

Finance Project

November 28, 2017

1 Finance Data Project

In this data project, I focused on exploratory data analysis of stock prices. Keep in mind, this project is just meant to practice my visualization and pandas skills, it is not meant to be a robust financial analysis or be taken as financial advice. I focused on bank stocks and see how they progressed throughout the financial crisis all the way to early 2016. ____ We'll focus on bank stocks and see how they progressed throughout the [financial crisis](#) all the way to early 2016.

1.1 Get the Data

I used pandas to directly read data from Google finance!

```
In [1]: from pandas_datareader import data, wb
import pandas as pd
import numpy as np
import datetime
%matplotlib inline
```

1.2 Data

I retrieved the data using pandas datareader. Stock information for the following banks: * Bank of America * CitiGroup * Goldman Sachs * JPMorgan Chase * Morgan Stanley * Wells Fargo

** Stock data from Jan 1st 2006 to Jan 1st 2016 for each of these banks. Set each bank to be a separate dataframe, with the variable name for that bank being its ticker symbol. This will involve a few steps:** 1. Use datetime to set start and end datetime objects. 2. Figure out the ticker symbol for each bank. 2. Figure out how to use datareader to grab info on the stock.

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

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

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

# Goldman Sachs
```

```

GS = data.DataReader("GS", 'google', start, end)

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

# Morgan Stanley
MS = data.DataReader("MS", 'google', start, end)

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

In [4]: # Could also do this for a Panel Object
df = data.DataReader(['BAC', 'C', 'GS', 'JPM', 'MS', 'WFC'], 'google', start, end)

** Created a list of the ticker symbols (as strings) in alphabetical order.**

In [5]: tickers = ['BAC', 'C', 'GS', 'JPM', 'MS', 'WFC']

** Used pd.concat to concatenate the bank dataframes together to a single data frame called
bank_stocks. Set the keys argument equal to the tickers list.**

In [6]: bank_stocks = pd.concat([BAC, C, GS, JPM, MS, WFC], axis=1, keys=tickers)

** Column name levels.**

In [7]: bank_stocks.columns.names = ['Bank Ticker', 'Stock Info']

** The head of the bank_stocks dataframe.**

In [8]: bank_stocks.head()

```

Out [8]:	Bank Ticker	BAC					C					\
	Stock Info	Open	High	Low	Close	Volume	Open	High	Low	Close		
	Date											
	2006-01-03	46.92	47.18	46.15	47.08	16296700	490.0	493.8	481.1	492.9		
	2006-01-04	47.00	47.24	46.45	46.58	17757900	488.6	491.0	483.5	483.8		
	2006-01-05	46.58	46.83	46.32	46.64	14970900	484.4	487.8	484.0	486.2		
	2006-01-06	46.80	46.91	46.35	46.57	12599800	488.8	489.0	482.0	486.2		
	2006-01-09	46.72	46.97	46.36	46.60	15620000	486.0	487.4	483.0	483.9		

	Bank Ticker		...	MS				WFC	\
	Stock Info	Volume	...	Open	High	Low	Close	Volume	Open
	Date		...						
	2006-01-03	1537660	...	57.17	58.49	56.74	58.31	5377000	31.60
	2006-01-04	1871020	...	58.70	59.28	58.35	58.35	7977800	31.80
	2006-01-05	1143160	...	58.55	58.59	58.02	58.51	5778000	31.50
	2006-01-06	1370250	...	58.77	58.85	58.05	58.57	6889800	31.58
	2006-01-09	1680740	...	58.63	59.29	58.62	59.19	4144500	31.68

Bank Ticker					
Stock Info	High	Low	Close	Volume	
Date					
2006-01-03	31.98	31.20	31.90	11016400	
2006-01-04	31.82	31.36	31.53	10871000	
2006-01-05	31.56	31.31	31.50	10158000	
2006-01-06	31.78	31.38	31.68	8403800	
2006-01-09	31.82	31.56	31.68	5619600	

[5 rows x 30 columns]

2 EDA

Used [Multi-Level Indexing](#) and [Using .xs](#).

**** The max Close price for each bank's stock throughout the time period.****

