

Assigment 1

Mgmt 237E: Empirical Methods

Ian Laker, PrasanthKumar, Nitish Ramkumar

Problem 1

1

Let us generate the moment generating function for r_t

Moment generating function $Mg(s) = \mathbb{E}(exp r_t s)$

$$\begin{aligned} &= \mathbb{E}(e^{[\mu + \sigma \epsilon_t + \beta_t(\mu_j + \sigma_j \delta_t)]s}) \\ &= \mathbb{E}(e^{(\mu + \sigma \epsilon_t)s} e^{(\beta_t(\mu_j + \sigma_j \delta_t))s}) \\ &= \mathbb{E}(e^{(\mu + \sigma \epsilon_t)s}) \mathbb{E}(e^{\beta_t(\mu_j + \sigma_j \delta_t)s}) \\ &= e^{s\mu + \frac{1}{2}\sigma^2 s^2} (p \mathbb{E}(e^{(\mu_j + \sigma_j \delta_t)s}) + (1-p)e^0) \\ &= e^{s\mu + \frac{1}{2}\sigma^2 s^2} [\mathbf{p} e^{s\mu_j + \frac{1}{2}\sigma_j^2 s^2} + (\mathbf{1} - \mathbf{p})] \end{aligned}$$

Mean

Lets keep $A = s\mu + \frac{1}{2}\sigma^2 s^2 + s\mu_j + \frac{1}{2}\sigma_j^2 s^2$, $B = s\mu + \frac{1}{2}\sigma^2 s^2$,

so $Mg(s) = pe^A + (1-p)e^B$

We know Mean = 1st Moment (M_1) = $\frac{\partial Mg}{\partial s}(s=0)$

$$\frac{\partial Mg}{\partial s} = pe^A \frac{\partial A}{\partial s} + (1-p)e^B \frac{\partial B}{\partial s}$$

We can calculate $\frac{\partial A}{\partial s}(s=0) = \mu + \mu_j$, $\frac{\partial B}{\partial s}(s=0) = \mu$

$$Mean(\mu_{r_t}) = M_1 = \frac{\partial Mg}{\partial s}(s=0) = \mu + \mathbf{p}\mu_j$$

Variance

We know Variance = $M_2 - \mu_{r_t}^2$

$$M_2 = \frac{\partial^2 Mg}{\partial s^2}(s=0)$$

$$\frac{\partial^2 Mg}{\partial s^2} = pe^A \frac{\partial^2 A}{\partial s^2} + pe^A \frac{\partial^2 A}{\partial s^2} + e^B \frac{\partial^2 B}{\partial s^2} + e^B \frac{\partial^2 B}{\partial s^2} - pe^A \frac{\partial B}{\partial s} - pe^B \frac{\partial^2 B}{\partial s^2}$$

We can calculate $\frac{\partial^2 A}{\partial s^2}(s=0) = \sigma^2 + \sigma_j^2$, $\frac{\partial^2 B}{\partial s^2}(s=0) = \sigma^2$

So, $M_2 = p\mu_j^2 + 2p\mu\mu_j + p\sigma^2 + p\sigma_j^2 + \mu^2 + \sigma^2$

$$\text{Variance } (\sigma_{r_t}^2) = \sigma^2 + \mathbf{p}\sigma_j^2 + \mathbf{p}\mu_j^2 - \mathbf{p}^2\mu_j^2$$

