5261project

Jiayi Yuan

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Descriptive Statistics

```r
library(readxl)
library(moments)
library(reshape)
library(corrgram)
library(tidyr)
```

```
##
## Attaching package: 'tidyr'

## The following objects are masked from 'package:reshape':
##
##     expand, smiths
```

```r
library(tseries)
```

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

```r
library(fGarch)
```

```
## Loading required package: timeDate

##
## Attaching package: 'timeDate'

## The following objects are masked from 'package:moments':
##
##     kurtosis, skewness

## Loading required package: timeSeries

## Loading required package: fBasics
```

```r
asset <- read_xlsx("12Assetdata.xlsx", sheet = "Price")
return <- read_xlsx("12Assetdata.xlsx", sheet = "Return")
asset[,-1] <- round(asset[,-1], 4)
asset$Date <- as.Date(asset$Date)
return$Date <- as.Date(return$Date)
```

Means SDs Skewness Kurtosis Betas

```r
means <- sapply(asset[,2:14], mean)
means
```

```
##       MSFT       TSLA       AAPL       TWTR       AMZN         FB       NFLX
##  117.50850  203.20226   58.86989   34.92101 1550.22788  171.00727  264.86528
##        AAL        DAL        BAC       NVDA        WBD     S&P500
##   33.15034   42.93120   23.75602   64.03213   29.02633 2770.63828
```

```r
means_r <- sapply(return[,2:14], mean)
means_r
```

```
##        MSFT        TSLA        AAPL        TWTR        AMZN          FB
## 0.024946532 0.048015901 0.027737763 0.005061345 0.025953512 0.016357391
##        NFLX         AAL         DAL         BAC        NVDA         WBD
## 0.025691372 0.001117527 0.008395770 0.013984216 0.051459413 0.001060357
##      S&P500
## 0.010358383
```

```r
### SDs
sds <- sapply(asset[,2:14], sd)
sds
```

```
##        MSFT        TSLA        AAPL        TWTR        AMZN          FB
##   86.816870  298.244528   45.183336   14.228913 1062.254285   80.592563
##        NFLX         AAL         DAL         BAC        NVDA         WBD
##  176.639466   11.579518    8.402903    9.368711   74.026077    6.327468
##      S&P500
##  799.620131
```

```r
sds_r <- sapply(return[,2:14], sd)
sds_r
```

```
##       MSFT       TSLA       AAPL       TWTR       AMZN         FB       NFLX
## 0.05917747 0.17296293 0.07743821 0.14535005 0.08163112 0.08122604 0.11741366
##        AAL        DAL        BAC       NVDA        WBD     S&P500
## 0.11493264 0.09510284 0.08191269 0.11778168 0.11332111 0.04002103
```

```r
### Skewness
skews <- sapply(asset[,2:14], skewness)
skews
```

```
##        MSFT        TSLA        AAPL        TWTR        AMZN          FB
##  1.02751185  1.79579212  1.25136725  0.63979815  0.54077583  0.70211095
##        NFLX         AAL         DAL         BAC        NVDA         WBD
##  0.44730875 -0.35031528 -0.05642907  0.68530412  1.67311570  1.07671210
##      S&P500
##  0.95119157
```

```r
skews_r <- sapply(return[,2:14], skewness)
skews_r
```

```
##        MSFT        TSLA        AAPL        TWTR        AMZN          FB
##  0.22793365  1.27334807 -0.22966311  0.41006779  0.39545316 -0.32966287
##        NFLX         AAL         DAL         BAC        NVDA         WBD
##  0.46509511 -0.09465125 -0.18437061 -0.15661734  0.06986737  0.84068916
##      S&P500
## -0.38746520
```

```r
### Kurtosis
kurtosis <- sapply(asset[,2:14], kurtosis)
kurtosis
```

```
##          MSFT         TSLA         AAPL         TWTR         AMZN           FB
## -0.138676463  1.873876650  0.225458829 -0.004106557 -1.090615618 -0.295180805
##          NFLX          AAL          DAL          BAC         NVDA          WBD
## -1.036773152 -0.941063372 -0.647993063 -0.320107115  2.157497699  1.362829418
##        S&P500
## -0.110939419
```

```
kurtosis_r <- sapply(return[,2:14], kurtosis)
kurtosis_r
```

```
##        MSFT       TSLA       AAPL       TWTR       AMZN         FB       NFLX
##  0.6159448  2.2335358 -0.2720155  0.3760462  0.6509264  2.7725659  1.0312261
##         AAL        DAL        BAC       NVDA        WBD     S&P500
##  0.2174945  2.6293047  1.0251537  0.4181741  1.1073195  1.3428217
```

```
### Betas
betas <- list()
for (i in 2:13){
  betas[i-1] <- lm(unlist(return[,i])-return$`Treasury Bill 3 month (rf)`~
               return$`S&P500`- return$`Treasury Bill 3 month (rf)`)$coefficients[2]
}
names <- colnames(asset)[2:13]
rbind(names, unlist(betas))
```

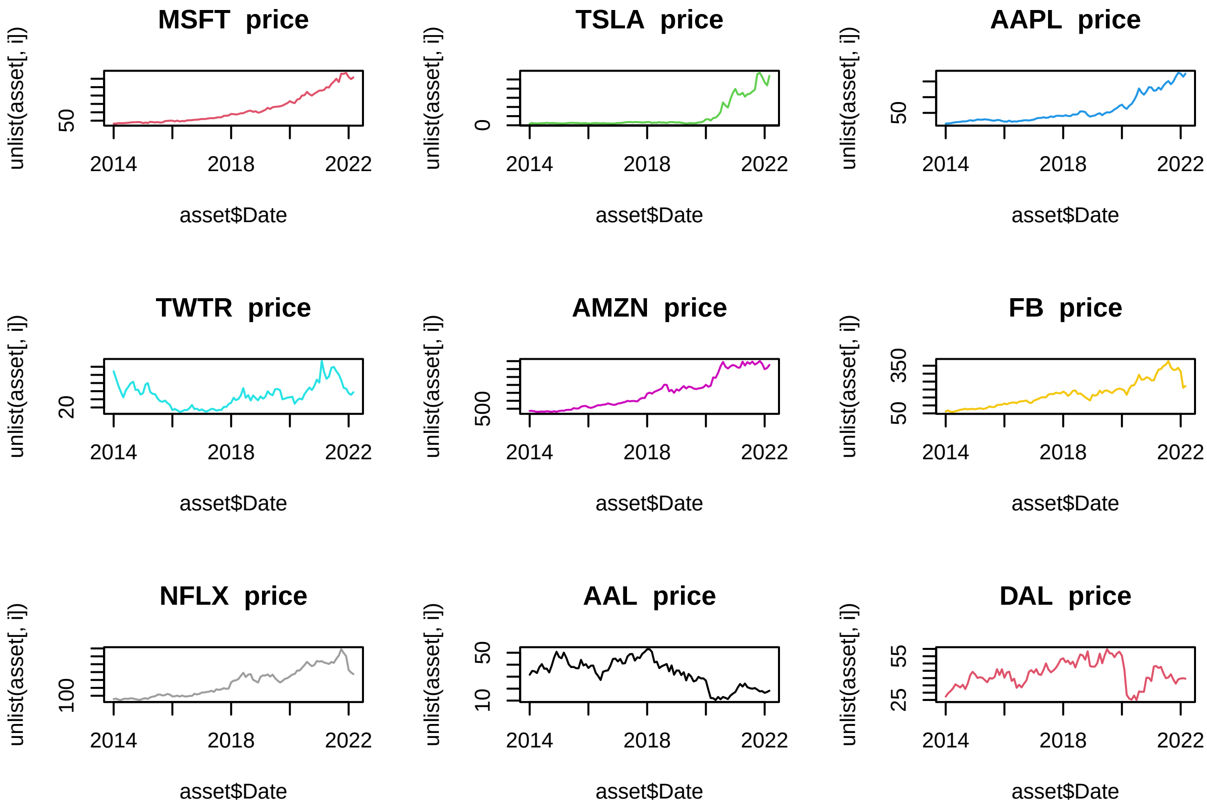
```
##       [,1]               [,2]               [,3]              [,4]
## names "MSFT"             "TSLA"             "AAPL"            "TWTR"
##       "2.62313579319408" "3.61192558378254" "2.8665143599088" "2.4884584653062"
##       [,5]               [,6]               [,7]
## names "AMZN"             "FB"               "NFLX"
##       "2.79378397789643" "2.83834274379434" "2.56064597670338"
##       [,8]               [,9]              [,10]
## names "AAL"              "DAL"             "BAC"
##       "3.17804029866847" "2.8024812841754" "3.05680636875636"
##       [,11]              [,12]
## names "NVDA"             "WBD"
##       "3.07147751026545" "2.86285142567178"
```