```
In [9]: bank_stocks.xs(key='Close',axis=1,level='Stock Info').max()
```

```
Out [9]: Bank Ticker
BAC      54.90
C        564.10
GS       247.92
JPM       70.08
MS        89.30
WFC       58.52
dtype: float64
```

**** Created a new empty DataFrame called returns. This dataframe will 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 [10]: returns = pd.DataFrame()
```

**** Used pct_change() method on the Close column to create a column representing this return value.****

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

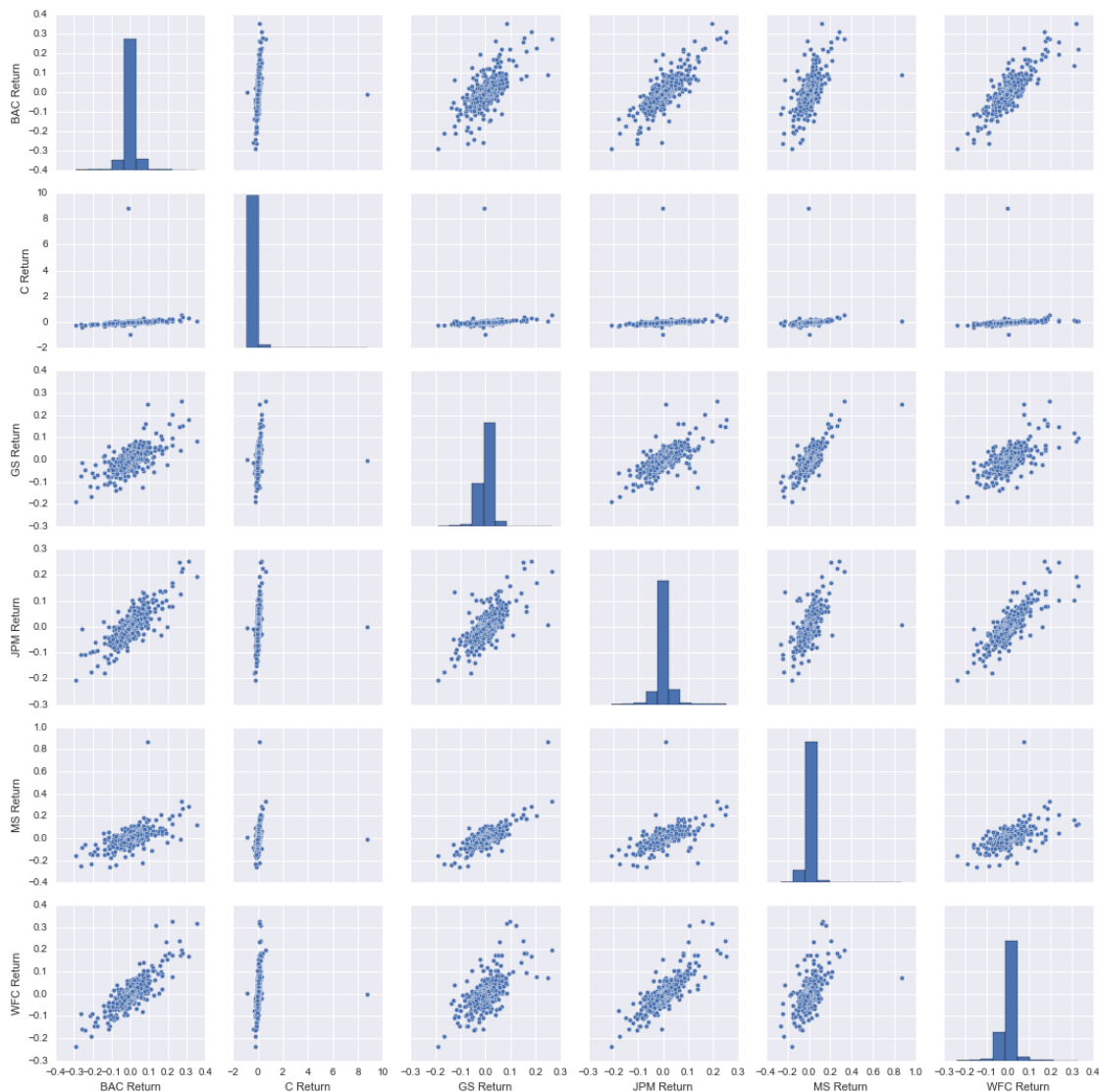
```
Out [11]:
```

	BAC Return	C Return	GS Return	JPM Return	MS Return	WFC Return
Date						
2006-01-03	NaN	NaN	NaN	NaN	NaN	NaN
2006-01-04	-0.010620	-0.018462	-0.013812	-0.014183	0.000686	-0.011599
2006-01-05	0.001288	0.004961	-0.000393	0.003029	0.002742	-0.000951
2006-01-06	-0.001501	0.000000	0.014169	0.007046	0.001025	0.005714
2006-01-09	0.000644	-0.004731	0.012030	0.016242	0.010586	0.000000

**** Create a pairplot using seaborn of the returns dataframe. What stock stands out to you? Can you figure out why?****

```
In [13]: #returns[1:]
import seaborn as sns
sns.pairplot(returns[1:])
```

Out[13]: <seaborn.axisgrid.PairGrid at 0x113fb4da0>



Background on [Citigroup's Stock Crash](#) available [here](#).

I noticed the enormous crash in value once I took a look at the stock price plot.

**** Using this returns DataFrame, I figured out on what dates each bank stock had the best and worst single day returns. I noticed that 4 of the banks share the same day for the worst drop...their worst day was Inauguration day!****

```
