Stock Market Analysis

February 26, 2017

1.) What was the change in price of the stock over time?
2.) What was the daily return of the stock on average?
3.) What was the moving average of the various stocks?
4.) What was the correlation between different stocks' closing prices?
5.) How much value do we put at risk by investing in a particular stock?
6.) How can we attempt to predict future stock behavior?

In [5]:
```
import pandas as pd
import numpy as np
from pandas import DataFrame, Series
```

In [9]:
```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

sns.set_style('whitegrid')
```

In [39]:
```
#### for reading stock datda from internet

#### from pandas.io import data, wb # becomes

import pandas_datareader as pdr
```

In [40]:
```
from datetime import datetime
```

In [41]:
```
from __future__ import division
```

In [42]:
```
tech_list = ['AAPL','GOOG','MSFT','AMZN']
```

In [43]:
```
end = datetime.now()   #today's date

start = datetime(end.year-1,end.month,end.day)
```

In [47]:
```
for stock in tech_list:
    globals()[stock] = pdr.get_data_yahoo(stock, start, end)
```

In [51]:
```
AAPL.head()
```

```
Out[51]:                 Open       High        Low      Close    Volume  Adj Clos
         Date
         2016-02-09  94.290001  95.940002  93.930000  94.989998  44331200  93.4267
         2016-02-10  95.919998  96.349998  94.099998  94.269997  42343600  92.7186
         2016-02-11  93.790001  94.720001  92.589996  93.699997  50074700  92.1580
         2016-02-12  94.190002  94.500000  93.010002  93.989998  40351400  92.4432
         2016-02-16  95.019997  96.849998  94.610001  96.639999  49057900  95.0496
```

```
In [52]: AAPL.describe()
```

```
Out[52]:              Open        High         Low       Close        Volume  \
         count  253.000000  253.000000  253.000000  253.000000  2.530000e+02
         mean   106.894664  107.788814  106.212885  107.070316  3.532467e+07
         std      8.832067    8.863153    8.933903    8.945718  1.511942e+07
         min     90.000000   91.669998   89.470001   90.339996  1.142440e+07
         25%     98.669998   99.349998   98.110001   98.779999  2.628200e+07
         50%    107.779999  108.750000  106.940002  107.930000  3.156190e+07
         75%    113.650002  114.339996  112.629997  113.550003  3.830350e+07
         max    131.350006  132.220001  131.220001  132.039993  1.146021e+08

                 Adj Close
         count  253.000000
         mean   106.272008
         std      9.343109
         min     89.394274
         25%     97.745922
         50%    107.179719
         75%    112.989884
         max    132.039993
```

