703
## 3                         242.199
## 4                          268.81
## 5                         253.185
## 6                          260.77
## 7                         249.859
```

```r
# Column names of the us_energy.df dataset
colnames(us_energy.df)
```

```
## [1] "Month"                             "Total.Biomass.Energy.Production"
## [3] "Total.Renewable.Energy.Production" "Hydroelectric.Power.Consumption"
```

```r
# Renaming the column names for convenience
colnames(us_energy.df) <- c("my_date","TBEP", "TREP", "HEPC")
colnames(us_energy.df)
```

```
## [1] "my_date" "TBEP"    "TREP"    "HEPC"
```

```r
head(us_energy.df)
```

```
##   my_date    TBEP    TREP    HEPC
## 2   26665 129.787 403.981 272.703
## 3   26696 117.338   360.9 242.199
## 4   26724 129.938 400.161  268.81
## 5   26755 125.636  380.47 253.185
## 6   26785 129.834 392.141  260.77
## 7   26816 125.611 377.232 249.859
```

```r
# Checking the class of the object created
is.data.frame(us_energy.df)
```

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

```r
# Checking the data types of the selected variables
sapply(us_energy.df, class)
```

```
##     my_date        TBEP        TREP        HEPC
##   "numeric" "character" "character" "character"
```

```r
# Formatting the my_date column to "Date"
start_date <- as.Date("01/01/1973", format = "%m/%d/%Y") # the date format in the dataset is m/d/y
us_energy.df$my_date <- seq(start_date, by= "month", length.out=585)
```

```r
# Changing the data types into numeric
us_energy.df$TBEP <- as.numeric(us_energy.df$TBEP)
us_energy.df$TREP <- as.numeric(us_energy.df$TREP)
us_energy.df$HEPC <- as.numeric(us_energy.df$HEPC)
head(us_energy.df)
```

```
##      my_date    TBEP    TREP    HEPC
## 2 1973-01-01 129.787 403.981 272.703
## 3 1973-02-01 117.338 360.900 242.199
## 4 1973-03-01 129.938 400.161 268.810
## 5 1973-04-01 125.636 380.470 253.185
## 6 1973-05-01 129.834 392.141 260.770
## 7 1973-06-01 125.611 377.232 249.859
```

```r
# Structure of the dataset
str(us_energy.df)
```

```
## 'data.frame':    585 obs. of  4 variables:
##  $ my_date: Date, format: "1973-01-01" "1973-02-01" ...
##  $ TBEP   : num  130 117 130 126 130 ...
##  $ TREP   : num  404 361 400 380 392 ...
##  $ HEPC   : num  273 242 269 253 261 ...
```

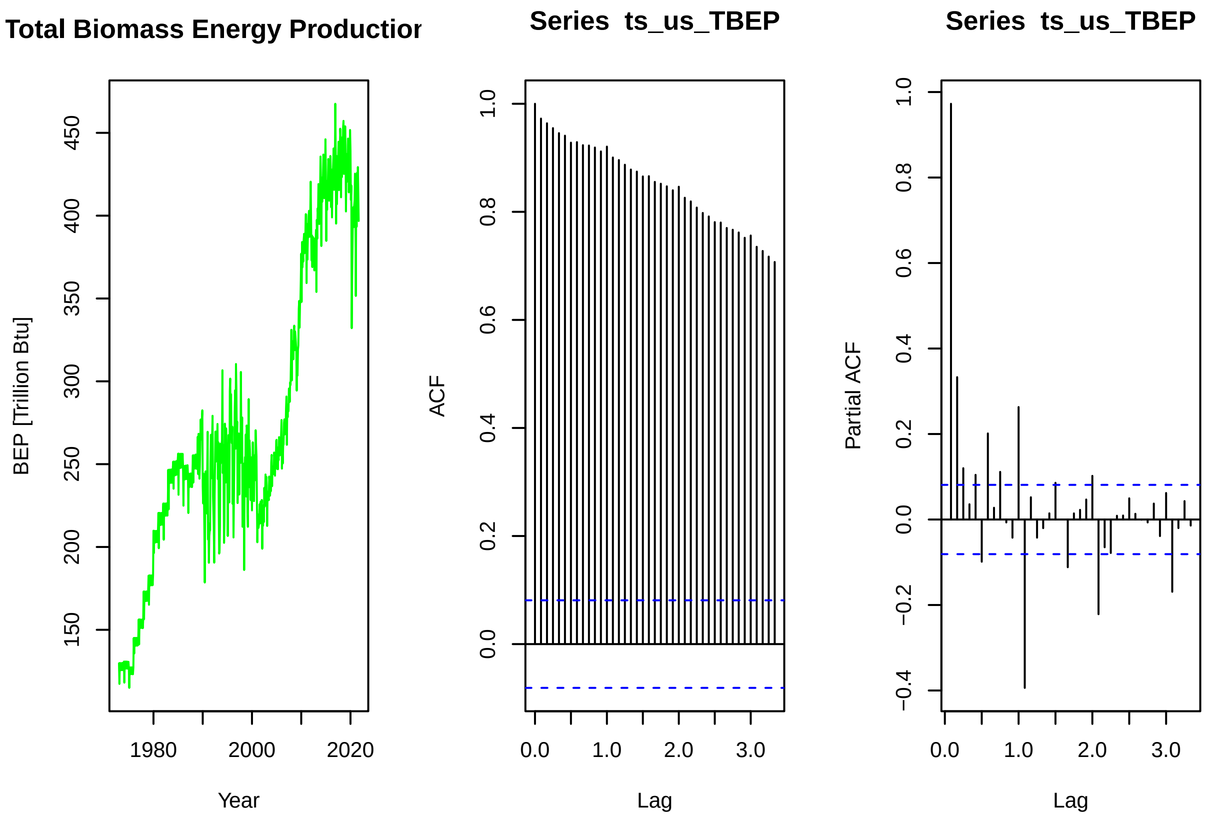
##Trend Component

Q1

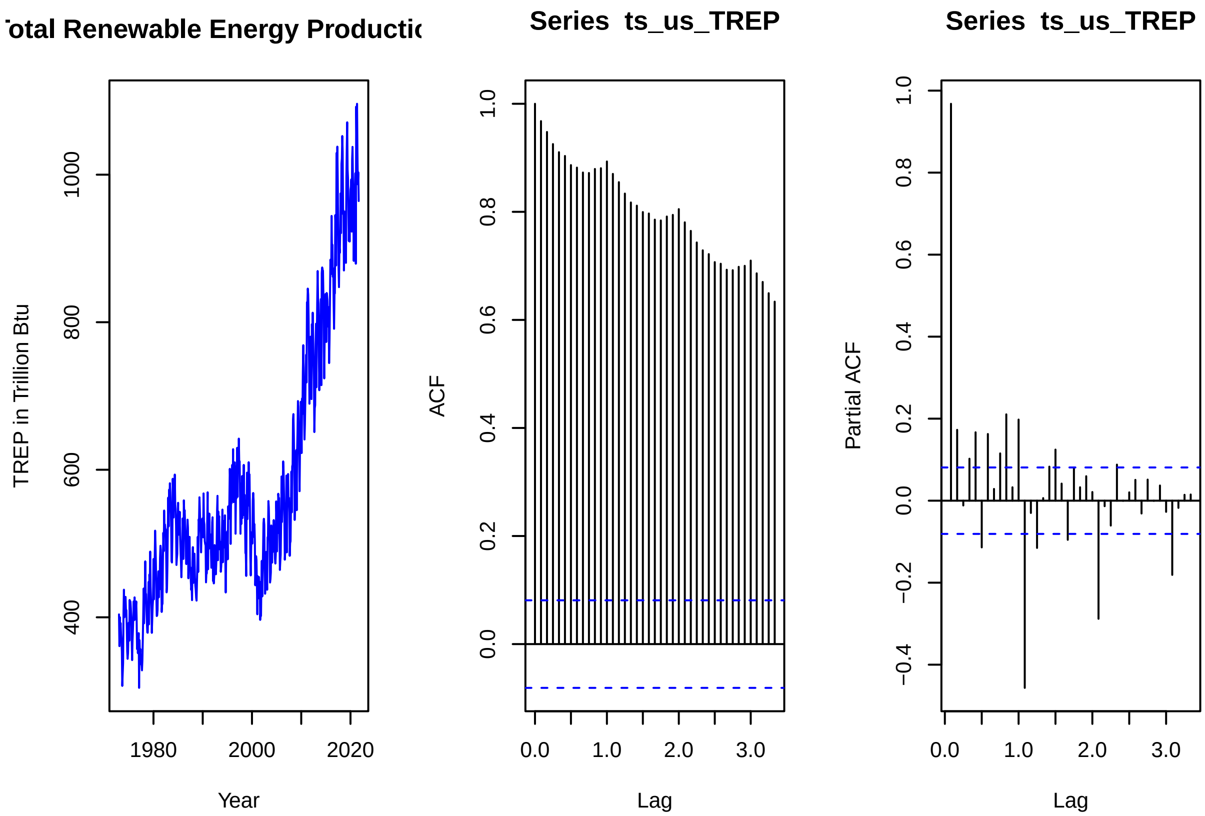
Create a plot window that has one row and three columns. And then for each object on your data frame, fill the plot window with time series plot, ACF and PACF. You may use the some code form A2, but I want all three plots on the same window this time. (Hint: use par() function)

