

# IST772 Week 10 Practice Quiz #4

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Week 10: Practice Exam (Fifth practice exam, third practice leading up to final)

Instructions: Complete the analysis specified below by writing and running the appropriate Rcode.

1. Import the provided data. These data comprise multiple time series indicating the relative values of bond market indices across the world. These times series begin in December 1993 with all indices normalized to 100. These are dollar-calibrated indices, so you can think of this as being what would happen if you had invested \$100 in the respective bond market starting in December 1993. From 1993 to 2013, each bond market index floats up or down depending on prevailing financial conditions in the country or region. For the research questions in this exam, we are only concerned with comparisons among four regional composites that appear as columns in the data set: Developing Asia, Latin America/Caribbean, Sub-Saharan Africa, and Russian Federation.

```
#Read in the data and subset for the 4 regions
bond <- read.csv("/Users/johnfields/Library/Mobile Documents/com~apple~CloudDocs/Syracuse/IST772/Week 10/bond.csv")

bond.sub <- bond[,c("obs", "Developing.Asia", "Latin.America...Caribbean", "Sub.Saharan.Africa",
                  "Russian.Federation")]

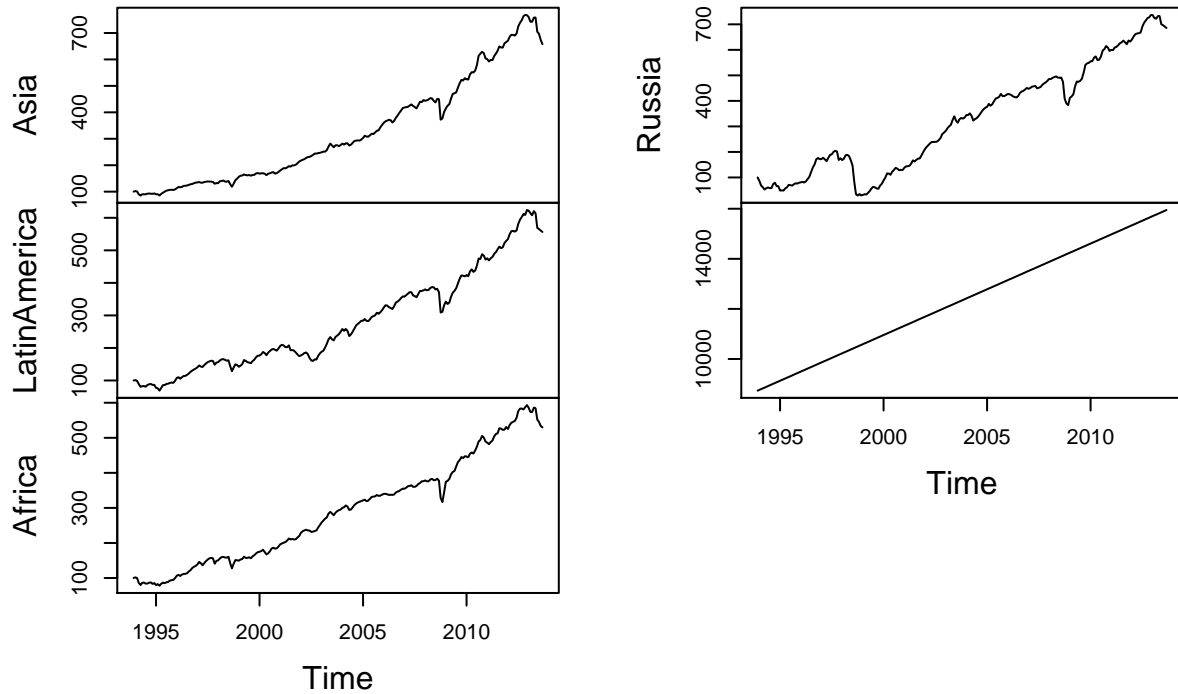
#Extract the date information and create a new variable
bond.sub$obs <- gsub("M", "-", bond.sub$obs)
library(zoo)

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

bond.sub$date <- as.yearmon(bond.sub$obs, "%Y-%m")
bond.sub$date <- as.Date(as.yearmon(bond.sub$date, "%m-%Y"))
bond.sub <- bond.sub[,-1]
colnames(bond.sub) <- c("Asia", "LatinAmerica", "Africa", "Russia")
bond.sub.ts <- ts(bond.sub, start=c(1993,12), frequency=12)

plot(bond.sub.ts)
```

## bond.sub.ts

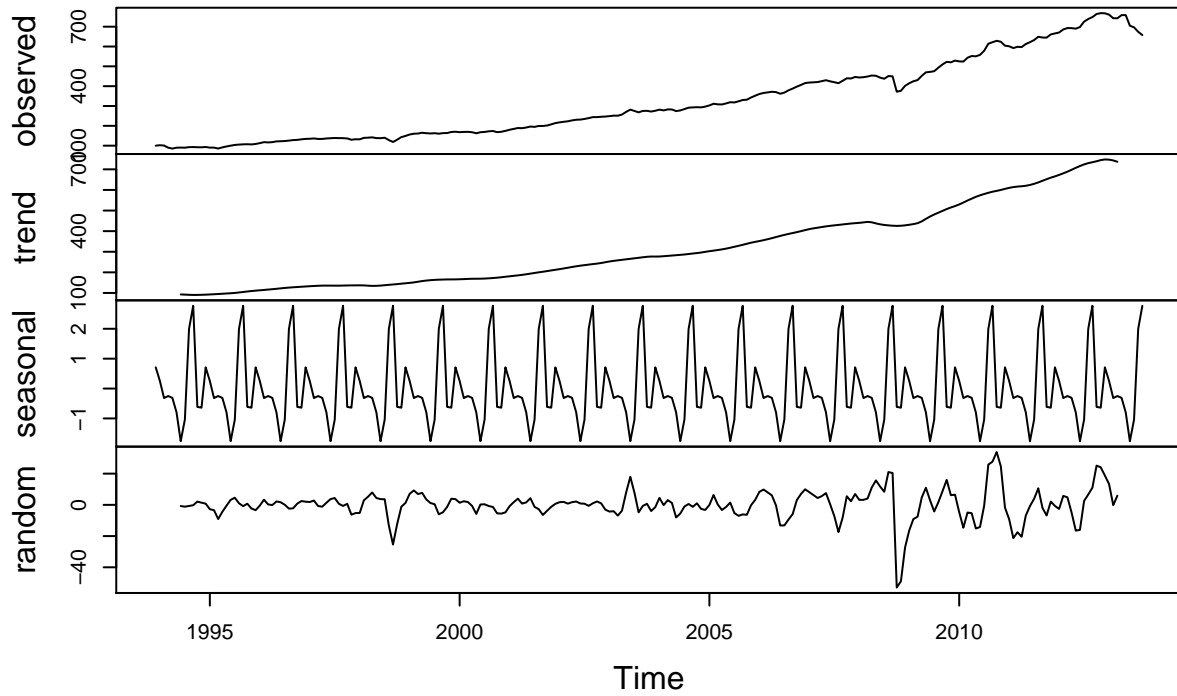


2. For certain of the research questions below, you will need to work with stationary time series. Run the appropriate diagnostics and transformations to create a stationary time series for each region. *OPTIONAL:* Extract date information from the first column of the data set and label all of your time series data with actual dates.

```
dec1 <- decompose(bond.sub.ts[, "Asia"])
dec2 <- decompose(bond.sub.ts[, "LatinAmerica"])
dec3 <- decompose(bond.sub.ts[, "Africa"])
dec4 <- decompose(bond.sub.ts[, "Russia"])

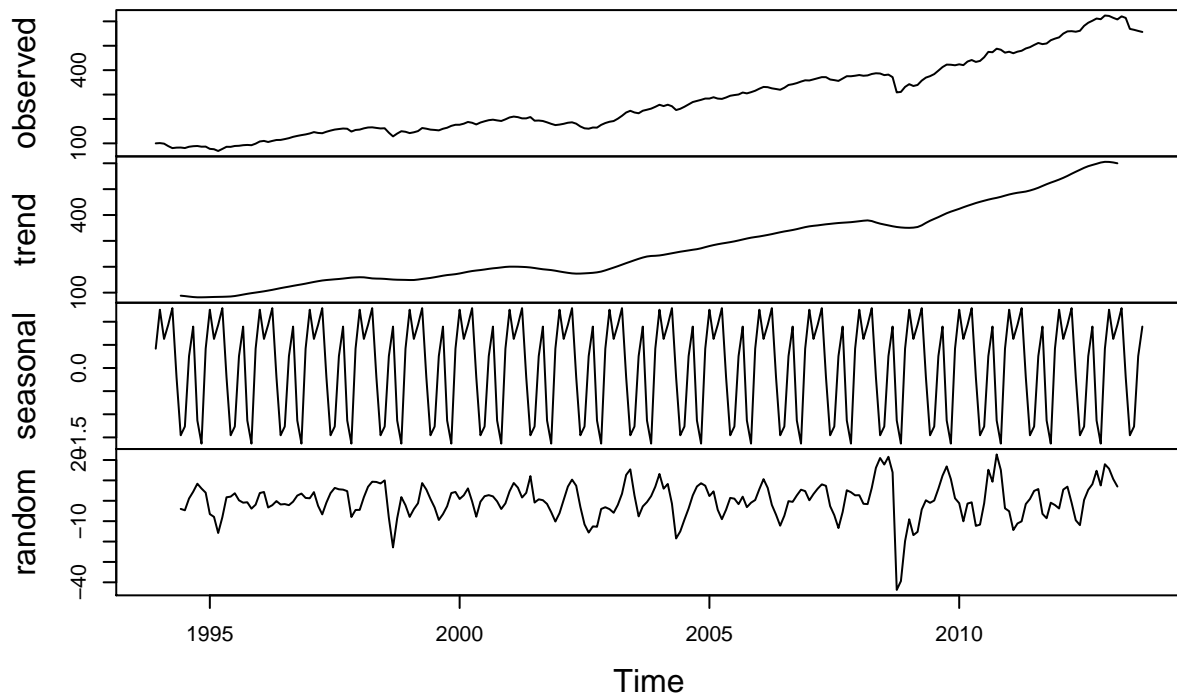
plot(dec1)
```

