Stock_Prices

September 1, 2020

1 Stock Price Exploration & Analysis - Kaushal Rao

1.0.1 This analysis focuses on bank stocks and and how they progressed through the financial crisis (2007-2008) all the way until early 2016. More information on the financial crisis can be found here: https://en.wikipedia.org/wiki/Financial_crisis_of_2007%E2%80%932008.

1.0.2 For this project, we will be using pandas to directly read in data from Stooq.

```
In [1]: from pandas_datareader import data, wb
        import pandas as pd
        import numpy as np
        import datetime
        import seaborn as sns
        %matplotlib inline
        # importing relevant modules
```

1.1 Data

We need to get data using pandas datareader. We will get stock information for the following banks: * Bank of America * CitiGroup * Goldman Sachs * JPMorgan Chase * Morgan Stanley * Wells Fargo

```
In [2]: start = datetime.datetime(2006, 1, 1)
        end = datetime.datetime(2016, 1, 1)
        # relevant timeframe
```

```
In [3]: # Bank of America
        BAC = data.DataReader("BAC", 'stooq', start, end)

        # CitiGroup
        C = data.DataReader("C", 'stooq', start, end)

        # Goldman Sachs
        GS = data.DataReader("GS", 'stooq', start, end)

        # JPMorgan Chase
        JPM = data.DataReader("JPM", 'stooq', start, end)
```

```python
# Morgan Stanley
MS = data.DataReader("MS", 'stooq', start, end)

# Wells Fargo
WFC = data.DataReader("WFC", 'stooq', start, end)

# importing data
```

In [4]:
```python
df = data.DataReader(['BAC', 'C', 'GS', 'JPM', 'MS', 'WFC'],'stooq', start, end)
```

In [5]:
```python
tickers = ['BAC', 'C', 'GS', 'JPM', 'MS', 'WFC']
# creating a list of ticker symbols (as strings) in alphabetical order
```

In [6]:
```python
bank_stocks = pd.concat([BAC, C, GS, JPM, MS, WFC],axis=1,keys=tickers)
# concatenating bank dataframes together into a single dataframe
# keys is set to the tickers list
```

In [7]:
```python
bank_stocks.columns.names = ['Bank Ticker','Stock Info']
# setting column name levels
```

In [8]:
```python
bank_stocks.head()
```

Out[8]:
```
Bank Ticker     BAC                                                C          \
Stock Info     Open    High     Low   Close      Volume    Open    High
Date
2006-01-03   41.731  41.958  41.044  41.872  18323290.0  440.07  443.45
2006-01-04   41.801  42.017  41.312  41.428  19966326.0  438.82  440.96
2006-01-05   41.428  41.650  41.197  41.481  16666543.0  435.02  438.07
2006-01-06   41.622  41.721  41.225  41.419  14161016.0  438.98  439.15
2006-01-09   41.552  41.775  41.232  41.446  17561765.0  436.45  437.71

Bank Ticker                                ...      MS                          \
Stock Info      Low   Close     Volume     ...    Open    High     Low   Close
Date                                       ...
2006-01-03   432.05  442.67  1712139.0  ...  40.034  40.954  39.727  40.827
2006-01-04   434.20  434.48  2083320.0  ...  41.106  41.510  40.860  40.860
2006-01-05   434.66  436.62  1264127.0  ...  40.860  41.028  40.622  40.971
2006-01-06   432.87  436.62  1525744.0  ...  41.154  41.205  40.649  41.012
2006-01-09   433.75  434.57  1871527.0  ...  41.051  41.518  41.043  41.441

Bank Ticker                  WFC
Stock Info      Volume    Open    High     Low   Close      Volume
Date
2006-01-03   6374568.0  23.702  23.986  23.403  23.927  14687538.0
2006-01-04   9457881.0  23.849  23.864  23.520  23.649  14492354.0
2006-01-05   6849966.0  23.626  23.664  23.482  23.626  13507351.0
2006-01-06   8168027.0  23.689  23.829  23.545  23.760  11204308.0
2006-01-09   4913405.0  23.760  23.864  23.664  23.760   7492296.0

[5 rows x 30 columns]
```

