Stats_C183_Project_3_Charles_Liu

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Loading Necessary Packages:

```
library(readr)
```

Two periods: 1. 01-Jan-2012 to 01-Jan-2017 2. 01-Jan-2017 to 31-Mar-2020

a.1)

```
a1 <- read.csv("C:/Users/cliuk/Documents/UCLA Works/UCLA Spring 2020/Stats C183/Project/stockData_2012-2

# Convert adjusted close prices into returns:
r1 <- (a1[-1,3:ncol(a1)]-a1[-nrow(a1),3:ncol(a1)])/a1[-nrow(a1),3:ncol(a1)]

# Regression of all the other stocks on S&P500:
q <- lm(r1$X.GSPC ~ r1$BHP + r1$GOLD + r1$VALE + r1$GOOG + r1$T + r1$NFLX +
          r1$AMZN + r1$MCD + r1$MCD + r1$TSLA + r1$WMT + r1$KO + r1$COST +
          r1$XOM + r1$CVX + r1$TRP + r1$BRK.B + r1$V + r1$JPM + r1$JNJ +
          r1$AMGN + r1$CVS + r1$UNP + r1$BA + r1$GE + r1$DLR + r1$BXP +
          r1$O + r1$MSFT + r1$AAPL + r1$NVDA)


# Get the estimates of alpha, beta, and sigma^2:
alpha_estimate <- q$coefficients[1]
beta_estimate <- q$coefficients[2:31]
sigma2_estimate <- sum(q$residuals^2)/(nrow(a1)-2)

# Values for our estimates:
alpha_estimate
```

```
##  (Intercept)
## -0.005143286
```

```
beta_estimate
```

```
##       r1$BHP      r1$GOLD      r1$VALE      r1$GOOG         r1$T      r1$NFLX
## -0.020598889  0.000244562  0.003455800  0.015786036  0.017328617  0.020981427
##      r1$AMZN       r1$MCD      r1$TSLA       r1$WMT        r1$KO      r1$COST
##  0.022596159  0.109648066  0.008684094 -0.022231709 -0.038986399  0.025372061
##       r1$XOM       r1$CVX       r1$TRP     r1$BRK.B         r1$V       r1$JPM
##  0.032269525  0.050534350  0.074097308  0.049718480  0.077236133  0.082880681
##       r1$JNJ      r1$AMGN       r1$CVS       r1$UNP        r1$BA        r1$GE
##  0.067562805  0.037942498  0.057004014  0.054442737  0.020566745  0.051484280
```

```
##       r1$DLR       r1$BXP         r1$O      r1$MSFT      r1$AAPL      r1$NVDA 
## -0.043166491  0.024077700  0.022098949 -0.017361046  0.105048394  0.030582495
```

```r
sigma2_estimate
```

```
## [1] 3.221254e-05
```

a.2)

```r
# Compute the variance covariance matrix of the returns for each period:
covmat1 <- var(r1[-1])

# Covariance-Variance Matrix (30 x 30):
covmat1 # without ^GSPC
```

```
##                 BHP          GOLD          VALE          GOOG             T
## BHP    7.748147e-03  4.855666e-03  0.0099444081  2.311498e-04  3.829624e-04
## GOLD   4.855666e-03  2.376655e-02  0.0080539570 -1.378819e-03  6.781616e-04
## VALE   9.944408e-03  8.053957e-03  0.0224114792 -1.358072e-03  1.040170e-03
## GOOG   2.311498e-04 -1.378819e-03 -0.0013580719  3.647911e-03  9.364433e-05
## T      3.829624e-04  6.781616e-04  0.0010401703  9.364433e-05  1.697029e-03
## NFLX   2.001101e-03 -1.386586e-03  0.0027738937  2.527836e-03 -2.167026e-03
## AMZN   1.886136e-03  2.855098e-04  0.0005043397  2.590451e-03  3.890235e-04
## MCD    5.020881e-04 -5.416970e-04  0.0002572934  8.173256e-04  5.651528e-04
## TSLA   1.548559e-03  9.310711e-04  0.0028657617  8.510017e-04 -1.534212e-03
## WMT   -9.788692e-04 -9.140933e-04 -0.0009698061 -3.558177e-04  6.617766e-04
## KO     2.339596e-04 -9.111147e-04  0.0002338107  5.882435e-04  7.794825e-04
## COST  -1.545056e-04 -1.897969e-03 -0.0007708018  