## Decomposition of additive time series



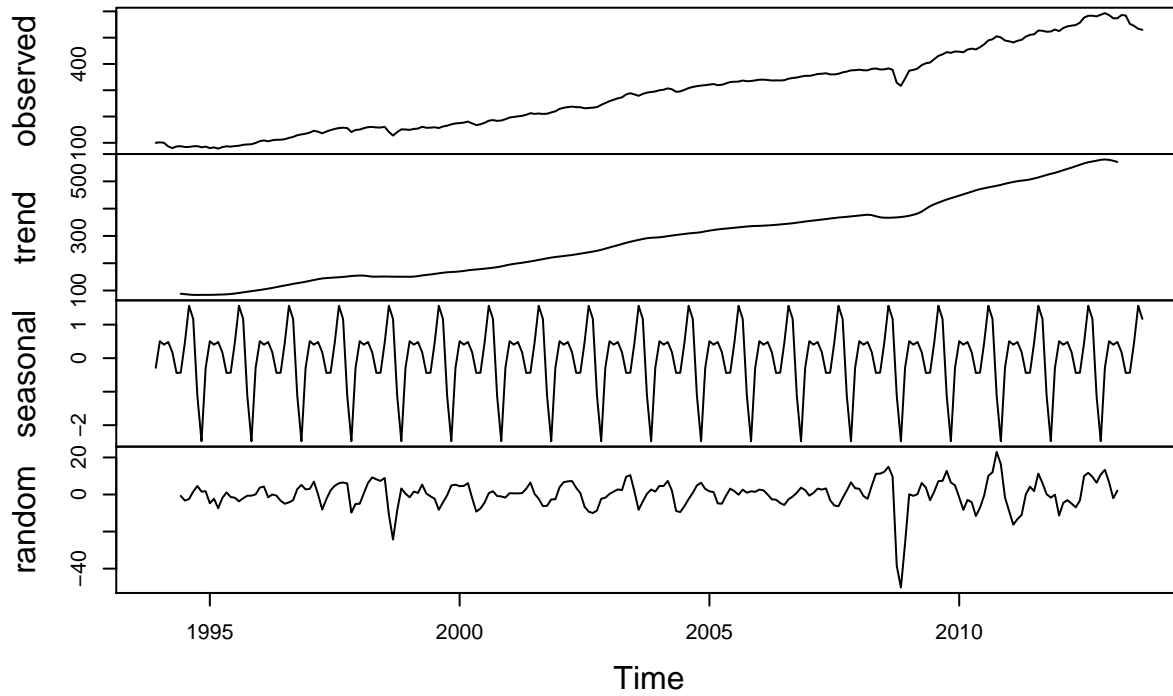
```
plot(dec2)
```

## Decomposition of additive time series



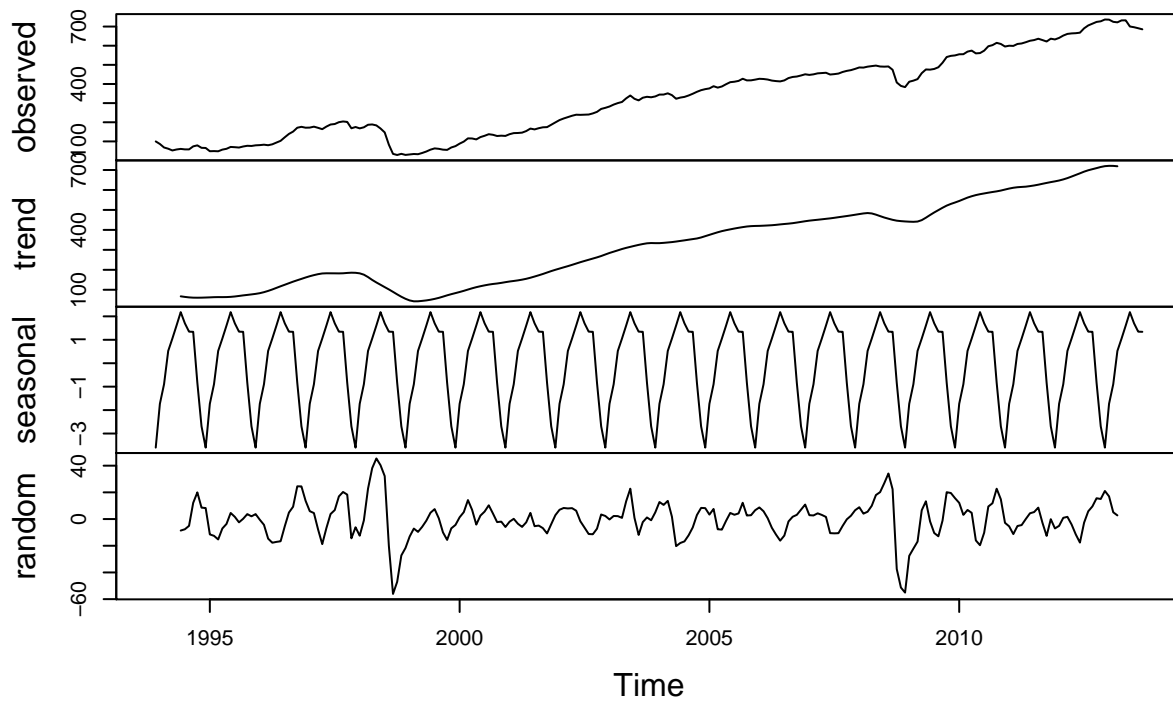
```
plot(dec3)
```

## Decomposition of additive time series



```
plot(dec4)
```

## Decomposition of additive time series

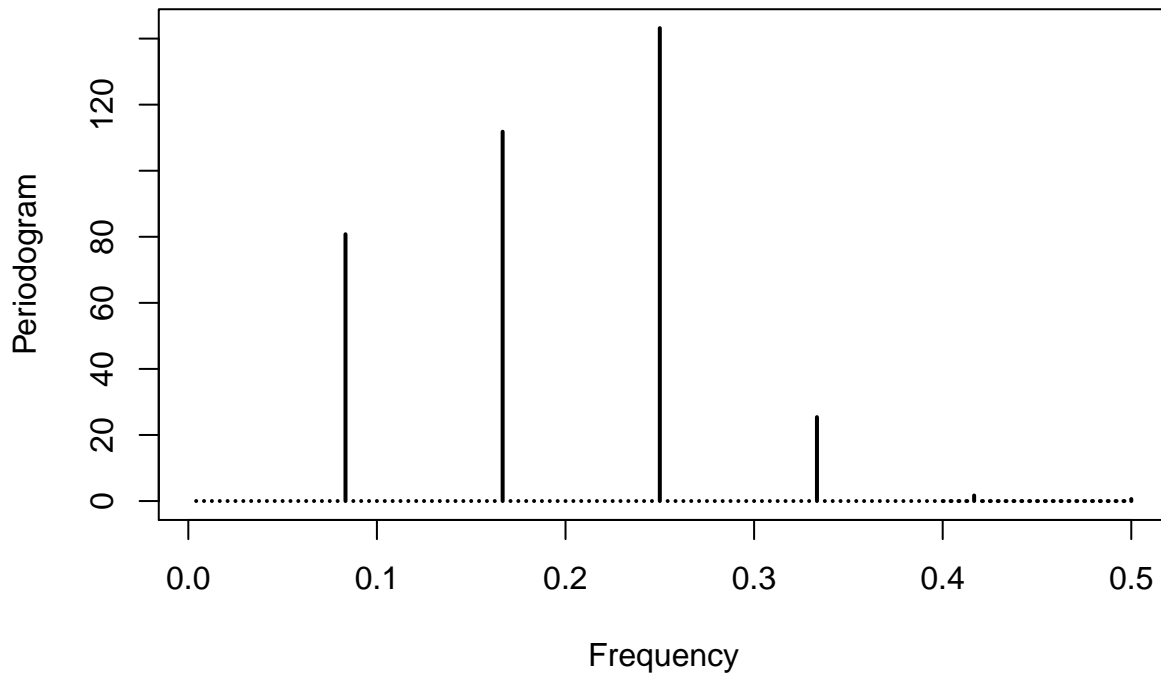


Run the `periodogram()` function on the seasonal component of each of the time series. A periodogram displays the intensity of cyclical energy at different frequencies.

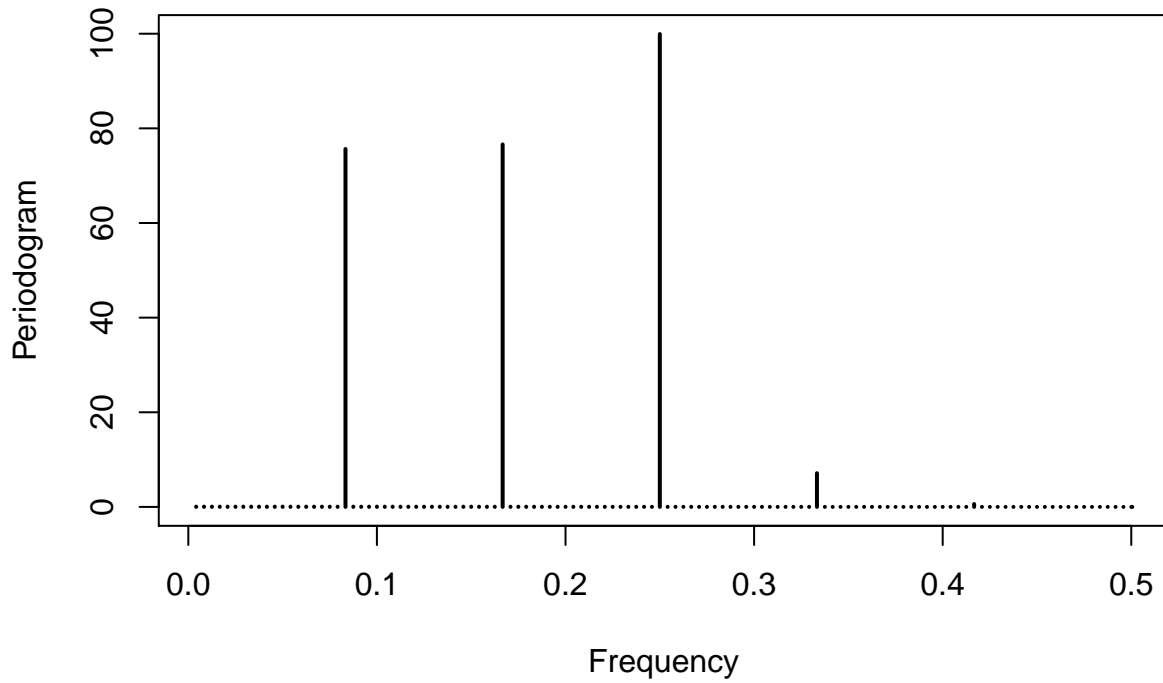
```
library(TSA)
```

```
##  
## Attaching package: 'TSA'  
## The following objects are masked from 'package:stats':  
##  
##   acf, arima  
## The following object is masked from 'package:utils':  
##  
##   tar
```