1.2 Exploratory Data Analysis (EDA)

```
In [9]: bank_stocks.xs(key='Close',axis=1,level='Stock Info').max()
        # max close price for each bank's stock during the time period
```

```
Out[9]: Bank Ticker
        BAC      48.825
        C       506.600
        GS      215.190
        JPM      61.008
        MS       62.530
        WFC      49.079
        dtype: float64
```

```
In [10]: returns = pd.DataFrame()
         # creating a new dataframe to contain the returns for each bank's stock
```

Returns are typically defined by:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} = \frac{p_t}{p_{t-1}} - 1$$

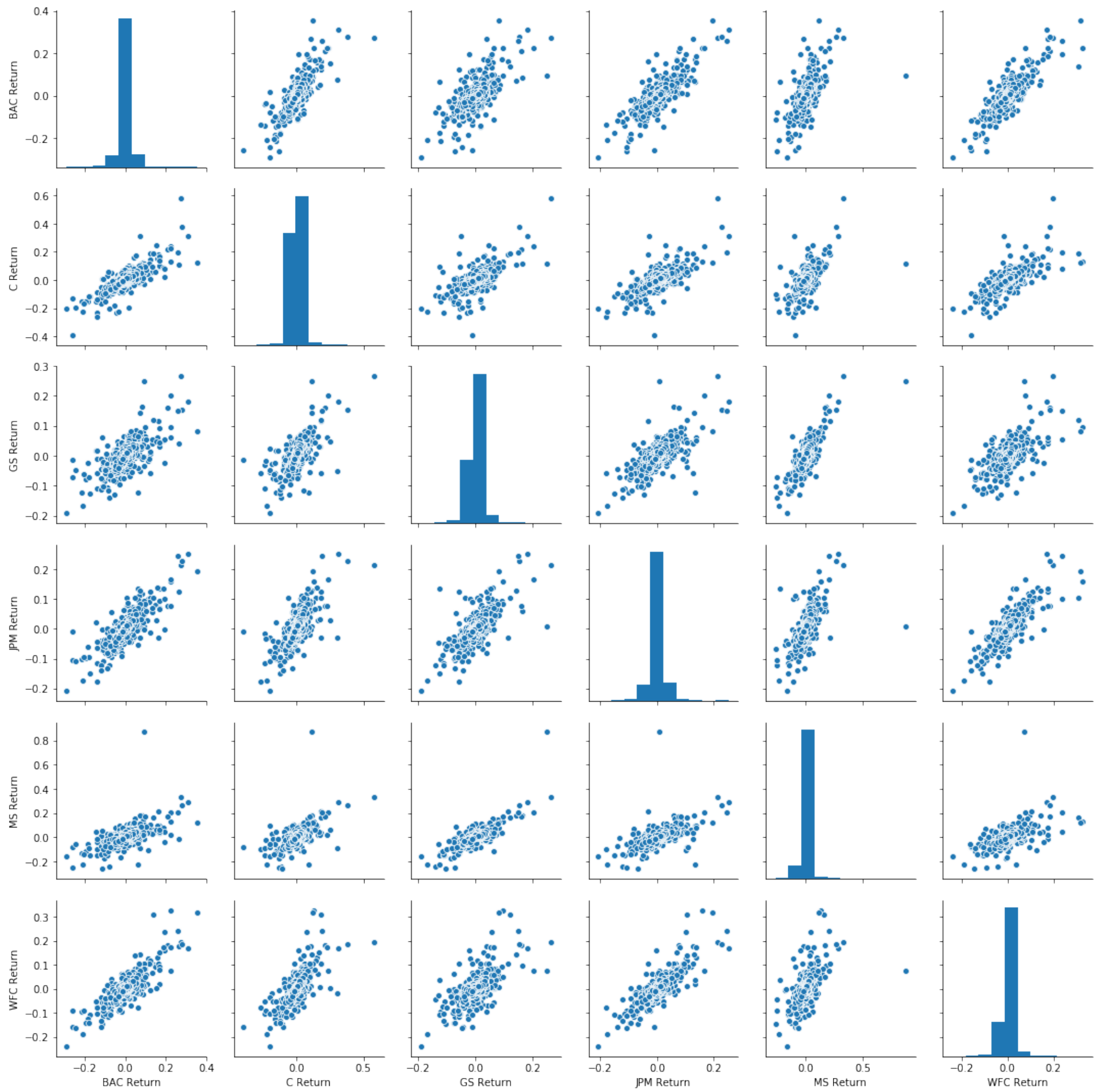
```
In [11]: for tick in tickers:
             returns[tick+' Return'] = bank_stocks[tick]['Close'].pct_change()
         returns.head()
         # returns values in terms of percentages
```