9.580781e-04  2.555209e-04
## XOM    1.845357e-03  1.657912e-03  0.0019842258  2.381927e-04  6.377879e-04
## CVX    2.816762e-03  1.625964e-03  0.0038268388  4.441476e-04  7.410662e-04
## TRP    2.491393e-03  2.889658e-03  0.0033114531  1.377051e-04  8.961018e-04
## BRK.B  7.891160e-04 -5.032713e-04  0.0010562926  2.494723e-04  4.603056e-04
## V      6.100190e-04 -1.868576e-03 -0.0003145544  1.469173e-03 -7.836584e-05
## JPM    1.830633e-03 -1.872775e-03  0.0022719469  1.018394e-03  6.905348e-05
## JNJ    7.465983e-04  3.318862e-04  0.0006871809  4.196962e-04  6.323445e-04
## AMGN   1.103206e-03 -1.483320e-03 -0.0004822487  1.484653e-03  4.393943e-04
## CVS    1.705037e-04 -1.173528e-03 -0.0004724071  9.008776e-04  3.923708e-04
## UNP    1.700574e-03 -1.529057e-05  0.0023682465 -3.851531e-04  3.377529e-04
## BA     1.801999e-03 -6.014222e-04  0.0022909724  8.002579e-04  3.895986e-05
## GE     1.491632e-03  5.402230e-04  0.0019309914  1.179125e-03  9.948010e-04
## DLR    1.838881e-05  9.270448e-04  0.0002053460  2.478125e-06  6.227127e-04
## BXP    1.072871e-03 -5.124243e-04  0.0009726301  4.329655e-04  2.326998e-04
## O      1.031648e-04  1.034446e-03 -0.0010377903  7.243207e-04  4.227715e-04
## MSFT   8.152036e-04 -1.498196e-03  0.0012228660  1.547084e-03  5.376552e-04
## AAPL   9.334894e-04 -7.181216e-05 -0.0001310055  1.184917e-03  5.882153e-04
## NVDA   1.394646e-03 -5.084382e-04  0.0021393314  1.146761e-03  3.201178e-04
##                NFLX          AMZN           MCD          TSLA           WMT
## BHP    2.001101e-03  0.0018861359  5.020881e-04  1.548559e-03 -9.788692e-04
## GOLD  -1.386586e-03  0.0002855098 -5.416970e-04  9.310711e-04 -9.140933e-04
## VALE   2.773894e-03  0.0005043397  2.572934e-04  2.865762e-03 -9.698061e-04
## GOOG   2.527836e-03  0.0025904510  8.173256e-04  8.510017e-04 -3.558177e-04
## T     -2.167026e-03  0.0003890235  5.651528e-04 -1.534212e-03  6.617766e-04
## NFLX   2.998780e-02  0.0029497331  2.289049e-04  6.971062e-03 -1.418532e-03
## AMZN   2.949733e-03  0.0065603727  9.833801e-04  6.404036e-04 -1.347462e-04
```

```
## MCD    2.289049e-04  0.0009833801  1.441285e-03 -8.486424e-04  7.058419e-05
## TSLA   6.971062e-03  0.0006404036 -8.486424e-04  2.841189e-02 -1.339544e-03
## WMT   -1.418532e-03 -0.0001347462  7.058419e-05 -1.339544e-03  2.247506e-03
## KO     7.032831e-05  0.0011915003  7.841289e-04 -3.077473e-04  6.949887e-04
## COST   1.037074e-03  0.0012618490  6.356513e-04  5.388358e-04  5.450780e-04
## XOM   -1.707215e-04  0.0007248233  6.504423e-04  1.317717e-04 -3.044714e-05
## CVX    2.188047e-04  0.0007931767  1.036410e-03  9.729429e-04 -1.601043e-04
## TRP   -9.099275e-04  0.0004449998  4.407169e-04 -5.132016e-04  3.564542e-04
## BRK.B  2.726352e-04  0.0005717952  5.469309e-04  1.095620e-03  4.429955e-04
## V      1.056374e-03  0.0017569227  5.499369e-04  1.433594e-03 -2.789198e-04
## JPM    2.836236e-03  0.0014747582  8.074072e-04  2.696524e-03 -4.604061e-04
## JNJ    3.159082e-04  0.0008478010  6.993962e-04 -5.023155e-05  6.598170e-04
## AMGN  -4.087134e-04  0.0020441628  6.149499e-04  5.761273e-04  2.418380e-04
## CVS    7.371570e-04  0.0008294531  4.797429e-04  5.375774e-04  4.690284e-04