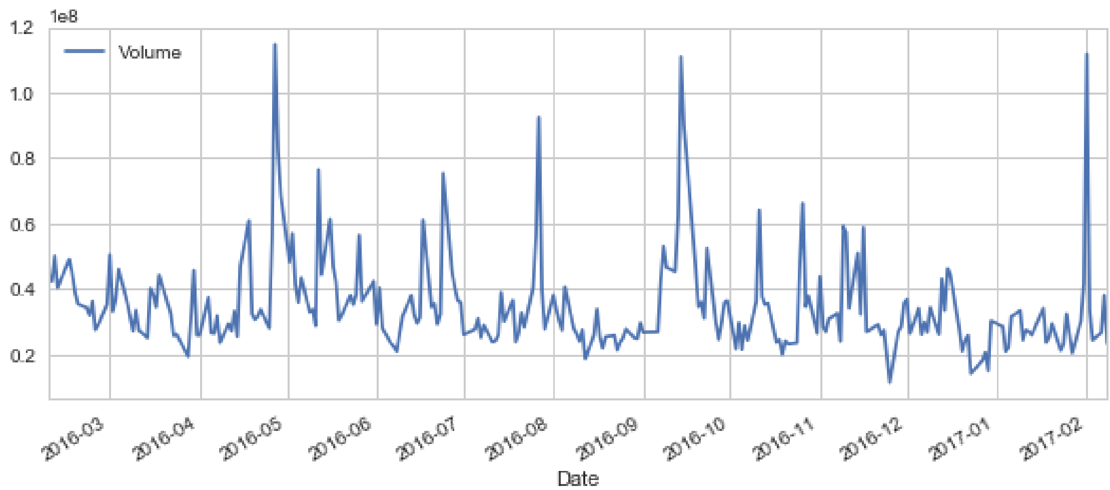
```
In [53]: AAPL.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 253 entries, 2016-02-09 to 2017-02-08
Data columns (total 6 columns):
Open         253 non-null float64
High         253 non-null float64
Low          253 non-null float64
Close        253 non-null float64
Volume       253 non-null int64
Adj Close    253 non-null float64
dtypes: float64(5), int64(1)
memory usage: 13.8 KB
```

```
In [56]: AAPL['Adj Close'].plot(legend=True,figsize=(10,4))
```

```
Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x11b871250>
```


```
In [57]: AAPL['Volume'].plot(legend=True,figsize=(10,4))

Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x11ec56510>
```




```
In [58]: ## Moving Averages

In [59]: ma_day = [10,20,50]

         for ma in ma_day:
             column_name = "MA for %s days" %(str(ma))
             AAPL[column_name] = pd.rolling_mean(AAPL['Adj Close'],ma)

/Users/arnavsomani/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:5: Fu
        Series.rolling(window=10,center=False).mean()
```

```
/Users/arnavsomani/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:5: Fu
        Series.rolling(window=20,center=False).mean()
/Users/arnavsomani/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:5: Fu
        Series.rolling(window=50,center=False).mean()
```

```
In [62]: AAPL[['Adj Close','MA for 10 days','MA for 20 days','MA for 50 days']].plo
```

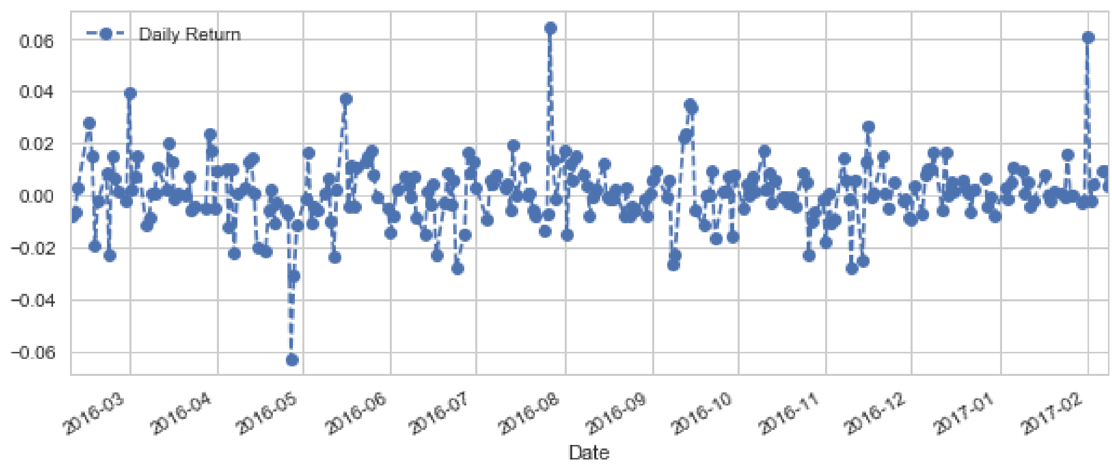
```
Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x11f0ad390>
```


```
In [63]: # Daily Returns
```

```
In [66]: AAPL['Daily Return'] = AAPL['Adj Close'].pct_change()
```

```
In [67]: AAPL['Daily Return'].plot(figsize=(10,4),legend=True,linestyle='--',marker
```