Out[11]:

Date	BAC Return	C Return	GS Return	JPM Return	MS Return	WFC Return
2006-01-03	NaN	NaN	NaN	NaN	NaN	NaN
2006-01-04	-0.010604	-0.018501	-0.013590	-0.014228	0.000808	-0.011619
2006-01-05	0.001279	0.004925	-0.000363	0.003051	0.002717	-0.000973
2006-01-06	-0.001495	0.000000	0.013873	0.007064	0.001001	0.005672
2006-01-09	0.000652	-0.004695	0.012162	0.016236	0.010460	0.000000

```
In [12]: sns.pairplot(returns[1:])
         # plotting pairplot of stock returns
```

```
Out[12]: <seaborn.axisgrid.PairGrid at 0x1a1dc765c0>
```




```
In [13]: # worst drop for the stocks (4 of them on Obama's inauguration day)
         returns.idxmin()
```

```
Out[13]: BAC Return    2009-01-20
         C Return      2009-02-27
         GS Return     2009-01-20
         JPM Return    2009-01-20
         MS Return     2008-10-09
         WFC Return    2009-01-20
         dtype: datetime64[ns]
```

```
In [14]: # best single day gain
         # Citigroup stock split in May 2011, but also JPM day after inauguration.
         returns.idxmax()
```

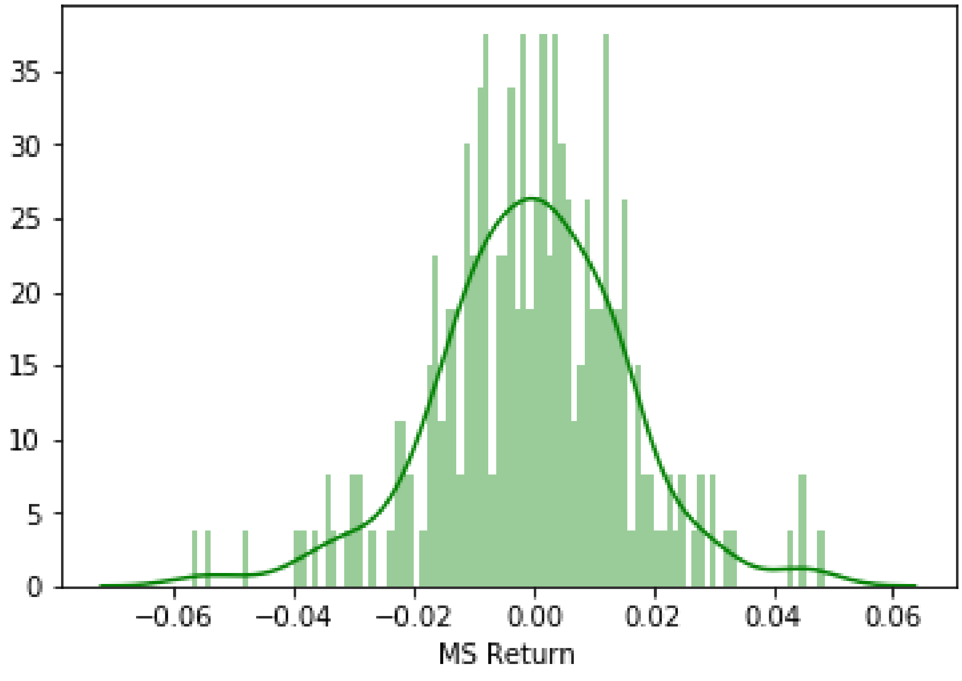
```
Out[14]: BAC Return   2009-04-09
         C Return     2008-11-24
         GS Return    2008-11-24
         JPM Return   2009-01-21
         MS Return    2008-10-13
         WFC Return   2008-07-16
         dtype: datetime64[ns]
```

```
In [15]: returns.std()
         # Citigroup riskiest in this time period, highest std
```

```
Out[15]: BAC Return    0.036604
         C Return      0.038616
         GS Return     0.025370
         JPM Return    0.027668
         MS Return     0.037705
         WFC Return    0.030220
         dtype: float64
```