Skewness

We know Skewness = $\frac{M_3 - 3\mu_{r_t}\sigma_{r_t}^2 - \mu_{r_t}^3}{\sigma_{r_t}^{\frac{3}{2}}}$

$$M_3 = \frac{\partial^3 Mg}{\partial s^3}$$

$$\frac{\partial^3 Mg}{\partial s^3} = pe^A \frac{\partial^3 A}{\partial s^3} + 3pe^A \frac{\partial A}{\partial s} \frac{\partial^2 A}{\partial s^2} + pe^A \frac{\partial^3 A}{\partial s^3} + e^B \frac{\partial^3 B}{\partial s^3} + 3e^B \frac{\partial B}{\partial s} \frac{\partial^2 B}{\partial s^2} + e^B \frac{\partial^3 B}{\partial s^3} - pe^B \left(\frac{\partial B}{\partial s}\right)^3 - 3pe^B \frac{\partial B}{\partial s} \frac{\partial^2 B}{\partial s^2} - pe^B \frac{\partial^3 B}{\partial s^3}$$

We can calculate $\frac{\partial^3 A}{\partial s^3}(s=0) = 0$, $\frac{\partial^3 B}{\partial s^3}(s=0) = 0$

$$M_3 = p(\mu + \mu_j)^3 + 3p(\mu + \mu_j)(\sigma^2 + \sigma_j^2) + (1-p)(\mu^3 + 3\mu\sigma^2)$$

$$\text{So Skewness} = \frac{p\mu_j^3 + 3p\mu_j\sigma_j^2 - 3p^2\mu_j\sigma_j^2 - 3p^2\mu_j^3 + 2p^3\mu_j^3}{(\sigma^2 + p\sigma_j^2 + p\mu_j^2 - p^2\mu_j^2)^{\frac{3}{2}}}$$

$$= \frac{\mu_j p(\mu_j^2(2p^2 - 3p + 1) - 3\sigma_j^2(p - 1))}{(\sigma^2 + p\sigma_j^2 + p\mu_j^2 - p^2\mu_j^2)^{\frac{3}{2}}}$$

Kurtosis

$$\text{We know Kurtosis} = \frac{M_4 - 4\mu_{r_t} M_3 + 6\mu_{r_t}^2 M_2 - 3\mu_{r_t}^4}{\sigma_{r_t}^2}$$

$$M_4 = \frac{\partial^4 M g}{\partial s^4}$$

$$\frac{\partial^4 M g}{\partial s^4} = pe^A \frac{\partial^1 M g}{\partial s^1}^4 + 6pe^A \frac{\partial^1 M g}{\partial s^1}^2 \frac{\partial^2 M g}{\partial s^2} + 4pe^A \frac{\partial^1 M g}{\partial s^1} \frac{\partial^3 M g}{\partial s^3} + 3pe^A \frac{\partial^2 M g}{\partial s^2}^2 + pe^A \frac{\partial^4 M g}{\partial s^4}$$

$$\frac{\partial^4 A}{\partial s^4} = 0, \frac{\partial^4 B}{\partial s^4} = 0$$

$$M_4 = p(\mu + \mu_j)^4 + 6p(\mu + \mu_j)^2(\sigma^2 + \sigma_j^2) + 3p(\sigma^2 + \sigma_j^2)^2 + (1 - p)(\mu^4 + 6\mu^2\sigma^2 + 3\sigma^3)$$

$$\text{So Kurtosis} = \frac{3\sigma_j^4 p(1 - p) + \mu_j^4 p(-6p^3 + 12p^2 - 7p + 1) + \mu_j^3 \sigma_j^3 p(12p^2 - 18p_6)}{(\sigma^2 + p\sigma_j^2 + p\mu_j^2 - p^2\mu_j^2)^2}$$

2

The general stock returns are distributed with skew and thick tails. A log normal distribution doesn't cover the skew and the thick tails which are necessary to represent general stock returns.