## UNP   -3.247242e-05  0.0003045148  2.113626e-04  9.024259e-04  3.413359e-04
## BA     1.439889e-03  0.0023904047  7.838103e-04  1.924291e-03 -4.218825e-05
## GE     8.502136e-04  0.0018104368  9.600072e-04  6.832744e-04  8.948322e-05
## DLR   -1.089217e-03  0.0000593629  5.501491e-04 -1.398991e-03 -1.655555e-04
## BXP   -6.180579e-04  0.0008522401  4.760243e-04  1.100338e-03  1.250472e-04
## O      5.479562e-04  0.0005510363  3.561283e-04  6.338305e-05  7.196134e-04
## MSFT   2.026926e-03  0.0012864580  9.456272e-04  1.920389e-03 -2.728010e-04
## AAPL  -1.244245e-03  0.0014097765  9.217228e-05  1.188949e-03  2.791378e-04
## NVDA   1.723173e-03  0.0012974591  7.198121e-04  2.766286e-03 -9.963917e-05
##                  KO          COST           XOM           CVX           TRP
## BHP    2.339596e-04 -0.0001545056  1.845357e-03  0.0028167622  0.0024913935
## GOLD  -9.111147e-04 -0.0018979693  1.657912e-03  0.0016259642  0.0028896583
## VALE   2.338107e-04 -0.0007708018  1.984226e-03  0.0038268388  0.0033114531
## GOOG   5.882435e-04  0.0009580781  2.381927e-04  0.0004441476  0.0001377051
## T      7.794825e-04  0.0002555209  6.377879e-04  0.0007410662  0.0008961018
## NFLX   7.032831e-05  0.0010370739 -1.707215e-04  0.0002188047 -0.0009099275
## AMZN   1.191500e-03  0.0012618490  7.248233e-04  0.0007931767  0.0004449998
## MCD    7.841289e-04  0.0006356513  6.504423e-04  0.0010364096  0.0004407169
## TSLA  -3.077473e-04  0.0005388358  1.317717e-04  0.0009729429 -0.0005132016
## WMT    6.949887e-04  0.0005450780 -3.044714e-05 -0.0001601043  0.0003564542
## KO     1.629724e-03  0.0007884232  6.353458e-04  0.0007421989  0.0006737945
## COST   7.884232e-04  0.0020046479  5.685993e-04  0.0007052038  0.0001540788
## XOM    6.353458e-04  0.0005685993  1.867113e-03  0.0019409254  0.0011891774
## CVX    7.421989e-04  0.0007052038  1.940925e-03  0.0031000901  0.0017142684
## TRP    6.737945e-04  0.0001540788  1.189177e-03  0.0017142684  0.0025905008
## BRK.B  6.864826e-04  0.0007561471  7.595967e-04  0.0009289583  0.0005515314
## V      7.461370e-04  0.0009061730  5.923954e-04  0.0005514727  0.0003256241
## JPM    4.091389e-04  0.0008041593  1.375919e-03  0.0018585680  0.0004663779
## JNJ    9.285728e-04  0.0008785303  9.063259e-04  0.0010374755  0.0009258945
## AMGN   5.787204e-04  0.0011539948  4.342179e-04  0.0007339036  0.0010999241
## CVS    7.875818e-04  0.0009087623  6.030706e-04  0.0004565288  0.0004865982
## UNP    2.573125e-04  0.0004432002  8.780799e-04  0.0008230443  0.0007244734
## BA     9.200834e-04  0.0011089998  7.183726e-04  0.0010175669  0.0002889270
## GE     1.073758e-03  0.0010582223  1.338835e-03  0.0016447877  0.0006895268
## DLR    4.499390e-04  0.0004783741  4.257687e-04  0.0005829187  0.0007941104
## BXP    2.770587e-04  0.0008792674  3.933996e-04  0.0007066821  0.0004802721
## O      6.019975e-04  0.0011890952  3.648332e-04  0.0002325241  0.0007746340
## MSFT   8.544004e-04  0.0006320439  6.227529e-04  0.0014296665  0.0009139663
## AAPL   9.954865e-04  0.0010866404  5.520179e-04  0.0009735261  0.0006476408
## NVDA   3.434617e-04  0.0010594172  8.788404e-04  0.0015985084  0.0001249172
```

```