Plots

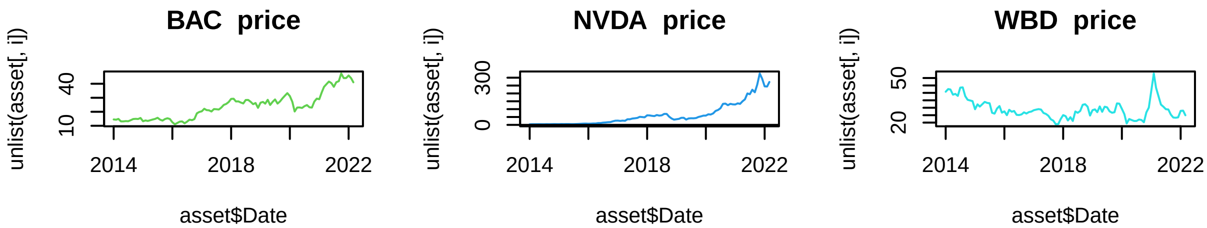
```
library(ggplot2)
### Plots
# asset_l <- asset[,1:14] %>%
#   pivot_longer(!Date,  names_to = "Asset", values_to = "Price")
# return_l <- return[,1:14] %>%
#   pivot_longer(!Date,  names_to = "Asset", values_to = "Return")
#
# ggplot(return_l, aes(x = Date, y = Return, col = Asset)) +
#   geom_line()

par(mfrow = c(3,3))
### Price
for(i in 2:13){
  plot(asset$Date, unlist(asset[,i]), type = "l", col = i,
       main = paste(colnames(asset[,i])," price"))
  abline(h=0)
```

```
}
```

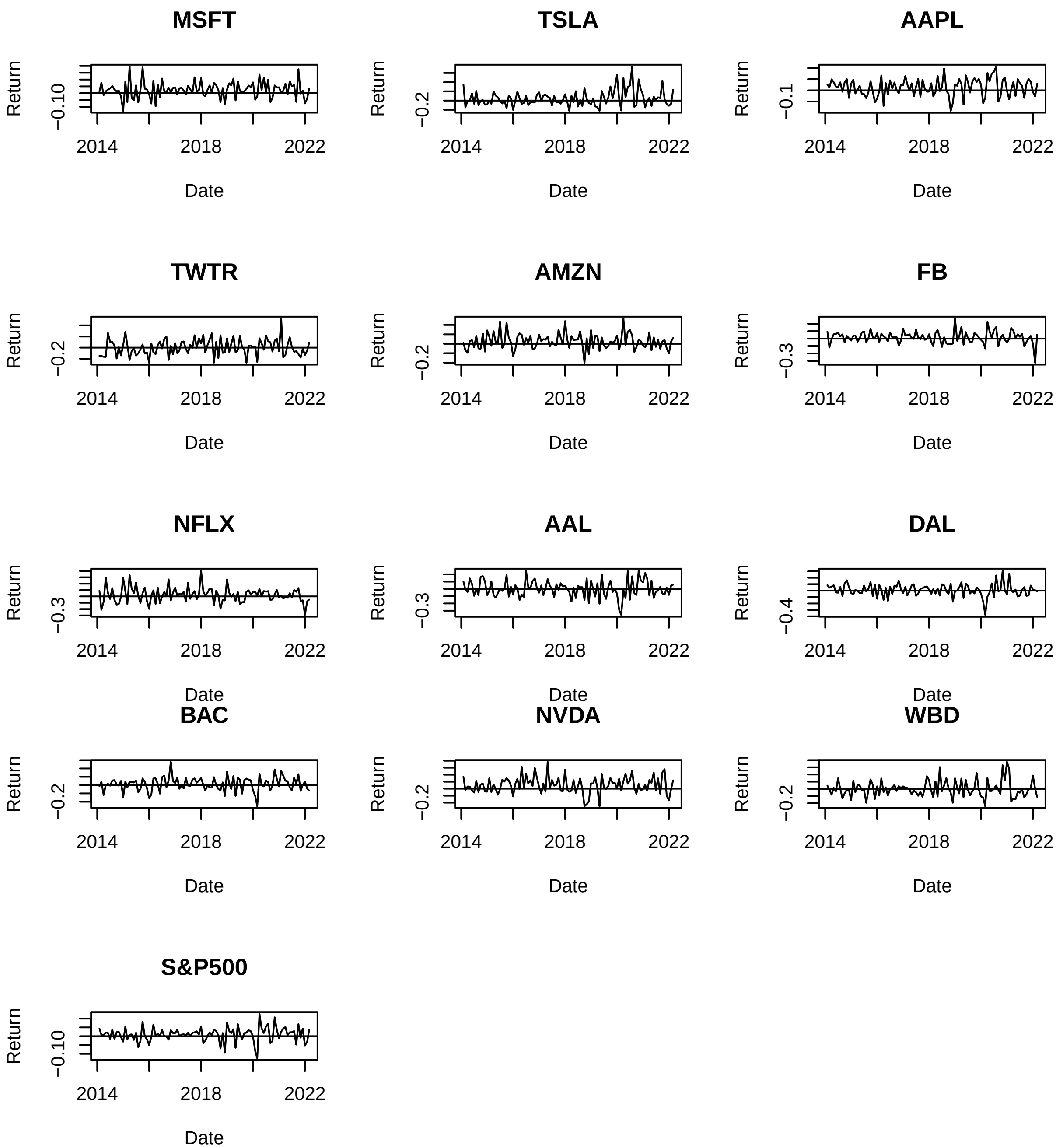



```
### Return
# for(i in 2:13){
#   plot(return$Date, unlist(return[,i]), type = "l", col = i,
#        main = paste(colnames(return[,i])," return"))
#   abline(h=0)
# }
```



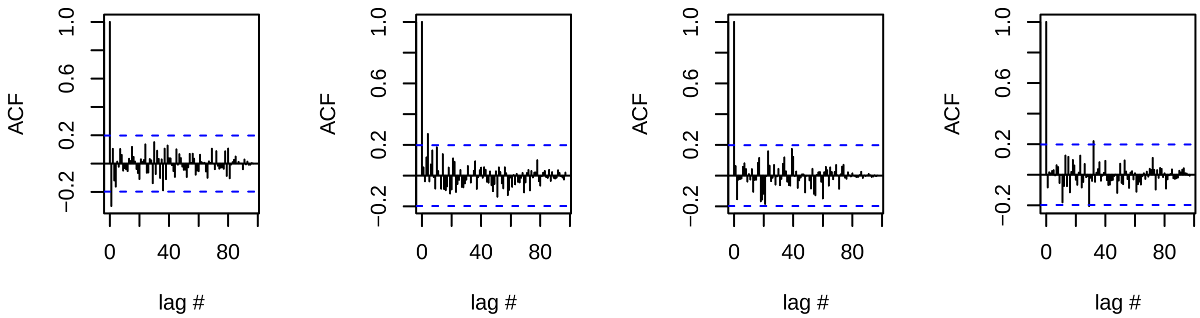
Equity curve ??