3

Get the SP500 monthly data to use as baseline

```
# Function to get data #
getData <- function(sql, n = -1){
  #setup connection
  res <- dbSendQuery(wrds, sql)
  dbHasCompleted(res)

  #perform fetch
  returnData <- fetch(res, n)

  #clear memory
  dbClearResult(res)
  return(returnData)
}

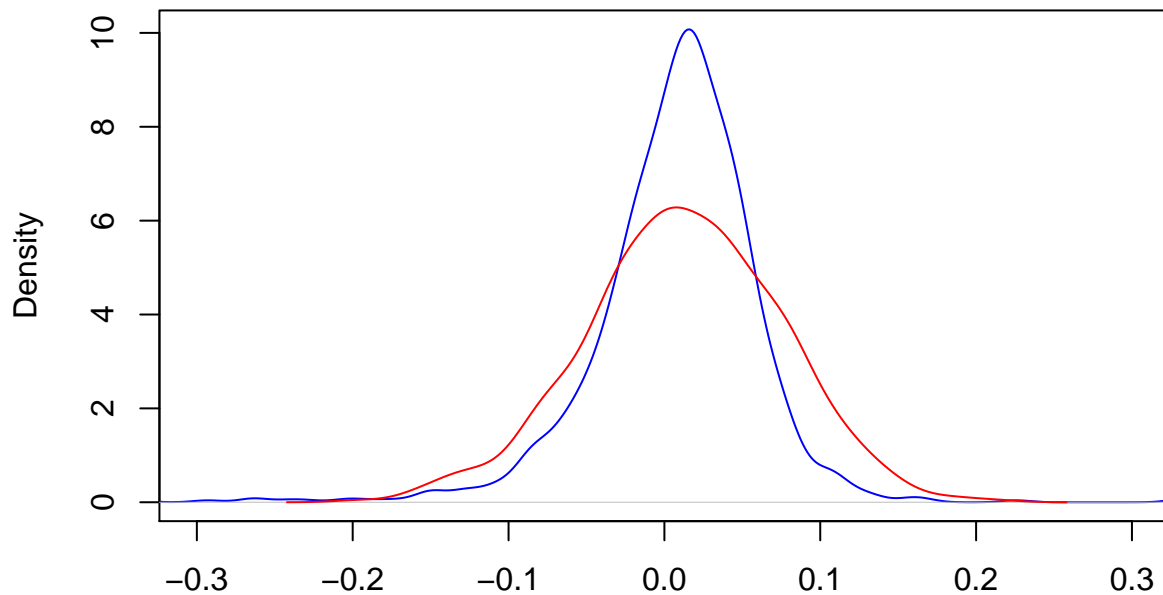
sql3 <- "SELECT * FROM CRSP.MSP500"
msp500.all <- getData(sql3)
msp500.all$caldt <- as.Date(msp500.all$caldt)
msp500.all.xts <- xts::xts(log(1+msp500.all$vwretd[-1]),order.by = msp500.all$caldt[-1])
colnames(msp500.all.xts) <- "vwretd"
```

If the returns are normally distributed, the distribution will look like this compared to the monthly SP returns.

```
plot(density(msp500.all.xts),col="blue", type="l",xlim=c(-0.3,0.3))

#only normal
lines(density(rnorm(n = 600,mean = 0.008,sd = 0.063)),col="red",type="l")
```

density.default(x = msp500.all.xts)



N = 1080 Bandwidth = 0.009205

If we take the bernoulli-normal mix, the distribution will look like this compared to the monthly SP returns.

```
#normalBernoullimix
normalBernoulliMix <- function(normalMean,normalSD,bernProb,jumpMean,jumpSD,n)
{
  SecondTerm <- jumpMean + jumpSD*rnorm(n)
  jt <- rbinom(n,1,bernProb)*(SecondTerm)
  normalMean + normalSD * rnorm(n) + jt
}
```

```
normalBernoulliDist <- normalBernoulliMix(0.012,0.05,0.15,-0.03,0.1,600)
```

```
#mean, SD, skewness, Kurtosis
mean(normalBernoulliDist)
```

```
## [1] 0.006821567
```

```
sd(normalBernoulliDist)
```

```
## [1] 0.06773343
```

```
library(moments)
```

```
## Warning: package 'moments' was built under R version 3.3.2
```

```
skewness(normalBernoulliDist)
```

```
## [1] -0.3376926
```

```
kurtosis(normalBernoulliDist)
```

```
## [1] 6.128758
```

```
#plot sp500
```