```r
# Creating the time series object for each series
## Time series object of TBEP, TREP, HEPC
ts_us_TBEP <- ts(us_energy.df$TBEP, start = c(1973, 1), frequency= 12)
ts_us_TREP <- ts(us_energy.df$TREP, start = c(1973, 1), frequency= 12)
ts_us_HEPC <- ts(us_energy.df$HEPC, start = c(1973, 1), frequency= 12)
```

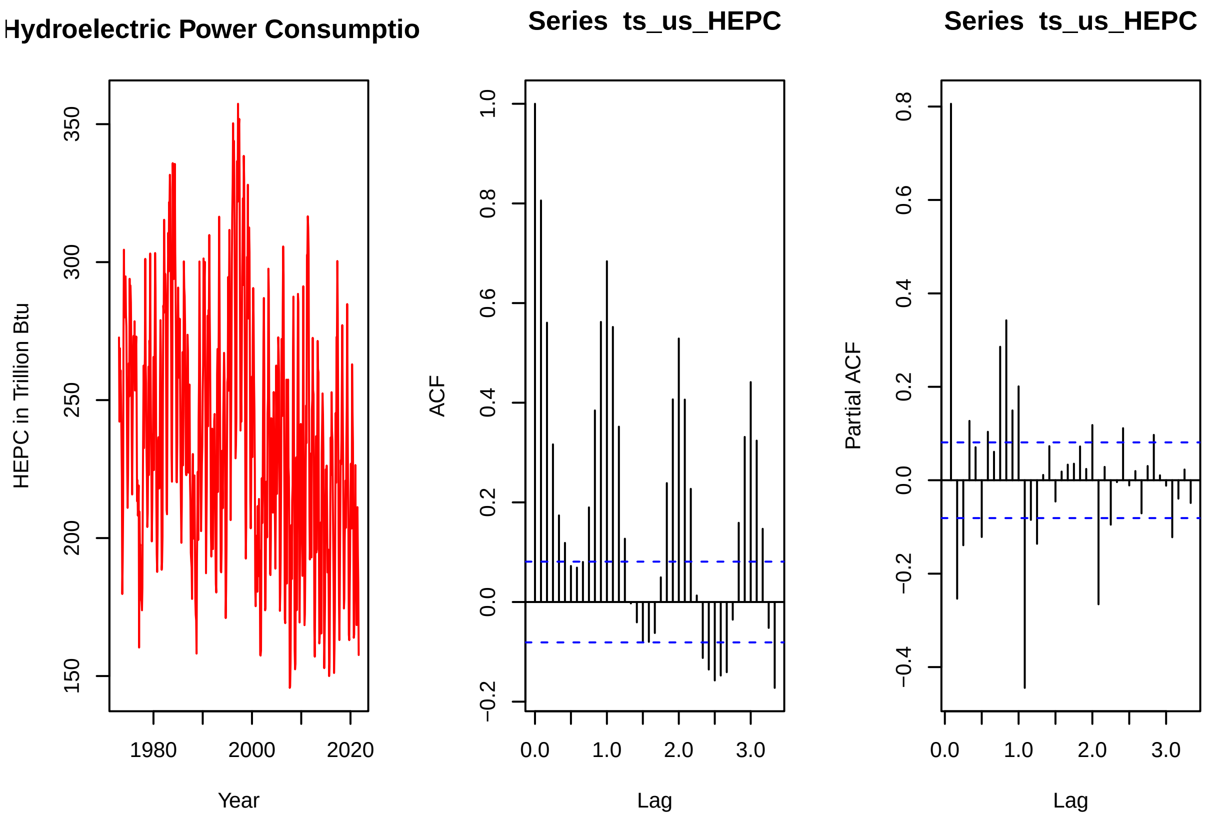
```r
par(mfrow= c(1,3))
plot(ts_us_TBEP,type="l",col="green",xlab="Year",ylab="BEP [Trillion Btu]",
main="U.S.Total Biomass Energy Production (TBEP)")
acf(ts_us_TBEP, lag.max = 40,plot = TRUE)
pacf(ts_us_TBEP, lag.max = 40,plot = TRUE)
```




```
par(mfrow= c(1,3))
plot(ts_us_TREP, type="l", col="blue", xlab="Year", ylab="TREP in Trillion Btu", main="U.S. Total Renewa
acf(ts_us_TREP, lag.max = 40,plot = TRUE)
pacf(ts_us_TREP, lag.max = 40,plot = TRUE)
```




```
par(mfrow= c(1,3))
plot(ts_us_HEPC, type="l", col="red", xlab="Year", ylab="HEPC in Trillion Btu", main="U.S. Hydroelectri
acf(ts_us_HEPC, lag.max = 40,plot = TRUE)
pacf(ts_us_HEPC, lag.max = 40,plot = TRUE)
```



Q2

From the plot in Q1, do the series Total Biomass Energy Production, Total Renewable Energy Production, Hydroelectric Power Consumption appear to have a trend? If yes, what kind of trend?

Yes, there is a trend in all the three series. In general, the Total Biomass Energy Production (TBEP) and the Total Renewable Energy Production (TREP) show a significant increasing trend whereas the Hydroelectric Power Consumption show a decreasing trend overtime. Closely looking at the TBEP and TREP, the TBEP started showing a decrease at the final year of the observation period, however, the TREP shows a continued increase even at the end of the observation period.

Q3

Use the *lm()* function to fit a linear trend to the three time series. Ask R to print the summary of the regression. Interpret the regression output, i.e., slope and intercept. Save the regression coefficients for further analysis.

```
# Total Biomass Energy Production (TBEP) linear trend and regression

t <- c(1:585) # Creating vector 't'

linear_trend_TBEP = lm(ts_us_TBEP ~ t)
summary(linear_trend_TBEP)
```

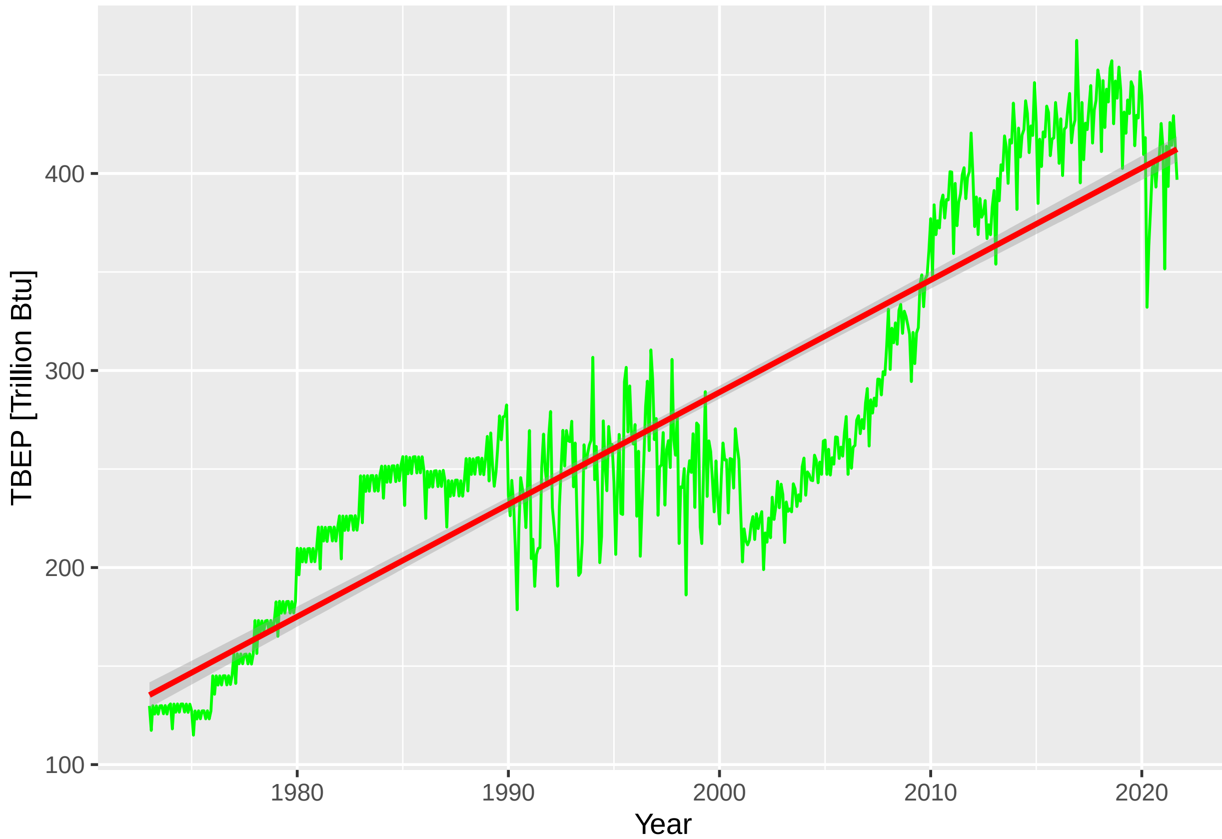
```
##
## Call:
## lm(formula = ts_us_TBEP ~ t)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -101.892  -24.306    4.932   33.103   82.292
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.348e+02  3.282e+00   41.07   <2e-16 ***
## t           4.744e-01  9.705e-03   48.88   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.64 on 583 degrees of freedom
## Multiple R-squared:  0.8039, Adjusted R-squared:  0.8035
## F-statistic:  2389 on 1 and 583 DF,  p-value: < 2.2e-16
```

The slope is 0.474 and it tells us that as time (t) increases by one unit, the TBEP increases by 0.474 Trillion Btu. And the interecept is 134.79 and it tells us, though not realistic and does not make sense in the real world, when the time (t) is zero, the TBEP will be 134.79 Trillion Btu.