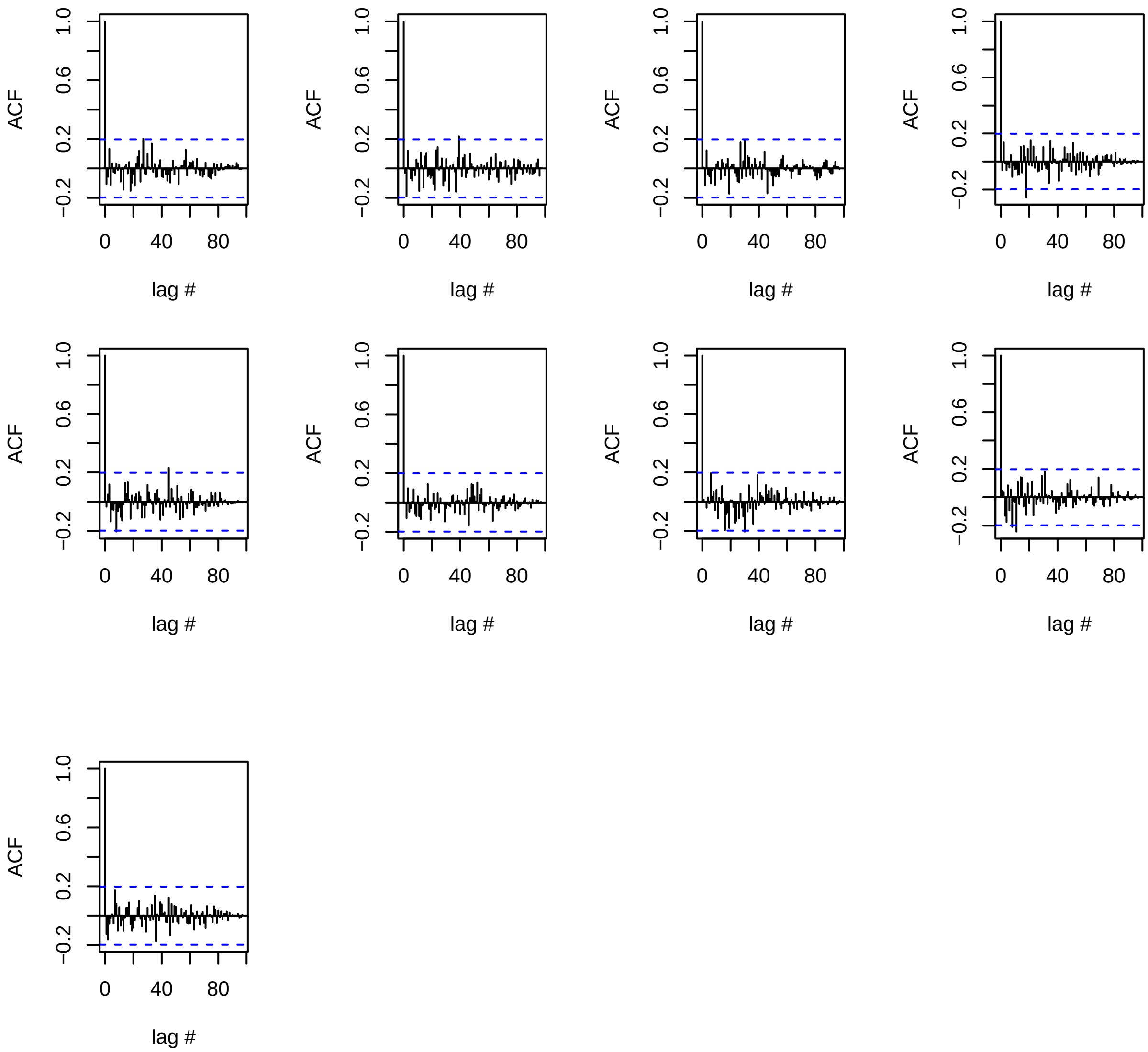
```
### Equity curve
par(mfrow = c(3,3))
for (i in 2:14) {
  plot(return$Date, unlist(return[, i]), type = "l",
       ylab = "Return", xlab = "Date", main = colnames(return[, i]))
  abline(h=0)
}
```



Stationary Test

```r
### Stationary Test
par(mfrow = c(2,4))
for(i in 2:14){
  acf(unlist(return[,i]),lag.max = length(return$MSFT),
          xlab = "lag #", ylab = 'ACF', main=' ')
}
```