In [14]: # Worst Drop (4 of them on Inauguration day)
         returns.idxmin()
```

```
Out[14]: BAC Return    2009-01-20
         C Return      2011-05-06
         GS Return     2009-01-20
         JPM Return    2009-01-20
         MS Return     2008-10-09
         WFC Return    2009-01-20
         dtype: datetime64[ns]
```

****** I noticed that Citigroup's largest drop and biggest gain were very close to one another. Something significant happened... ******

Citigroup had a stock split.

```
In [15]: # Best Single Day Gain
         # citigroup stock split in May 2011, but also JPM day after inauguration.
         returns.idxmax()
```

```
Out[15]: BAC Return    2009-04-09
         C Return      2011-05-09
         GS Return     2008-11-24
         JPM Return    2009-01-21
         MS Return     2008-10-13
         WFC Return    2008-07-16
         dtype: datetime64[ns]
```

****** Standard deviation of the returns, I noticed that Citigroup classified as the riskiest over the entire time period.******

```
In [16]: returns.std() # Citigroup riskiest
```

```
Out[16]: BAC Return    0.036650
         C Return      0.179969
         GS Return     0.025346
         JPM Return    0.027656
         MS Return     0.037820
         WFC Return    0.030233
         dtype: float64
```

```
In [17]: returns.ix['2015-01-01':'2015-12-31'].std() # Very similar risk profiles, but Morgan .
```