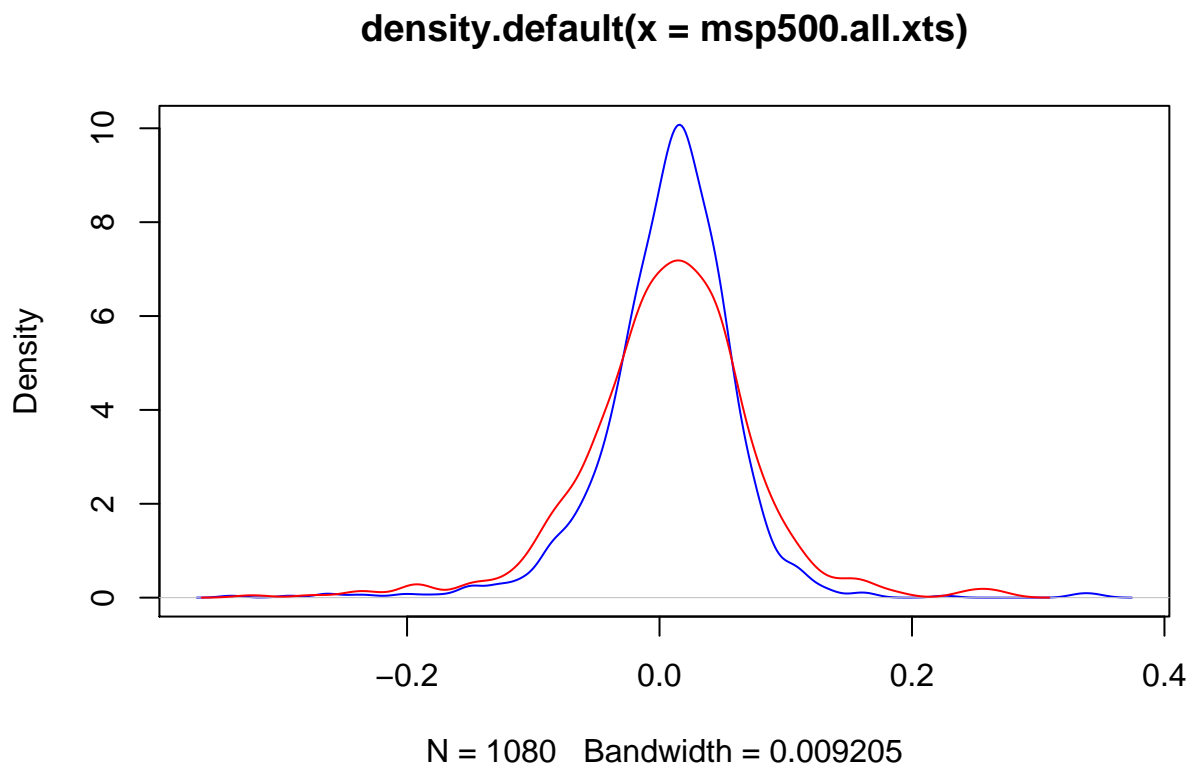
```
plot(density(msp500.all.xts),col="blue", type="l")
```

```
#density
```

```
lines(density(normalBernoulliDist),type="l",col="red", ylim=c(0,9))
```

```
#actual values
```

```
lines(normalBernoulliDist,type="l",col="blue")
```



Problem 2

Get the necessary data

```
#this.dir <- dirname(rstudioapi::getActiveDocumentContext())$path)
setwd("C:/_UCLA/237E_Empirical/Assignments/Assignment1")
library("readxl")
```

```
## Warning: package 'readxl' was built under R version 3.3.2
```

```
library("xts")
```

```
## Warning: package 'xts' was built under R version 3.3.2
```