##             BRK.B             V           JPM           JNJ          AMGN
## BHP    0.0007891160  6.100190e-04  1.830633e-03  7.465983e-04  0.0011032061
## GOLD  -0.0005032713 -1.868576e-03 -1.872775e-03  3.318862e-04 -0.0014833201
## VALE   0.0010562926 -3.145544e-04  2.271947e-03  6.871809e-04 -0.0004822487
## GOOG   0.0002494723  1.469173e-03  1.018394e-03  4.196962e-04  0.0014846526
## T      0.0004603056 -7.836584e-05  6.905348e-05  6.323445e-04  0.0004393943
## NFLX   0.0002726352  1.056374e-03  2.836236e-03  3.159082e-04 -0.0004087134
## AMZN   0.0005717952  1.756923e-03  1.474758e-03  8.478010e-04  0.0020441628
## MCD    0.0005469309  5.499369e-04  8.074072e-04  6.993962e-04  0.0006149499
## TSLA   0.0010956198  1.433594e-03  2.696524e-03 -5.023155e-05  0.0005761273
## WMT    0.0004429955 -2.789198e-04 -4.604061e-04  6.598170e-04  0.0002418380
## KO     0.0006864826  7.461370e-04  4.091389e-04  9.285728e-04  0.0005787204
## COST   0.0007561471  9.061730e-04  8.041593e-04  8.785303e-04  0.0011539948
## XOM    0.0007595967  5.923954e-04  1.375919e-03  9.063259e-04  0.0004342179
## CVX    0.0009289583  5.514727e-04  1.858568e-03  1.037475e-03  0.0007339036
## TRP    0.0005515314  3.256241e-04  4.663779e-04  9.258945e-04  0.0010999241
## BRK.B  0.0013421726  4.589377e-04  1.323847e-03  6.764858e-04  0.0006740474
## V      0.0004589377  2.601358e-03  1.164677e-03  3.655056e-04  0.0016475850
## JPM    0.0013238468  1.164677e-03  4.668844e-03  7.176723e-04  0.0008660074
## JNJ    0.0006764858  3.655056e-04  7.176723e-04  1.480479e-03  0.0009707743
## AMGN   0.0006740474  1.647585e-03  8.660074e-04  9.707743e-04  0.0039873362
## CVS    0.0007094923  1.233093e-03  5.797252e-04  7.332845e-04  0.0011047889
## UNP    0.0010247252  4.242364e-04  9.850819e-04  6.242674e-04  0.0012721888
## BA     0.0008663759  1.203128e-03  9.725619e-04  8.515903e-04  0.0010289869
## GE     0.0010757449  8.155074e-04  1.635349e-03  9.082000e-04  0.0006785495
## DLR   -0.0001752187  1.890503e-04 -9.048928e-04  2.326573e-04  0.0006186017
## BXP    0.0004444848  4.527994e-04  2.163801e-04  5.029961e-04  0.0014711137
## O      0.0001208648  1.044431e-04 -1.179069e-03  8.355780e-04  0.0010325344
## MSFT   0.0004745814  1.095269e-03  1.729727e-03  6.429524e-04  0.0010457597
## AAPL   0.0004211565  1.027027e-03  8.132366e-04  2.592947e-04  0.0010385110
## NVDA   0.0007713044  4.335336e-04  2.234615e-03  2.157436e-04  0.0004657287
##               CVS           UNP            BA            GE           DLR
## BHP    0.0001705037  1.700574e-03  1.801999e-03  1.491632e-03  1.838881e-05
## GOLD  -0.0011735277 -1.529057e-05 -6.014222e-04  5.402230e-04  9.270448e-04
## VALE  -0.0004724071  2.368247e-03  2.290972e-03  1.930991e-03  2.053460e-04
## GOOG   0.0009008776 -3.851531e-04  8.002579e-04  1.179125e-03  2.478125e-06
## T      0.0003923708  3.377529e-04  3.895986e-05  9.948010e-04  6.227127e-04
## NFLX   0.0007371570 -3.247242e-05  1.439889e-03  8.502136e-04 -1.089217e-03
## AMZN   0.0008294531  3.045148e-04  2.390405e-03  1.810437e-03  5.936290e-05
## MCD    0.0004797429  2.113626e-04  7.838103e-04  9.600072e-04  5.501491e-04
## TSLA   0.0005375774  9.024259e-04  1.924291e-03  