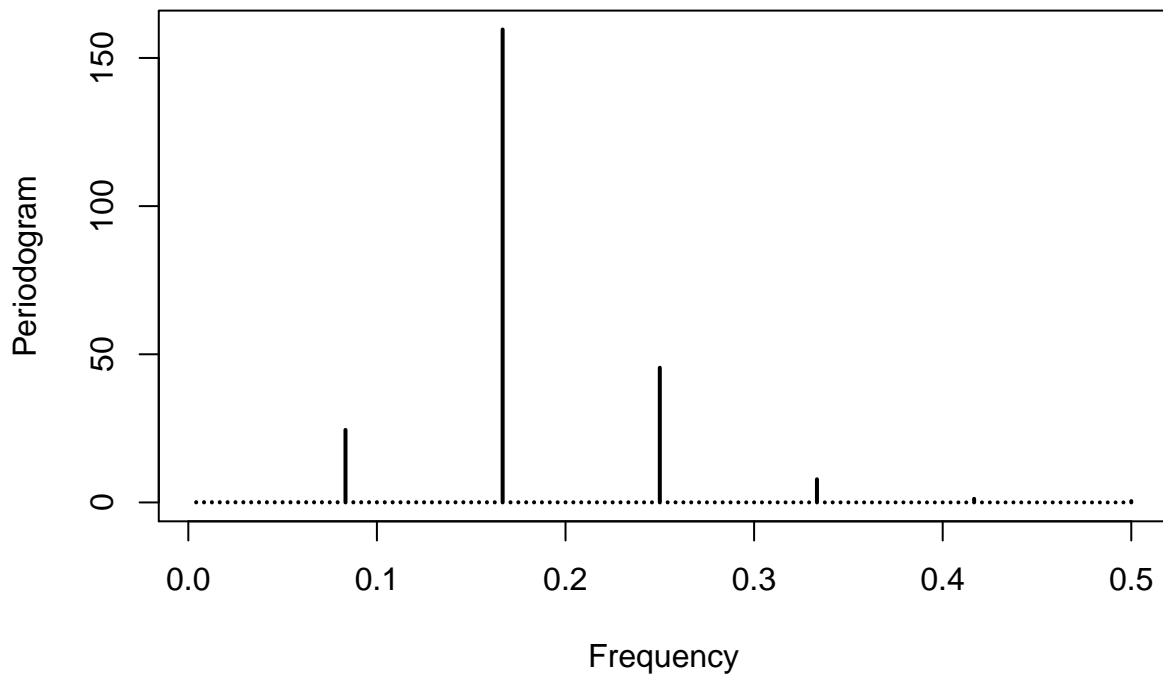
```
p1 <- periodogram(dec1$seasonal)
```



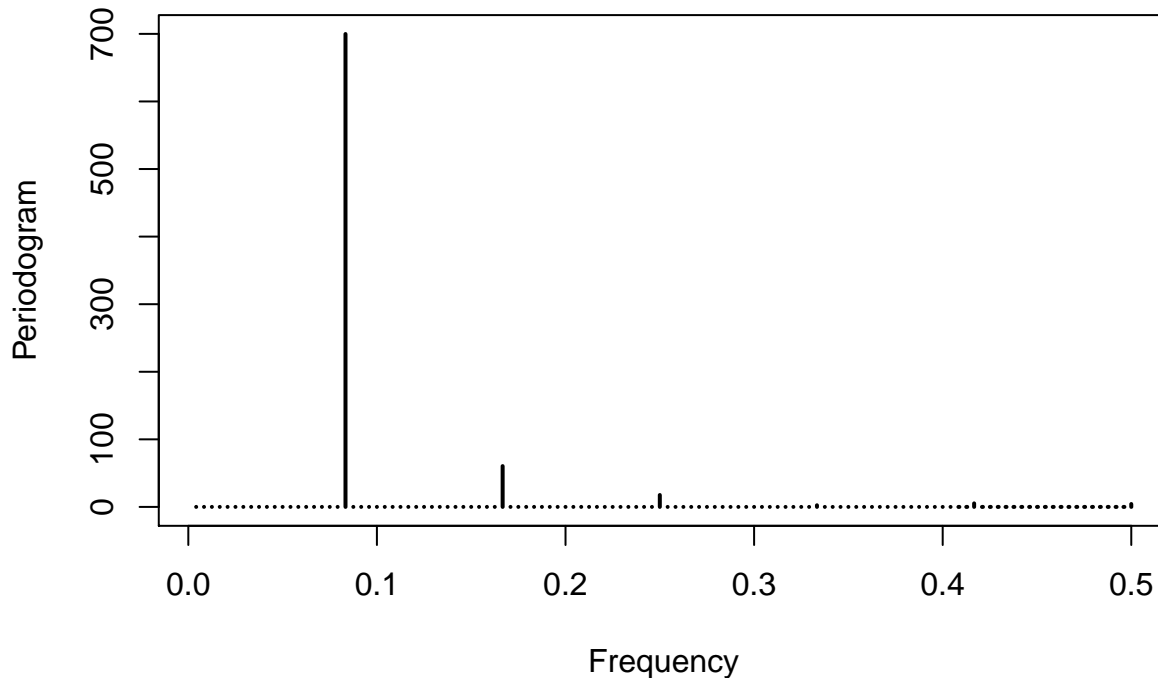
```
p2 <- periodogram(dec2$seasonal)
```



```
p3 <- periodogram(dec3$seasonal)
```



```
p4 <- periodogram(dec4$seasonal)
```



Determine the length of the strongest cycle by inverting the appropriate frequency in the periodogram object.

```
1/p1$freq[which.max(p1$spec)]
```

```
## [1] 4
```

```
1/p2$freq[which.max(p2$spec)]
```

```
## [1] 4
```

```
1/p3$freq[which.max(p3$spec)]
```

```
## [1] 6
```

```
1/p4$freq[which.max(p4$spec)]
```

```
## [1] 12
```

Check the stationarity of the random component of each of the time series. The following three lines put the random components into a data frame, remove any missing data, and convert to a times series:

```
regions <- data.frame(dec1$random, dec2$random, dec3$random, dec4$random)
regions <- regions[complete.cases(regions),]
regions <- ts(regions,start=c(1994,12),frequency=12)
summary(regions)
```

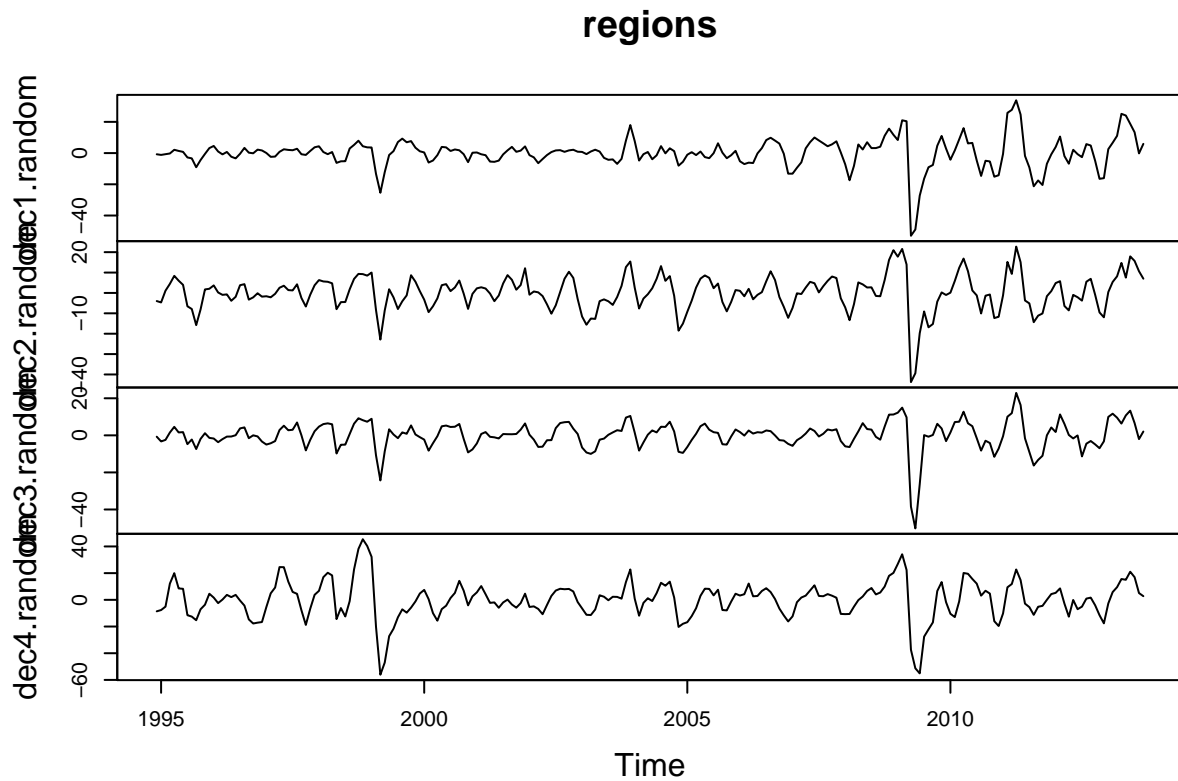
```
##   dec1.random      dec2.random      dec3.random      dec4.random
## Min.   :-52.9694   Min.    :-43.7302   Min.    :-50.20504  Min.    :-56.09190
## 1st Qu.: -3.6365   1st Qu.: -4.0792   1st Qu.: -2.88751  1st Qu.: -6.99636
## Median :  0.6642   Median :  0.2416   Median :  0.53935  Median :  1.26354
## Mean   :  0.1431   Mean    :  0.1172   Mean    :  0.06519  Mean    :  0.09432
## 3rd Qu.:  3.9477   3rd Qu.:  5.4854   3rd Qu.:  4.15961  3rd Qu.:  6.92526
## Max.   : 33.8163   Max.    : 22.7305   Max.    : 22.89595  Max.    : 45.40200
```

```
str(regions)
```

```
## Time-Series [1:226, 1:4] from 1995 to 2014: -0.762 -1.167 -0.703 -0.261 2.118 ...
```

```
## - attr(*, "dimnames")=List of 2
## ..$ : NULL
## ..$ : chr [1:4] "dec1.random" "dec2.random" "dec3.random" "dec4.random"
```