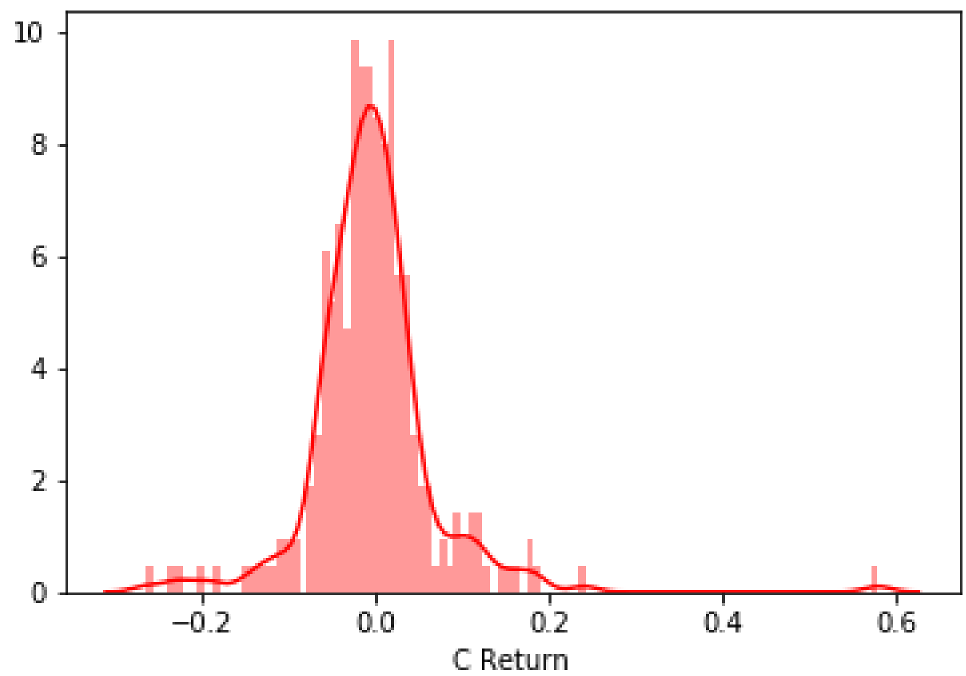
```
In [16]: sns.distplot(returns.loc['2015-01-01':'2015-12-31']['MS Return'],color='green',bins=1(
         # 2015 returns of Morgan Stanley
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1a20182710>
```




```
In [17]: sns.distplot(returns.loc['2008-01-01':'2008-12-31']['C Return'],color='red',bins=100)
         # 2008 returns for Citigroup
```

```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x1a20832b70>
```