6.832744e-04 -1.398991e-03
## WMT    0.0004690284  3.413359e-04 -4.218825e-05  8.948322e-05 -1.655555e-04
## KO     0.0007875818  2.573125e-04  9.200834e-04  1.073758e-03  4.499390e-04
## COST   0.0009087623  4.432002e-04  1.109000e-03  1.058222e-03  4.783741e-04
## XOM    0.0006030706  8.780799e-04  7.183726e-04  1.338835e-03  4.257687e-04
## CVX    0.0004565288  8.230443e-04  1.017567e-03  1.644788e-03  5.829187e-04
## TRP    0.0004865982  7.244734e-04  2.889270e-04  6.895268e-04  7.941104e-04
## BRK.B  0.0007094923  1.024725e-03  8.663759e-04  1.075745e-03 -1.752187e-04
## V      0.0012330930  4.242364e-04  1.203128e-03  8.155074e-04  1.890503e-04
## JPM    0.0005797252  9.850819e-04  9.725619e-04  1.635349e-03 -9.048928e-04
## JNJ    0.0007332845  6.242674e-04  8.515903e-04  9.082000e-04  2.326573e-04
## AMGN   0.0011047889  1.272189e-03  1.028987e-03  6.785495e-04  6.186017e-04
## CVS    0.0022985009  4.012040e-04  8.054225e-04  8.363778e-04  2.963083e-04
## UNP    0.0004012040  2.560365e-03  1.018762e-03  3.246695e-04 -1.878799e-05
```

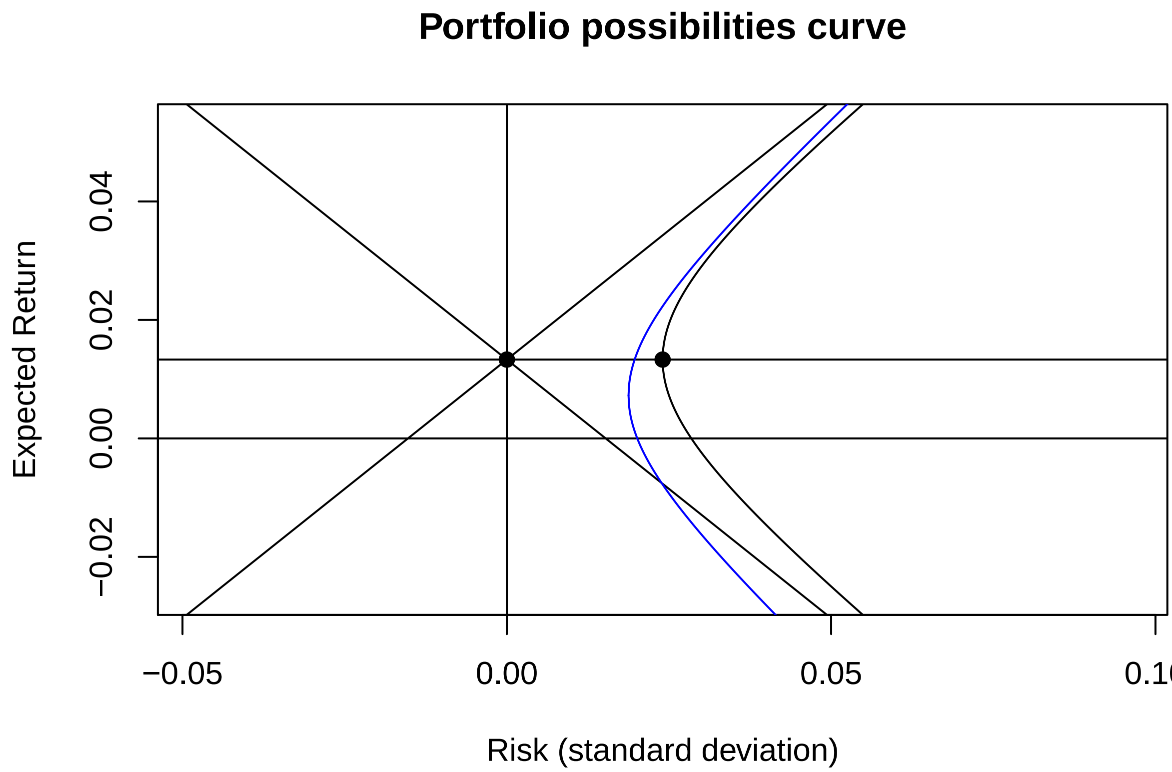
```
## BA      0.0008054225  1.018762e-03  3.438727e-03  1.129346e-03  3.597267e-05
## GE      0.0008363778  3.246695e-04  1.129346e-03  2.389325e-03 -3.933749e-05
## DLR     0.0002963083 -1.878799e-05  3.597267e-05 -3.933749e-05  3.882016e-03
## BXP     0.0004983219  1.089482e-03  9.578231e-04  3.644761e-04  1.408965e-03
## O       0.0008460200  3.029695e-04  2.609143e-04  1.799104e-05  2.234922e-03
## MSFT    0.0004475811  2.702698e-04  6.497406e-04  1.297647e-03  3.087507e-04
## AAPL    0.0011363774 -6.170500e-05  1.043197e-03  1.245755e-03  3.385149e-04
## NVDA   -0.0005221295  1.020592e-03  1.053423e-03  1.534196e-03  6.542407e-04
##                 BXP             O          MSFT          AAPL          NVDA
## BHP     0.0010728714  1.031648e-04  0.0008152036  9.334894e-04  1.394646e-03
## GOLD   -0.0005124243  1.034446e-03 -0.0014981958 -7.181216e-05 -5.084382e-04
## VALE    0.0009726301 -1.037790e-03  0.0012228660 -1.310055e-04  2.139331e-03
## GOOG    0.0004329655  7.243207e-04  0.0015470836  1.184917e-03  1.146761e-03
## T       0.0002326998  4.227715e-04  0.0005376552  5.882153e-04  3.201178e-04
## NFLX   -0.0006180579  5.479562e-04  0.0020269260 -1.244245e-03  1.723173e-03
## AMZN    0.0008522401  5.510363e-04  0.0012864580  1.409777e-03  1.297459e-03
## MCD     0.0004760243  3.561283e-04  0.0009456272  9.217228e-05  7.198121e-04
## TSLA    0.0011003384  6.338305e-05  0.0019203893  1.188949e-03  2.766286e-03
## WMT     0.0001250472  7.196134e-04 -0.0002728010  2.791378e-04 -9.963917e-05
## KO      0.0002770587  6.019975e-04  0.0008544004  9.954865e-04  3.434617e-04
## COST    0.0008792674  1.189095e-03  0.0006320439  1.086640e-03  1.059417e-03
## XOM     0.0003933996  3.648332e-04  0.0006227529  5.520179e-04  8.788404e-04
## CVX     0.0007066821  2.325241e-04  0.0014296665  9.735261e-04  1.598508e-03
## TRP     0.0004802721  7.746340e-04  0.0009139663  6.476408e-04  1.249172e-04
## BRK.B   0.0004444848  1.208648e-04  0.0004745814  4.211565e-04  7.713044e-04
## V       0.0004527994  1.044431e-04  0.0010952689  1.027027e-03  4.335336e-04
## JPM     