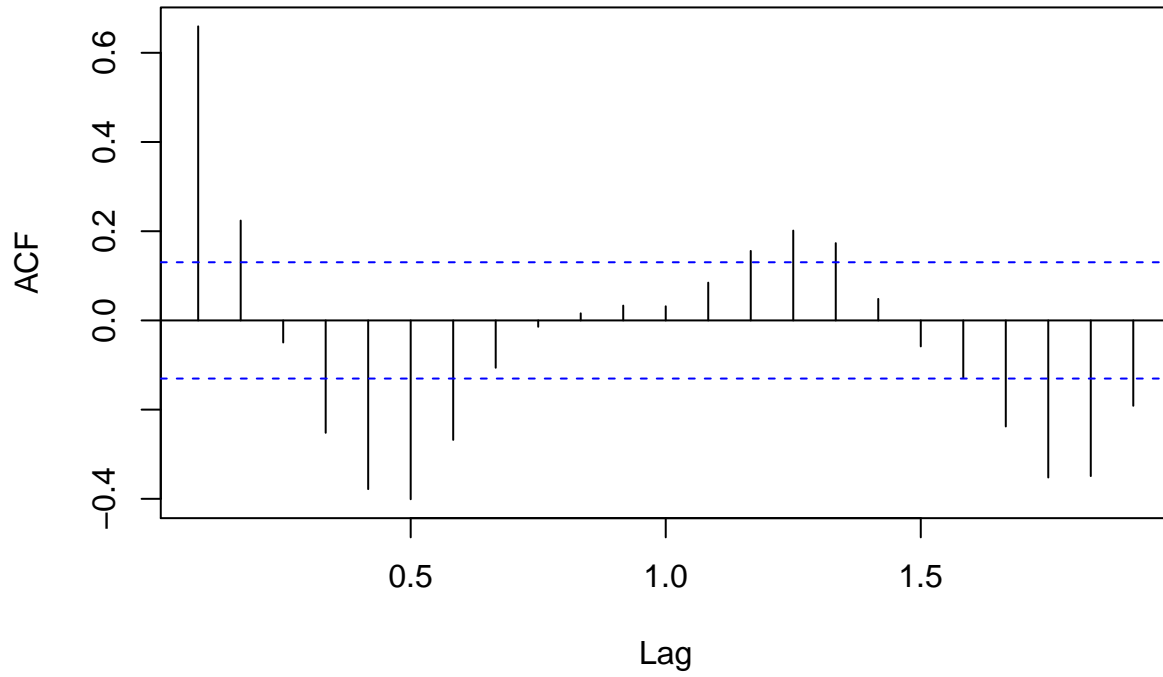
```
plot(regions)
```



The auto-correlation function (ACF) creates graphs for each time series. The ACF provides an informal way of reviewing the time structure of a time series, particularly cycles and stationarity. This code compares the decomposed random data with simple differencing for the regions.