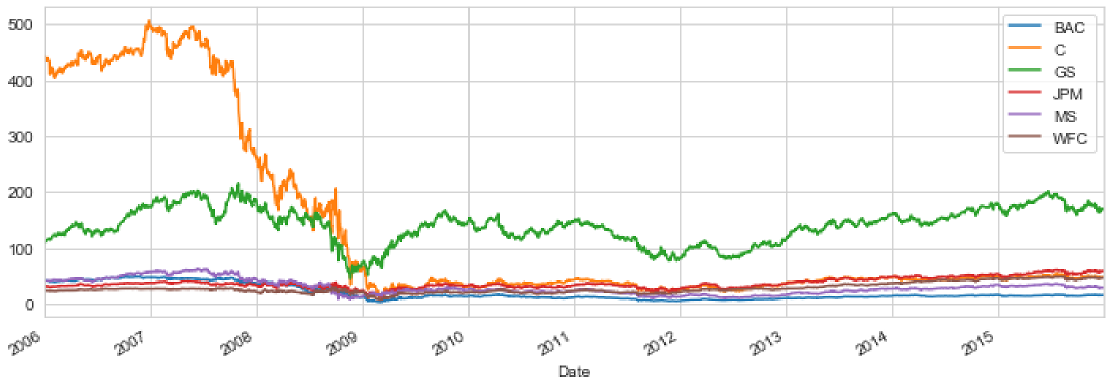
1.3 More Visualization

```
In [18]: import matplotlib.pyplot as plt
         sns.set_style('whitegrid')
         %matplotlib inline

         # Optional Plotly Method Imports
         import plotly
         import cufflinks as cf
         cf.go_offline()
```

```
In [19]: for tick in tickers:
             bank_stocks[tick]['Close'].plot(figsize=(12,4),label=tick)
         plt.legend()
         # line plot showing close price for each bank in the time period
         # Citigroup didn't recover from their 2008-2009 crash in the time period
```

```
Out[19]: <matplotlib.legend.Legend at 0x1c226ab470>
```

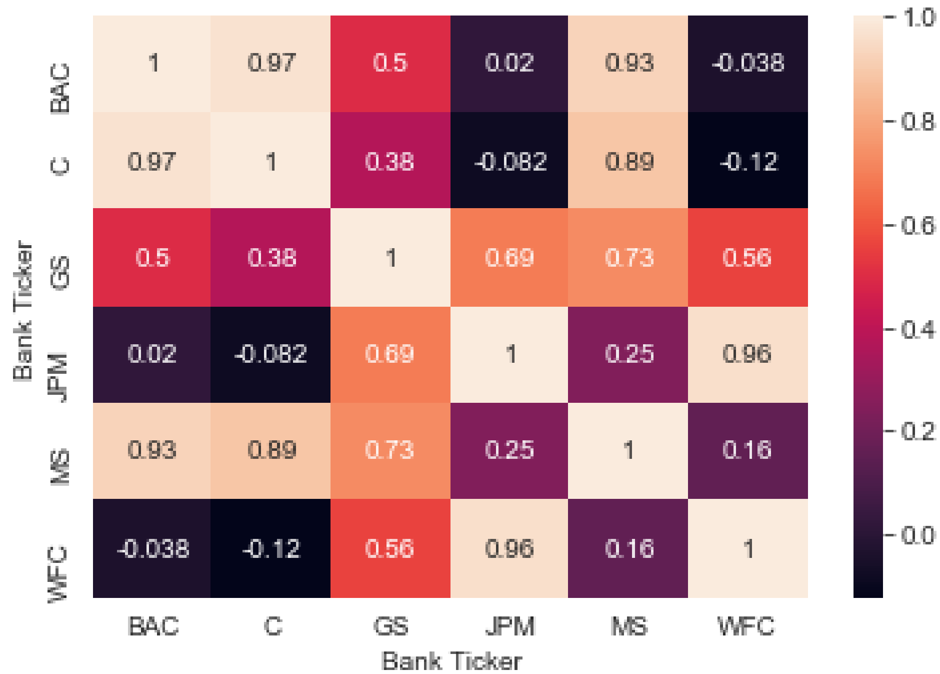



```
In [20]: # plotly iplot
         bank_stocks.xs(key='Close',axis=1,level='Stock Info').iplot()
```