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

```
## Warning: package 'zoo' was built under R version 3.3.2
```

```
##
```

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

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      as.Date, as.Date.numeric
```

```
dbv <- read_excel("DBV.xlsx")
gspc <- read_excel("GSPC.xlsx")
```

```
dbv$Date <- as.Date(dbv$Date)
gspc$Date <- as.Date(gspc$Date)
dbv.xts <- xts(dbv[, -1], order.by = dbv$Date)
gspc.xts <- xts(gspc[, -1], order.by = gspc$Date)
```

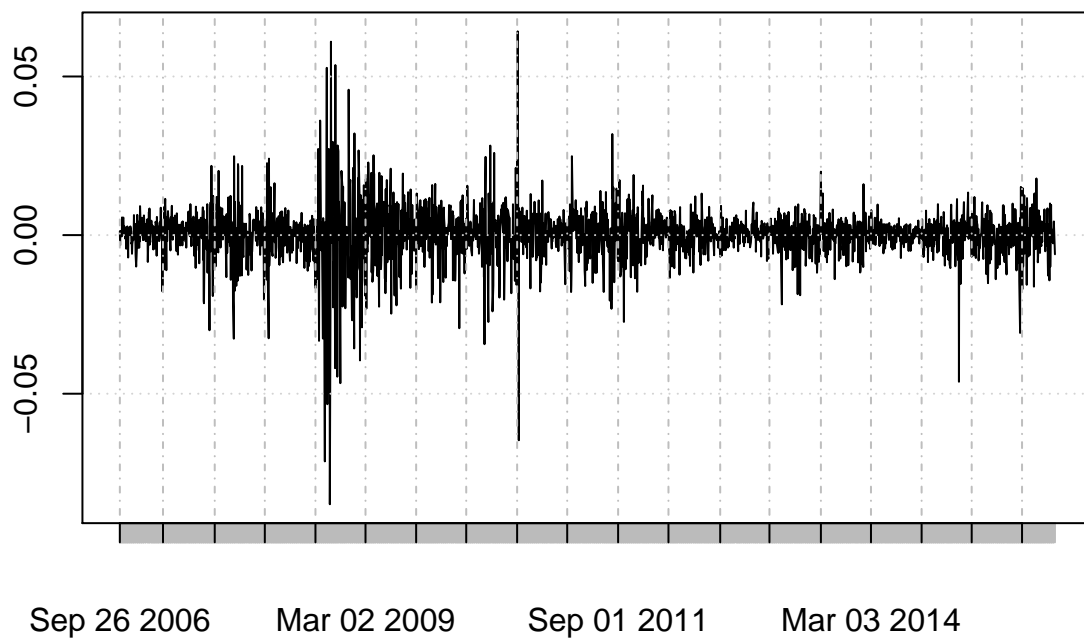
Calculate the log returns