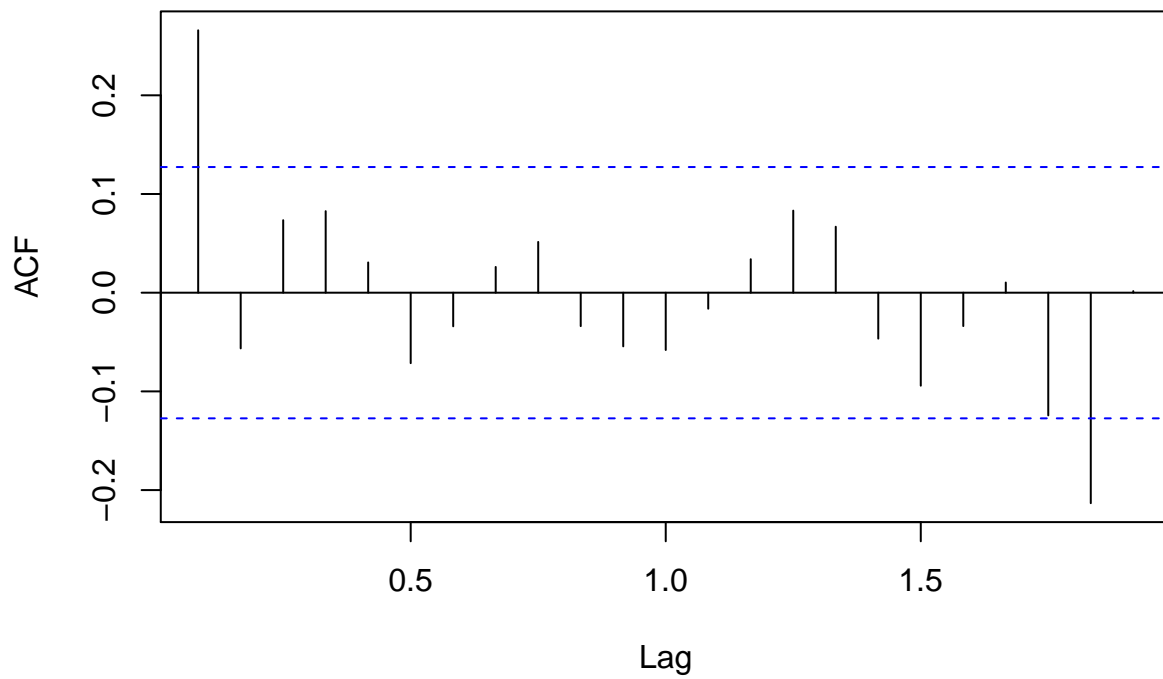
```
acf(regions[,1])
```

### Series regions[, 1]



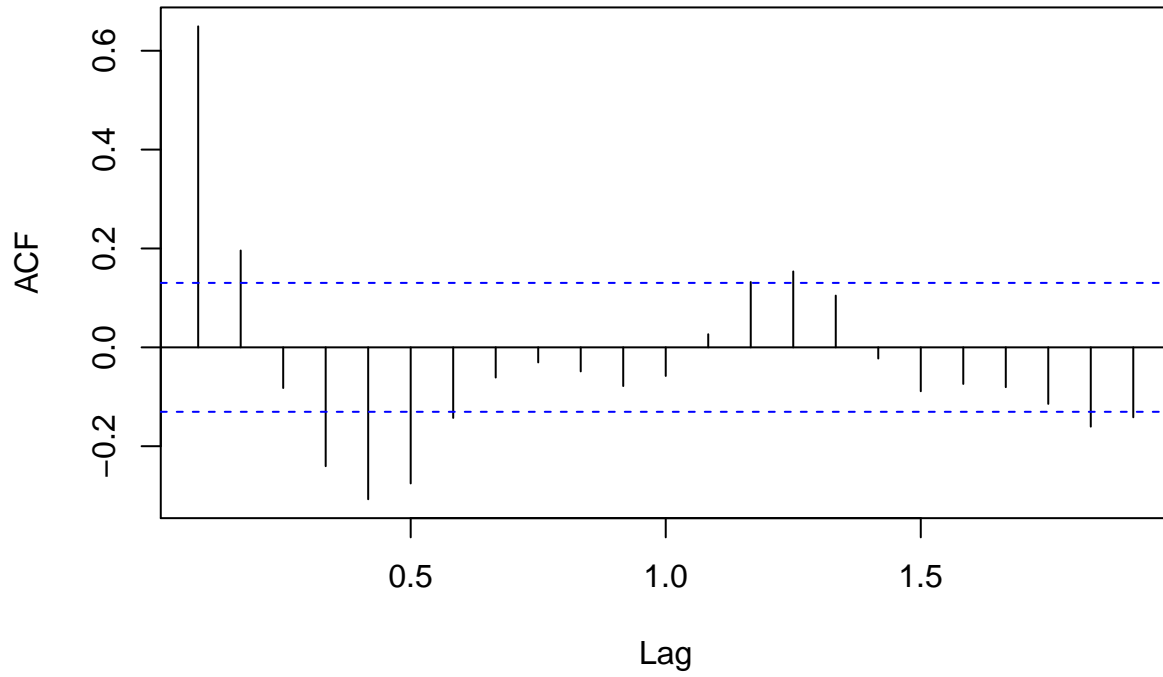
```
acf(diff(bond.sub.ts[,1]))
```

### Series diff(bond.sub.ts[, 1])



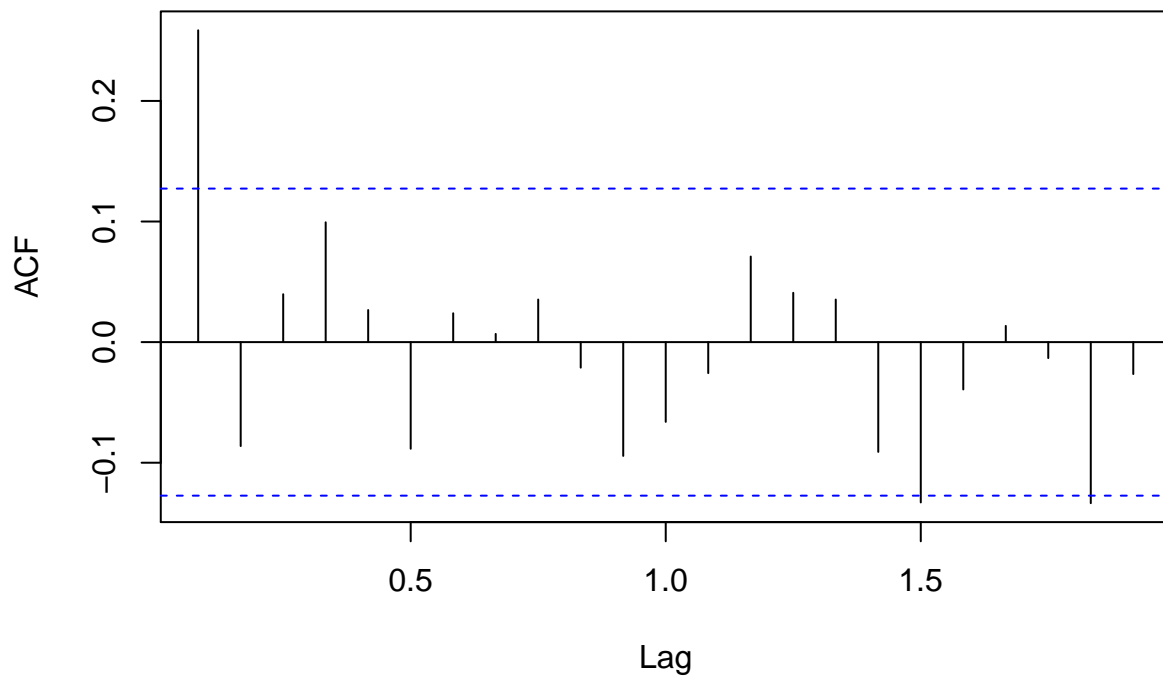
```
acf(regions[,2])
```

### Series regions[, 2]



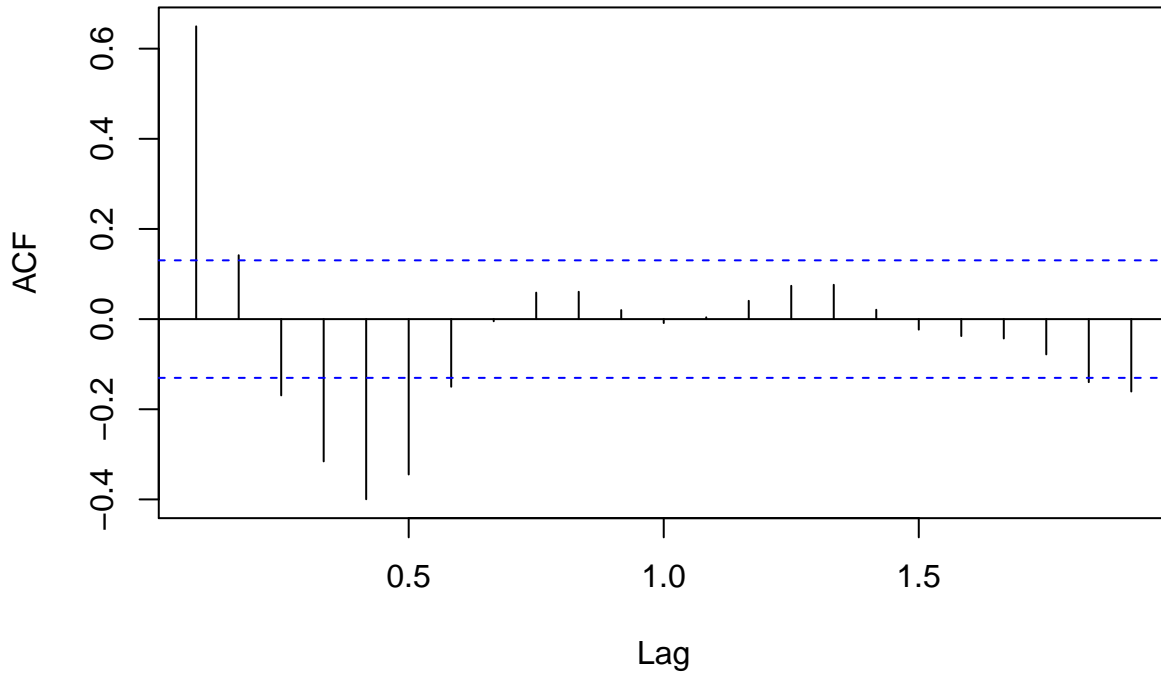
```
acf(diff(bond.sub.ts[,2]))
```

### Series diff(bond.sub.ts[, 2])



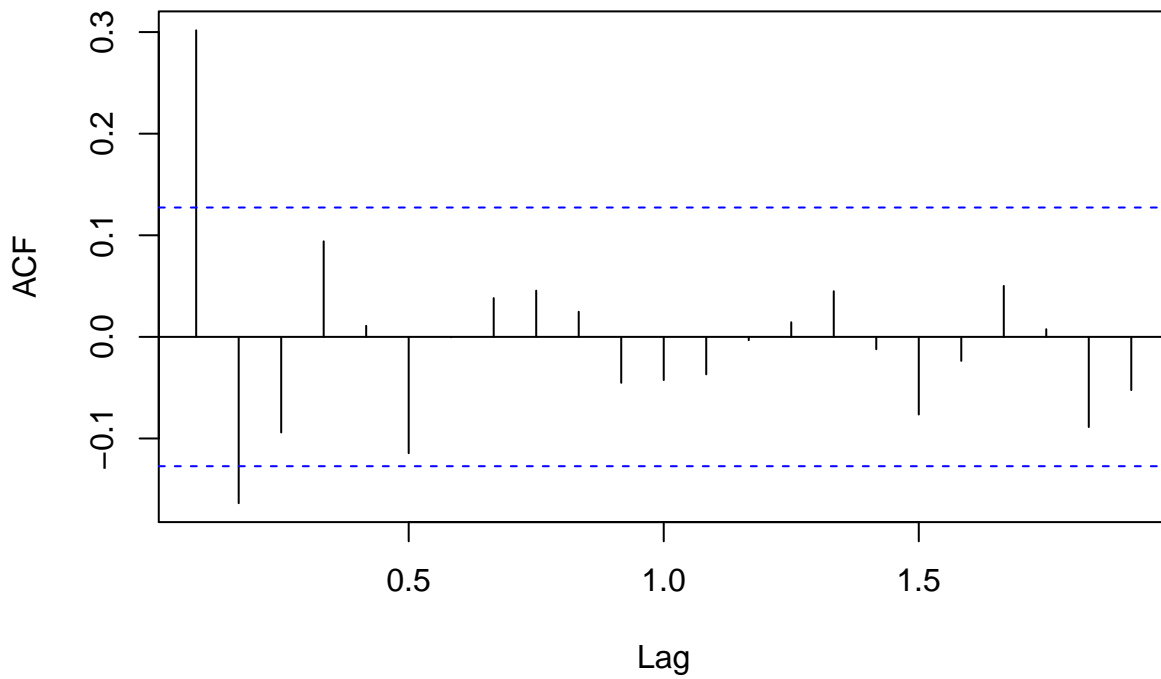
```
acf(regions[,3])
```

### Series regions[, 3]



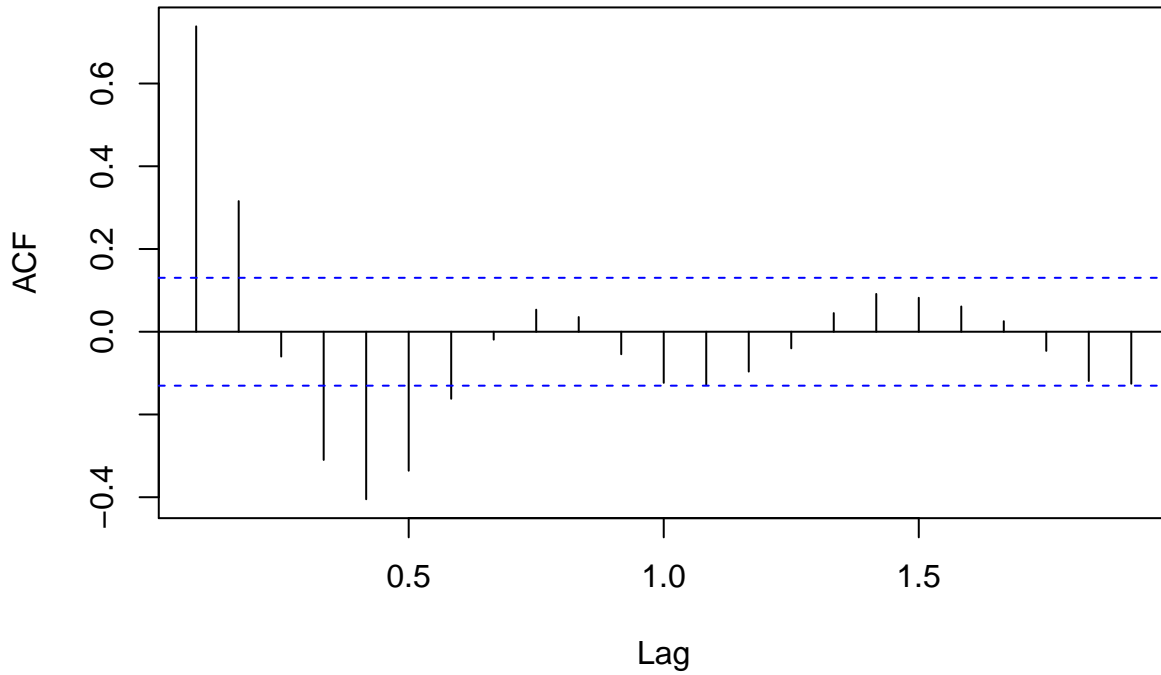
```
acf(diff(bond.sub.ts[,3]))
```

### Series diff(bond.sub.ts[, 3])



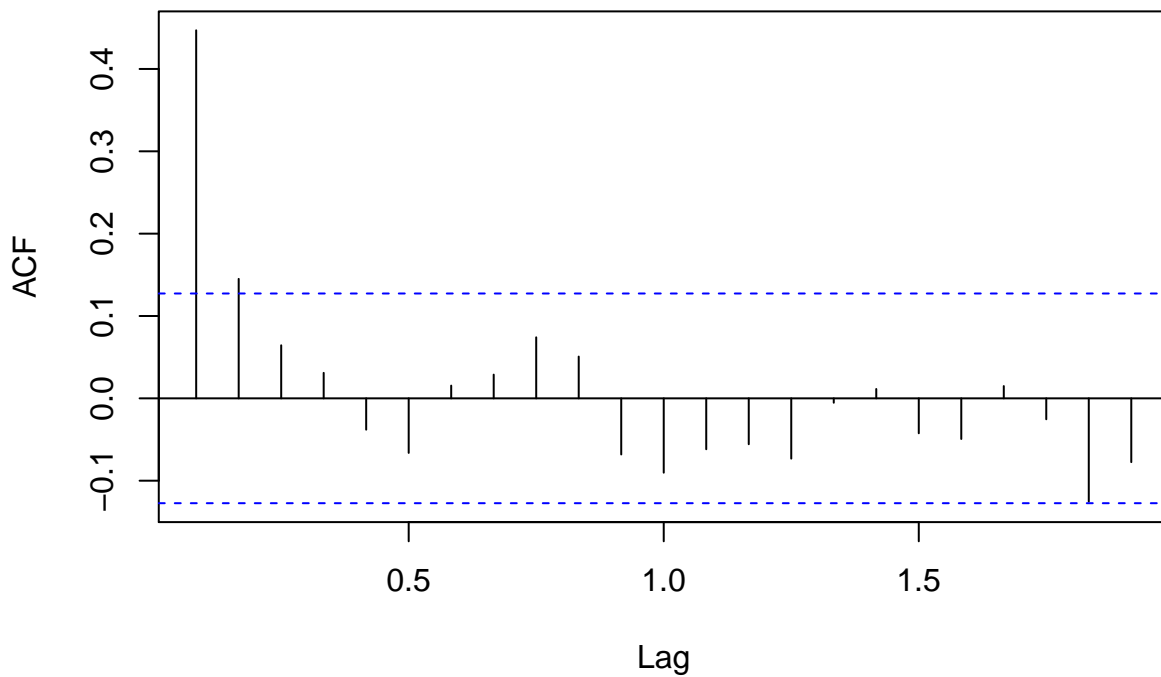
```
acf(regions[,4])
```

### Series regions[, 4]



```
acf(diff(bond.sub.ts[,4]))
```

### Series diff(bond.sub.ts[, 4])

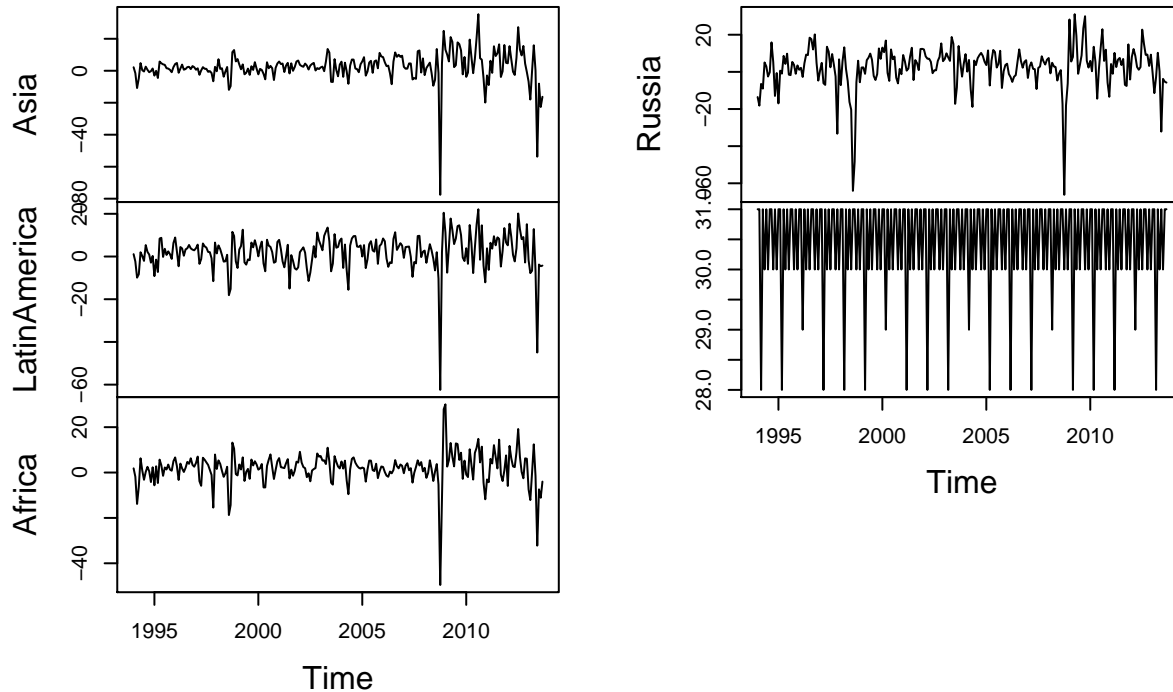


The autocorrelation plots above with differencing is now a stationary process. Although the plots below show a severe decrease in all regions around 2009 that is likely due to the global economic recession that occurred around this time. There is also a second anomaly in the Russian Federation around 1998. This is likely due

to the 1998 Russian financial crisis when the Central Bank devalued the ruble and defaulted on its debt.

```
plot(diff(bond.sub.ts))
```

### diff(bond.sub.ts)



An Augmented Dickey-Fuller Test below was also conducted which showed the differencing has made all four time series stationary with p-values of 0.01.

```
library(tseries)
```

```
## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo
```

```
adf.test(diff(bond.sub.ts[, "Asia"]))
```

```
## Warning in adf.test(diff(bond.sub.ts[, "Asia"])): p-value smaller than printed
## p-value
```

```
##
## Augmented Dickey-Fuller Test
##
## data: diff(bond.sub.ts[, "Asia"])
## Dickey-Fuller = -4.7172, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary
```

```
adf.test(diff(bond.sub.ts[, "LatinAmerica"]))
