Morningstar Risk Rating Analysis

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0.1 # Morningstar Risk Rating Analysis

Investments Dartmouth College, Winter 2019

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In this script we use a web scraper to gather daily historical closing prices of ten American mutual funds, two of which have a one-star Morningstar risk rating, two have two stars, and two have three, four, and five stars. These funds are then analyzed along with the scoring method used by Morningstar.

0.2 Imports

Standard vector based computation libraries in addition to packages necessary for web scraping, data analytics, and plotting

```
In [288]: import pandas as pd
          import numpy as np

          import quandl
          import pystan
          import pytrends

          import datetime as dt
          import pandas_datareader as web

          import matplotlib.pyplot as plt
          import matplotlib

          import time
```

```
In [262]: start = dt.datetime(2006, 1, 1)
          end = dt.datetime.now()

          Tickers = ['FDGRX', 'PMEGX', 'FLPSX', 'TRMCX', 'RSVAX', 'ODMCX', 'MSSGX', 'MPSSX', '
          tickers = Tickers

          #df = web.DataReader("VMVAX", 'yahoo', start, end)
          df = web.DataReader('WHIBX', 'yahoo', start, end)
```

0.3 Find height and length of target closing price matrix

Note, we change 'height' by changing the 'start' time from which we begin scraping data

```
In [195]: #Note, we change 'height' by changing the 'start' time from which we begin scraping 
          #Find height and width of storage matrix
          test_length = web.DataReader('WHIBX', 'yahoo', start, end)
          height = test_length.shape[0]
          length = len(Tickers)
          length = 1

          print('Number of stock prices retrieved:', height)
```

```
Number of stock prices retrieved: 3309
```

0.4 Scrape and store data in initialized matrix

```
In [196]: #initialize storage matrix
          close_price_data = pd.DataFrame(np.zeros((height, length)))
          print("Fund return matrix has dimensionality:", height, length)

          tic = time.time()
          for i in range (len(Tickers)):

              #scrape fund values from yahoo
              df = web.DataReader(Tickers[i], 'yahoo', start, end)
              #exrtract close prices from matrix
              close_price_vector = df.iloc[:, 5]
              #convert to dataframe for concatenation
              temp_price_vec = pd.DataFrame(close_price_vector)
              #store close price vector outside loop
              close_price_data = pd.concat([close_price_data, close_price_vector], axis = 1)

              print("...Gathering data on fund:", Tickers[i], "...")
              print(close_price_vector.head(3))
              print(close_price_data.shape)

          toc = time.time()
```

```
Fund return matrix has dimensionality: 3309 1
...Gathering data on fund: FDGRX ...
Date
2006-01-03    4.383930
2006-01-04    4.435291
2006-01-05    4.455565
Name: Adj Close, dtype: float64
(6618, 2)
...Gathering data on fund: PMEGX ...
```

```
Date
2006-01-03    13.688994
2006-01-04    13.820620
2006-01-05    13.836415
Name: Adj Close, dtype: float64
(6618, 3)
...Gathering data on fund: FLPSX ...
Date
2006-01-03    16.985451
2006-01-04    17.141167
2006-01-05    17.149363
Name: Adj Close, dtype: float64
(6618, 4)
...Gathering data on fund: TRMCX ...
Date
2006-01-03    9.219388
2006-01-04    9.281815
2006-01-05    9.250602
Name: Adj Close, dtype: float64
(6618, 5)
...Gathering data on fund: RSVAX ...
Date
2006-01-03     9.951518
2006-01-04    10.015538
2006-01-05     9.967520
Name: Adj Close, dtype: float64
(6618, 6)
...Gathering data on fund: ODMCX ...
Date
2006-01-03    6.213886
2006-01-04    6.281904
2006-01-05    6.285907
Name: Adj Close, dtype: float64
(6618, 7)
...Gathering data on fund: MSSGX ...
Date
2006-01-03    4.439095
2006-01-04    4.490198
2006-01-05    4.456129
Name: Adj Close, dtype: float64
(6618, 8)
...Gathering data on fund: MPSSX ...
Date
2006-01-03    7.351733
2006-01-04    7.405751
2006-01-05    7.425395
Name: Adj Close, dtype: float64
(6618, 9)
```

```
...Gathering data on fund: PAGRX ...
Date
2006-01-03    25.775120
2006-01-04    26.000015
2006-01-05    26.074186
Name: Adj Close, dtype: float64
(6618, 10)
...Gathering data on fund: SCMVX ...
Date
2006-01-03    8.452030
2006-01-04    8.496157
2006-01-05    8.540281
Name: Adj Close, dtype: float64
(6618, 11)
```

```
/anaconda3/lib/python3.6/site-packages/pandas/core/indexes/api.py:107: RuntimeWarning: Cannot c
  result = result.union(other)
```

```
In [197]: # We can use the 'time' package to measure how long it takes to train the model
          train_time = toc - tic
          secs = train_time%60
          mins = (train_time - secs)/60

          print('Time taken to scrape data was:', mins, 'minutes and', secs, 'seconds.')
```

```
Time taken to scrape data was: 0.0 minutes and 10.281468152999878 seconds.
```

