FX Movements

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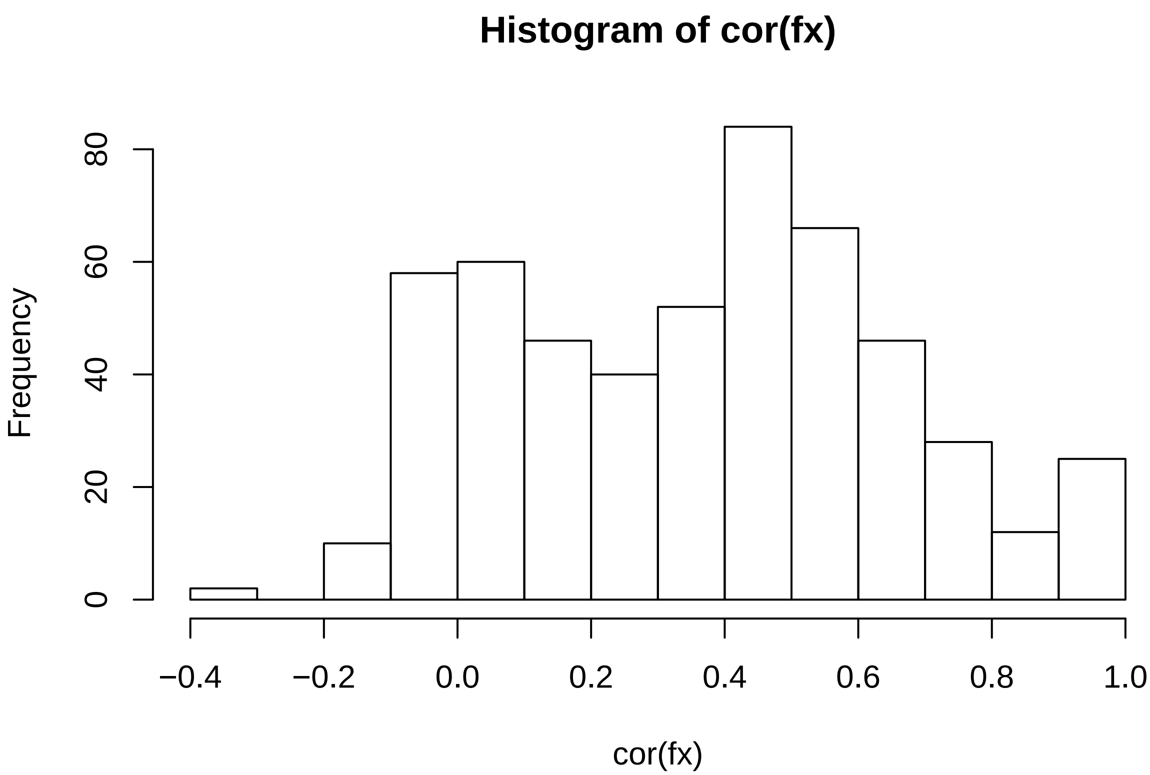
1. Correlations among FX Movements