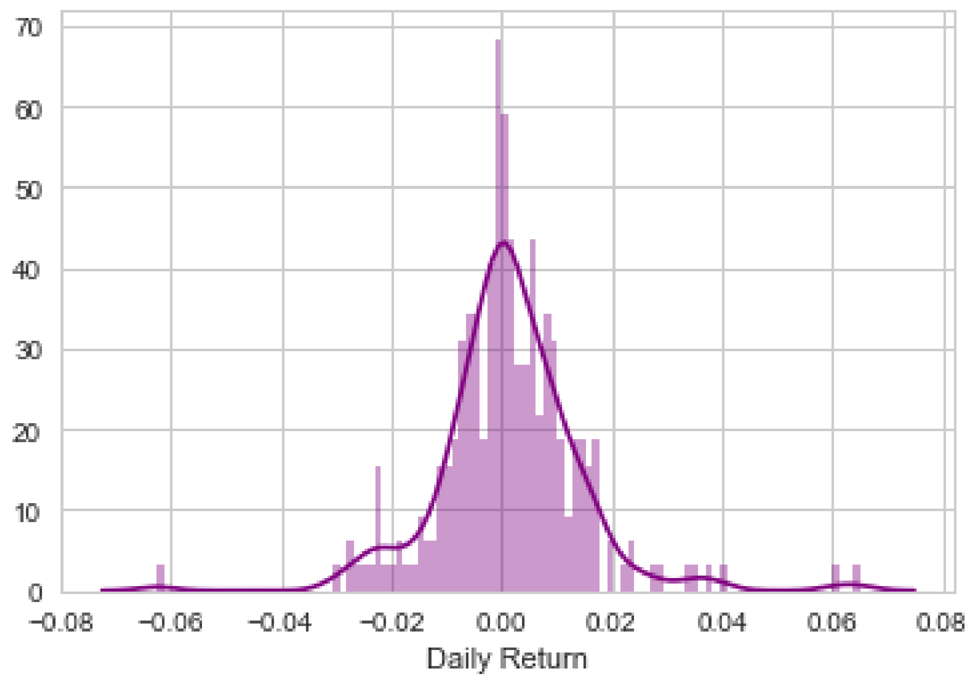
```
Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0x11f23ef90>
```



In [70]: # Average Daily Return through seaborn

In [71]:
```
sns.distplot(AAPL['Daily Return'].dropna(),bins=100,color='purple')
```

Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x11f788c90>



In [72]:
```
AAPL.head()
```

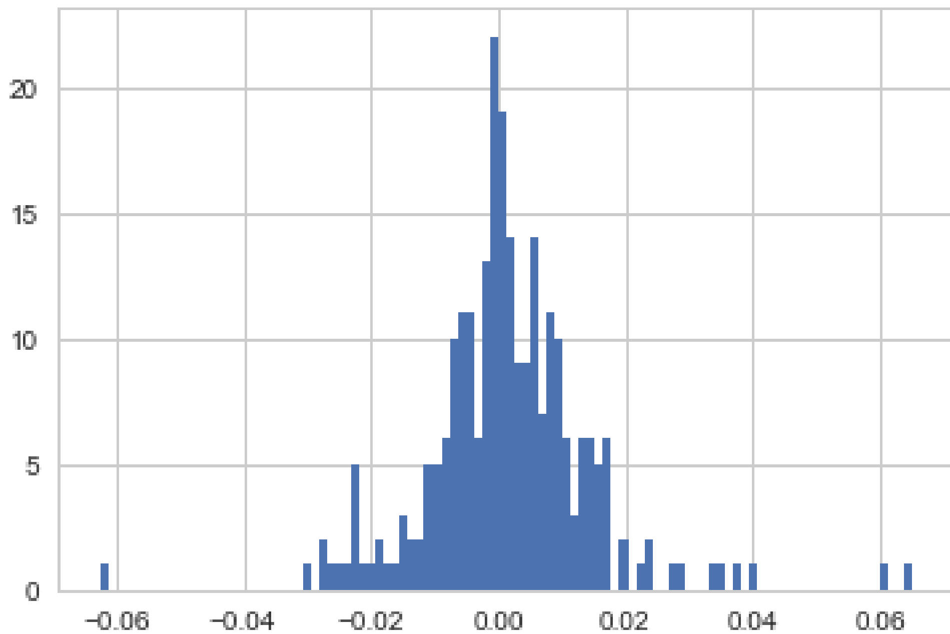
Out[72]:

Date	Open	High	Low	Close	Volume	Adj Clos
2016-02-09	94.290001	95.940002	93.930000	94.989998	44331200	93.4267
2016-02-10	95.919998	96.349998	94.099998	94.269997	42343600	92.7186
2016-02-11	93.790001	94.720001	92.589996	93.699997	50074700	92.1580
2016-02-12	94.190002	94.500000	93.010002	93.989998	40351400	92.4432
2016-02-16	95.019997	96.849998	94.610001	96.639999	49057900	95.0496

Date	MA for 10 days	MA for 20 days	MA for 50 days	Daily Return
2016-02-09	NaN	NaN	NaN	NaN
2016-02-10	NaN	NaN	NaN	-0.007580
2016-02-11	NaN	NaN	NaN	-0.006046
2016-02-12	NaN	NaN	NaN	0.003095
2016-02-16	NaN	NaN	NaN	0.028195

```
In [75]: AAPL['Daily Return'].hist(bins=100)   #built histogram function
```

```
Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0x11f9006d0>
```




```
In [76]: # Analyze the returns the stock on our list

In [77]: closing_df = pdr.get_data_yahoo(tech_list, start, end)['Adj Close']

In [79]: closing_df.head()
```

```
Out[79]:                  AAPL        AMZN        GOOG       MSFT
         Date
         2016-02-09  93.426774  482.070007  678.109985  47.963861
         2016-02-10  92.718621  490.480011  684.119995  48.382377
         2016-02-11  92.158002  503.820007  683.109985  48.362910
         2016-02-12  92.443230  507.079987  682.400024  49.151279
         2016-02-16  95.049622  521.099976  691.000000  50.082544
```