```
# Storing the regression coefficients
beta0_TBEP <- as.numeric(linear_trend_TBEP$coefficients[1]) # Intercept
beta1_TBEP <- as.numeric(linear_trend_TBEP$coefficients[2]) # Slope
```

```
ggplot(us_energy.df, aes(x=my_date, y=us_energy.df[,2]))+
 geom_line(color="green")+
 ylab("TBEP [Trillion Btu]")+
 xlab("Year")+
 geom_smooth(color = "red", method = "lm")
```

```
## `geom_smooth()` using formula 'y ~ x'
```




```r
# Total Renewable Energy Production linear trend and regression

linear_trend_TREP = lm(ts_us_TREP ~ t)
summary(linear_trend_TREP)
```

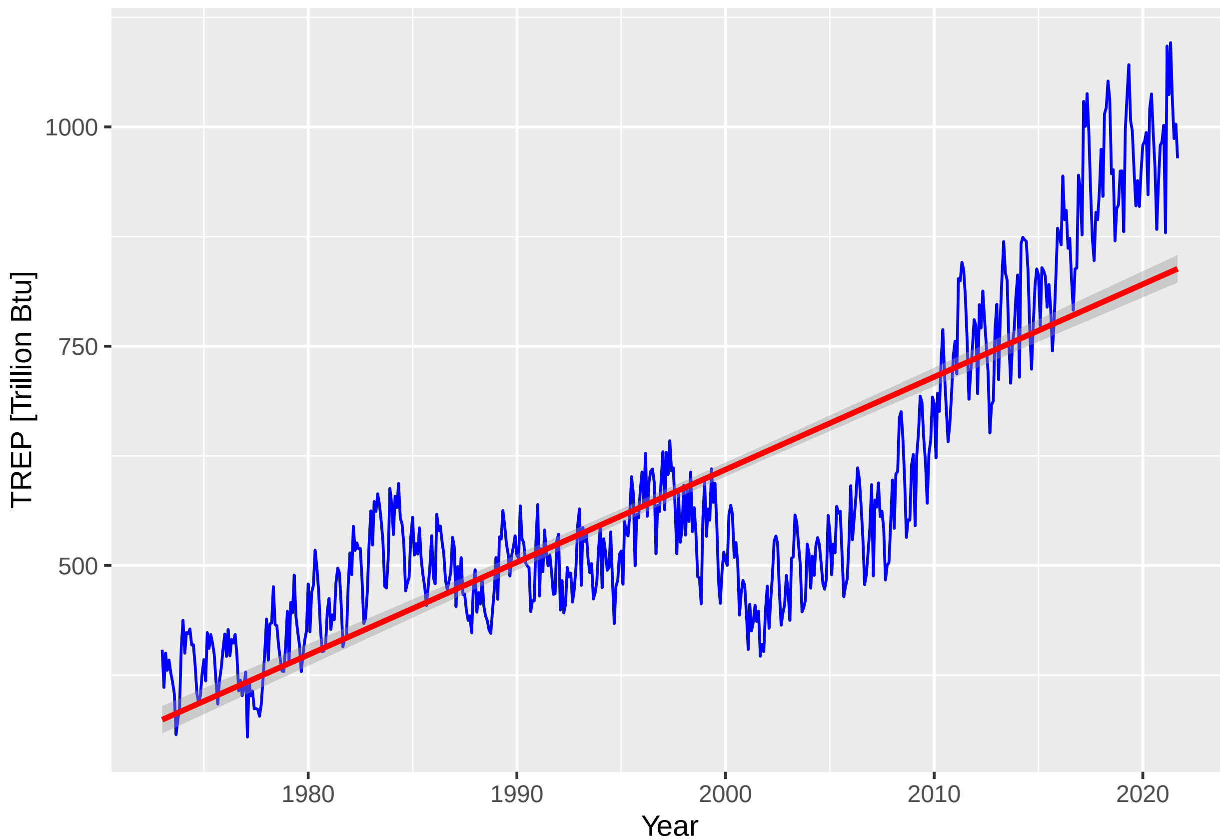
```
##
## Call:
## lm(formula = ts_us_TREP ~ t)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -230.488  -57.869    5.595   62.090  261.349
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 323.18243    8.02555   40.27   <2e-16 ***
## t             0.88051    0.02373   37.10   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 96.93 on 583 degrees of freedom
## Multiple R-squared:  0.7025, Adjusted R-squared:  0.702
## F-statistic:  1377 on 1 and 583 DF,  p-value: < 2.2e-16
```

The slope is 0.88 and it tells us that, as the time (t) increases by one unit, the TREP increases by 0.88 Trillion Btu. And the interecept is 323.1834 and it tells us, though not realistic and does not make sense in the real world, when the time (t) is zero, the TREP will be 323.18 Trillion Btu.

```
# Storing the regression coefficients
beta0_TREP <- as.numeric(linear_trend_TREP$coefficients[1]) # Intercept
beta1_TREP <- as.numeric(linear_trend_TREP$coefficients[2]) # Slope
```

```
ggplot(us_energy.df, aes(x=my_date, y=us_energy.df[,3]))+
 geom_line(color="blue")+
 ylab("TREP [Trillion Btu]")+
 xlab("Year")+
 geom_smooth(color = "red", method = "lm")
```