```

```
## Warning in adf.test(diff(bond.sub.ts[, "LatinAmerica"])): p-value smaller than
## printed p-value
```

```
##
## Augmented Dickey-Fuller Test
##
```

```

## data: diff(bond.sub.ts[, "LatinAmerica"])
## Dickey-Fuller = -4.808, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary
adf.test(diff(bond.sub.ts[, "Africa"]))

## Warning in adf.test(diff(bond.sub.ts[, "Africa"])): p-value smaller than printed
## p-value

##
## Augmented Dickey-Fuller Test
##
## data: diff(bond.sub.ts[, "Africa"])
## Dickey-Fuller = -5.1238, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary
adf.test(diff(bond.sub.ts[, "Russia"]))

## Warning in adf.test(diff(bond.sub.ts[, "Russia"])): p-value smaller than printed
## p-value

##
## Augmented Dickey-Fuller Test
##
## data: diff(bond.sub.ts[, "Russia"])
## Dickey-Fuller = -5.076, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary

```

3. Conduct the appropriate analyses to answer the following research questions. Each question should be answered with a brief narrative that stands on its own (i.e., it contains any key statistics, results, or graphics needed to support the narrative):

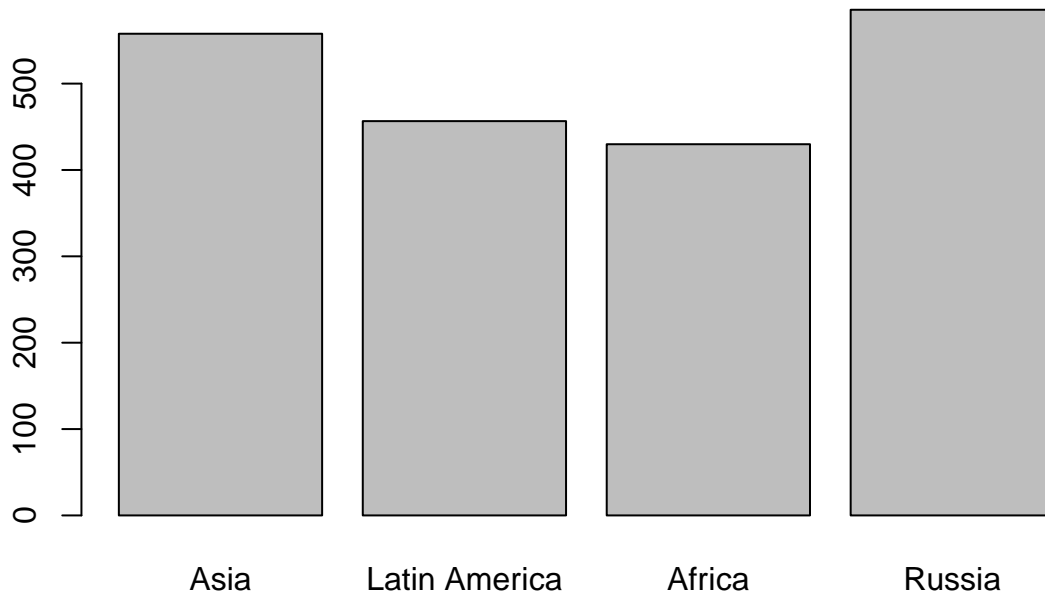
- a. Which of the four regions had exhibited the most growth by September 2013?

The Russian Federation exhibited the most growth of the four regions as shown in the barplot below. The Russian Federation grew from 100 in December 1993 to 685.5 in September 2013.

```

G1 <- (bond.sub$Asia[238])-(bond.sub$Asia[1])
G2 <- (bond.sub$LatinAmerica[238])-(bond.sub$LatinAmerica[1])
G3 <- (bond.sub$Africa[238])-(bond.sub$Africa[1])
G4 <- (bond.sub$Russia[238])-(bond.sub$Russia[1])
barplot(c(G1,G2,G3,G4),names.arg = c("Asia", "Latin America", "Africa", "Russia"))

```



```
(bond.sub$Russia[238])-(bond.sub$Russia[1])
```

```
## [1] 585.4956
```

b. Which of the four regions was least strongly affected by the financial downturn in 2008-2009?