0.5 Prune resulting matrix for final dataframe

Final df will contain closing prices for all of the funds with tickers stored in the vector 'Tickers'

```
In [198]: #Prune resulting matrix
          #Delete first 'height' rows of dataframe
          df1 = close_price_data.iloc[height:]
          #delete column of NANs leftover from initialization
          df2 = df1.drop(0, 1)
```

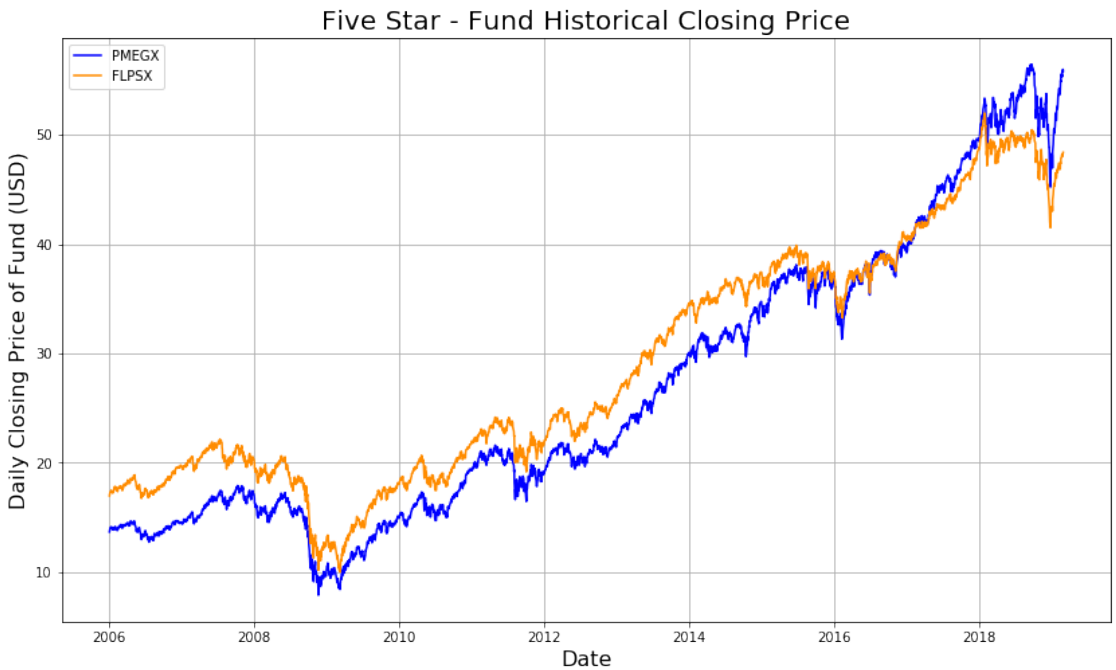
We can now observe the first five rows of our final matrix containing the columns which represent the

```
In [199]: #Resulting Matrix
          results = df2
          results.head(5)
          #results.shape
```

```
Out[199]:                      Adj Close  Adj Close  Adj Close  Adj Close  Adj Close  \
          2006-01-03 00:00:00   4.383930  13.688994  16.985451   9.219388   9.951518
          2006-01-04 00:00:00   4.435291  13.820620  17.141167   9.281815  10.015538
          2006-01-05 00:00:00   4.455565  13.836415  17.149363   9.250602   9.967520
          2006-01-06 00:00:00   4.528552  14.010160  17.292789   9.336436  10.055552
          2006-01-09 00:00:00   4.563694  14.089136  17.419819   9.387156  10.075560

                               Adj Close  Adj Close  Adj Close  Adj Close  Adj Close
          2006-01-03 00:00:00   6.213886   4.439095   7.351733  25.775120   8.452030
          2006-01-04 00:00:00   6.281904   4.490198   7.405751  26.000015   8.496157
          2006-01-05 00:00:00   6.285907   4.456129   7.425395  26.074186   8.540281
          2006-01-06 00:00:00   6.341925   4.490198   7.508883  26.478531   8.592429
          2006-01-09 00:00:00   6.389940   4.544707   7.553082  26.772821   8.680680
```

```
In [ ]: #Get S&P500 data for reference
        SP500 = test_length = web.DataReader('^GSPC', 'yahoo', start, end)
        SP500_data = SP500.iloc[:,5]
```

```
In [266]: chosen_fund = 1
          chosen_ticker = Tickers[chosen_fund]
          chosen_ticker2 = Tickers[chosen_fund+1]

          x = range(0,500)
          y = range(0,1)
          fig = plt.figure(figsize=(14, 8))
          ax1 = fig.add_subplot(111)

          plt.plot(results.iloc[:,chosen_fund], 'b', label=chosen_ticker)
          plt.plot(results.iloc[:,(chosen_fund+1)], 'darkorange', label=chosen_ticker2)
          #plt.plot(SP500_data, 'r-', label='S&P 500')
          plt.legend(loc='upper left');
          plt.xlabel('Date', fontsize = '16')
          plt.ylabel('Daily Closing Price of Fund (USD)', fontsize = '16')
          plt.title('Five Star - Fund Historical Closing Price', fontsize = '20')
          plt.grid()
```