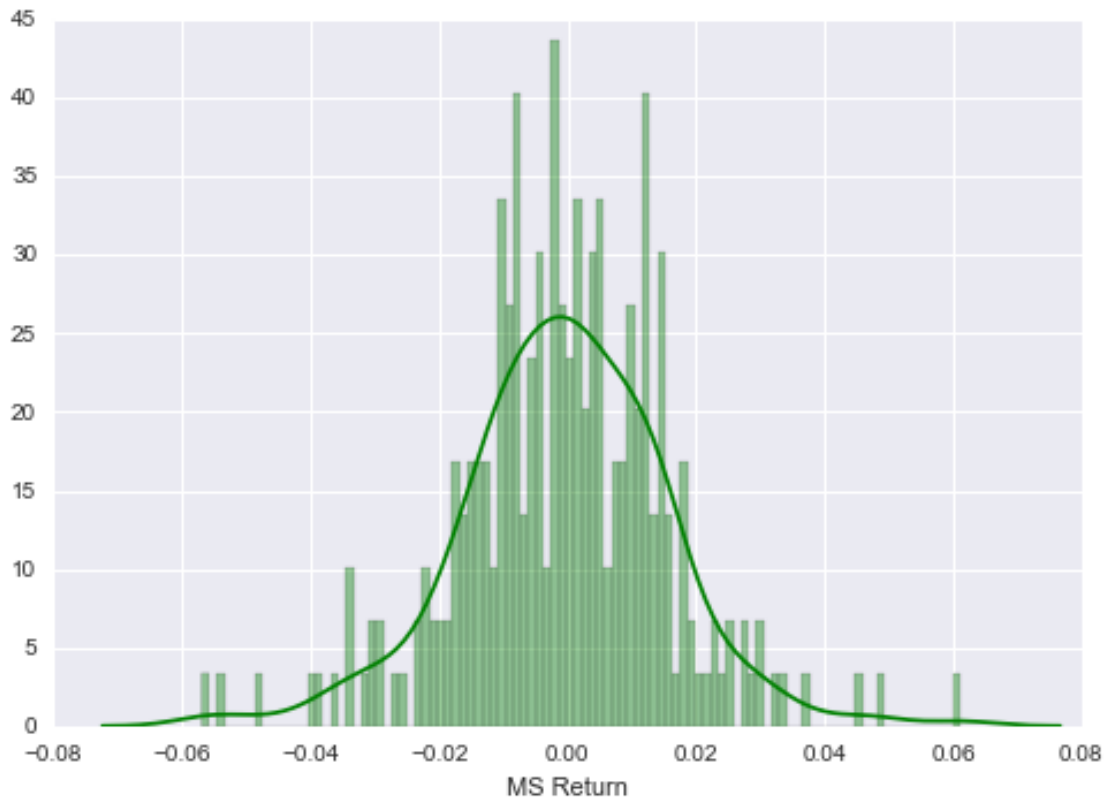
```
Out[17]: BAC Return    0.016163
         C Return      0.015289
         GS Return     0.014046
         JPM Return    0.014017
         MS Return     0.016249
         WFC Return    0.012591
         dtype: float64
```

**** Created a distplot using seaborn of the 2015 returns for Morgan Stanley ****

```
In [18]: sns.distplot(returns.ix['2015-01-01':'2015-12-31']['MS Return'],color='green',bins=100)
```

```
/Users/marci/anaconda/lib/python3.5/site-packages/statsmodels/nonparametric/kdetools.py:20: Vi  
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x11cc84828>
```