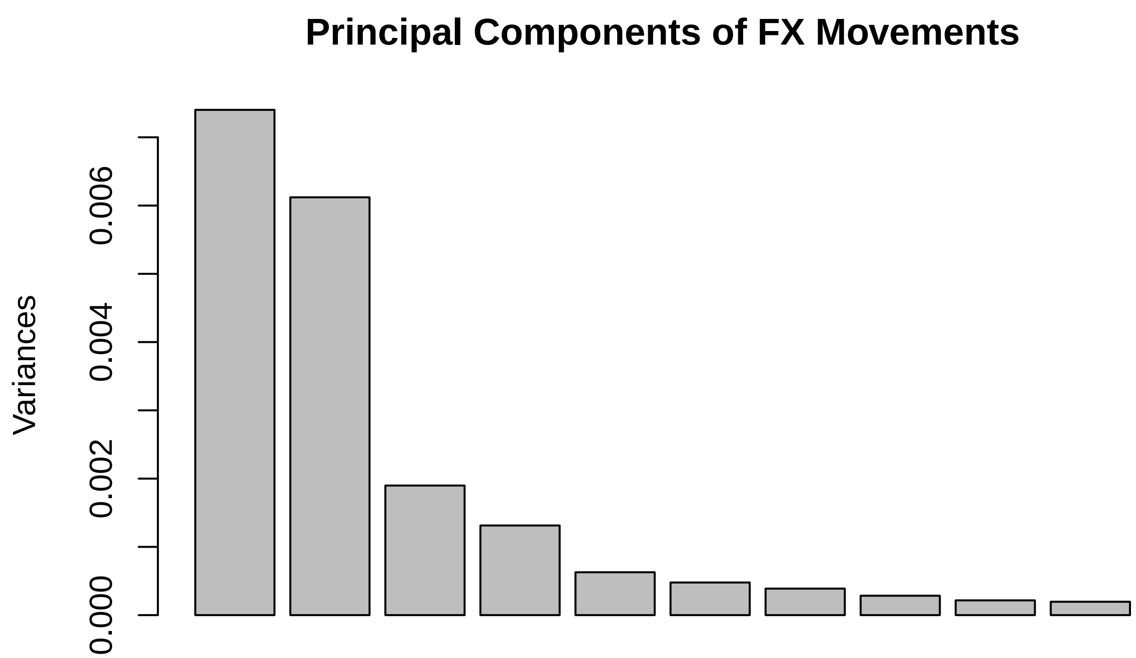
A brief look at the correlations among FX rates' movements reveals that there are many correlations that are significant - say, above 0.5.



This suggests that there can be underlying factors driving various subgroups of currencies, and that we can attempt to find such factors for dimensionality reduction purposes.

2. Principal Components of FX Movements

We now run PCA over the FX movements to discover major linear principal components:




```
## Importance of components:
##                            PC1     PC2     PC3     PC4     PC5     PC6
## Standard deviation     0.08603 0.07823 0.04357 0.03624 0.02506 0.02186
## Proportion of Variance 0.37345 0.30878 0.09577 0.06626 0.03170 0.02411
## Cumulative Proportion  0.37345 0.68223 0.77800 0.84426 0.87595 0.90007
##                            PC7     PC8     PC9    PC10    PC11    PC12
## Standard deviation     0.01971 0.01685 0.01471 0.01400 0.01191 0.01182
## Proportion of Variance 0.01960 0.01433 0.01091 0.00989 0.00715 0.00705
## Cumulative Proportion  0.91967 0.93400 0.94491 0.95480 0.96195 0.96900
##                           PC13    PC14    PC15     PC16     PC17     PC18
## Standard deviation     0.01077 0.01042 0.01005 0.009681 0.008117 0.007275
## Proportion of Variance 0.00585 0.00547 0.00510 0.004730 0.003320 0.002670
## Cumulative Proportion  0.97485 0.98033 0.98543 0.990160 0.993480 0.996150
##                           PC19     PC20    PC21    PC22      PC23
## Standard deviation     0.00664 0.004653 0.00304 0.00107 0.0003966
## Proportion of Variance 0.00222 0.001090 0.00047 0.00006 0.0000100
## Cumulative Proportion  0.99838 0.999470 0.99993 0.99999 1.0000000
```

We can see from the above that the first two principal components dominate the total variance in the data, accounting for about 40% and 30% of the variance respectively. Let's now take a look at the loadings on the different currencies of these two principal components:

```
##     australia brazil canada china denmark hong kong india japan
## PC1     -0.36  -0.29  -0.19 -0.01   -0.25         0 -0.12 -0.05
## PC2      0.03   0.14   0.02  0.01    0.03         0  0.00 -0.01
##     south korea malaysia mexico new zealand norway singapore south africa
## PC1       -0.27    -0.07  -0.17        -0.3  -0.28     -0.11        -0.36
## PC2       -0.03     0.00   0.05         0.0  -0.01      0.01         0.02
##     sri lanka sweden switzerland taiwan thailand    uk venezuela  euro
## PC1         0  -0.31       -0.20  -0.09    -0.09 -0.21      0.08 -0.25
## PC2         0   0.01        0.01  -0.01     0.00  0.01      0.99  0.03
```

The first PC's loadings are of the same sign, suggesting that it captures the overall movement of the US Dollar versus all other currencies, i.e. an overall appreciation or overall devaluation.