```
## `geom_smooth()` using formula 'y ~ x'
```




```
# Hydroelectirc Power Consumption linear trend and regression

linear_trend_HEPC = lm(ts_us_HEPC ~ t)
summary(linear_trend_HEPC)
```

```
##
```

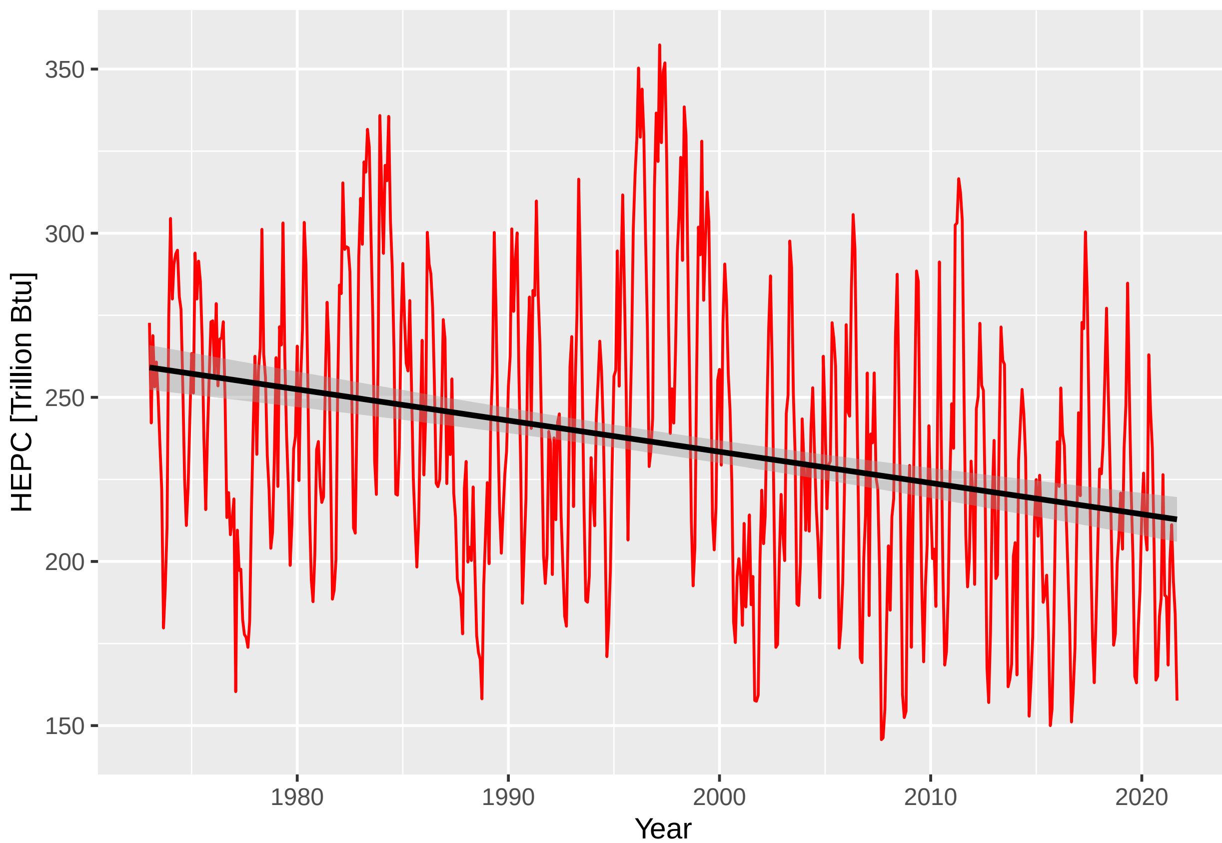
```
## Call:
## lm(formula = ts_us_HEPC ~ t)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -94.892 -31.300  -2.414  27.876 121.263
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 259.18303    3.47464  74.593  < 2e-16 ***
## t            -0.07924    0.01027  -7.712 5.36e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 41.97 on 583 degrees of freedom
## Multiple R-squared:  0.09258,    Adjusted R-squared:  0.09103
## F-statistic: 59.48 on 1 and 583 DF,  p-value: 5.364e-14
```

The slope is -0.079 and it tells us that, as the time (t) increases by one unit, the HEPC decreases by 0.079 Trillion Btu. And the interecept is 259.18 and it tells us, though not realistic and does not make sense in the real world, when the time (t) is zero, the HEPC will be 259.18 Trillion Btu.

```r
# Storing the regression coefficients
beta0_HEPC <- as.numeric(linear_trend_HEPC$coefficients[1]) # Intercept
beta1_HEPC <- as.numeric(linear_trend_HEPC$coefficients[2]) # Slope
```

```r
ggplot(us_energy.df, aes(x=my_date, y=us_energy.df[,4]))+
 geom_line(color="red")+
 ylab("HEPC [Trillion Btu]")+
 xlab("Year")+
 geom_smooth(color = "black", method = "lm")
```

```
## `geom_smooth()` using formula 'y ~ x'
```

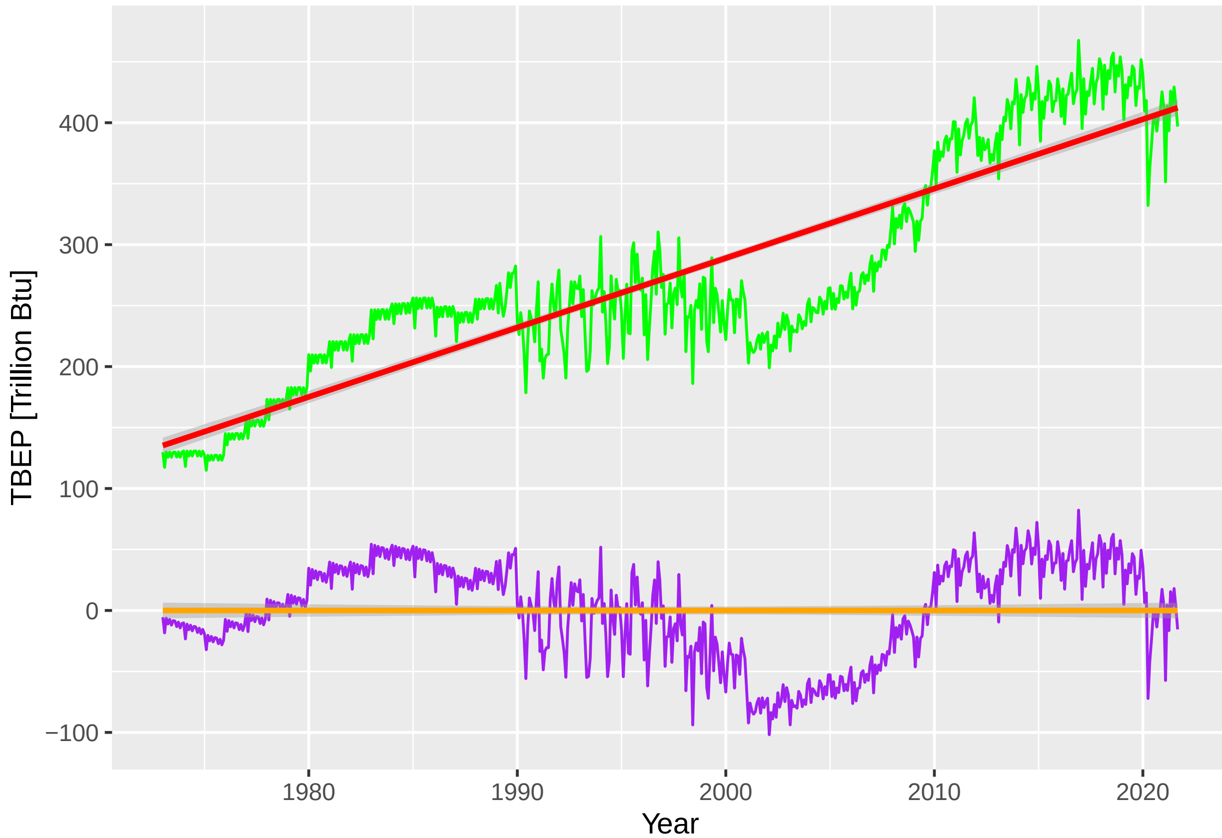


Q4

Use the regression coefficients from Q3 to detrend the series. Plot the detrended series and compare with the plots from Q1. What happened? Did anything change?

```
# Removing the trend from the TBEP series

detrend_ts_us_TBEP <- ts_us_TBEP - (beta0_TBEP + beta1_TBEP * t)