0.0002163801 -1.179069e-03  0.0017297269  8.132366e-04  2.234615e-03
## JNJ     0.0005029961  8.355780e-04  0.0006429524  2.592947e-04  2.157436e-04
## AMGN    0.0014711137  1.032534e-03  0.0010457597  1.038511e-03  4.657287e-04
## CVS     0.0004983219  8.460200e-04  0.0004475811  1.136377e-03 -5.221295e-04
## UNP     0.0010894816  3.029695e-04  0.0002702698 -6.170500e-05  1.020592e-03
## BA      0.0009578231  2.609143e-04  0.0006497406  1.043197e-03  1.053423e-03
## GE      0.0003644761  1.799104e-05  0.0012976465  1.245755e-03  1.534196e-03
## DLR     0.0014089647  2.234922e-03  0.0003087507  3.385149e-04  6.542407e-04
## BXP     0.0021752555  1.830304e-03  0.0004432037  6.188209e-04  9.626850e-04
## O       0.0018303040  4.259402e-03 -0.0003320189  2.728045e-04  1.260743e-04
## MSFT    0.0004432037 -3.320189e-04  0.0040225675  1.473716e-03  2.246446e-03
## AAPL    0.0006188209  2.728045e-04  0.0014737156  5.243954e-03  2.137486e-03
## NVDA    0.0009626850  1.260743e-04  0.0022464464  2.137486e-03  7.965541e-03
```

a.3)

```
# Setting up Project 2 Problem (b-1):
a <- read.csv("C:/Users/cliuk/Documents/UCLA Works/UCLA Spring 2020/Stats C183/Project/stockData_all.cs
r <- (a[-1,3:ncol(a)]-a[-nrow(a),3:ncol(a)])/a[-nrow(a),3:ncol(a)]
means <- colMeans(r[-1])
covmat <- cov(r[-1])
cormat <- cor(r[-1])
variances <- diag(covmat)
stdev <- diag(covmat)^.5
ones <- rep(1, 30)
A <- t(ones) %*% solve(covmat) %*% means
B <- t(means) %*% solve(covmat) %*% means
```

```r
C <- t(ones) %*% solve(covmat) %*% ones
D <- B * C - A^2
E <- seq(-5,5,.1)
sigma2 <- (C*E^2 - 2*A*E +B) /D

# Hyperbola Method from Project 2 Problem (b-1):
plot(0, A/C, main = "Portfolio possibilities curve", xlab = "Risk (standard deviation)",
     ylab = "Expected Return", type = "n",
     xlim = c(-2*sqrt(1/C), 4*sqrt(1/C)),
     ylim = c(-2*A/C, 4*A/C))
points(0, A/C, pch = 19)
abline(v = 0)
abline(h = A/C)
abline(h = 0)
points(sqrt(1/C), A/C, pch=19)
V <- seq(-1, 1, 0.001)
A1 <- A/C + V * sqrt(D/C)
A2 <- A/C - V * sqrt(D/C)
points(V, A1, type = "l")
points(V, A2, type = "l")

# Efficient frontier:
minvar <- 1/C
minE <- A/C
sdeff <- seq((minvar)^0.5, 1, by = 0.0001)
options(warn = -1)
y1 <- (A + sqrt(D*(C*sdeff^2 - 1)))*(1/C)
y2 <- (A - sqrt(D*(C*sdeff^2 - 1)))*(1/C)
options(warn = 0)
points(sdeff, y1, type = "l")
points(sdeff, y2, type = "l")



# 01-Jan-2012 to 01-Jan-2017 Set up:
means1 <- colMeans(r1[-1])
covmat1 <- cov(r1[-1])
var1 <- diag(covmat1)
stdev1 <- diag(covmat1)^.5
A1 <- t(ones) %*% solve(covmat1) %*% means1
B1 <- t(means1) %*% solve(covmat1) %*% means1
C1 <- t(ones) %*% solve(covmat1) %*% ones
D1 <- B1 * C1 - A1^2
E <- seq(-5,5,.1)
sigma2_1 <- (C1*E^2 - 2*A1*E +B1) /D1

# SIM Frontier (BLUE):
SIM_Var <- 1/C1
SIM_E <- A1/C1
sdeff1 <- seq((SIM_Var)^0.5, 1, by = 0.0001)
options(warn = -1)
y1_1 <- (A1 + sqrt(D1*(C1*sdeff1^2 - 1)))*(1/C1)
y2_1 <- (A1 - sqrt(D1*(C1*sdeff1^2 - 1)))*(1/C1)
```

```r
options(warn = 0)
points(sdeff1, y1_1, type = "l", col = "blue")
points(sdeff1, y2_1, type = "l", col = "blue")
```



b) Blume's Technique

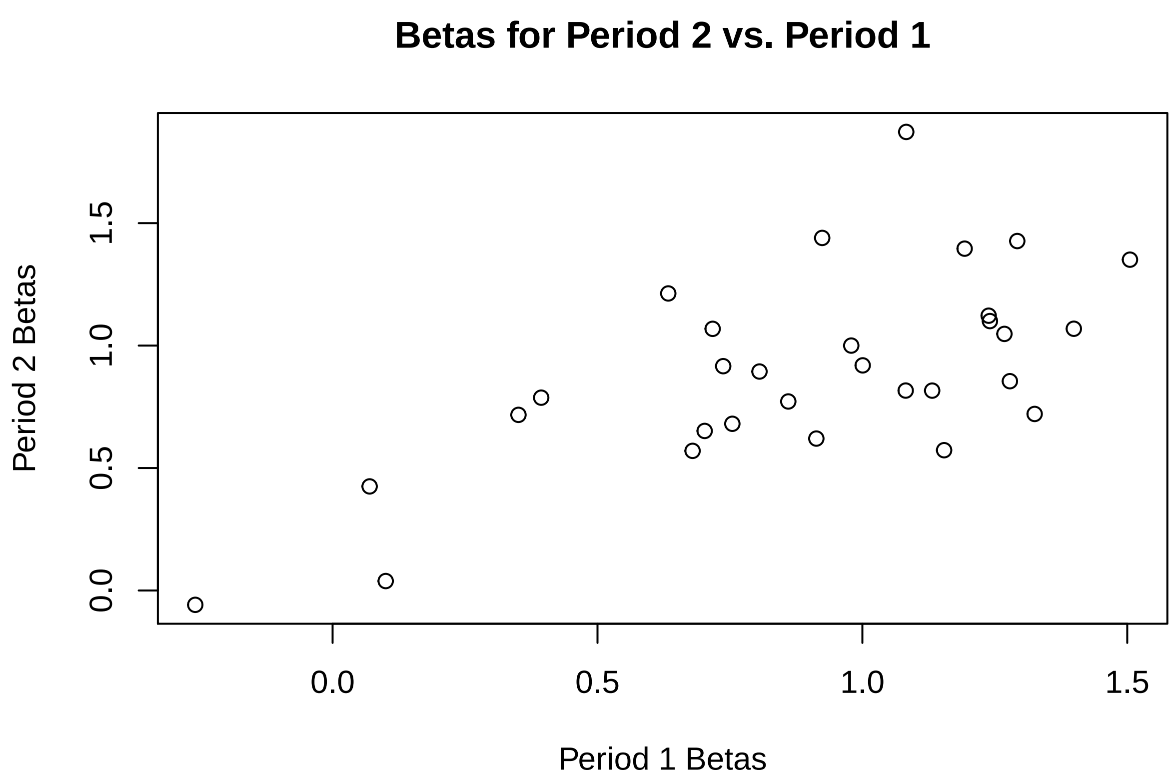
```r
# Loading the data for (2012 - 2017) & (2017 - 2020):
a1 <- read.csv("C:/Users/cliuk/Documents/UCLA Works/UCLA Spring 2020/Stats C183/Project/stockData_2012-2