Reviewing the difference plot above shows that Sub-Saharan Africa was least effected by the downturn with a value of about -50. The code below shows that the exact number for Sub-Saharan Africa is -49.6, followed by the Latin America - Caribbean region at -62.5.

```
diff <- diff(bond.sub.ts)
diff[which.min(diff),]
```

```
##      Asia LatinAmerica      Africa      Russia      <NA>
## -77.5905    -62.4601   -49.5657   -66.2121   30.0000
```

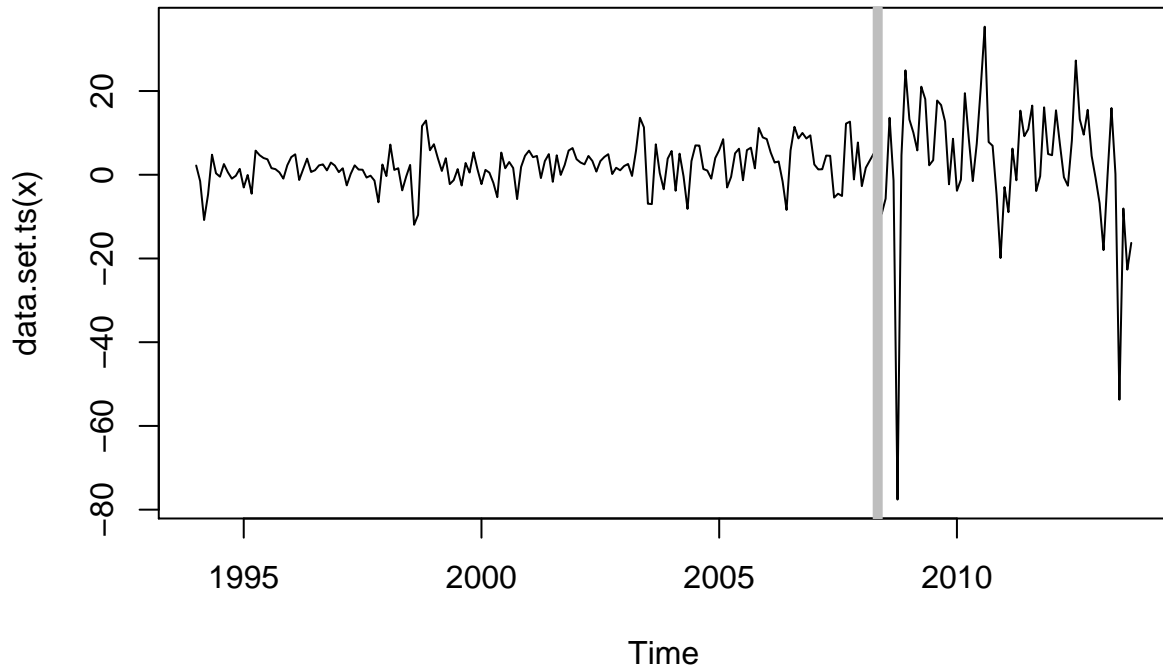
c. Which of the four regions had the greatest overall amount of volatility?

A change point analysis of variance was conducted to determine the region with the largest amount of volatility. The Russian Federation region had the greatest amount of volatility overall with a disruption in 1998 due to a financial crisis in Russia and again in 2008-2009 due to the global financial crisis. However, if you look at the overall magnitude of the crisis in 2008-2009, The Developing Asia region was at -77.6 and the Russian Federation at -66.2.

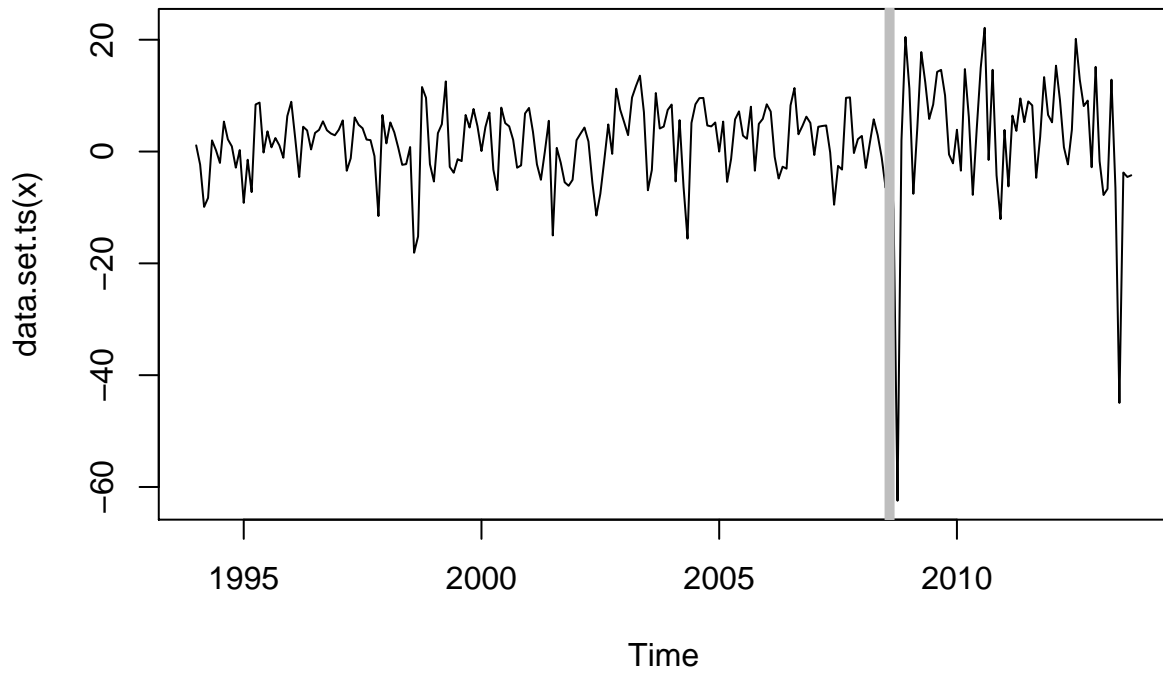
```
library(changepoint)
```

```
## Successfully loaded changepoint package version 2.2.2
## NOTE: Predefined penalty values changed in version 2.2. Previous penalty values with a postfix 1 i
P1.cp <- cpt.var(diff(bond.sub.ts["Asia"]))
P2.cp <- cpt.var(diff(bond.sub.ts["LatinAmerica"]))
P3.cp <- cpt.var(diff(bond.sub.ts["Africa"]))
P4.cp <- cpt.var(diff(bond.sub.ts["Russia"]))

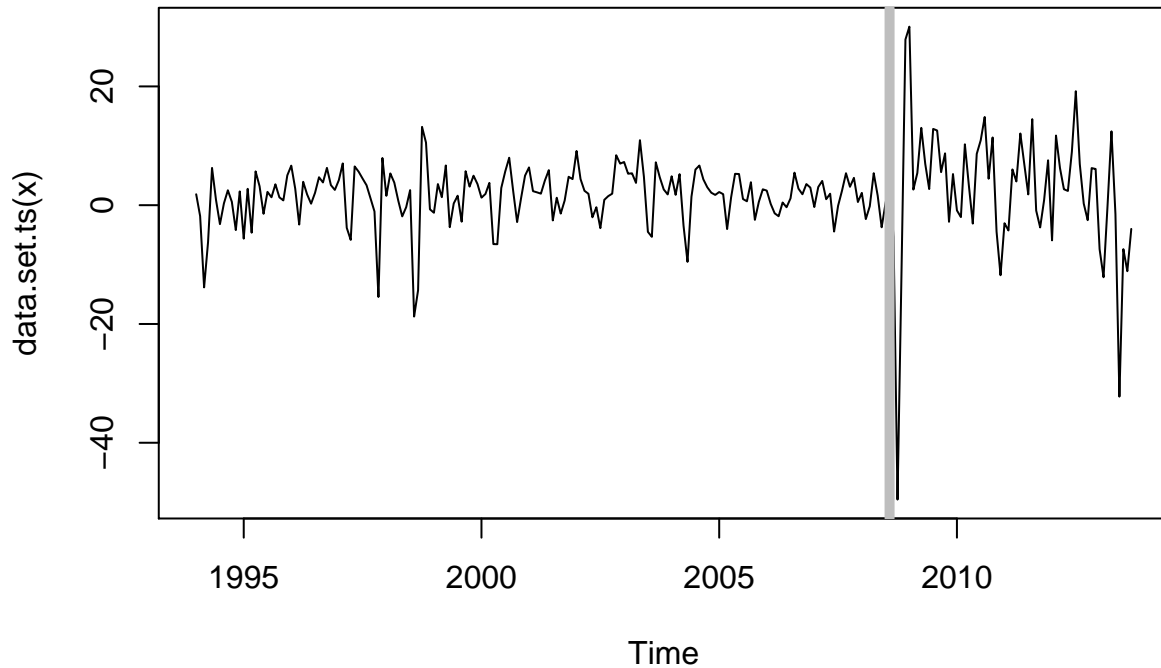
plot (P1.cp,cpt.col="grey",cpt.width=5)
```



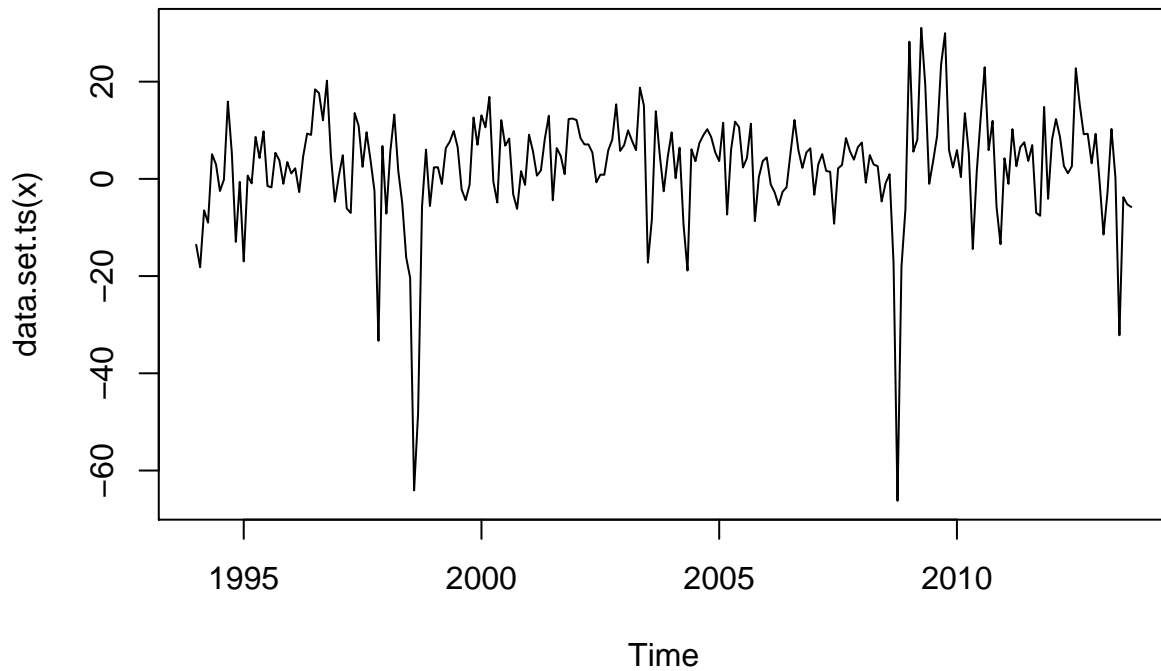
```
plot (P2.cp,cpt.col="grey",cpt.width=5)
```



```
plot (P3.cp,cpt.col="grey",cpt.width=5)
```



```
plot (P4.cp,cpt.col="grey",cpt.width=5)
```



d. For each of the four regions, document the number of change points in variance throughout the whole time period. Hint: Use method= "PELT" to detect multiple changes in variance.