0.6 # Analysis of Risk Rating

0.7 Average Returns

In [338]:
```
# Load CSV file from bloomberg for factors
path1='/Users/spencerbertsch/Desktop/Investments/Final Project/INVFundsTimeData.csv'
df = pd.read_csv(path1)

path2='/Users/spencerbertsch/Desktop/Investments/Final Project/Correlations.csv'
correlation_data = pd.read_csv(path2)

df.head(5)
```

Out[338]:

	Unnamed: 0	FDGRX US Equity	PMEGX US Equity	FLPSX US Equity	\
0	1/31/01	-2.1435	3.7802	6.6609	
1	2/28/01	-16.0476	-7.8193	-0.6488	
2	3/30/01	-10.5227	-9.9579	-1.9184	
3	4/30/01	11.8366	13.5752	6.5751	
4	5/31/01	0.3073	1.2365	3.3971	

	TRMCX US Equity	RSVAX US Equity	ODMCX US Equity	MSSGX US Equity	\
0	2.0460	2.3593	1.4706	6.4604	
1	-0.5639	-0.4433	-5.6897	-15.0427	
2	-3.5287	-2.5824	-7.7405	-12.1730	
3	6.4010	2.5594	10.0555	13.2875	
4	3.3763	4.9020	1.6256	1.0111	

```
   MPSSX US Equity  PAGRX US Equity  SCMVX US Equity  Mkt-RF   SMB    HML  \
0           3.0253           7.0388          12.4835    3.13  5.81  -4.90
1          -7.2222          -7.8172          -4.3453  -10.05  2.66  12.90
2          -5.0470          -7.8068          -4.7268   -7.26  2.31   6.45
3           9.5495          10.7990           5.8634    7.94 -0.64  -4.69
4           2.0559           3.1179           5.2343    0.72  3.58   3.14

    RMW   CMA    RF
0 -4.43 -6.54  0.54
1  9.00  9.58  0.38
2  3.38  3.95  0.42
3 -2.71 -3.97  0.39
4  0.18  2.19  0.32
```