ggplot(us_energy.df, aes(x=my_date, y=us_energy.df[,2]))+
  geom_line(color="green")+
  ylab("TBEP [Trillion Btu]")+
  xlab("Year")+
  geom_smooth(color = "red", method = "lm")+
  geom_line(aes(y=detrend_ts_us_TBEP), color="purple")+
  geom_smooth(aes(y=detrend_ts_us_TBEP), color="orange", method="lm")
```

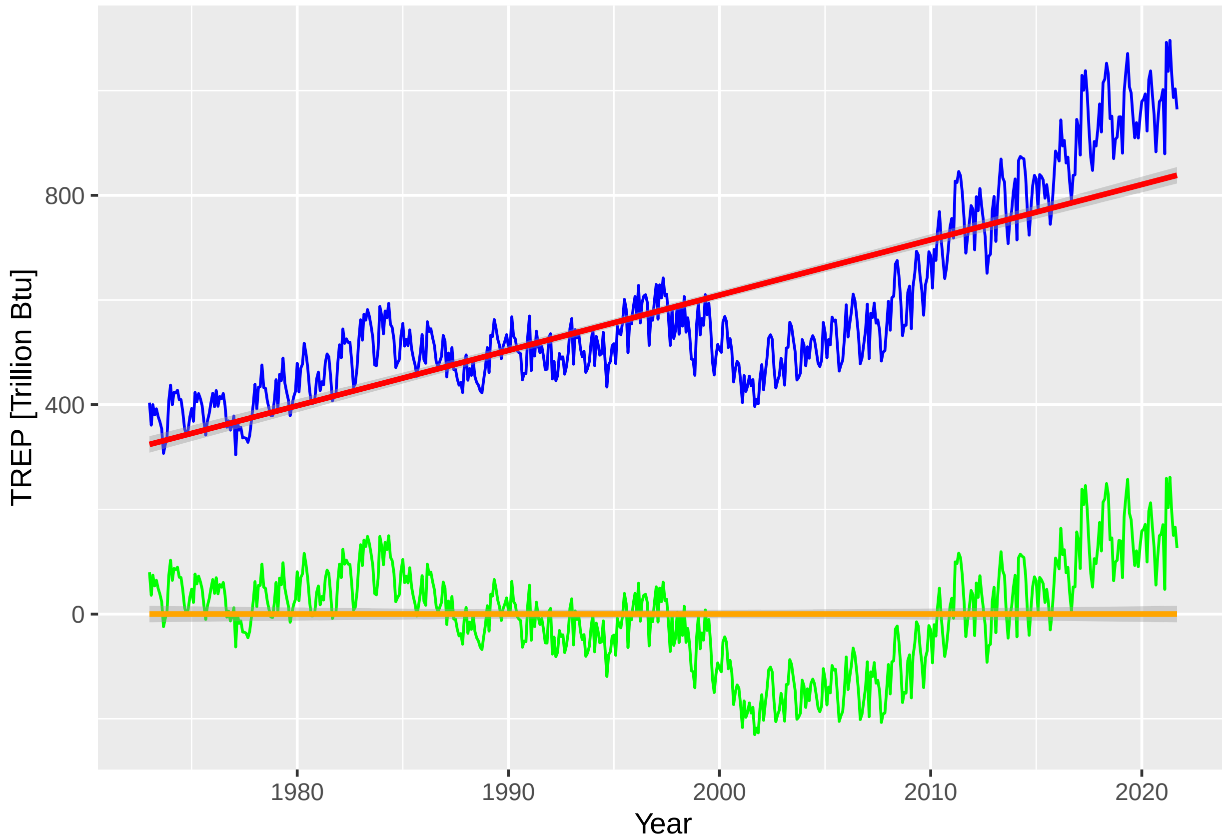
```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```



In the TBEP plot, the series in green is the original series with a red trend line that show a significantly increasing trend overtime. When we remove the trend from the original series, we get the new detrend series shown in purple with an orange trend line that has a zero slope. When the trend component removed from the series, the series still continues to follow almost the same pattern as before the detrend series, i.e. there is no change in its pattern.

```
# Removing the trend from the TREP series

detrend_ts_us_TREP <- ts_us_TREP - (beta0_TREP + beta1_TREP * t)

ggplot(us_energy.df, aes(x=my_date, y=us_energy.df[,3]))+
  geom_line(color="blue")+
  ylab("TREP [Trillion Btu]")+
  xlab("Year")+
  geom_smooth(color = "red", method = "lm")+
  geom_line(aes(y=detrend_ts_us_TREP), color="green")+
  geom_smooth(aes(y=detrend_ts_us_TREP), color="orange", method="lm")
```

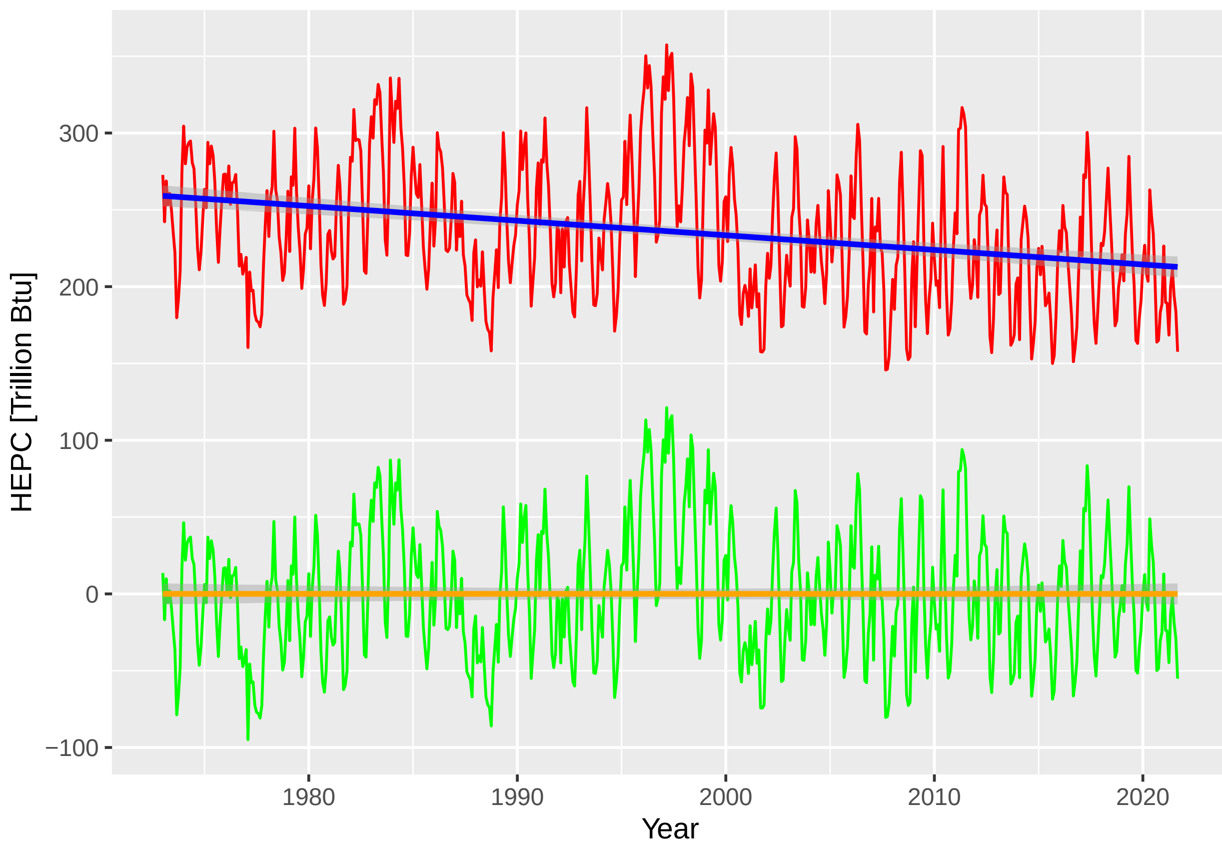
```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```



In the TREP plot, the series in blue is the original series with a red trend line that show a significant increasing trend overtime. When we remove the trend from the original series, we get the new detrend series shown in green with an orange trend line that has a zero slope. When the trend component removed from the series, the series still continues to follow the same pattern as before the detrend series, i.e. there is no change in its pattern.

```
# Removing the trend from the HEPC series

detrend_ts_us_HEPC <- ts_us_HEPC - (beta0_HEPC + beta1_HEPC * t)

ggplot(us_energy.df, aes(x=my_date, y=us_energy.df[,4]))+
  geom_line(color="red")+
  ylab("HEPC [Trillion Btu]")+
  xlab("Year")+
  geom_smooth(color = "blue", method = "lm")+
  geom_line(aes(y=detrend_ts_us_HEPC), color="green")+
  geom_smooth(aes(y=detrend_ts_us_HEPC), color="orange", method="lm")
```