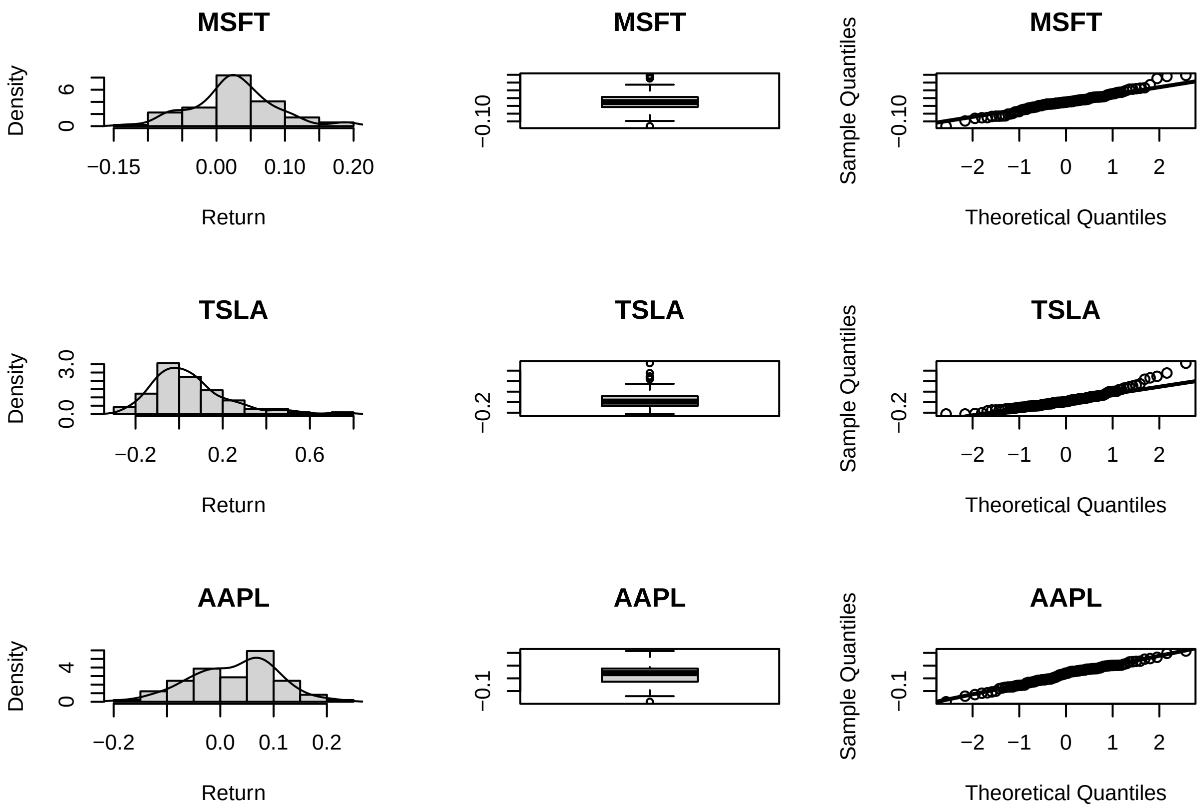


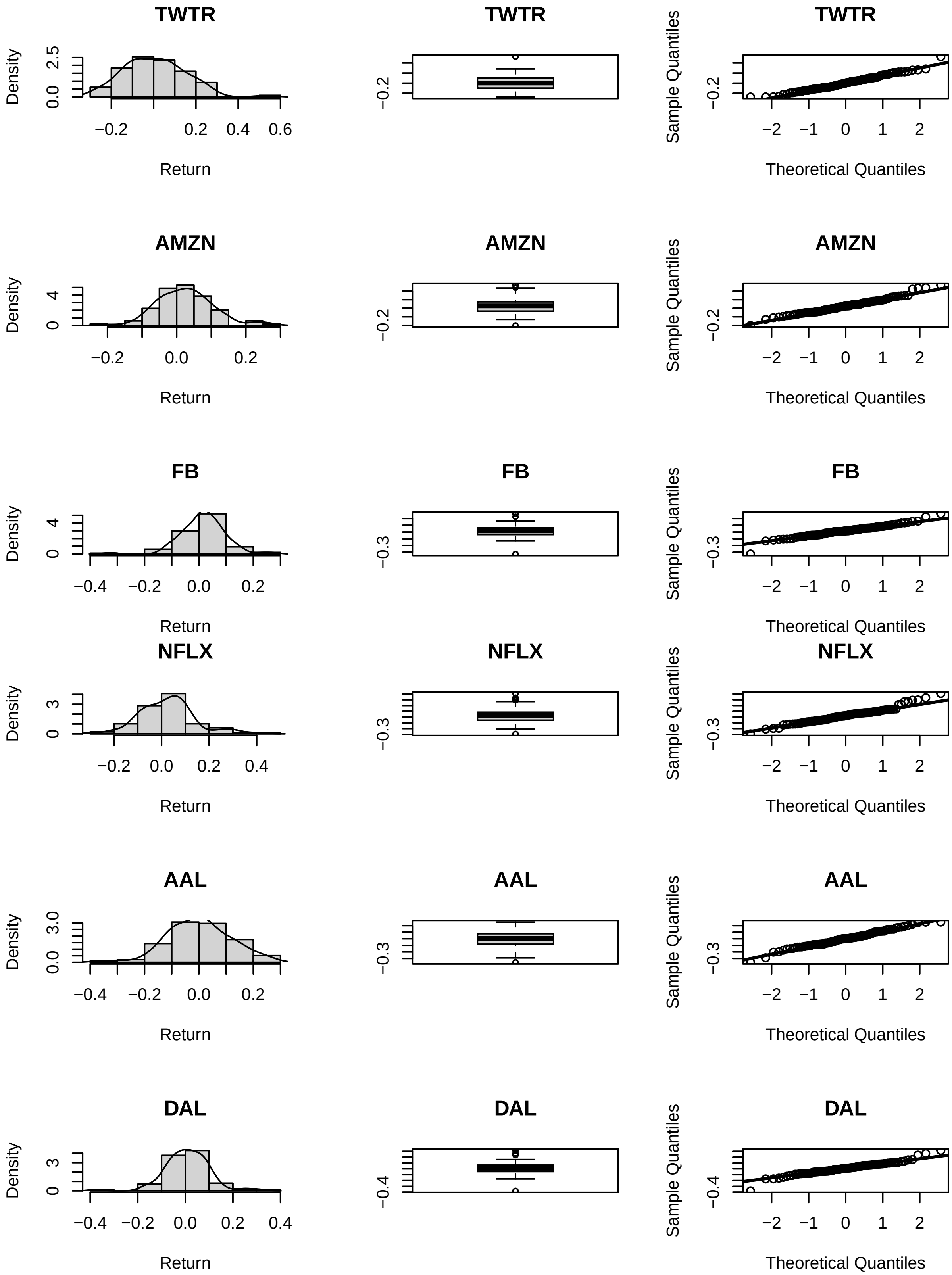


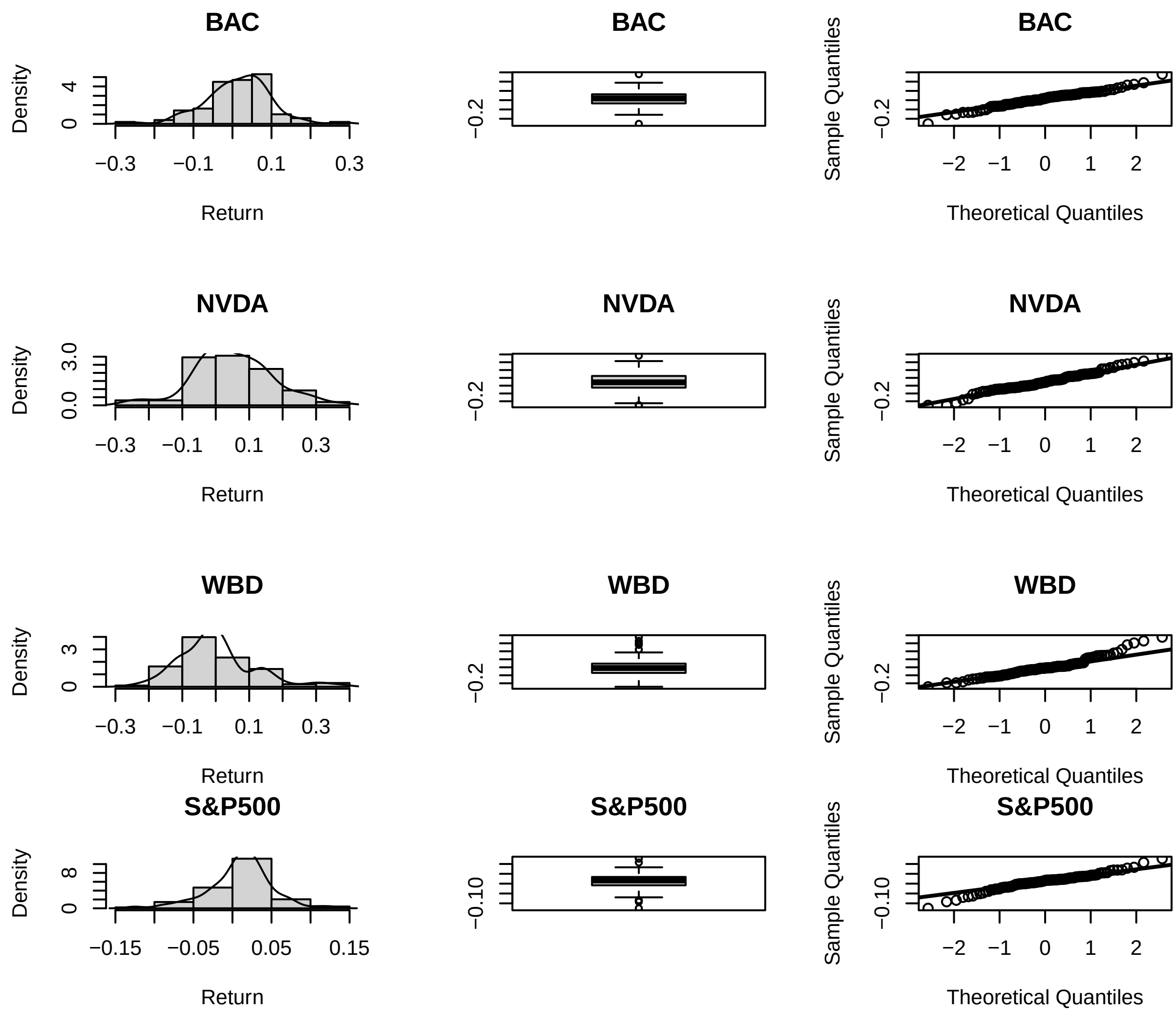
Hist, Boxplot, qqplot

```
### Hist, Boxplot, qqplot
par(mfrow = c(3,3))
```

```
for(i in 2:14){
  hist(unlist(return[,i]), freq = FALSE,
       main = colnames(return)[i], xlab = "Return")
  lines(density(unlist(return[,i])))
  boxplot(unlist(return[,i]), main = colnames(return)[i])
  qqnorm(unlist(return[,i]), pch = 1, main = colnames(return)[i])
  qqline(unlist(return[,i]), lwd = 2)
}
```




TWTR
Density
0.0 2.5
−0.2 0.2 0.4 0.6
Return
TWTR
−0.2
TWTR
Sample Quantiles
−0.2
−2 −1 0 1 2
Theoretical Quantiles
AMZN
Density
0 4
−0.2 0.0 0.2
Return
AMZN
−0.2
AMZN
Sample Quantiles
−0.2
−2 −1 0 1 2
Theoretical Quantiles
FB
Density
0 4
−0.4 −0.2 0.0 0.2
Return
FB
−0.3
FB
Sample Quantiles
−0.3
−2 −1 0 1 2
Theoretical Quantiles
NFLX
Density
0 3
−0.2 0.0 0.2 0.4
Return
NFLX
−0.3
NFLX
Sample Quantiles
−0.3
−2 −1 0 1 2
Theoretical Quantiles
AAL
Density
0.0 3.0
−0.4 −0.2 0.0 0.2
Return
AAL
−0.3
AAL
Sample Quantiles
−0.3
−2 −1 0 1 2
Theoretical Quantiles
DAL
Density
0 3
−0.4 −0.2 0.0 0.2 0.4
Return
DAL
−0.4
DAL
Sample Quantiles
−0.4
−2 −1 0 1 2
Theoretical Quantiles



Distributions

```
#### t
namesd <- data.frame(colnames(asset[1,2:13]))
tdis <- rep(NA, 12)
normal <- rep(NA, 12)
ged <- rep(NA, 12)

tdis_fun <- function(return) {
  start = c(mean(return), sd(return), 5)
  loglik_t = function(beta)
    sum(-dt((return - beta[1]) / beta[2],
            beta[3], log = TRUE) + log(beta[2]))
  fit_t = optim(
    start,
    loglik_t,
    hessian = T,
    method = "L-BFGS-B",
    lower = c(-1, 0.001, 1)
  )
```

```r
  AIC_t = 2 * fit_t$value + 2 * 3
  #return(AIC_t)
  return(fit_t$value)
}

for (i in 2:13){
  tdis[i-1] <- lapply(return[,i], tdis_fun)
}
tdis <- data.frame(unlist(tdis))

#### normal
ndis_fun <- function(return) {
  AIC_n <- 2 * snormFit(return, hessian = TRUE)$objective + 2 * 3
  AIC_n
}
for(i in 2:13){
  normal[i-1] <- lapply(return[,i], ndis_fun)
}
normal <- data.frame(unlist(normal))

#### ged
ged_fun <- function(return) {
  AIC_ged <- 2 * gedFit(return, hessian = TRUE)$objective + 2 * 3
  AIC_ged
}
for(i in 2:13){
  ged[i-1] <- lapply(return[,i], ged_fun)
}
ged <- data.frame(unlist(ged))

dis_df <- cbind(namesd,tdis,normal,ged)
dis_df
```

```
##    colnames.asset.1..2.13.. unlist.tdis. unlist.normal. unlist.ged.
## 1                      MSFT   -139.66549     -271.25573  -276.23424
## 2                      TSLA    -38.58013      -80.34437   -69.20914
## 3                      AAPL   -112.15671     -220.30961  -218.90939
## 4                      TWTR    -50.63192      -97.29781   -94.90164
## 5                      AMZN   -107.95913     -209.86197  -209.57404
## 6                        FB   -111.98310     -209.20876  -217.11195
## 7                      NFLX    -73.72148     -138.40822  -140.89449
## 8                       AAL    -73.60630     -140.92136  -141.25665
## 9                       DAL    -96.76172     -178.09420  -184.85237
## 10                      BAC   -108.18352     -207.92323  -209.41384
## 11                     NVDA    -71.69179     -136.35263  -137.27907
## 12                      WBD    -77.72453     -151.06318  -153.27377
```