In [255]:

```
fivestar =df.iloc[:, 1:3]
five_star_avg = fivestar.mean()

fourstar =df.iloc[:, 3:5]
four_star_avg = fourstar.mean()

threestar =df.iloc[:, 5:7]
three_star_avg = threestar.mean()

twostar =df.iloc[:, 7:9]
two_star_avg = twostar.mean()

onestar =df.iloc[:, 9:11]
one_star_avg = onestar.mean()

five_star_average_return = ((five_star_avg[0] + five_star_avg[1])/2)
four_star_average_return = ((four_star_avg[0] + four_star_avg[1])/2)
three_star_average_return = ((three_star_avg[0] + three_star_avg[1])/2)
two_star_average_return = ((two_star_avg[0] + two_star_avg[1])/2)
one_star_average_return = ((one_star_avg[0] + one_star_avg[1])/2)

print("Five star rated fund return:", five_star_average_return)
print("Four star rated fund return:", four_star_average_return)
print("Three star rated fund return:", three_star_average_return)
print("Two star rated fund return:", two_star_average_return)
print("One star rated fund return:", one_star_average_return)
```

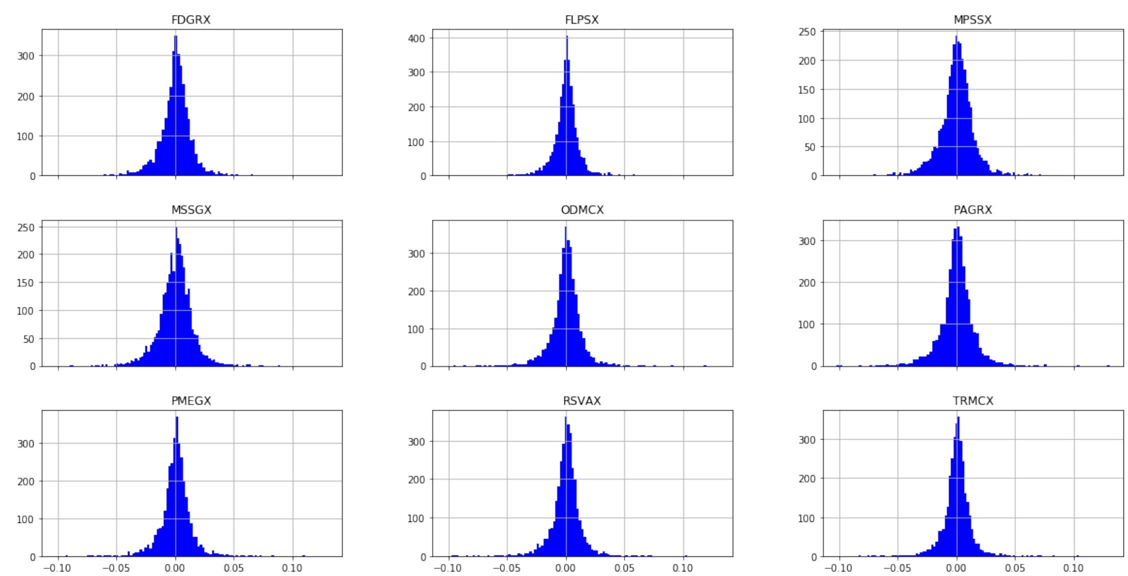
```
Five star rated fund return: 0.874926721438636
Four star rated fund return: 0.9409100376659093
Three star rated fund return: 0.7686285130568182
Two star rated fund return: 0.7383682811318182
One star rated fund return: 0.8527005435681818
```

This initial analysis would be much more informative if we had data for many, many more funds. Becasue we only have data for two funds of each morningstar rating, we can't draw signigicant conclusions from these results. Still, if the dataset were much larger (1000 funds instead of 10), we could use this same methodology to determine whether or not the funds consistently rated higher by morningstar outperformed lower rated funds.