```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```

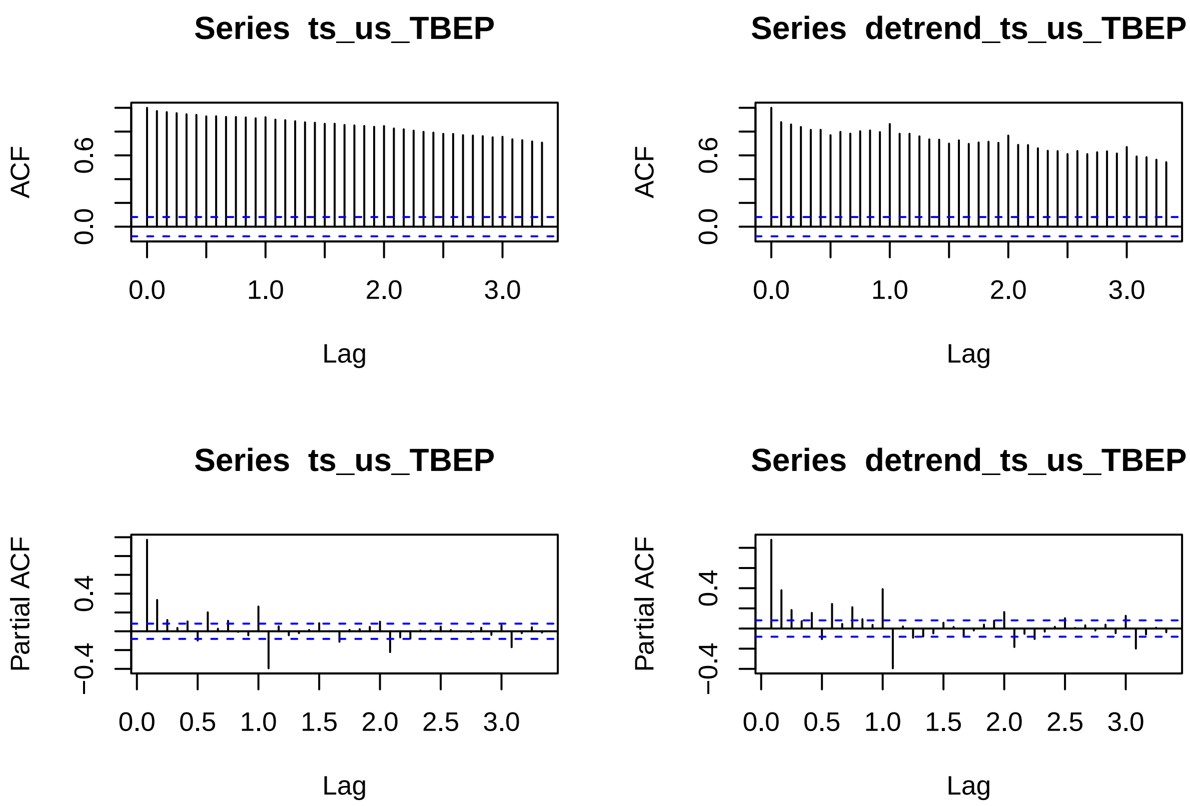


In the HEPC plot, the series in red is the original series with a blue trend line that show a decreasing trend overtime. When we remove the trend from the original series, we get the new detrend series shown in green with an orange trend line that has a zero slope. When the trend component removed from the series, the series shows clearly its seasonal pattern.

Q5

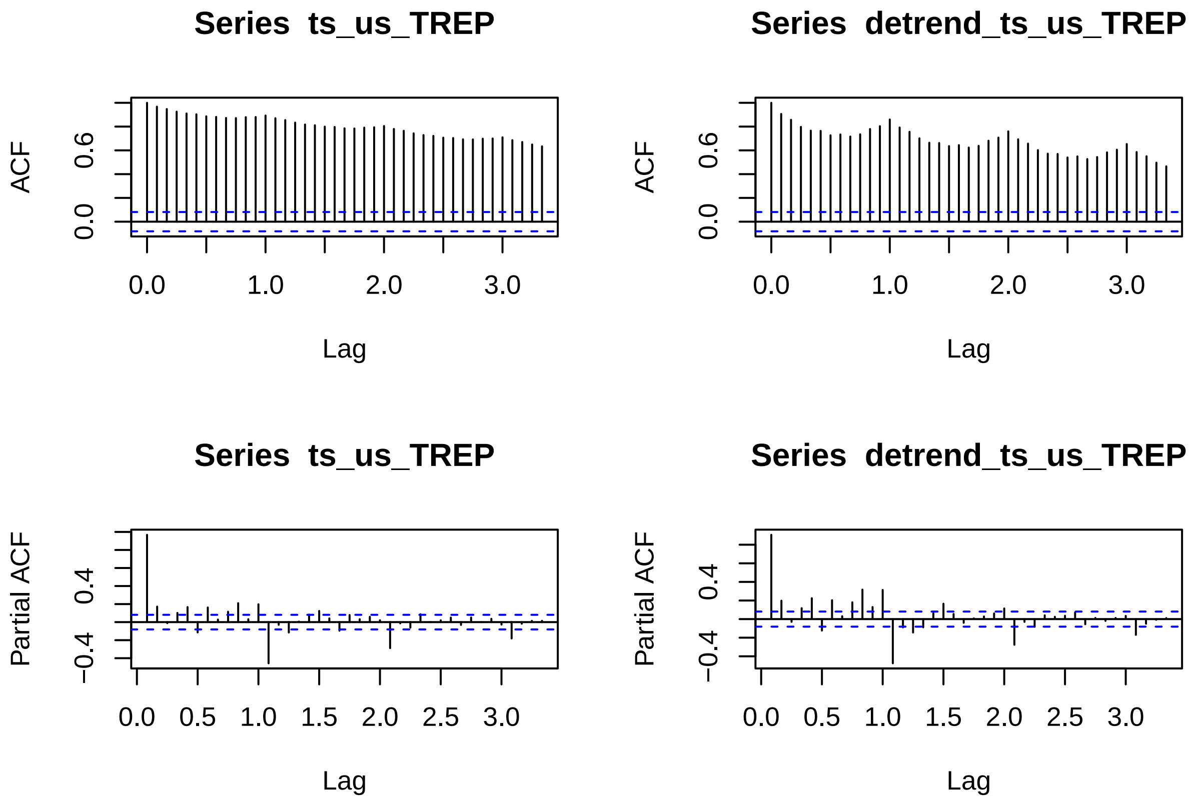
Plot ACF and PACF for the detrended series and compare with the plots from Q1. Did the plots change? How?

```
# ACF and PACF of the detrended series for TBEP

par(mfrow = c(2,2))
acf(ts_us_TBEP, lag.max = 40,plot = TRUE)
acf(detrend_ts_us_TBEP, lag.max = 40, plot=TRUE)
pacf(ts_us_TBEP, lag.max = 40,plot = TRUE)
pacf(detrend_ts_us_TBEP, lag.max = 40, plot = TRUE)
```



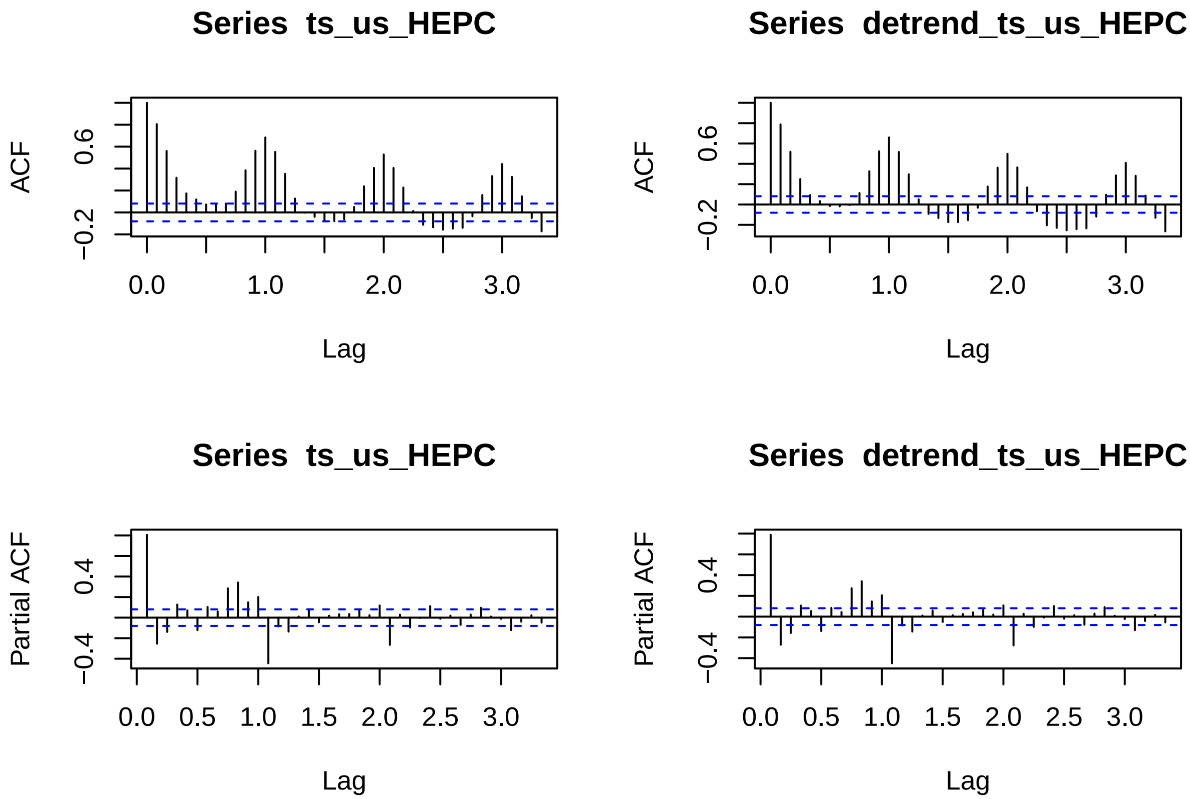
Yes, there is difference in the ACF and PACF plots of TBEP before and after the detrend. Before detrended, the ACF originally showed a slight decreasing trend overtime. When detrend, the ACF showed significant decreasing trend overtime. Similarly, in the case of PACF when detrended, there is a significant increasing trend in the correlation between the observations right after lag 1 to around lag 0.9 and at lag 2 which is higher than the original PACF.

```
# ACF and PACF of the detrended series for TREP

par(mfrow=c(2,2))
acf(ts_us_TREP, lag.max = 40,plot = TRUE)
acf(detrend_ts_us_TREP, lag.max = 40, plot=TRUE)
pacf(ts_us_TREP, lag.max = 40,plot = TRUE)
pacf(detrend_ts_us_TREP, lag.max = 40, plot = TRUE)
```