```
dbv.logreturns <- log(dbv.xts$'Adj Close'[-1,]/lag(dbv.xts$'Adj Close')[-1,])
gspc.logreturns <- log(gspc.xts$'Adj Close'[-1,]/lag(gspc.xts$'Adj Close')[-1,])
```

1

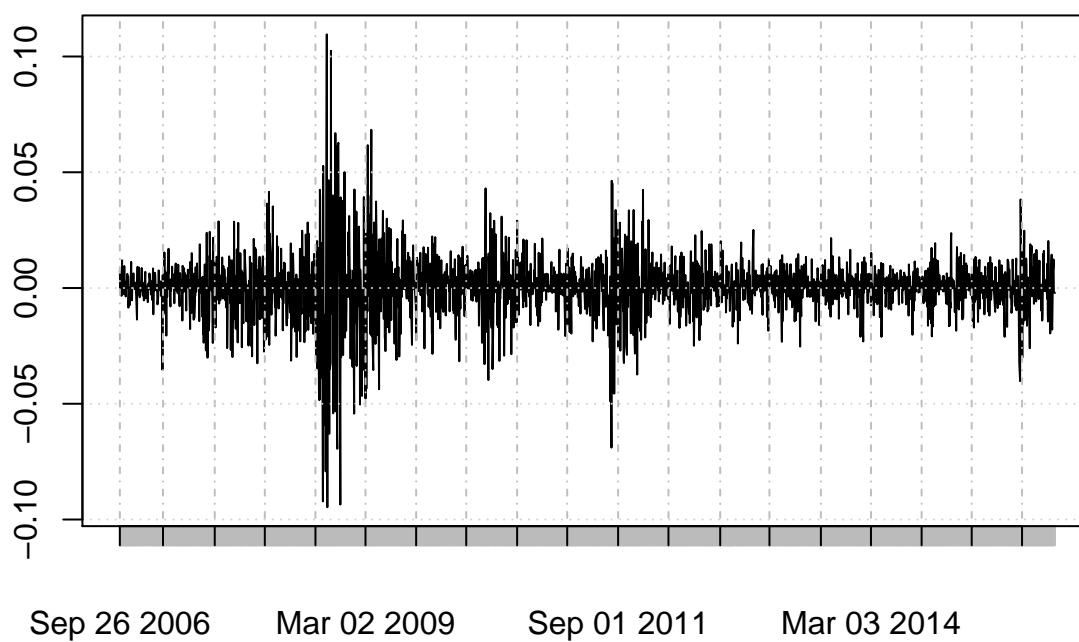
```
#1
plot(dbv.logreturns)