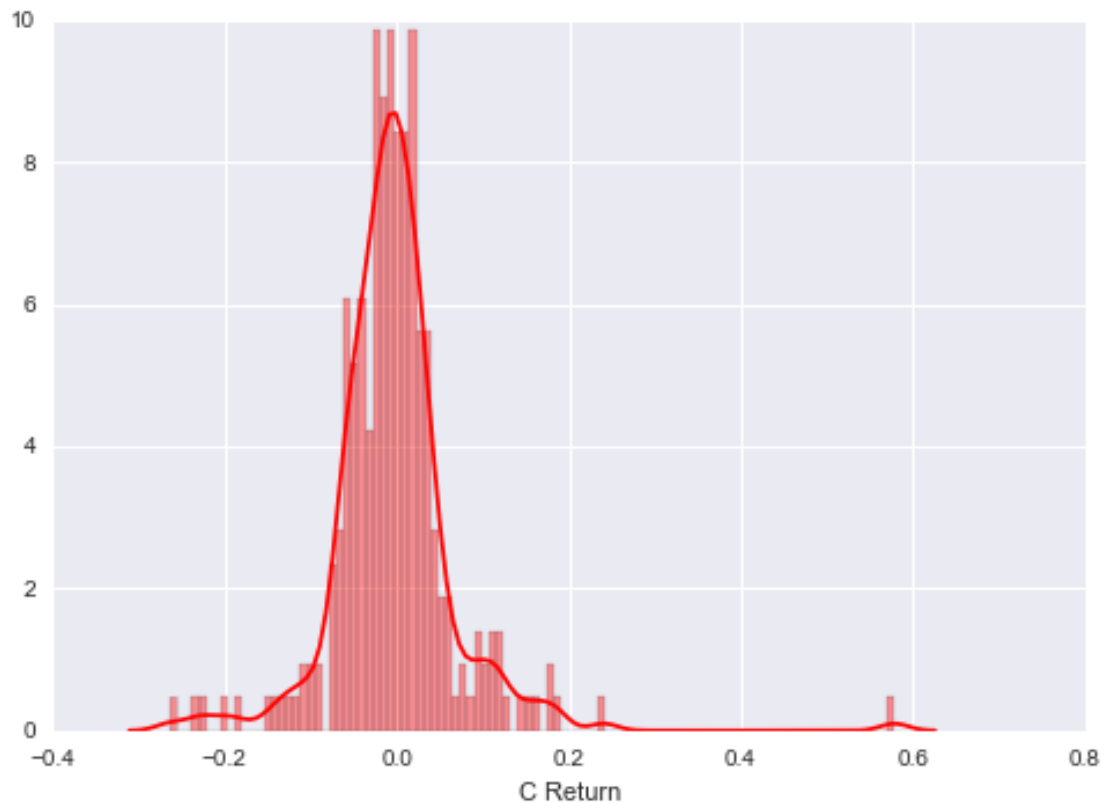


**** Created a distplot using seaborn of the 2008 returns for CitiGroup ****

```
In [19]: sns.distplot(returns.ix['2008-01-01':'2008-12-31']['C Return'],color='red',bins=100)
```

```
/Users/marci/anaconda/lib/python3.5/site-packages/statsmodels/nonparametric/kdetools.py:20: Vi  
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

```
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x11efb9518>
```



3 More Visualization

A lot of this project will focus on visualizations: seaborn, matplotlib, plotly and cufflinks, or just pandas.

```
In [20]: import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
%matplotlib inline