a2 <- read.csv("C:/Users/cliuk/Documents/UCLA Works/UCLA Spring 2020/Stats C183/Project/stockData_2017-2

# Convert adjusted close prices into returns:
r1 <- (a1[-1,3:ncol(a1)]-a1[-nrow(a1),3:ncol(a1)])/a1[-nrow(a1),3:ncol(a1)]
r2 <- (a2[-1,3:ncol(a2)]-a2[-nrow(a2),3:ncol(a2)])/a2[-nrow(a2),3:ncol(a2)]

# Compute the variance covariance matrix of the returns for each period:
covmat1 <- var(r1)
covmat2 <- var(r2)

# Compute the betas in each period:
beta1 <- covmat1[1,-1] / covmat1[1,1]
beta2 <- covmat2[1,-1] / covmat2[1,1]

# Values of our Betas for Period 1 and Period 2:
beta1
```

```
##          BHP        GOLD        VALE        GOOG           T        NFLX
##   1.27845369 -0.25924761  1.13179876  0.97902205  0.39376375  1.26815114
##         AMZN         MCD        TSLA         WMT          KO        COST
##   1.39914510  0.67950082  1.32518504  0.06990075  0.70230532  0.91311617
##          XOM         CVX         TRP       BRK.B           V         JPM
##   0.92418972  1.23840115  0.73730733  0.80578326  1.00062653  1.50513212
##          JNJ        AMGN         CVS         UNP          BA          GE
##   0.75455155  1.15430465  0.86017343  0.71739577  1.08280381  1.19301559
##          DLR         BXP           O        MSFT        AAPL        NVDA
##   0.10022646  0.63362316  0.35084848  1.08178436  1.24074863  1.29236113
```

```
beta2
```

```
##          BHP        GOLD        VALE        GOOG           T        NFLX
##   0.85456878 -0.05859735  0.81608449  0.99997396  0.78727266  1.04767563
##         AMZN         MCD        TSLA         WMT          KO        COST
##   1.06869358  0.57004007  0.72082172  0.42488538  0.65144634  0.62027832
##          XOM         CVX         TRP       BRK.B           V         JPM
##   1.43952443  1.12206768  0.91593602  0.89397675  0.91915868  1.35082364
##          JNJ        AMGN         CVS         UNP          BA          GE
##   0.68065508  0.57274868  0.77171563  1.06833115  1.87233422  1.39572207
##          DLR         BXP           O        MSFT        AAPL        NVDA
##   0.03845247  1.21282005  0.71709312  0.81625709  1.10002073  1.42681825
```

```
# Here is the plot of the betas in period 2 against the betas in perod 1:
plot(beta1, beta2, main = "Betas for Period 2 vs. Period 1",
     xlab = "Period 1 Betas", ylab = "Period 2 Betas")
```



```r
# Correlation between the betas in the two periods:
cor(beta1, beta2)
```

```
## [1] 0.667318
```

```r
# Adjust betas using the Blume's technique:
q1 <- lm(beta2 ~ beta1)
beta3adj_blume <- q1$coef[1] + q1$coef[2]*beta2

# Value for Blume's Method
beta3adj_blume
```

```
##       BHP      GOLD      VALE      GOOG         T      NFLX      AMZN       MCD
## 0.8746841 0.3002135 0.8504737 0.9661581 0.8323483 0.9961671 1.0093895 0.6956878
##      TSLA       WMT        KO      COST       XOM       CVX       TRP     BRK.B
## 0.7905441 0.6043713 0.7469003 0.7272925 1.2426783 1.0429670 0.9132901 0.8994755
##         V       JPM       JNJ      AMGN       CVS       UNP        BA        GE
## 0.9153174 1.1868768 0.7652754 0.6973917 0.8225614 1.0091615 1.5149579 1.2151223
##       DLR       BXP         O      MSFT      AAPL      NVDA
## 0.3612673 1.1000591 0.7881985 0.8505823 1.0290973 1.2346848
```