0.8 Volatility

In [280]:
```
#Label each pandas column header
df_temp = results
header = ['FDGRX', 'PMEGX', 'FLPSX', 'TRMCX', 'RSVAX', 'ODMCX', 'MSSGX', 'MPSSX', 'PA
df_temp.columns = header
```

In [370]:
```
# Calculate the daily percentage change for `daily_close_px`
daily_fund_pct_change = df_temp.iloc[:,:9].pct_change()
# Plot the distributions
daily_fund_pct_change.hist(bins=100, sharex=True, figsize=(20,10), color='blue')

# Show the resulting plot
plt.show()
```



We can see that there is no appreciable difference in the variance (volatility) between the funds with five star ratings and those with lower ratings. This study would again be greatly imporved by increasing the size of the dataset, but this methodology could be used with much more data in oder to test the average volatility for five, four, three, two, and one star rated funds.

0.9 Covariance between funds and market factors

In [353]:
```
correlation_matrix = correlation_data.drop(['Unnamed: 0'], axis=1)
headers = list(correlation_matrix.columns.values)
```

```
correlation_data.head(5)
```

Out[353]:

```
         Unnamed: 0  FDGRX US Equity  PMEGX US Equity  FLPSX US Equity  \
0  FDGRX US Equity             1.00             0.94             0.83
1  PMEGX US Equity             0.94             1.00             0.92
2  FLPSX US Equity             0.83             0.92             1.00
3  TRMCX US Equity             0.82             0.92             0.95
4  RSVAX US Equity             0.77             0.88             0.91

   TRMCX US Equity  RSVAX US Equity  ODMCX US Equity  MSSGX US Equity  \
0             0.82             0.77             0.90             0.89
1             0.92             0.88             0.96             0.91
2             0.95             0.91             0.94             0.85
3             1.00             0.90             0.94             0.83
4             0.90             1.00             0.92             0.79

   MPSSX US Equity  PAGRX US Equity  SCMVX US Equity  Mkt-RF   SMB   HML  \
0             0.84             0.90             0.72    0.93  0.30 -0.19
1             0.91             0.94             0.80    0.95  0.41 -0.04
2             0.91             0.92             0.87    0.92  0.48  0.17
3             0.91             0.92             0.89    0.93  0.45  0.25
4             0.86             0.86             0.82    0.86  0.45  0.18

    RMW   CMA    RF   UMD
0 -0.64 -0.30 -0.11 -0.36
1 -0.58 -0.21 -0.08 -0.41
2 -0.49 -0.04 -0.04 -0.43
3 -0.49  0.03 -0.06 -0.47
4 -0.44 -0.02 -0.07 -0.32
```

In [354]:

```
correlation_matrix = correlation_data.drop(['Unnamed: 0'], axis=1)

print(correlation_matrix.shape)
correlation_matrix
```

```
(17, 17)
```

Out[354]:

```
    FDGRX US Equity  PMEGX US Equity  FLPSX US Equity  TRMCX US Equity  \
0          1.000000         0.940000          0.83000         0.820000
1          0.940000         1.000000          0.92000         0.920000
2          0.830000         0.920000          1.00000         0.950000
3          0.820000         0.920000          0.95000         1.000000
4          0.770000         0.880000          0.91000         0.900000
5          0.900000         0.960000          0.94000         0.940000
6          0.890000         0.910000          0.85000         0.830000
7          0.840000         0.910000          0.91000         0.910000
8          0.900000         0.940000          0.92000         0.920000
```

9	0.720000	0.800000	0.87000	0.890000
10	0.930000	0.950000	0.92000	0.930000
11	0.300000	0.410000	0.48000	0.450000
12	-0.190000	-0.040000	0.17000	0.250000
13	-0.640000	-0.580000	-0.49000	-0.490000
14	-0.300000	-0.210000	-0.04000	0.030000
15	-0.110000	-0.080000	-0.04000	-0.060000
16	-0.362118	-0.412834	-0.43378	-0.470003