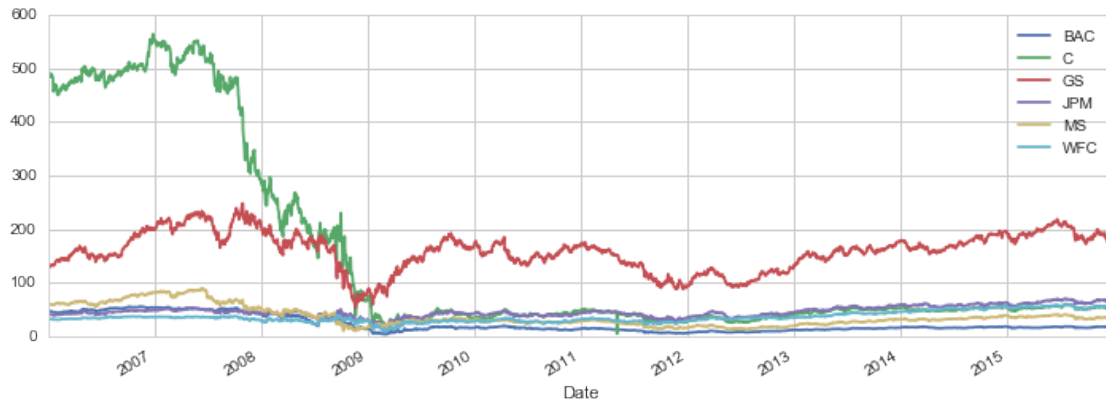
# Optional Plotly Method Imports
import plotly
import cufflinks as cf
cf.go_offline()
```

<IPython.core.display.HTML object>

**** Create a line plot showing Close price for each bank for the entire index of time. ****

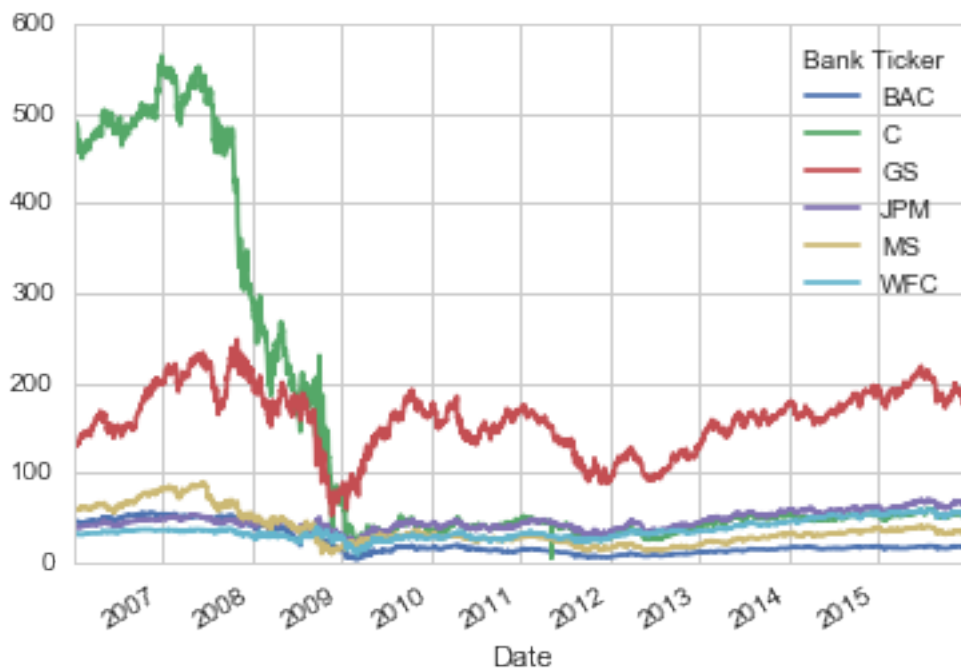
```
In [21]: for tick in tickers:
          bank_stocks[tick]['Close'].plot(figsize=(12,4),label=tick)
          plt.legend()
```

Out[21]: <matplotlib.legend.Legend at 0x116137748>



```
In [22]: bank_stocks.xs(key='Close',axis=1,level='Stock Info').plot()
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x11f7bd908>




```
In [23]: # plotly
bank_stocks.xs(key='Close',axis=1,level='Stock Info').iplot()
```