1.4 Heatmaps

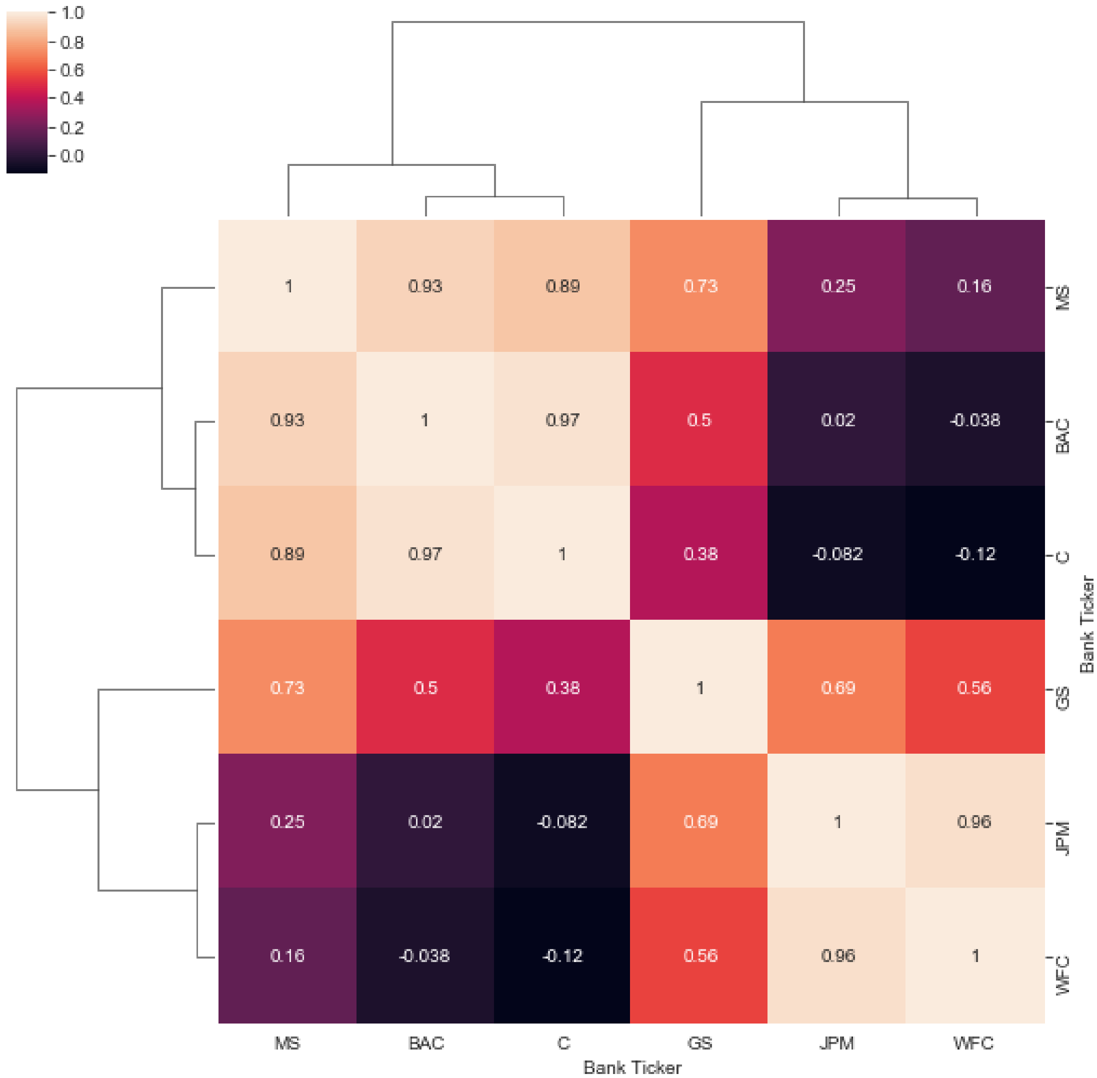
```
In [21]: sns.heatmap(bank_stocks.xs(key='Close',axis=1,level='Stock Info').corr(),annot=True)
         # heatmap of the correlation between stocks' close price
```

```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1c23654eb8>
```



In [22]: sns.clustermap(bank_stocks.xs(key='Close',axis=1,level='Stock Info').corr(),annot=True)
clustermap

Out[22]: <seaborn.matrix.ClusterGrid at 0x1c2280af98>




```
In [23]: close_corr = bank_stocks.xs(key='Close',axis=1,level='Stock Info').corr()
         close_corr.iplot(kind='heatmap',colorscale='rdylbu')
         # plotly iplot of correlations

In [ ]:
```