	RSVAX US Equity	ODMCX US Equity	MSSGX US Equity	MPSSX US Equity	\
0	0.770000	0.900000	0.890000	0.840000	
1	0.880000	0.960000	0.910000	0.910000	
2	0.910000	0.940000	0.850000	0.910000	
3	0.900000	0.940000	0.830000	0.910000	
4	1.000000	0.920000	0.790000	0.860000	
5	0.920000	1.000000	0.890000	0.930000	
6	0.790000	0.890000	1.000000	0.900000	
7	0.860000	0.930000	0.900000	1.000000	
8	0.860000	0.940000	0.870000	0.900000	
9	0.820000	0.840000	0.780000	0.880000	
10	0.860000	0.950000	0.890000	0.900000	
11	0.450000	0.440000	0.520000	0.630000	
12	0.180000	0.070000	-0.090000	0.150000	
13	-0.440000	-0.510000	-0.600000	-0.500000	
14	-0.020000	-0.120000	-0.270000	-0.090000	
15	-0.070000	-0.090000	-0.080000	-0.070000	
16	-0.324771	-0.362709	-0.385288	-0.310412	

	PAGRX US Equity	SCMVX US Equity	Mkt-RF	SMB	HML	RMW	\
0	0.900000	0.720000	0.930000	0.300000	-0.190000	-0.640000	
1	0.940000	0.800000	0.950000	0.410000	-0.040000	-0.580000	
2	0.920000	0.870000	0.920000	0.480000	0.170000	-0.490000	
3	0.920000	0.890000	0.930000	0.450000	0.250000	-0.490000	
4	0.860000	0.820000	0.860000	0.450000	0.180000	-0.440000	
5	0.940000	0.840000	0.950000	0.440000	0.070000	-0.510000	
6	0.870000	0.780000	0.890000	0.520000	-0.090000	-0.600000	
7	0.900000	0.880000	0.900000	0.630000	0.150000	-0.500000	
8	1.000000	0.840000	0.950000	0.410000	0.070000	-0.560000	
9	0.840000	1.000000	0.820000	0.610000	0.310000	-0.540000	
10	0.950000	0.820000	1.000000	0.300000	0.040000	-0.570000	
11	0.410000	0.610000	0.300000	1.000000	0.200000	-0.310000	
12	0.070000	0.310000	0.040000	0.200000	1.000000	0.150000	
13	-0.560000	-0.540000	-0.570000	-0.310000	0.150000	1.000000	
14	-0.130000	0.070000	-0.160000	0.090000	0.570000	0.170000	
15	-0.050000	-0.060000	-0.130000	0.020000	0.070000	0.070000	
16	-0.438596	-0.483535	-0.446533	-0.153414	-0.054572	0.477448	

CMA RF UMD

```
0  -0.300000 -0.110000 -0.36
1  -0.210000 -0.080000 -0.41
2  -0.040000 -0.040000 -0.43
3   0.030000 -0.060000 -0.47
4  -0.020000 -0.070000 -0.32
5  -0.120000 -0.090000 -0.36
6  -0.270000 -0.080000 -0.39
7  -0.090000 -0.070000 -0.31
8  -0.130000 -0.050000 -0.44
9   0.070000 -0.060000 -0.48
10 -0.160000 -0.130000 -0.45
11  0.090000  0.020000 -0.15
12  0.570000  0.070000 -0.05
13  0.170000  0.070000  0.48
14  1.000000  0.020000  0.15
15  0.020000  1.000000  0.03
16  0.146514  0.033822  1.00
```