<IPython.core.display.HTML object>

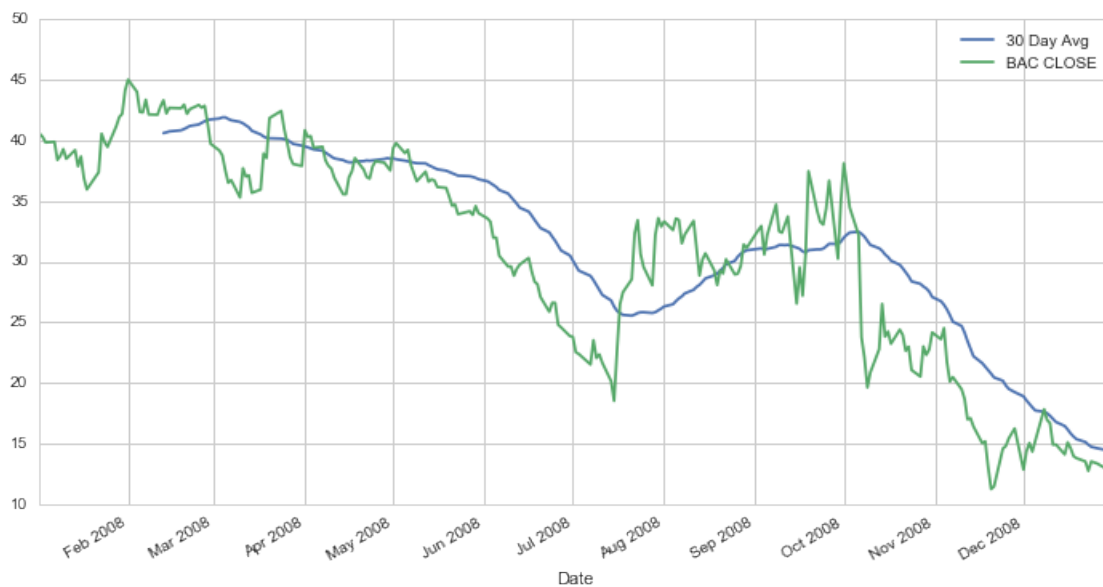
3.1 Moving Averages

I analyzed the moving averages for these stocks in the year 2008.

**** Plot the rolling 30 day average against the Close Price for Bank Of America's stock for the year 2008****

```
In [24]: plt.figure(figsize=(12,6))
BAC['Close'].ix['2008-01-01':'2009-01-01'].rolling(window=30).mean().plot(label='30 Day Avg')
BAC['Close'].ix['2008-01-01':'2009-01-01'].plot(label='BAC CLOSE')
plt.legend()
```

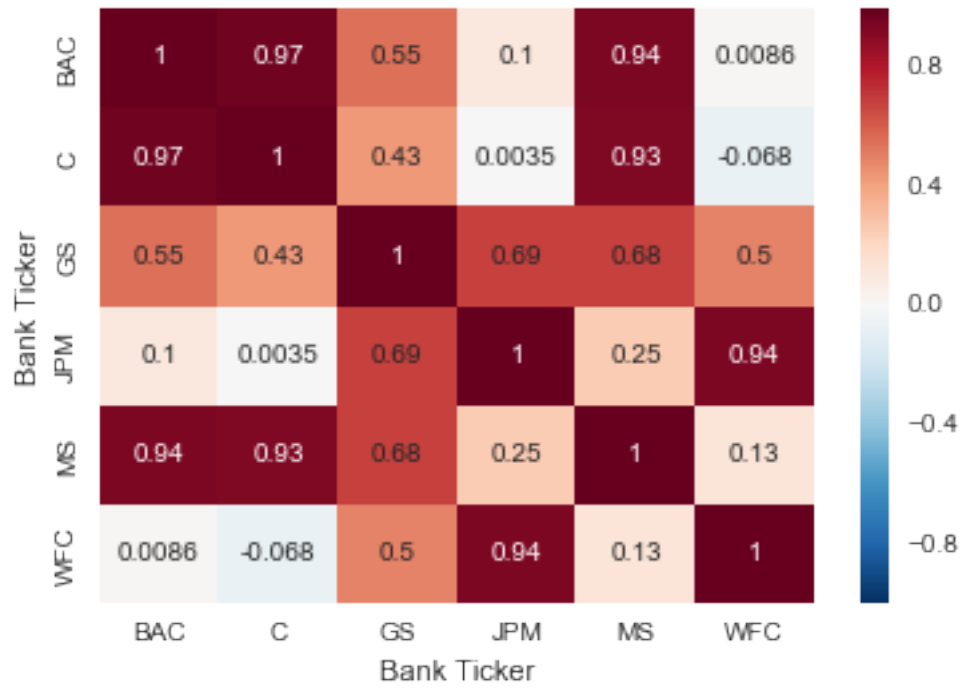
Out[24]: <matplotlib.legend.Legend at 0x11f966cf8>



**** Created a heatmap of the correlation between the stocks Close Price.****

```
In [25]: sns.heatmap(bank_stocks.xs(key='Close',axis=1,level='Stock Info').corr(),annot=True)
```

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x12045e2b0>



**** Used seaborn's clustermap to cluster the correlations together:****

In [26]: `sns.clustermap(bank_stocks.xs(key='Close',axis=1,level='Stock Info').corr(),annot=True)`

Out[26]: `<seaborn.matrix.ClusterGrid at 0x1204755c0>`