Change points in variance by region: Developing Asia = 173 Latin America & Caribbean = 176,178  
Sub-Saharan Africa = 128, 176, 181 Russian Federation = 53, 57, 176, 181

```
P1.cp.pelt <- cpt.var(diff(bond.sub.ts[,"Asia"]),method="PELT")
P1.cp.pelt
```

```
## Class 'cpt' : Changepoint Object
##          ~~~ : S4 class containing 12 slots with names
```

```

##          cpttype date version data.set method test.stat pen.type pen.value minseglen cpts ncpts
##
## Created on   : Fri Apr 26 15:58:35 2019
##
## summary(.)  :
## -----
## Created Using changepoint version 2.2.2
## Changepoint type      : Change in variance
## Method of analysis    : PELT
## Test Statistic       : Normal
## Type of penalty       : MBIC with value, 16.40418
## Minimum Segment Length : 2
## Maximum no. of cpts   : Inf
## Changepoint Locations : 173
P2.cp.pelt <- cpt.var(diff(bond.sub.ts[, "LatinAmerica"]), method="PELT")
P2.cp.pelt

## Class 'cpt' : Changepoint Object
##      ~~~ : S4 class containing 12 slots with names
##          cpttype date version data.set method test.stat pen.type pen.value minseglen cpts ncpts
##
## Created on   : Fri Apr 26 15:58:35 2019
##
## summary(.)  :
## -----
## Created Using changepoint version 2.2.2
## Changepoint type      : Change in variance
## Method of analysis    : PELT
## Test Statistic       : Normal
## Type of penalty       : MBIC with value, 16.40418
## Minimum Segment Length : 2
## Maximum no. of cpts   : Inf
## Changepoint Locations : 176 178
P3.cp.pelt <- cpt.var(diff(bond.sub.ts[, "Africa"]), method="PELT")
P3.cp.pelt

## Class 'cpt' : Changepoint Object
##      ~~~ : S4 class containing 12 slots with names
##          cpttype date version data.set method test.stat pen.type pen.value minseglen cpts ncpts
##
## Created on   : Fri Apr 26 15:58:35 2019
##
## summary(.)  :
## -----
## Created Using changepoint version 2.2.2
## Changepoint type      : Change in variance
## Method of analysis    : PELT
## Test Statistic       : Normal
## Type of penalty       : MBIC with value, 16.40418
## Minimum Segment Length : 2
## Maximum no. of cpts   : Inf
## Changepoint Locations : 128 176 181

```

```
P4.cp.pelt <- cpt.var(diff(bond.sub.ts[, "Russia"]), method="PELT")
P4.cp.pelt
```

```
## Class 'cpt' : Changepoint Object
##      ~~~ : S4 class containing 12 slots with names
##          cpttype date version data.set method test.stat pen.type pen.value minseglen cpts ncpts
##
## Created on   : Fri Apr 26 15:58:35 2019
##
## summary(.)  :
## -----
## Created Using changepoint version 2.2.2
## Changepoint type      : Change in variance
## Method of analysis    : PELT
## Test Statistic       : Normal
## Type of penalty       : MBIC with value, 16.40418
## Minimum Segment Length : 2
## Maximum no. of cpts   : Inf
## Changepoint Locations : 53 57 176 178
```

```
#plot (P1.cp.pelt, cpt.col="grey", cpt.width=5)
#plot (P2.cp.pelt, cpt.col="grey", cpt.width=5)
#plot (P3.cp.pelt, cpt.col="grey", cpt.width=5)
#plot (P4.cp.pelt, cpt.col="grey", cpt.width=5)
```

e. If you were risk-averse (i.e., fearful of volatility) which regional bond market should you have invested in?

The Developing Asia (DA) and Sub-Saharan Africa (SSA) regions have the least amount of volatility when comparing the four regions. The DA and SSA regions were typically in a range of -20 to +20 when comparing the variance of the differences. If I had to pick one, DA appears to be more consistent even though there was a larger impact of the 2008-2009 crisis on DA compared to SSA.

If you were risk-tolerant (i.e., not fearful of volatility) which regional bond market should you have invested in?

The Russian Federation had the most volatility of the four regions but also produced the highest overall mean of 326.0 compared to 323.2 for Developing Asia, 290.1 for Sub-Saharan Africa and 278.4 for Latin America & Caribbean.

```
mean(bond.sub$Asia)
```

```
## [1] 323.2482
```

```
mean(bond.sub$LatinAmerica)
```

```
## [1] 278.3963
```

```
mean(bond.sub$Africa)
```

```
## [1] 290.0995
```

```
mean(bond.sub$Russia)
```

```
## [1] 325.9826
```

4. Paste in all of your R code below. Provide the code from your code window, not code mixed in with results.

```

bond <- read.csv("/Users/johnfields/Library/Mobile Documents/com_apple CloudDocs/Syracuse/IST772/Week
10/Practice Quiz/EmergingMarketsBondIndex.csv", header = TRUE, stringsAsFactors = FALSE)

bond.sub <- bond[,c("obs", "Developing.Asia", "Latin.America... Caribbean", "Sub.Saharan.Africa", "Russian.Federation")]
bond.subobs <- gsub("M", " - ", bond.subobs)

library(zoo) bond.subdate <- as.yearmon(bond.subobs, "%Y-%m") bond.subdate <- as.Date(as.yearmon(bond.subdate, "%Y-%m"))

bond.sub <- bond.sub[,-1] colnames(bond.sub) <- c("Asia", "LatinAmerica", "Africa", "Russia") bond.sub.ts
<- ts(bond.sub, start=c(1993,12), frequency=12)

plot(bond.sub.ts)

dec1 <- decompose(bond.sub.ts[, "Asia"]) dec2 <- decompose(bond.sub.ts[, "LatinAmerica"]) dec3 <- decom-
pose(bond.sub.ts[, "Africa"]) dec4 <- decompose(bond.sub.ts[, "Russia"])

plot(dec1) plot(dec2) plot(dec3) plot(dec4)

library(TSA) p1 <- periodogram(dec1seasonal) p2 <- periodogram(dec2seasonal) p3 <- periodogram(dec3seasonal) p4 <-
periodogram(dec4seasonal)

1/p1freq[which.max(p1spec)] 1/p2freq[which.max(p2spec)] 1/p3freq[which.max(p3spec)] 1/p4freq[which.max(p4spec)]

regions <- data.frame(dec1random, dec2random, dec3random, dec4random) regions <- regions[complete.cases(regions),]
regions <- ts(regions, start=c(1994,12), frequency=12) summary(regions) str(regions) plot(regions)

acf(regions[,1]) acf(diff(bond.sub.ts[,1])) acf(regions[,2]) acf(diff(bond.sub.ts[,2])) acf(regions[,3])
acf(diff(bond.sub.ts[,3])) acf(regions[,4]) acf(diff(bond.sub.ts[,4]))

plot(diff(bond.sub.ts))

library(tseries) adf.test(diff(bond.sub.ts[, "Asia"])) adf.test(diff(bond.sub.ts[, "LatinAmerica"])) adf.test(diff(bond.sub.ts[, "Africa"])
adf.test(diff(bond.sub.ts[, "Russia"]))

G1 <- (bond.subAsia[238]) - (bond.subAsia[1]) G2 <- (bond.subLatinAmerica[238]) - (bond.subLatinAmerica[1])
G3 <- (bond.subAfrica[238]) - (bond.subAfrica[1]) G4 <- (bond.subRussia[238]) - (bond.subRussia[1])
barplot(c(G1, G2, G3, G4), names.arg = c("Asia", "Latin America", "Africa", "Russia")) (bond.subRussia[238]) -
(bond.subRussia[1])

diff <- diff(bond.sub.ts) diff[which.min(diff),]

library(changepoint) P1.cp <- cpt.var(diff(bond.sub.ts[, "Asia"])) P2.cp <- cpt.var(diff(bond.sub.ts[, "LatinAmerica"]))
P3.cp <- cpt.var(diff(bond.sub.ts[, "Africa"])) P4.cp <- cpt.var(diff(bond.sub.ts[, "Russia"]))

plot (P1.cp, cpt.col="grey", cpt.width=5) plot (P2.cp, cpt.col="grey", cpt.width=5) plot (P3.cp, cpt.col="grey", cpt.width=5)
plot (P4.cp, cpt.col="grey", cpt.width=5)

P1.cp.pelt <- cpt.var(diff(bond.sub.ts[, "Asia"]), method="PELT") P1.cp.pelt P2.cp.pelt <- cpt.var(diff(bond.sub.ts[, "LatinAmer
P2.cp.pelt P3.cp.pelt <- cpt.var(diff(bond.sub.ts[, "Africa"]), method="PELT") P3.cp.pelt P4.cp.pelt <-
cpt.var(diff(bond.sub.ts[, "Russia"]), method="PELT") P4.cp.pelt

mean(bond.subAsia) mean(bond.subLatinAmerica) mean(bond.subAfrica) mean(bond.subRussia)

```