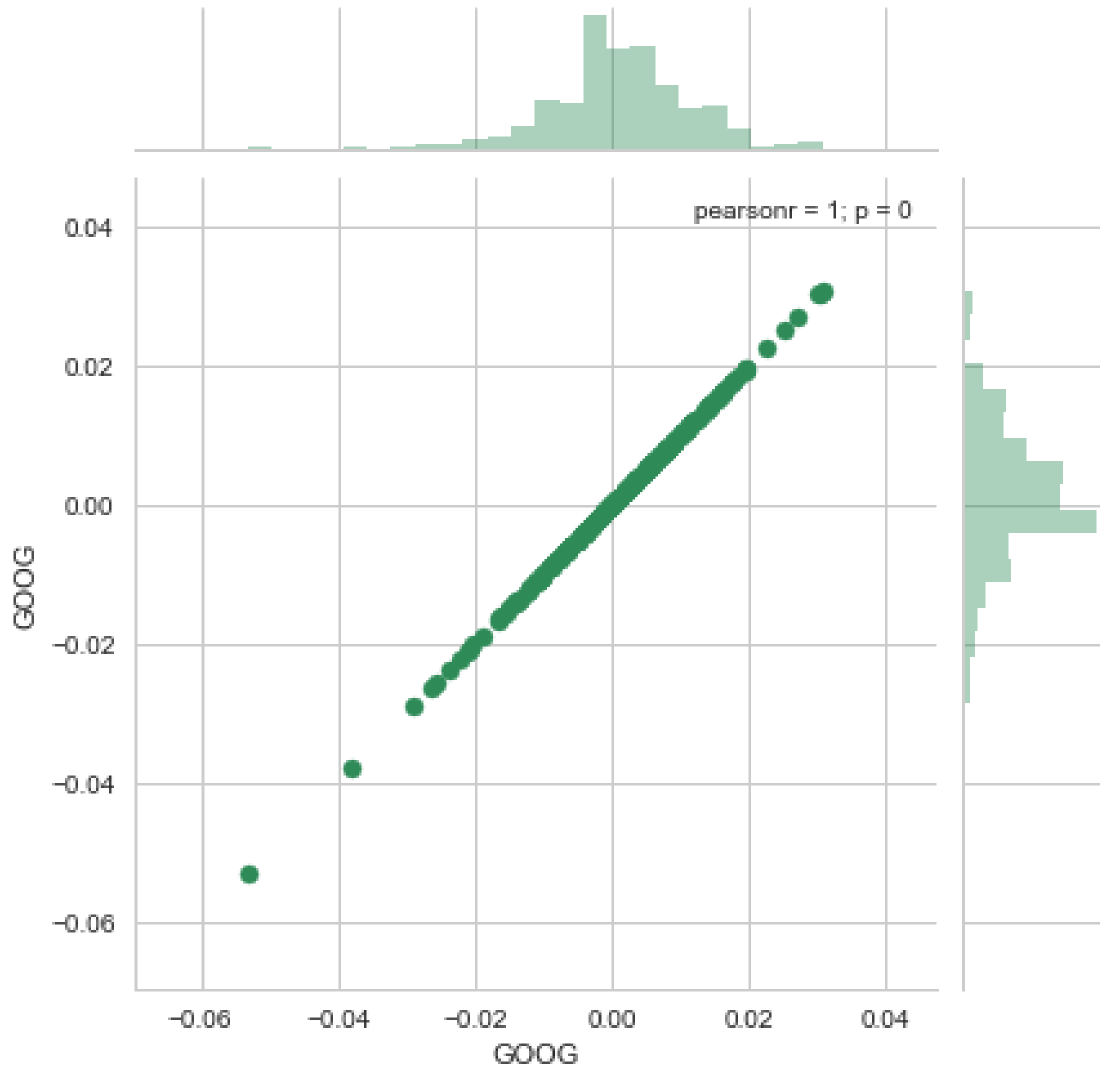
```
In [80]: # Daily Return for all the stocks

In [83]: tech_rets = closing_df.pct_change()

In [84]: tech_rets.head()
```

```
Out[84]:               AAPL      AMZN      GOOG      MSFT
         Date
         2016-02-09     NaN       NaN       NaN       NaN
```

```
2016-02-10 -0.007580  0.017446  0.008863  0.008726
2016-02-11 -0.006046  0.027198 -0.001476 -0.000402
2016-02-12  0.003095  0.006471 -0.001039  0.016301
2016-02-16  0.028195  0.027648  0.012603  0.018947
```