```

dbv.logreturns



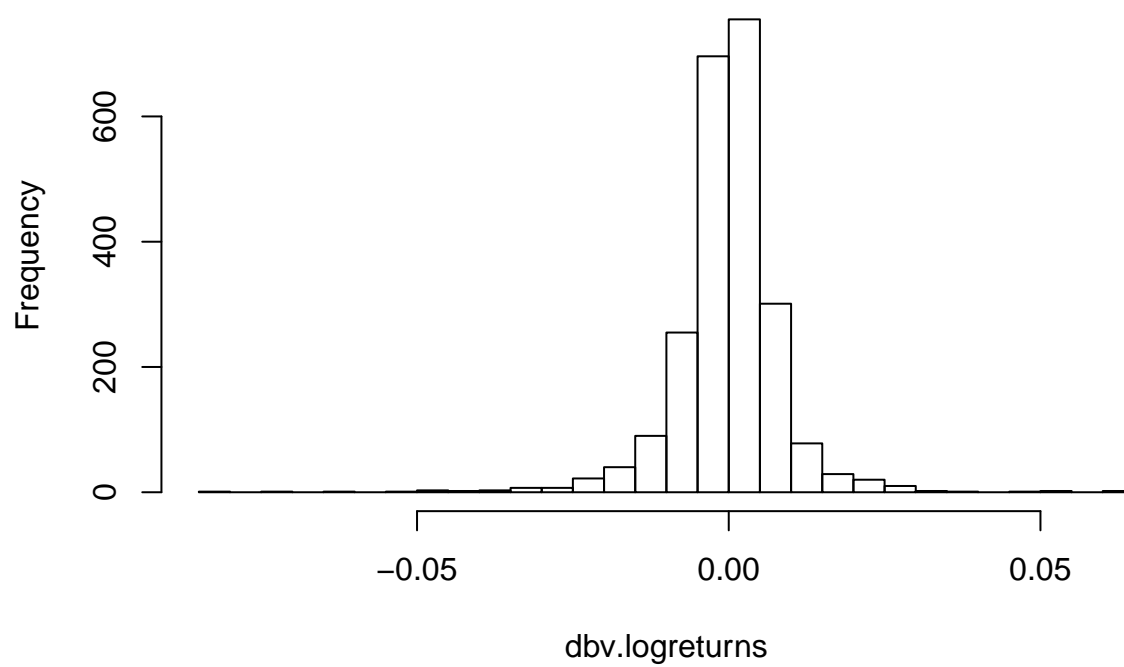
```
plot(gspc.logreturns)
```

gspc.logreturns



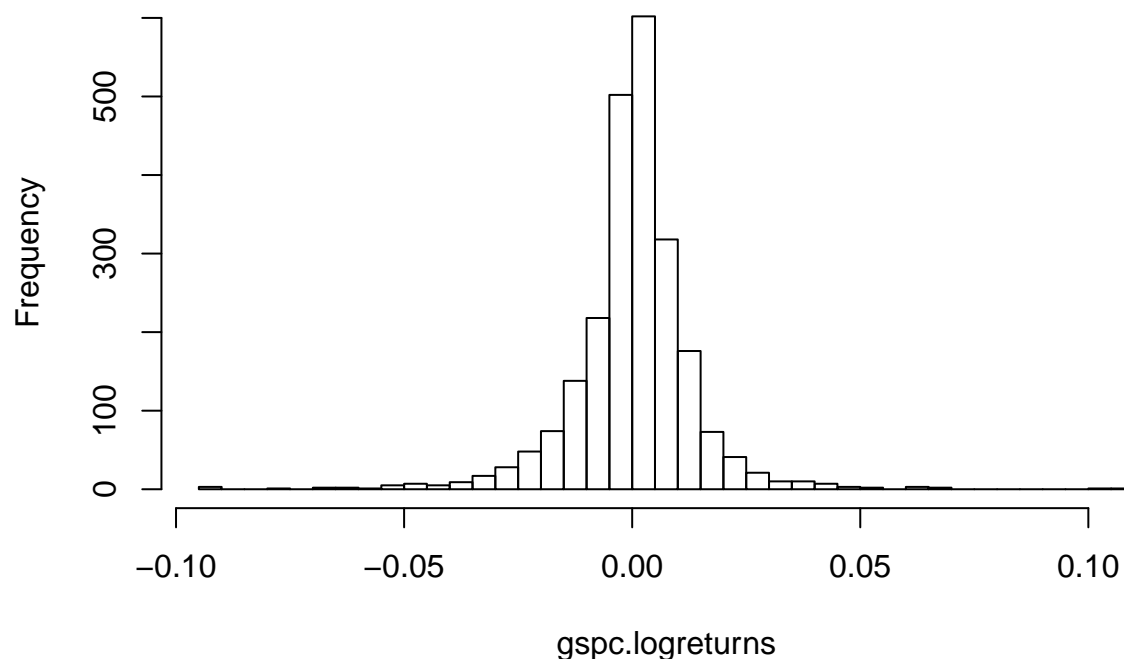
```
hist(dbv.logreturns,breaks = 50)
```

Histogram of dbv.logreturns