In the case of TREP, when detrended, the ACF plot show a seasonal decreasing pattern within a regular interval of about every lag. Similarly, in the PACF of the TREP, when detrended, the significance of the relationship among some observations around lags 0.9 and 1.5 get more pronounced than the trended series.

```r
# ACF and PACF of the detrended series for HEPC

par(mfrow=c(2,2))
acf(ts_us_HEPC, lag.max = 40,plot = TRUE)
acf(detrend_ts_us_HEPC, lag.max = 40, plot=TRUE)
pacf(ts_us_HEPC, lag.max = 40,plot = TRUE)
pacf(detrend_ts_us_HEPC, lag.max = 40, plot = TRUE)
```



In the trended and detrended acf and pacf plots of the HEPC, there is only one difference that can be observed in the detrended ACF and that is an increase in the correlation of the observations overtime around lags 1.5 and 2.5 which was smaller in the original ACF.

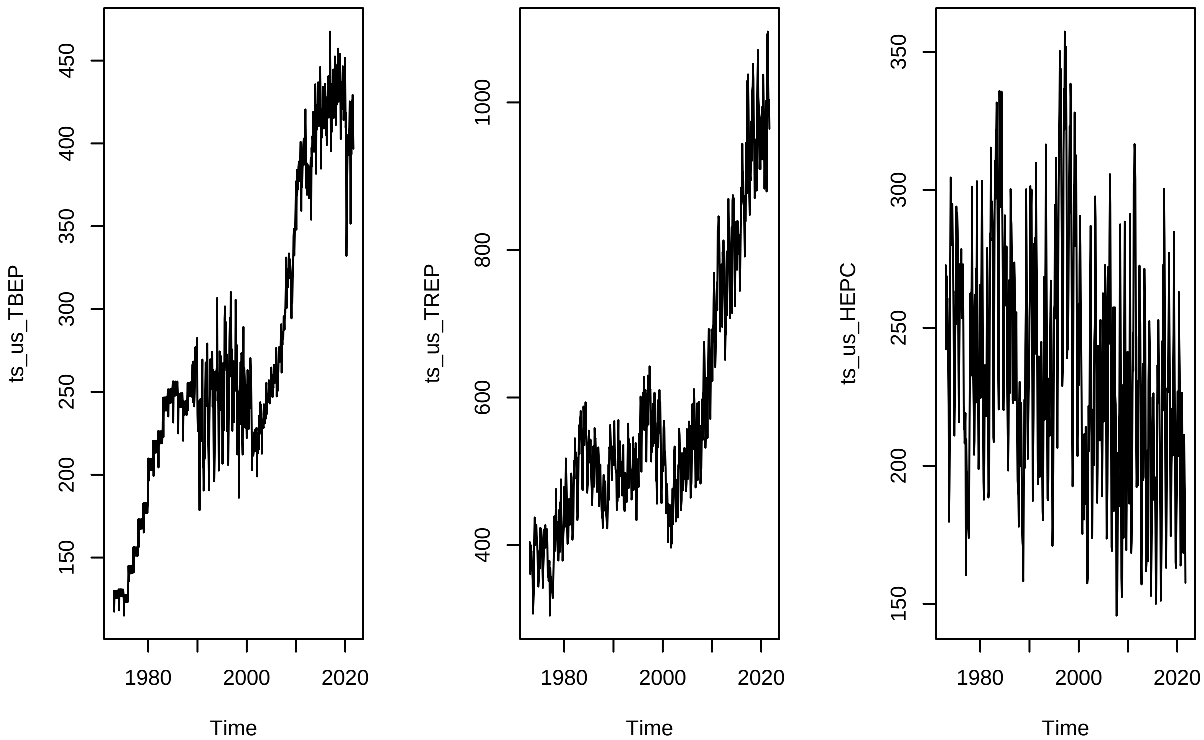
Seasonal Component

Set aside the detrended series and consider the original series again from Q1 to answer Q6 to Q8.

Q6

Do the series seem to have a seasonal trend? Which serie/series? Use function *lm()* to fit a seasonal means model (i.e. using the seasonal dummies) to this/these time series. Ask R to print the summary of the regression. Interpret the regression output. Save the regression coefficients for further analysis.

```
## Time series object of TBEP, TREP, HEPC
ts_us_TBEP <- ts(us_energy.df$TBEP, start = c(1973, 1), frequency= 12)
ts_us_TREP <- ts(us_energy.df$TREP, start = c(1973, 1), frequency= 12)
ts_us_HEPC <- ts(us_energy.df$HEPC, start = c(1973, 1), frequency= 12)

par(mfrow=c(1,3))
plot(ts_us_TBEP)
plot(ts_us_TREP)
plot(ts_us_HEPC)
```



Looking at the time series plots, the HEPC series have a seasonal trend.

```r
# Apply the seasonal means model to create the seasonal dummies

dummies_HEPC <- seasonaldummy(ts_us_HEPC)

# Fitting a linear model to the seasonal dummies

HEPC_seas_means_model=lm(us_energy.df$HEPC ~ dummies_HEPC)

summary(HEPC_seas_means_model)
```

```
##
## Call:
## lm(formula = us_energy.df$HEPC ~ dummies_HEPC)
##
## Residuals:
##     Min       1Q  Median      3Q     Max
## -90.253 -23.017  -3.042  21.487  99.478
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        237.841      4.892  48.616  < 2e-16 ***
## dummies_HEPCJan     13.558      6.883   1.970  0.04936 *
```

```
## dummies_HEPCFeb   -8.090      6.883  -1.175  0.24037
## dummies_HEPCMar   20.067      6.883   2.915  0.00369 **
## dummies_HEPCApr   16.619      6.883   2.414  0.01607 *
## dummies_HEPCMay   39.961      6.883   5.805 1.06e-08 ***
## dummies_HEPCJun   31.315      6.883   4.549 6.57e-06 ***
## dummies_HEPCJul   10.511      6.883   1.527  0.12732
## dummies_HEPCAug  -17.853      6.883  -2.594  0.00974 **
## dummies_HEPCSep  -49.852      6.883  -7.242 1.43e-12 ***
## dummies_HEPCOct  -48.086      6.919  -6.950 9.96e-12 ***
## dummies_HEPCNov  -32.187      6.919  -4.652 4.08e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 33.89 on 573 degrees of freedom
## Multiple R-squared:  0.4182, Adjusted R-squared:  0.4071
## F-statistic: 37.45 on 11 and 573 DF,  p-value: < 2.2e-16
```

From the regression summary, we can see that looking at the effect of each month within the year, holding the others constant; the HEPC (in Trillion Btu) will decrease in the months Feburary (by 8.09), August (by 17.85), September (by 49.85), October (by 48.07) and November (by 32.19), with the highest decrease observed in September (by 49.85). For example, keeping all the others constant, in the month of Feburary, the HEPC decreases by 8.09 Trillion Btu.

In the remaining months, the series shows an increase in the HEPC by a range of 10.51 - 39.96 Trillion Btu, except the month of February which show a decrease in the HEPC (by 8.090). The highest increase is in the month of May (by 39.96) and the lowest increase is in the month of July (by 10.51). For example, holding all the others constant, the HEPC increases in the month of May by 39.96 Trillion Btu.

These in general created a pattern of HEPC increase in some months (from March to July) and then decrease in consumption in the following months (from August to November).The exceptional observation (the decrease in the month of February) requires additional information to explain.

Note that the units of all the coefficients is in Trillion Btu.