Sharpe's Slope ??

```r
sharpes <- data.frame(matrix(ncol=13, nrow = 98))
colnames(sharpes) <- colnames(return[1,2:14])

for(i in 2:14){
```

```r
  sharpes[,i-1] = (unlist(return[,i])-unlist(return[,15])/100)/sds_r[i-1]
}
max(sharpes[,1])
```

```
## [1] 3.312572
```

```r
names_sh <- data.frame(colnames(return[1,2:14]))
sharpes_list <- rep(NA, 13)
for(i in 2:14){
  sharpes_list[i-1] = (mean(unlist(return[,i]))-mean(unlist(return[,15]))/100)/sd(unlist(return[,i]))
}
sharpes_list <- data.frame(sharpes_list)
shar_df <- cbind(names_sh,sharpes_list)
shar_df
```

```
##    colnames.return.1..2.14.. sharpes_list
## 1                       MSFT   0.30124000
## 2                       TSLA   0.23644366
## 3                       AAPL   0.26624907
## 4                       TWTR  -0.01416282
## 5                       AMZN   0.23071594
## 6                         FB   0.11372558
## 7                       NFLX   0.15817121
## 8                        AAL  -0.05222523
## 9                        DAL   0.01341556
## 10                       BAC   0.08380025
## 11                      NVDA   0.37645499
## 12                       WBD  -0.05347243
## 13                    S&P500   0.08091924
```

```r
(unlist(return[,2])-unlist(return[,15])/100)/sds_r[1]
```

```
##        MSFT1        MSFT2        MSFT3        MSFT4        MSFT5        MSFT6 
##  0.200994145  1.308859477 -0.248460277  0.220392725  0.429091880  0.587183109 
##        MSFT7        MSFT8        MSFT9       MSFT10       MSFT11       MSFT12 
##  0.883217621  0.450254770  0.212213132  0.305868321 -0.382054156 -2.205607530 
##       MSFT13       MSFT14       MSFT15       MSFT16       MSFT17       MSFT18 
##  1.440019484 -1.122494529  3.312571649 -0.621187831 -0.876324577  0.970551269 
##       MSFT19       MSFT20       MSFT21       MSFT22       MSFT23       MSFT24 
## -1.162828093  0.396880523  3.196881193  0.527861093  0.429125889 -0.161923703 
##       MSFT25       MSFT26       MSFT27       MSFT28       MSFT29       MSFT30 
## -1.344185710  1.526732264 -1.678506826  1.014245966 -0.514911171  1.769346746 
##       MSFT31       MSFT32       MSFT33       MSFT34       MSFT35       MSFT36 
##  0.182294745  0.097423283  0.625452980  0.020515920  0.559539976  0.596135221 
##       MSFT37       MSFT38       MSFT39       MSFT40       MSFT41       MSFT42 
## -0.263175993  0.477392061  0.532186478  0.190392706 -0.290650428  0.743922615 
##       MSFT43       MSFT44       MSFT45       MSFT46       MSFT47       MSFT48 
##  0.309733834 -0.147552421  1.789743741 -0.006646136  0.137895192  1.631959904 
##       MSFT49       MSFT50       MSFT51       MSFT52       MSFT53       MSFT54 
## -0.485495843 -0.659969503  0.119569977  0.646284823 -0.287156428  0.949372619 
##       MSFT55       MSFT56       MSFT57       MSFT58       MSFT59       MSFT60 
##  0.651916155  0.013787370 -1.497061129  0.252355094 -1.753169411  0.074605759 
##       MSFT61       MSFT62       MSFT63       MSFT64       MSFT65       MSFT66 
##  0.826188942  0.561461436  1.411250575 -1.292949319  1.105524424 -0.063239261 
##       MSFT67       MSFT68       MSFT69       MSFT70       MSFT71       MSFT72 
```

```
## -0.132275074 -0.119976797  0.249222541  0.683506920  0.505963465  1.085393870
##       MSFT73       MSFT74       MSFT75       MSFT76       MSFT77       MSFT78
## -1.072032283 -0.451968243  2.280346706  0.359399658  1.893570736  0.103123196
##       MSFT79       MSFT80       MSFT81       MSFT82       MSFT83       MSFT84
##  1.673777417 -1.119144452 -0.648465567  0.952759726  0.690351189  0.710661182
##       MSFT85       MSFT86       MSFT87       MSFT88       MSFT89       MSFT90
##  0.023393099  0.280711884  1.172618614 -0.170563880  1.472437590  0.865070645
##       MSFT91       MSFT92       MSFT93       MSFT94       MSFT95       MSFT96
##  0.997290593 -1.094168196  2.970235257 -0.061188411  0.314207018 -1.298465998
##       MSFT97       MSFT98
## -0.717445141  0.499525444
```

```
(return$MSFT-return$`Treasury Bill 3 month (rf)`/100)/sds_r[13]
```

```
##  [1]  0.297201871  1.935357301 -0.367388112  0.325885763  0.634480720
##  [6]  0.868243793  1.305977992  0.665773425  0.313790931  0.452275053
## [11] -0.564927950 -3.261342194  2.129298272 -1.659787028  4.898165036
## [16] -0.918525194 -1.295785527  1.435114708 -1.719426630  0.586851095
## [21]  4.727098262  0.780526739  0.634531008 -0.239429998 -1.987592766
## [26]  2.257516935 -2.481939810  1.499724279 -0.761378216  2.616261107
## [31]  0.269551829  0.144055849  0.924831896  0.030336058  0.827369017
## [36]  0.881480918 -0.389147642  0.705900234  0.786922511  0.281525955
## [41] -0.429772972  1.100008129  0.457990829 -0.218179767  2.646421314
## [46] -0.009827371  0.203900014  2.413112769 -0.717882967 -0.975870075
## [51]  0.176803265  0.955635096 -0.424606537  1.403798699  0.963961917
## [56]  0.020386824 -2.213643433  0.373147219 -2.592340339  0.110316503
## [61]  1.221652003  0.830210201  2.086758855 -1.911831598  1.634694024
## [66] -0.093509325 -0.195589775 -0.177404812  0.368515240  1.010673897
## [71]  0.748147608  1.604927792 -1.585170557 -0.668307068  3.371855975
## [76]  0.531429663  2.799946071  0.152484078  2.474946625 -1.654833406
## [81] -0.958859672  1.408807076  1.020794239  1.050825800  0.034590425
## [86]  0.415077251  1.733903476 -0.252205876  2.177233607  1.279144796
## [91]  1.474653058 -1.617902031  4.391966130 -0.090476815  0.464605145
## [96] -1.919988887 -1.060856965  0.738627967
```

```
sds[1]
```

```
##     MSFT
## 86.81687
```

M to Y

```
means_y <- means_r*12
means_y
```

```
##       MSFT       TSLA       AAPL       TWTR       AMZN         FB       NFLX
## 0.29935838 0.57619081 0.33285316 0.06073613 0.31144214 0.19628869 0.30829647
##        AAL        DAL        BAC       NVDA        WBD     S&P500
## 0.01341033 0.10074924 0.16781059 0.61751296 0.01272428 0.12430059
```