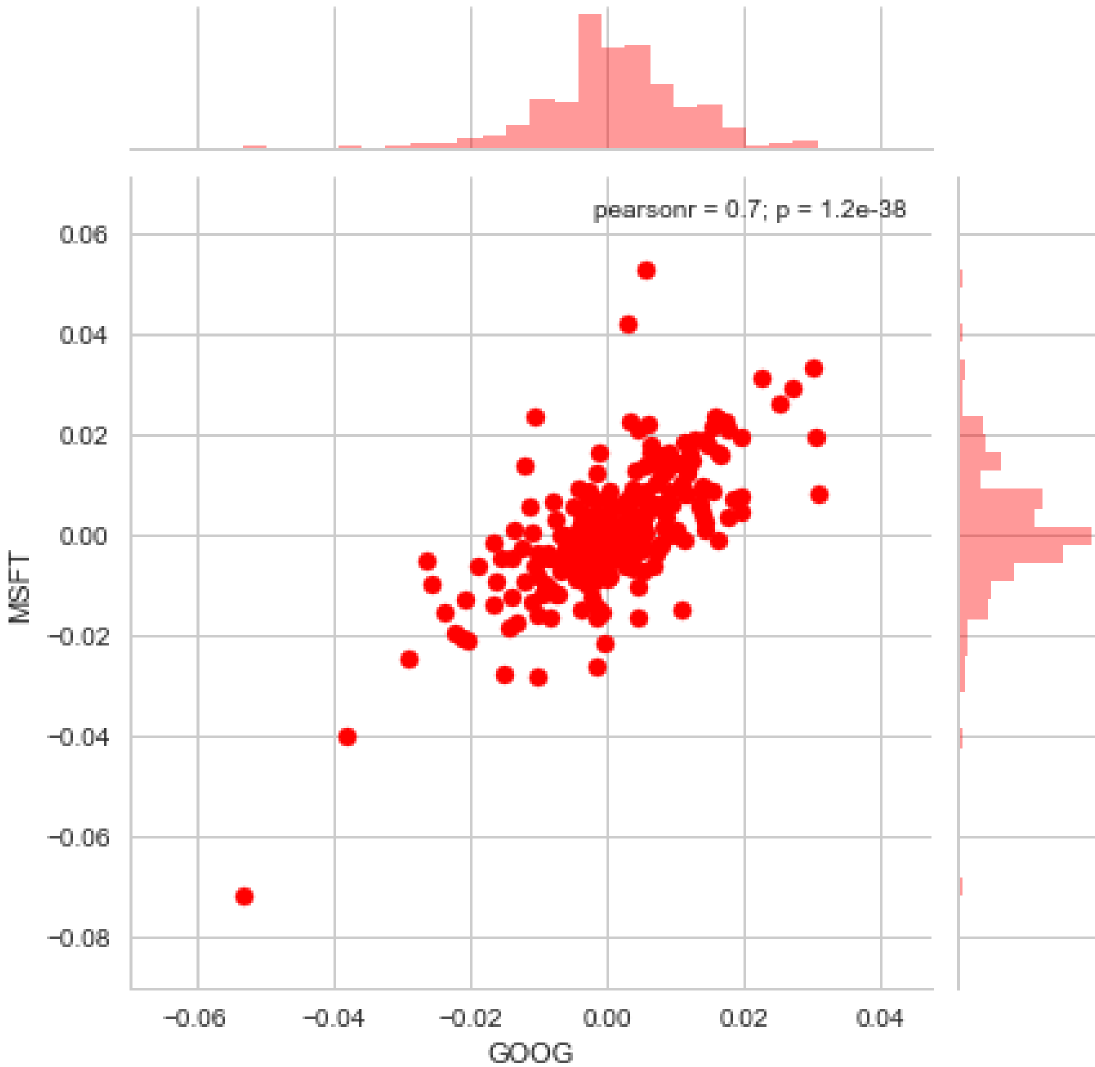
```
In [85]: sns.jointplot('GOOG','GOOG',tech_rets,kind='scatter',color='seagreen')
```

```
Out[85]: <seaborn.axisgrid.JointGrid at 0x11fdb5dd0>
```




```
In [87]: sns.jointplot('GOOG','MSFT',tech_rets,kind='scatter',color='red')
```

```
Out[87]: <seaborn.axisgrid.JointGrid at 0x11feb0190>
```