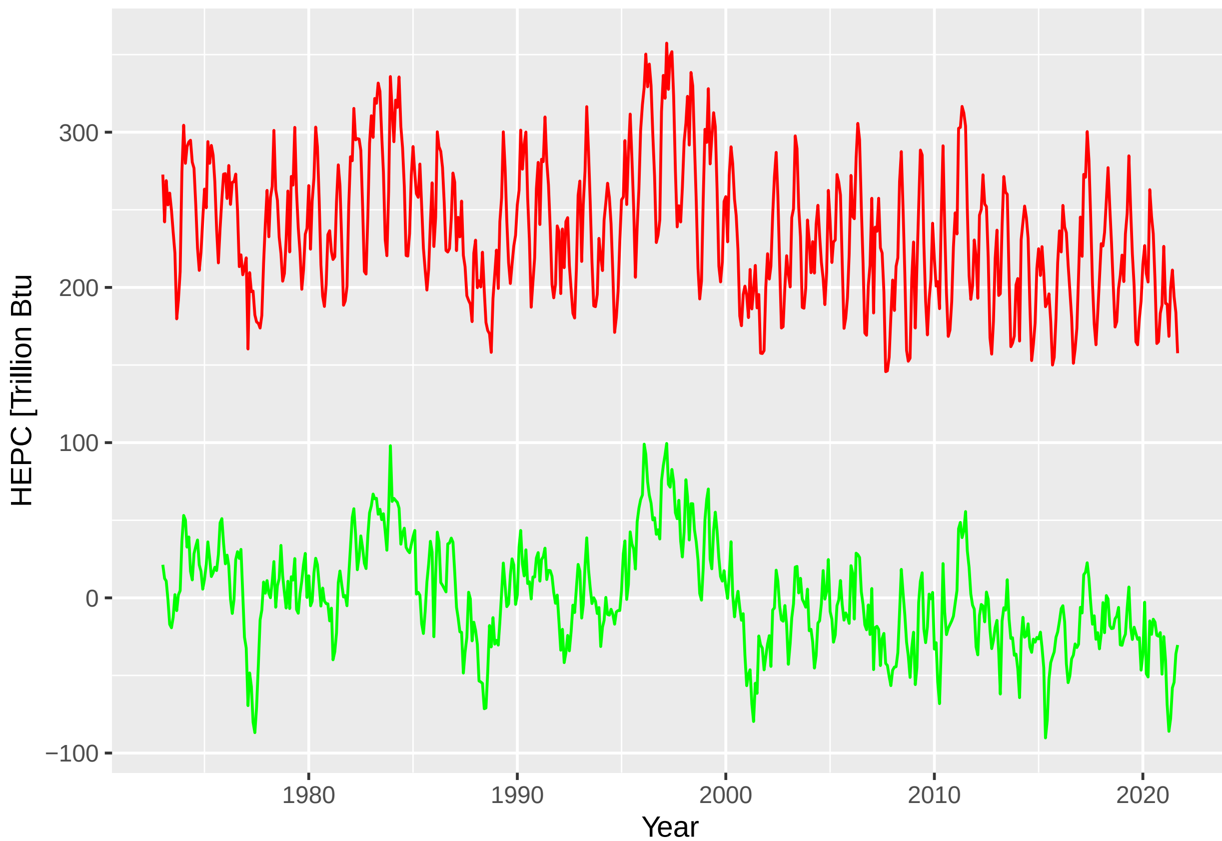
```r
# Storing the regression coefficients
beta0_int_HEPC = HEPC_seas_means_model$coefficients[1]
beta1_coeff_HEPC = HEPC_seas_means_model$coefficients[2:12]
```

Q7

Use the regression coefficients from Q6 to deseason the series. Plot the deseason series and compare with the plots from part Q1. Did anything change?

```r
# Compute the seasonal component
ts_us_HEPC_seas_comp=array(0,585)
for(i in 1:585)
  {
  ts_us_HEPC_seas_comp[i]=(beta0_int_HEPC+beta1_coeff_HEPC%*%dummies_HEPC[i,])
  }
```

```r
# Removing the seasonal component
deseason_ts_us_HEPC <- us_energy.df$HEPC - ts_us_HEPC_seas_comp

par(mfrow=c(1,2))
ggplot(us_energy.df, aes(x=my_date, y=HEPC)) +
            geom_line(color="red") +
            ylab("HEPC [Trillion Btu") +
            xlab("Year") +
            geom_line(aes(y=deseason_ts_us_HEPC), col="green")
```



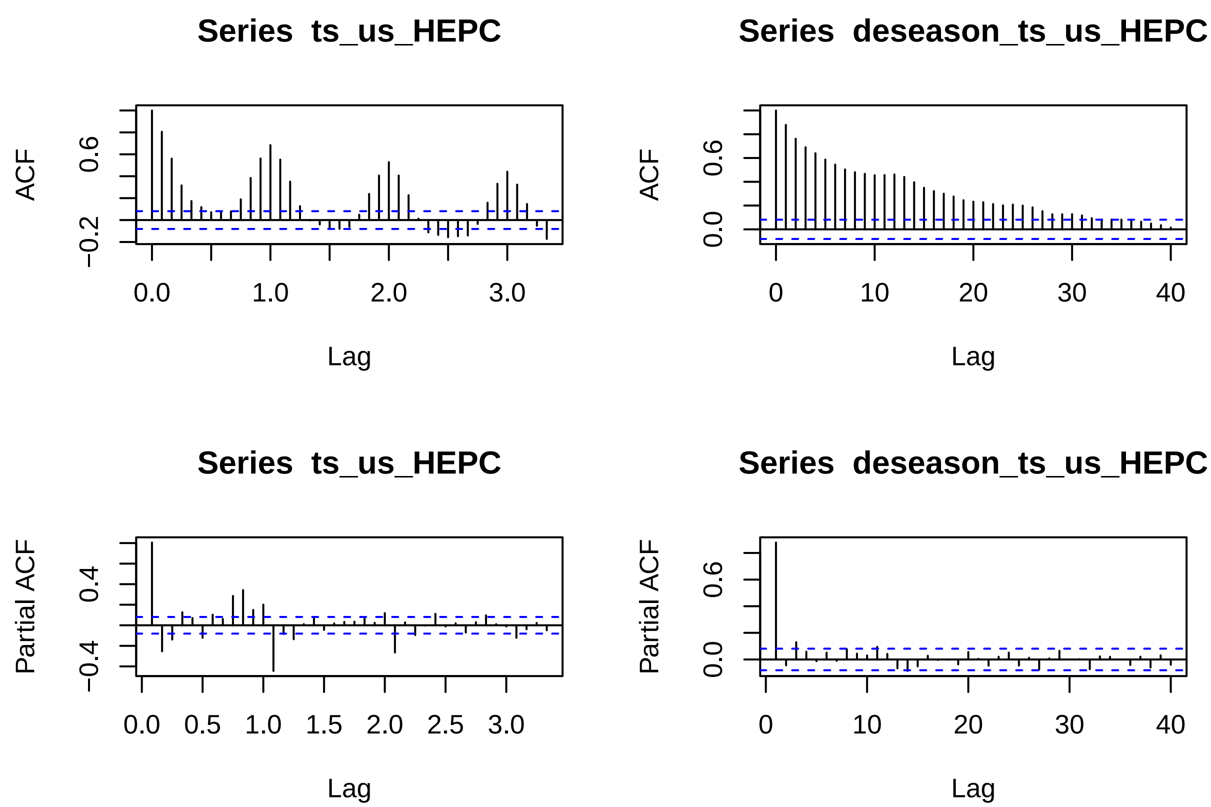
When compared with the original series (as shown in red) with the deseasoned series (as shown in green), yes, there is a change in the pattern. When deseasoned, the series losses its seasonal pattern and demonstrates a random movement overtime.

Q8

Plot ACF and PACF for the deseason series and compare with the plots from Q1. Did the plots change? How?

```r
# Comparing the acf and pacf plots of seasonal and deseason series of HEPC

par(mfrow=c(2,2))
acf(ts_us_HEPC, lag.max = 40,plot = TRUE)
acf(deseason_ts_us_HEPC, lag.max = 40)
```

```r
pacf(ts_us_HEPC, lag.max = 40,plot = TRUE)
pacf(deseason_ts_us_HEPC, lag.max = 40)
```



When comparing the ACF plots of the HEPC, there is a completely different pattern change from seasonal increase-decrease (in the original ACF) to a continuous gradual significant decrease as the lags increase reaching to insignificant correlation among the observations at lag 40. In case of the PACF, when the seasonal component removed, the significant correlation of observations after the first lag disappear along with it leaving the significance at lag one unchanged/ the same.