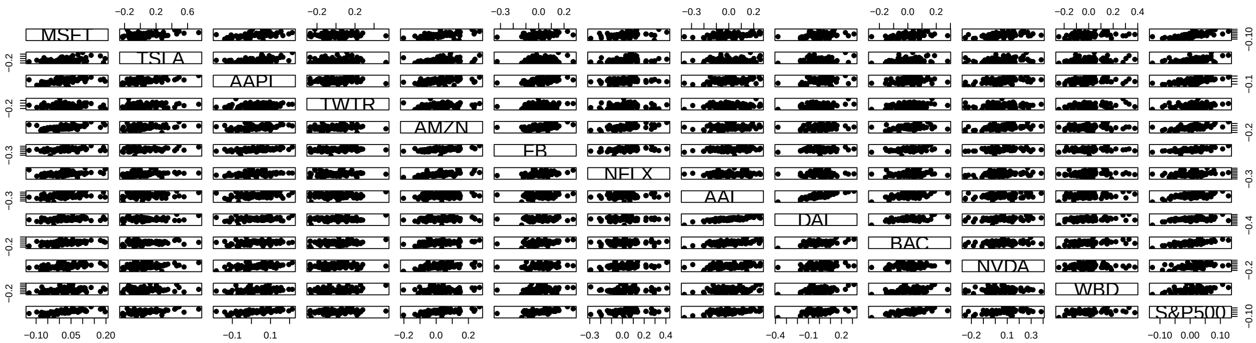
```
### SDs
sds_y <- means_r*sqrt(12)
sds_y
```

```
##        MSFT        TSLA        AAPL        TWTR        AMZN          FB
## 0.086417321 0.166331961 0.096086430 0.017533012 0.089905602 0.056663663
```

```
##        NFLX         AAL         DAL         BAC        NVDA         WBD 
## 0.088997525 0.003871229 0.029083800 0.048442744 0.178260637 0.003673184 
##      S&P500 
## 0.035882490
```

Pairewise

```r
pairs(return[,2:14],pch = 19)
```



Covariance Matrix

```r
cov_mat <- cov(return[,2:14])
cov_mat
```

```
##                MSFT        TSLA        AAPL         TWTR         AMZN
## MSFT   0.0035019726 0.003792370 0.002422600 0.0005161623 0.0026771843
## TSLA   0.0037923705 0.029916176 0.006264081 0.0035715448 0.0045237237
## AAPL   0.0024226004 0.006264081 0.005996676 0.0023691478 0.0028371440
## TWTR   0.0005161623 0.003571545 0.002369148 0.0211266367 0.0023404462
## AMZN   0.0026771843 0.004523724 0.002837144 0.0023404462 0.0066636395
## FB     0.0019051631 0.004147204 0.002966423 0.0029377213 0.0032040121
## NFLX   0.0025895014 0.005495064 0.002452145 0.0018368103 0.0055568361
## AAL    0.0020327162 0.003200935 0.002362101 0.0011806487 0.0014934263
## DAL    0.0013915040 0.002040954 0.001857155 0.0023083974 0.0007854177
## BAC    0.0021169649 0.003438923 0.001598663 0.0023991294 0.0019667441
## NVDA   0.0033625952 0.005936788 0.004657367 0.0019210966 0.0042224020
## WBD    0.0019834923 0.004282038 0.001944331 0.0049875654 0.0017281794
## S&P500 0.0015817662 0.003165494 0.001971581 0.0013660558 0.0018550904
##                  FB         NFLX         AAL          DAL         BAC
## MSFT   0.0019051631 2.589501e-03 0.002032716 1.391504e-03 0.002116965
## TSLA   0.0041472040 5.495064e-03 0.003200935 2.040954e-03 0.003438923
## AAPL   0.0029664228 2.452145e-03 0.002362101 1.857155e-03 0.001598663
## TWTR   0.0029377213 1.836810e-03 0.001180649 2.308397e-03 0.002399129
## AMZN   0.0032040121 5.556836e-03 0.001493426 7.854177e-04 0.001966744
## FB     0.0065976698 3.566622e-03 0.001852641 8.328816e-04 0.002330298
## NFLX   0.0035666217 1.378597e-02 0.001261644 9.966518e-05 0.001838108
## AAL    0.0018526414 1.261644e-03 0.013209512 8.577703e-03 0.004995109
## DAL    0.0008328816 9.966518e-05 0.008577703 9.044550e-03 0.003932212
## BAC    0.0023302976 1.838108e-03 0.004995109 3.932212e-03 0.006709689
## NVDA   0.0027697463 5.112035e-03 0.003194241 2.367829e-03 0.002712336
## WBD    0.0020686813 2.086063e-03 0.003924688 3.583663e-03 0.004257161
## S&P500 0.0019264594 1.481677e-03 0.002470547 1.869021e-03 0.002276369
##                NVDA          WBD      S&P500
```

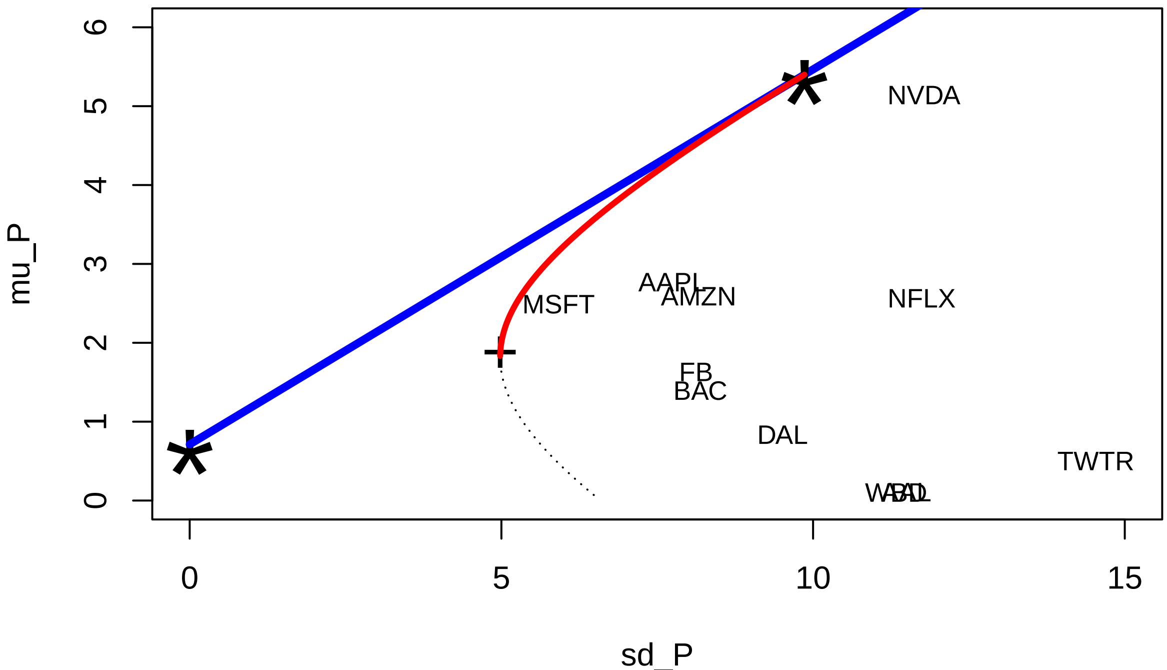
```
## MSFT   0.0033625952 0.0019834923 0.001581766
## TSLA   0.0059367881 0.0042820384 0.003165494
## AAPL   0.0046573671 0.0019443307 0.001971581
## TWTR   0.0019210966 0.0049875654 0.001366056
## AMZN   0.0042224020 0.0017281794 0.001855090
## FB     0.0027697463 0.0020686813 0.001926459
## NFLX   0.0051120350 0.0020860634 0.001481677
## AAL    0.0031942407 0.0039246877 0.002470547
## DAL    0.0023678293 0.0035836635 0.001869021
## BAC    0.0027123362 0.0042571614 0.002276369
## NVDA   0.0138725249 0.0007716842 0.002299867
## WBD    0.0007716842 0.0128416738 0.001965715
## S&P500 0.0022998673 0.0019657145 0.001601683
```