```
hist(gspc.logreturns, breaks = 50)
```


Histogram of gspc.logreturns



2

a

```
skewNullCheck <- function(returns,alpha=.05){
  criticalt <- qt(1-(alpha/2),df = length(returns))
  skewcap <- skewness(returns)
  skewt <- skewcap/(sqrt(6/length(returns)))
  returnVal <- c(skewcap-3,skewt,abs(skewt) > criticalt) #TRUE, so reject normal distribution, no skewness
  names(returnVal) <- c("Sample Skewness","Skewness t","Reject Null?")
  returnVal
}
```

```
skewNullCheck(dbv.logreturns)
```

```
## Sample Skewness      Skewness t      Reject Null?
##          -3.847038      -16.691872          1.000000
```

```
skewNullCheck(gspc.logreturns)
```

```
## Sample Skewness      Skewness t      Reject Null?
##          -3.324043      -6.385641          1.000000
```

```
#b
kurtosisNullCheck <- function(returns,alpha=.05){
  criticalt <- qt(1-(alpha/2),df = length(returns))
  kurtosiscap <- kurtosis(returns)
  kurtosist <- (kurtosiscap-3)/(sqrt(24/length(returns)))
  returnVal <- c(kurtosiscap-3,kurtosist,abs(kurtosist) > criticalt) #TRUE, so reject normal distribution
  names(returnVal) <- c("Sample Kurtosis","Kurtosis t","Reject Null?")
  returnVal
}

kurtosisNullCheck(dbv.logreturns)
```

```
## Sample Kurtosis      Kurtosis t      Reject Null?
##          13.51674          133.18159          1.00000
```

```
kurtosisNullCheck(gspc.logreturns)
```

```
## Sample Kurtosis      Kurtosis t      Reject Null?
##          9.797934          96.539900          1.000000
```

```
#c
jbTest <- function(returns,alpha=.05){
  criticalchi <- qchisq(1-alpha,df = 2)
  skewcap <- skewness(returns)
  kurtosiscap <- kurtosis(returns)
  jbt <- skewcap^2/(6/length(returns)) + (kurtosiscap-3)^2/(24/length(returns))
  returnVal <- c(jbt,abs(jbt) > criticalchi)
  names(returnVal) <- c("JBt","Reject Null?")
  returnVal
}

jbTest(dbv.logreturns)
```

```
##          JBt Reject Null?
##      18015.95          1.00
```

```
jbTest(gspc.logreturns)
```

```
##          JBt Reject Null?
##      9360.729          1.000
```

3

```
sqlDaily <- "SELECT caldt, vwret FROM CRSPQ.DSP500 WHERE year(caldt) >= 1973 AND year(caldt) < 2015"
dsp500 <- getData(sqlDaily)

skewKurtMat <- matrix(c(skewNullCheck(dbv.logreturns)[1],skewNullCheck(gspc.logreturns)[1],kurtosisNullCheck(dbv.logreturns)[1],kurtosisNullCheck(gspc.logreturns)[1]),
  colnames(skewKurtMat) <- c("Skewness","Kurtosis")
  row.names(skewKurtMat) <- c("DBV","GSPC")
  skewKurtMat
```

```
##      Skewness  Kurtosis
## DBV   -3.847038 13.516736
## GSPC  -3.324043  9.797934
```

4

The expected return to standard deviation ratio covers only the first 2 moments of the return. It doesn't show the difference in skewness and kurtosis between the two investments.

As GSPC has lower negative skewness, there is lesser chance of getting a negative tail value.

It also has lower kurtosis, which means there is lesser chance of getting an extreme value

5

a

Both assumptions valid (i.e. homoskedastic and normal)

```
lm <- lm(dbv.logreturns ~ gspc.logreturns)
reg1Summ <- summary(lm)
reg1Summ$coefficients[,2]
```

```
##      (Intercept) gspc.logreturns
##      0.0001361433      0.0101101940
```

```
vcov(lm)
```

```
##              (Intercept) gspc.logreturns
## (Intercept)  1.853500e-08 -1.923941e-08
## gspc.logreturns -1.923941e-08  1.022160e-04
```

```
library(DataAnalytics)
reg2Summ <- lmSumm(lm(dbv.logreturns ~ gspc.logreturns), HAC = T)
```

```
## Multiple Regression Analysis:
##      2 regressors(including intercept) and 2330 observations
##      with heteroskedastic|autocorrelation consistent standard errors
##      Lag truncation = 0
##
## lm(formula = dbv.logreturns ~ gspc.logreturns)
##
## Coefficients:
##              Estimate Std Error t value p value
## (Intercept)   -9.579e-05  0.000137   -0.70  0.484
## gspc.logreturns  4.309e-01  0.018280   23.57  0.000
## ---
## Standard Error of the Regression:  0.006571
## Multiple R-squared:  0.438  Adjusted R-squared:  0.438
```

```
reg2Summ$coef.table[,2]
```

```
##      (Intercept)  gspc.logreturns  
##           0.000137           0.018280
```