b) Vasicek's Technique

```r
# Vasicek's method:
beta1 <- rep(0,30)
alpha1 <- rep(0,30)
sigma_e1 <- rep(0,30)
var_beta1 <- rep(0,30)

for(i in 1:30){
  q <- lm(data=r1, formula=r1[,i+1] ~ r1[,1])
  beta1[i] <- q$coefficients[2]
  alpha1[i] <- q$coefficients[1]
  sigma_e1[i] <- summary(q)$sigma^2
  var_beta1[i] <- vcov(q)[2,2]
}


#Adjusting the betas using the Vasicek's technique:
beta3adj_vasicek <- var_beta1*mean(beta1)/(var(beta1)+var_beta1) +
  var(beta1)*beta1/(var(beta1)+var_beta1)

#Now let's compare:
#Note:
#beta2:  Betas in period 1 that can be used as forecasts for period 2.
#beta3adj_blume:  Adjusted betas (Blume) that can be used as forecast
#                 for period 3 (01-Aor-2020 to 01-Apr-2024).
#beta3adj_vasicek:  Adjusted betas (Vasicek) that can be used as forecast
#                 for period 2.

cbind(beta1, beta2, beta3adj_blume, beta3adj_vasicek)
```

```
##             beta1       beta2 beta3adj_blume beta3adj_vasicek
## BHP    1.27845369  0.85456878      0.8746841        1.1177084
```

```
## GOLD  -0.25924761 -0.05859735      0.3002135        0.5674470
## VALE   1.13179876  0.81608449      0.8504737        0.9591019
## GOOG   0.97902205  0.99997396      0.9661581        0.9569712
## T      0.39376375  0.78727266      0.8323483        0.4655778
## NFLX   1.26815114  1.04767563      0.9961671        0.9777747
## AMZN   1.39914510  1.06869358      1.0093895        1.2212408
## MCD    0.67950082  0.57004007      0.6956878        0.7004138
## TSLA   1.32518504  0.72082172      0.7905441        0.9966202
## WMT    0.06990075  0.42488538      0.6043713        0.2309696
## KO     0.70230532  0.65144634      0.7469003        0.7234574
## COST   0.91311617  0.62027832      0.7272925        0.9097073
## XOM    0.92418972  1.43952443      1.2426783        0.9199533
## CVX    1.23840115  1.12206768      1.0429670        1.1817920
## TRP    0.73730733  0.91593602      0.9132901        0.7650854
## BRK.B  0.80578326  0.89397675      0.8994755        0.8119366
## V      1.00062653  0.91915868      0.9153174        0.9823546
## JPM    1.50513212  1.35082364      1.1868768        1.3651179
## JNJ    0.75455155  0.68065508      0.7652754        0.7671768
## AMGN   1.15430465  0.57274868      0.6973917        1.0909523
## CVS    0.86017343  0.77171563      0.8225614        0.8639862
## UNP    0.71739577  1.06833115      1.0091615        0.7488614
## BA     1.08280381  1.87233422      1.5149579        1.0416205
## GE     1.19301559  1.39572207      1.2151223        1.1591566
## DLR    0.10022646  0.03845247      0.3612673        0.3343723
## BXP    0.63362316  1.21282005      1.1000591        0.6754808
## O      0.35084848  0.71709312      0.7881985        0.5180646
## MSFT   1.08178436  0.81625709      0.8505823        1.0332735
## AAPL   1.24074863  1.10002073      1.0290973        1.1345901
## NVDA   1.29236113  1.42681825      1.2346848        1.1230651
```

```r
PRESS_Vasicek <- sum((beta3adj_vasicek-beta1)^2) / 30

# Values of our PRESS's:
PRESS_Vasicek # Vasicek's Method
```

```
## [1] 0.03847683
```