Portfolio Theory

With Short Sale

```r
library(quadprog)
R = 100*return[,2:13]
mean_p <- apply(R,2,mean)
cov_p <- cov(R)
sd_vect_p <- sqrt(diag(cov_p))
# min(mean_p)
# max(mean_p)
### With shortsale
M_p = length(mean_p)
Amat_p <- cbind(rep(1,M_p),mean_p)
mu_P = seq(0.07, 5.4, length = 300)
# Target portfolio means for the expect portfolio return
sd_P = mu_P # set up storage for std dev's of portfolio returns
weights_p = matrix(0, nrow = 300, ncol = M_p) # storage for return
for (i in 1:length(mu_P)) { # find the optimal portfolios
  bvec_p <- c(1, mu_P[i])
  result_p = solve.QP(Dmat = 2 * cov_p, dvec = rep(0, M_p), Amat = Amat_p,
                      bvec = bvec_p, meq = 2)
  sd_P[i] = sqrt(result_p$value)
  weights_p[i, ] = result_p$solution
}
plot(sd_P, mu_P, type = "l", xlim = c(0,15), ylim = c(0, 6), lty = 3)
# plot efficient frontier (and inefficient portfolios below the min var portfolio)
mufree_p = mean(return$`Treasury Bill 3 month (rf)`)# input value of risk-free interest rate
points(0, mufree_p, cex = 4, pch = "*") # show risk-free asset
sharpe_p = (mu_P - mufree_p) / sd_P # compute Sharpes ratios
ind_p = (sharpe_p == max(sharpe_p)) # Find maximum Sharpes ratio
#weights_p[ind_p,] # print the weights of the tangency portfolio
lines(c(0, 15), mufree_p + c(0, 15) * (mu_P[ind_p] - mufree_p) / sd_P[ind_p], lwd = 4,
      lty = 1, col = "blue") # show line of optimal portfolios
points(sd_P[ind_p], mu_P[ind_p], cex = 4, pch = "*") # tangency portfolio
ind2_p = (sd_P == min(sd_P)) # find the minimum variance portfolio
points(sd_P[ind2_p], mu_P[ind2_p], cex = 2, pch = "+") # min var portfolio
ind3_p = (mu_P > mu_P[ind2_p])
lines(sd_P[ind3_p], mu_P[ind3_p], type = "l", xlim = c(0, 25), ylim = c(0,30),
      lwd = 3, col = 'red') # plot the efficient frontier
```

```r
for(i in 1:12){
  text(sd_vect_p[i], mean_p[i],colnames(return[,i+1]), cex=0.8)
}
```




```r
### MVP
(mvp_meanreturn <- mu_P[ind2_p])
```

```
## [1] 1.816957
```

```r
(mvp_sd <- sd_P[ind2_p])
```

```
## [1] 4.980327
```

```r
weights_mvp <- weights_p[ind2_p,]
weights_mvp <- t(data.frame(weights_mvp))
colnames(weights_mvp) <- colnames(return[2:13])
weights_mvp
```

```
##                  MSFT        TSLA      AAPL       TWTR       AMZN        FB
## weights_mvp 0.5017466 -0.04977035 0.1347946 0.04885673 0.03852826 0.1315965
##                  NFLX         AAL       DAL        BAC        NVDA         WBD
## weights_mvp 0.0430567 -0.09160249 0.2182182 0.08071435 -0.05955131 0.003412278
```

```r
(mvp_meanreturn_ann <- mvp_meanreturn*12)
```

```
## [1] 21.80348
```

```r
(mvp_sd_ann <- mvp_sd*sqrt(12))
```

```
## [1] 17.25236
```

```r
### Efficient Portfolio Frontier
EPF_mean <- mu_P[ind3_p]
EPF_sd <- sd_P[ind3_p]

### Tangency Portfolio
```

```r
(tan_meanreturn <- mu_P[ind_p])
```

```
## [1] 5.4
```

```r
(tan_sd <- sd_P[ind_p])
```

```
## [1] 9.86121
```

```r
(tan_var <- tan_sd^2)
```

```
## [1] 97.24347
```

```r
(tan_sharpes <- (tan_meanreturn-mufree_p)/tan_sd)
```

```
## [1] 0.4753989
```

```r
### Tail dependence can be seen among the assets, therefore we can fit
### our portfolio with multivariate t-distribution.

## MVP VaR&ES
library(MASS)
alpha = 0.05
return_mvp <- rowSums(data.frame(
  weights_mvp[1] * return[, 2],
  weights_mvp[2] * return[, 3],
  weights_mvp[3] * return[, 4],
  weights_mvp[4] * return[, 5],
  weights_mvp[5] * return[, 6],
  weights_mvp[6] * return[, 7],
  weights_mvp[7] * return[, 8],
  weights_mvp[8] * return[, 9],
  weights_mvp[9] * return[, 10],
  weights_mvp[10] * return[, 11],
  weights_mvp[11] * return[, 12],
  weights_mvp[12] * return[, 13]))
fitt_mvp = fitdistr(return_mvp,"t")
param_mvp = as.numeric(fitt_mvp$estimate)
mean_mvpfit = param_mvp[1]
df_mvpfit = param_mvp[3]
sd_mvpfit = param_mvp[2] * sqrt((df_mvpfit) / (df_mvpfit - 2))
lambda_mvpfit = param_mvp[2]
qalpha_mvp = qt(alpha, df = df_mvpfit)
VaR_par_mvp = -100000 * (mean_mvpfit + lambda_mvpfit * qalpha_mvp)
es1_mvp = dt(qalpha_mvp, df = df_mvpfit) / (alpha)
es2_mvp=(df_mvpfit+qalpha_mvp^2)/(df_mvpfit-1)
es3_mvp=-mean_mvpfit+lambda_mvpfit*es1_mvp*es2_mvp
ES_par_mvp = 100000*es3_mvp
VaR_par_mvp
```

VaR&ES

```
## [1] 6285.691
```

```r
ES_par_mvp
```

```
## [1] 8957.941
```

```r
## Asset VaR
S0 = 100000
qnalpha = qnorm(0.05)

### MSFT
q_msft = as.numeric(quantile(return$MSFT, alpha))
VAR_msft = -S0 * q_msft
#VAR_msft

### TSLA
fit_tsla <- fitdistr(return$TSLA, "normal")
param_tsla = as.numeric(fit_tsla$estimate)
mean_tsla = param_tsla[1]
sd_tsla = param_tsla[2]
VAR_tsla = -S0*(mean_tsla+qnalpha*sd_tsla)
#VAR_tsla

### AAPL
fit_aapl <- fitdistr(return$AAPL, "normal")
param_aapl = as.numeric(fit_aapl$estimate)
mean_aapl = param_aapl[1]
sd_aapl = param_aapl[2]
VAR_aapl = -S0*(mean_aapl+qnalpha*sd_aapl)
#VAR_aapl

### TWTR
fit_twtr <- fitdistr(return$TWTR, "normal")
param_twtr = as.numeric(fit_twtr$estimate)
mean_twtr = param_twtr[1]
sd_twtr = param_twtr[2]
VAR_twtr = -S0*(mean_twtr+qnalpha*sd_twtr)
#VAR_twtr

### AMZN
fit_amzn <- fitdistr(return$AMZN, "normal")
param_amzn = as.numeric(fit_amzn$estimate)
mean_amzn = param_amzn[1]
sd_amzn = param_amzn[2]
VAR_amzn = -S0*(mean_amzn+qnalpha*sd_amzn)
#VAR_amzn

### FB
q_fb = as.numeric(quantile(return$FB, alpha))
VAR_fb = -S0 * q_fb
#VAR_fb

### NFLX
q_nflx = as.numeric(quantile(return$NFLX, alpha))
VAR_nflx = -S0 * q_nflx
#VAR_nflx

### AAL
q_aal = as.numeric(quantile(return$AAL, alpha))
```

```r
VAR_aal = -S0 * q_aal
#VAR_aal

### DAL
q_dal = as.numeric(quantile(return$DAL, alpha))
VAR_dal = -S0 * q_dal
#VAR_dal

### BAC
q_bac = as.numeric(quantile(return$BAC, alpha))
VAR_bac = -S0 * q_bac
#VAR_bac

### NVDA
q_nvda = as.numeric(quantile(return$NVDA, alpha))
VAR_nvda = -S0 * q_nvda
#VAR_nvda

### WBD
q_wbd = as.numeric(quantile(return$WBD, alpha))
VAR_wbd = -S0 * q_wbd
#VAR_wbd

VAR_asset <- c(VAR_msft, VAR_tsla, VAR_aapl, VAR_twtr, VAR_amzn, VAR_fb, VAR_nflx,
               VAR_aal, VAR_dal, VAR_bac, VAR_nvda, VAR_wbd)
cbind(names, VAR_asset)
```

```
##       names  VAR_asset
##  [1,] "MSFT" "6918.17869693084"
##  [2,] "TSLA" "23502.7562034031"
##  [3,] "AAPL" "9898.52221650451"
##  [4,] "TWTR" "23279.5289061133"
##  [5,] "AMZN" "10763.0915501661"
##  [6,] "FB"   "10561.0446590248"
##  [7,] "NFLX" "13072.710950181"
##  [8,] "AAL"  "15706.0583956349"
##  [9,] "DAL"  "12891.9240002285"
## [10,] "BAC"  "13041.1530377474"
## [11,] "NVDA" "11974.7969532429"
## [12,] "WBD"  "14903.9099722124"
```

```r
data(SP500, package="Ecdat")
n=2783
SPreturn = SP500$r500[(n - 999):n]
year = 1981 + (1:n) * (1991.25 - 1981) / n
year = year[(n - 999):n]
alpha = 0.05
q = as.numeric(quantile(SPreturn, alpha))
VaR_nonp = -20000 * q
IEVaR = (SPreturn < q)
sum(IEVaR)
```

```
## [1] 50
```

```r
ES_nonp = -20000 * sum(SPreturn * IEVaR) / sum(IEVaR)
options(digits = 5)
VaR_nonp
```

```
## [1] 337.55
```

```r
ES_nonp
```

```
## [1] 619.3
```

```r
names_sh <- data.frame(colnames(return[1,2:14]))
sharpes_list <- rep(NA, 13)
for(i in 2:14){
  sharpes_list[i-1] = (mean(unlist(return[,i]))-mean(unlist(return[,15]))/100)/sd(unlist(return[,i]))
}
sharpes_list <- data.frame(sharpes_list)
shar_df <- cbind(names_sh,sharpes_list)
shar_df
```