The second PC interestingly has a huge loading on the currency of Venezuela, making it unmistakably oil-related! This PC is likely to capture the effects of the world price of oil.

3. Regressions on Principal Components

We now run a number of regressions of the S&P 500 returns, first using GLM on the first 10 principal components:

```
##
## Call:
## glm(formula = sp500_returns$sp500 ~ fx_pca_fit[, 1:10])
##
## Deviance Residuals:
##       Min         1Q     Median         3Q        Max
## -0.109770  -0.016373   0.000723   0.022139   0.093901
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             0.0004431  0.0035351   0.125 0.900488
## fx_pca_fit[, 1:10]PC1   0.2479809  0.0412636   6.010 2.56e-08 ***
## fx_pca_fit[, 1:10]PC2  -0.1243118  0.0453796  -2.739 0.007203 **
## fx_pca_fit[, 1:10]PC3   0.3159550  0.0814818   3.878 0.000182 ***
## fx_pca_fit[, 1:10]PC4   0.0485769  0.0979655   0.496 0.621003
## fx_pca_fit[, 1:10]PC5   0.2000312  0.1416389   1.412 0.160748
## fx_pca_fit[, 1:10]PC6  -0.2123349  0.1623874  -1.308 0.193792
## fx_pca_fit[, 1:10]PC7   0.0687996  0.1801005   0.382 0.703207
## fx_pca_fit[, 1:10]PC8   0.2273690  0.2106644   1.079 0.282861
## fx_pca_fit[, 1:10]PC9   0.4351896  0.2414194   1.803 0.074235 .
## fx_pca_fit[, 1:10]PC10 -0.4221512  0.2535611  -1.665 0.098833 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.001487176)
##
##     Null deviance: 0.26463  on 118  degrees of freedom
## Residual deviance: 0.16062  on 108  degrees of freedom
## AIC: -424.63
##
## Number of Fisher Scoring iterations: 2
```

We next consider running a LASSO regression of the S&P 500 returns on all principal components.

```
## 24 x 1 sparse Matrix of class "dgCMatrix"
##                   seg60
## intercept  0.0004430924
## PC1        0.2320405505
## PC2       -0.1067813232
## PC3        0.2844780447
## PC4        0.0107321834
## PC5        0.1453151283
## PC6       -0.1496035616
## PC7        .
## PC8        0.1459879557
## PC9        0.3419277042
## PC10      -0.3241988499
## PC11       .
```

```
## PC12      -0.3297395908
## PC13      -0.3273071049
## PC14      -0.7651088126
## PC15      -0.0711631183
## PC16       0.4579418147
## PC17       .
## PC18       .
## PC19       0.5244008042
## PC20       0.7638457263
## PC21       1.6494130618
## PC22       2.6170680611
## PC23      18.5238988178
```

We see pretty similar results. Principal components 1 & 2 seem to be statistically significant. The US stock returns tend to increase when the dollar is weaker (presumably boosting exports), and to perform weaker when the world price of oil (which is denominated in USD) increases.

4. Regression on Original FX Movements

We now run a LASSO regression on the original covariates:

```
## 24 x 1 sparse Matrix of class "dgCMatrix"
##                    seg77
## intercept     0.00597478
## australia    -0.25667784
## brazil       -0.13998420
## canada        0.15982750
## china         1.69919373
## denmark       .
## hong kong    -2.65598234
## india        -0.04012166
## japan         0.13308603
## south korea   .
## malaysia     -0.20443923
## mexico       -0.56241299
## new zealand   0.10834203
## norway        0.41301093
## singapore     0.59614902
## south africa -0.11711219
## sri lanka     0.05420333
## sweden       -0.90802974
## switzerland   .
## taiwan        .
## thailand      .
## uk            0.30215118
## venezuela    -0.05829675
## euro          .
```

When we run the regression model this way, it is very difficult to interprete the results, as the covariates are correlated (unlike the PCs, which are uncorrelated). In this particular regression, the coefficient on the Chinese currency is large at 1.69, suggesting that US stock returns tend to perform stronger when the USD appreciates against the Yuan, which is counter-intuitive given that that would make US exports more expensive.