In [355]:
```
type(correlation_matrix.values[1,1])
```

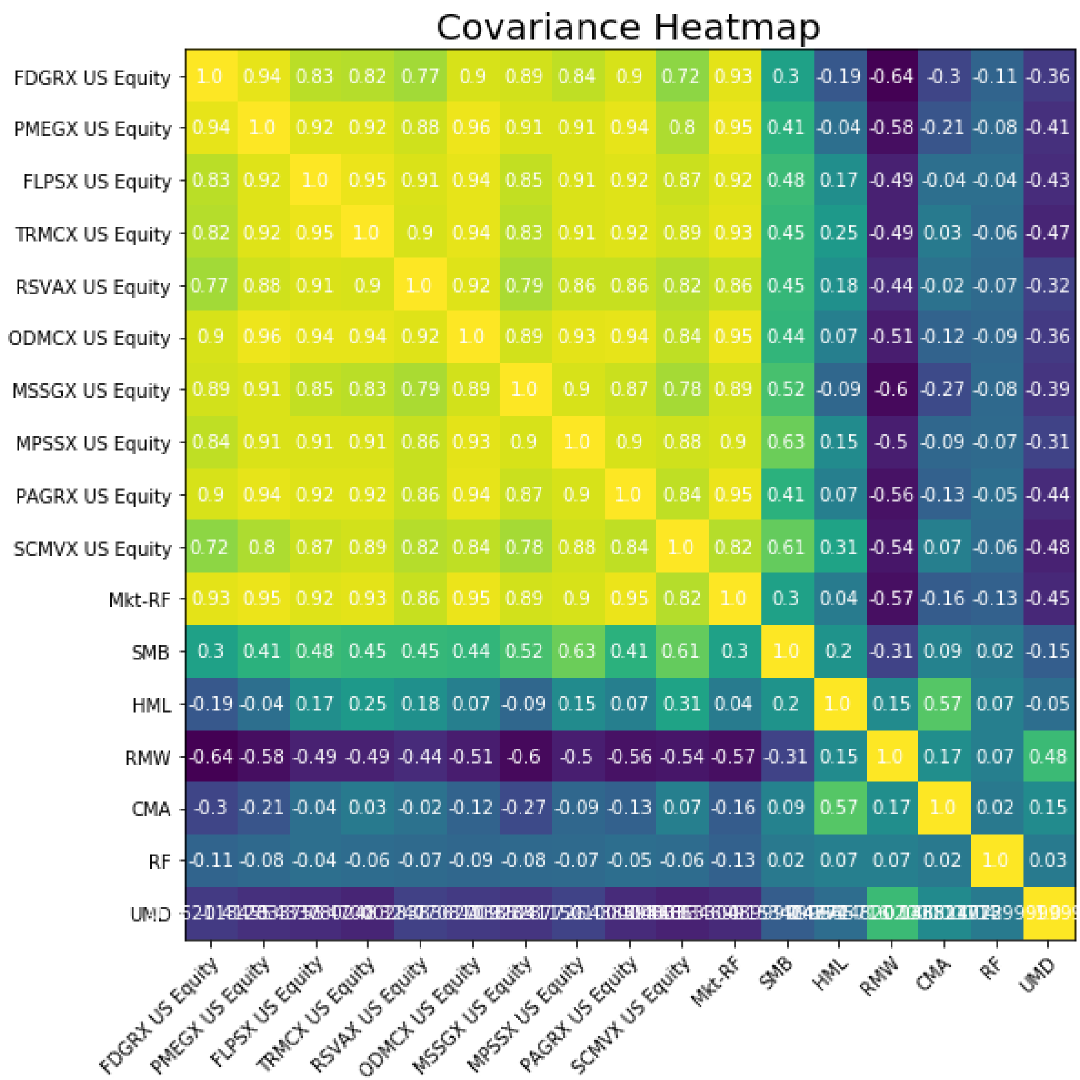
Out[355]: numpy.float64

In [356]:
```
len(farmers)
```

Out[356]: 18

In [371]:
```
data = correlation_matrix.values

#fig = plt.figure(figsize=(8, 8))
#ax1 = fig.add_subplot(111)

fig, ax = plt.subplots(figsize=(9, 9))
im = ax.imshow(harvest)

# We want to show all ticks...
ax.set_xticks(np.arange(len(headers)))
ax.set_yticks(np.arange(len(headers)))
# ... and label them with the respective list entries
ax.set_xticklabels(headers)
ax.set_yticklabels(headers)

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

# Loop over data dimensions and create text annotations.
for i in range(len(headers)):
    for j in range(len(headers)):
        text = ax.text(j, i, data[i, j],
```

```
                    ha="center", va="center", color="w")

ax.set_title("Covariance Heatmap", fontsize = 20)
#fig.tight_layout()
plt.show()
```



We can see from the above covariance matrix that, as expected, our chosen index funds are highly correlated with eachother. We can also see that each fund is strongly negatively correlated with RMW, and relatively highly correlated with SMB. By expanding this analysis to a larger amount of funds, we could develop a more complete analysis of which market factors are used more by morningstar to rate the funds in question. Still, it's useful to see the relative correlation of differently rated funds with each of the FF5 and momentum factors.

Note that, with this limited number of funds being analyzed, there is no appreciable difference in correlation with market factors for funds with different morningstar ratings.