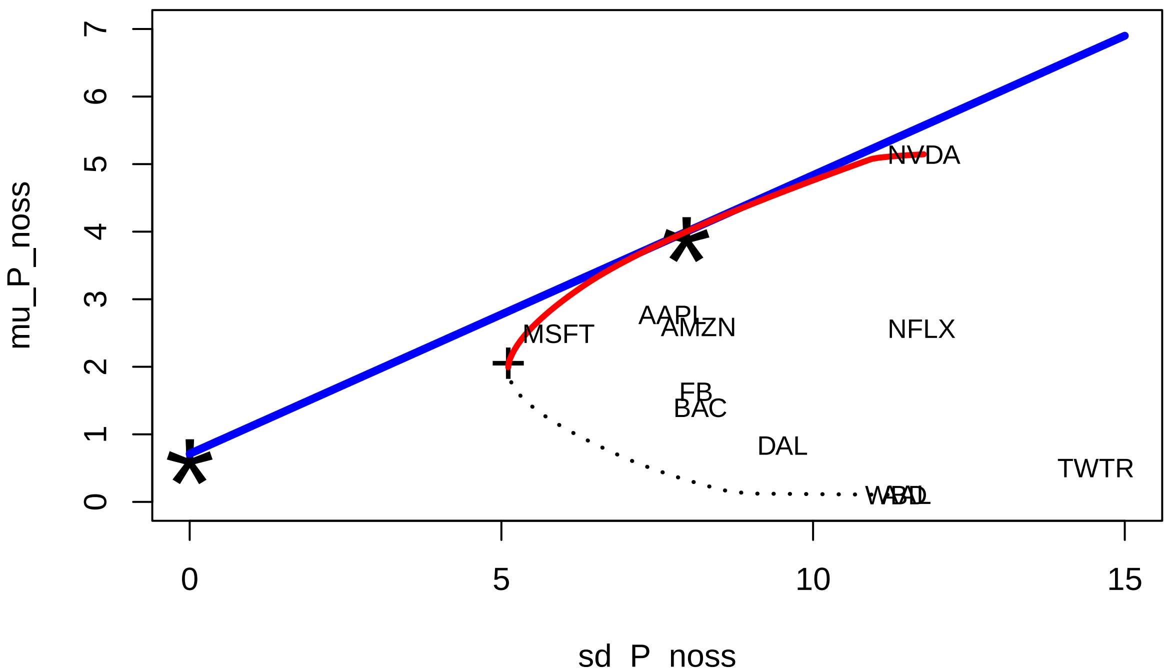
Assets' Sharpe's Ratios

```
##    colnames.return.1..2.14.. sharpes_list
## 1                       MSFT     0.301240
## 2                       TSLA     0.236444
## 3                       AAPL     0.266249
## 4                       TWTR    -0.014163
## 5                       AMZN     0.230716
## 6                         FB     0.113726
## 7                       NFLX     0.158171
## 8                        AAL    -0.052225
## 9                        DAL     0.013416
## 10                       BAC     0.083800
## 11                      NVDA     0.376455
## 12                       WBD    -0.053472
## 13                    S&P500     0.080919
```

Without shortshale

```r
### Without shortsale
#R = 100*return[,2:13]
#mean_p <- apply(R,2,mean)
#cov_p <- cov(R)
#sd_vect_p <- sqrt(diag(cov_p))
### With shortsale
#M_p = length(mean_p)
Amat_p_noss <- cbind(rep(1,M_p),mean_p, diag(1,nrow=M_p))
mu_P_noss = seq(min(mean_p)+0.0001, max(mean_p)-0.0001, length = 300)
# Target portfolio means for the expect portfolio return
sd_P_noss = mu_P_noss # set up storage for std dev's of portfolio returns
weights_p_noss = matrix(0, nrow = 300, ncol = M_p) # storage for return
for (i in 1:length(mu_P_noss)) { # find the optimal portfolios
  bvec_p_noss <- c(1, mu_P_noss[i], rep(0,M_p))
  result_noss = solve.QP(Dmat = 2 * cov_p, dvec = rep(0, M_p), Amat = Amat_p_noss,
                    bvec = bvec_p_noss, meq = 2)
```

```
  sd_P_noss[i] = sqrt(result_noss$value)
  weights_p_noss[i, ] = result_noss$solution
}
plot(sd_P_noss, mu_P_noss, type = "l", lty = 3,
     lwd = 2, xlim = c(0,15), ylim = c(0,7))
# plot efficient frontier (and inefficient portfolios below the min var portfolio)
#mufree_p = mean(return$`Treasury Bill 3 month (rf)`) # input value of risk-free interest rate
points(0, mufree_p, cex = 4, pch = "*") # show risk-free asset
sharpe_p_noss = (mu_P_noss - mufree_p) / sd_P_noss # compute Sharpes ratios
ind_p_noss = (sharpe_p_noss == max(sharpe_p_noss)) # Find maximum Sharpes ratio
#weights_p[ind_p,] # print the weights of the tangency portfolio
lines(c(0, 15), mufree_p + c(0, 15) * (mu_P_noss[ind_p_noss] - mufree_p) / sd_P_noss[ind_p_noss], lwd =
      lty = 1, col = "blue") # show line of optimal portfolios
points(sd_P_noss[ind_p_noss], mu_P_noss[ind_p_noss], cex = 4, pch = "*") # tangency portfolio
ind2_p_noss = (sd_P_noss == min(sd_P_noss)) # find the minimum variance portfolio
points(sd_P_noss[ind2_p_noss], mu_P_noss[ind2_p_noss], cex = 2, pch = "+") # min var portfolio
ind3_p_noss = (mu_P_noss > mu_P_noss[ind2_p_noss])
lines(sd_P_noss[ind3_p_noss], mu_P_noss[ind3_p_noss], type = "l",
      lwd = 3, col = 'red') # plot the efficient frontier
for(i in 1:12){
  text(sd_vect_p[i], mean_p[i],colnames(return[,i+1]), cex=0.8)
}
```




```
### MVP
(mvp_meanreturn_noss <- mu_P_noss[ind2_p_noss])
```

```
## [1] 1.9771
```

```
(mvp_sd_noss <- sd_P_noss[ind2_p_noss])
```

```
## [1] 5.1105
```

```
weights_mvp_noss <- weights_p_noss[ind2_p_noss,]
weights_mvp_noss <- t(data.frame(weights_mvp_noss))
```

```r
colnames(weights_mvp_noss) <- colnames(return[2:13])
weights_mvp_noss
```

```
##                     MSFT        TSLA     AAPL     TWTR     AMZN      FB
## weights_mvp_noss 0.48797 -1.7643e-18 0.065926 0.056099 0.032476 0.13469
##                      NFLX         AAL      DAL      BAC       NVDA       WBD
## weights_mvp_noss 0.022567 -2.9314e-17 0.14605 0.044533 6.4414e-18 0.0096996
```

```r
(mvp_meanreturn_ann_noss <- mvp_meanreturn_noss*12)
```

```
## [1] 23.725
```

```r
(mvp_sd_ann_noss <- mvp_sd_noss*sqrt(12))
```

```
## [1] 17.703
```

```r
### Efficient Portfolio Frontier
EPF_mean_noss <- mu_P_noss[ind3_p_noss]
EPF_sd_noss <- sd_P_noss[ind3_p_noss]

### Tangency Portfolio
(tan_meanreturn_noss <- mu_P_noss[ind_p_noss])
```

```
## [1] 3.9997
```

```r
(tan_sd_noss <- sd_P_noss[ind_p_noss])
```

```
## [1] 7.9697
```

```r
(tan_var_noss <- tan_sd_noss^2)
```

```
## [1] 63.516
```

```r
(tan_sharpes_noss <- (tan_meanreturn_noss-mufree_p)/tan_sd_noss)
```

```
## [1] 0.41253
```