In [88]: # pearsonr = pearson product moment correlation coefficient

In [89]: # Comparision Analysis Plot

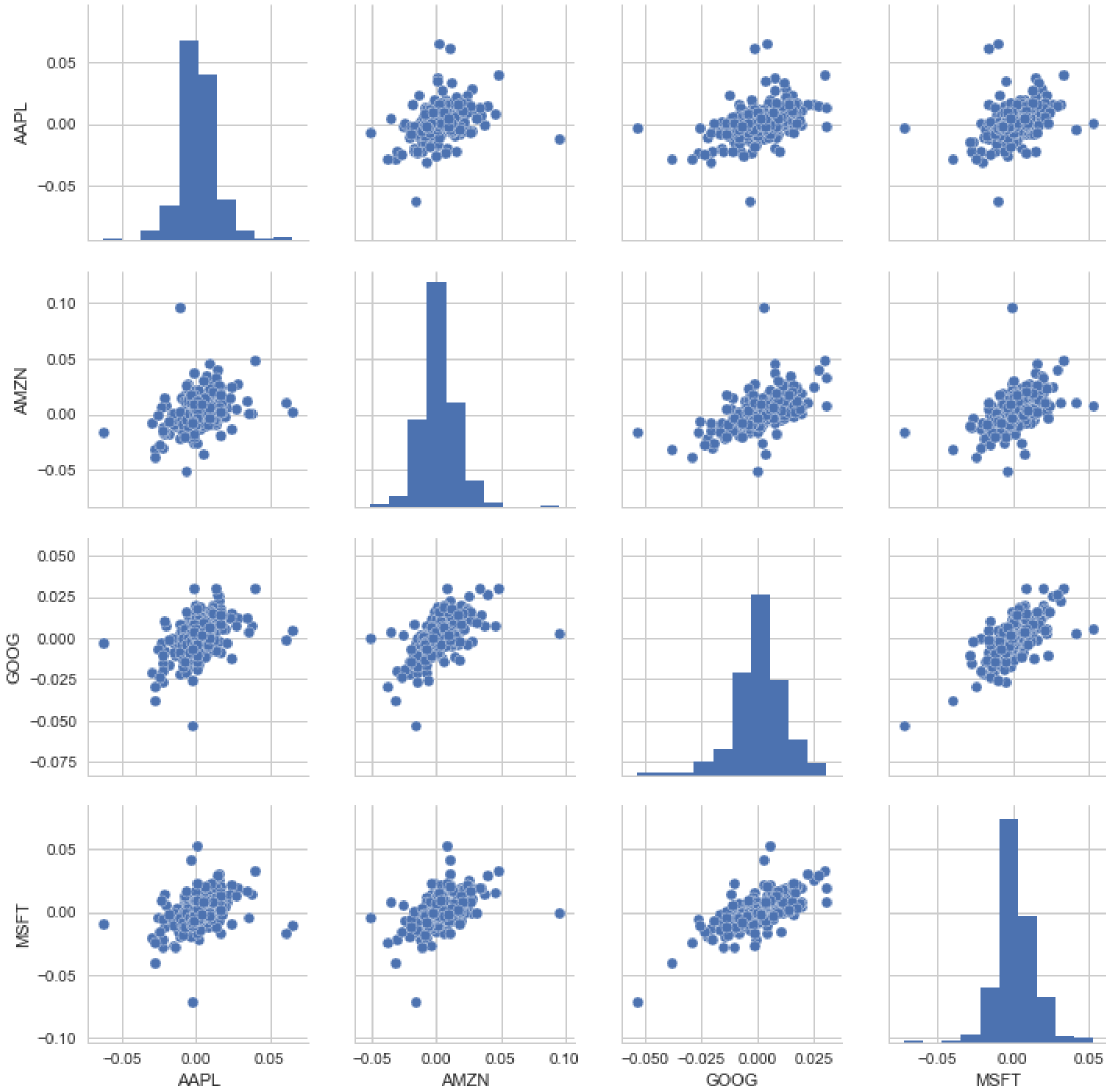
In [90]: tech_rets.head()

Out[90]:

```
                AAPL      AMZN      GOOG      MSFT
Date
2016-02-09       NaN       NaN       NaN       NaN
2016-02-10 -0.007580  0.017446  0.008863  0.008726
2016-02-11 -0.006046  0.027198 -0.001476 -0.000402
2016-02-12  0.003095  0.006471 -0.001039  0.016301
2016-02-16  0.028195  0.027648  0.012603  0.018947
```

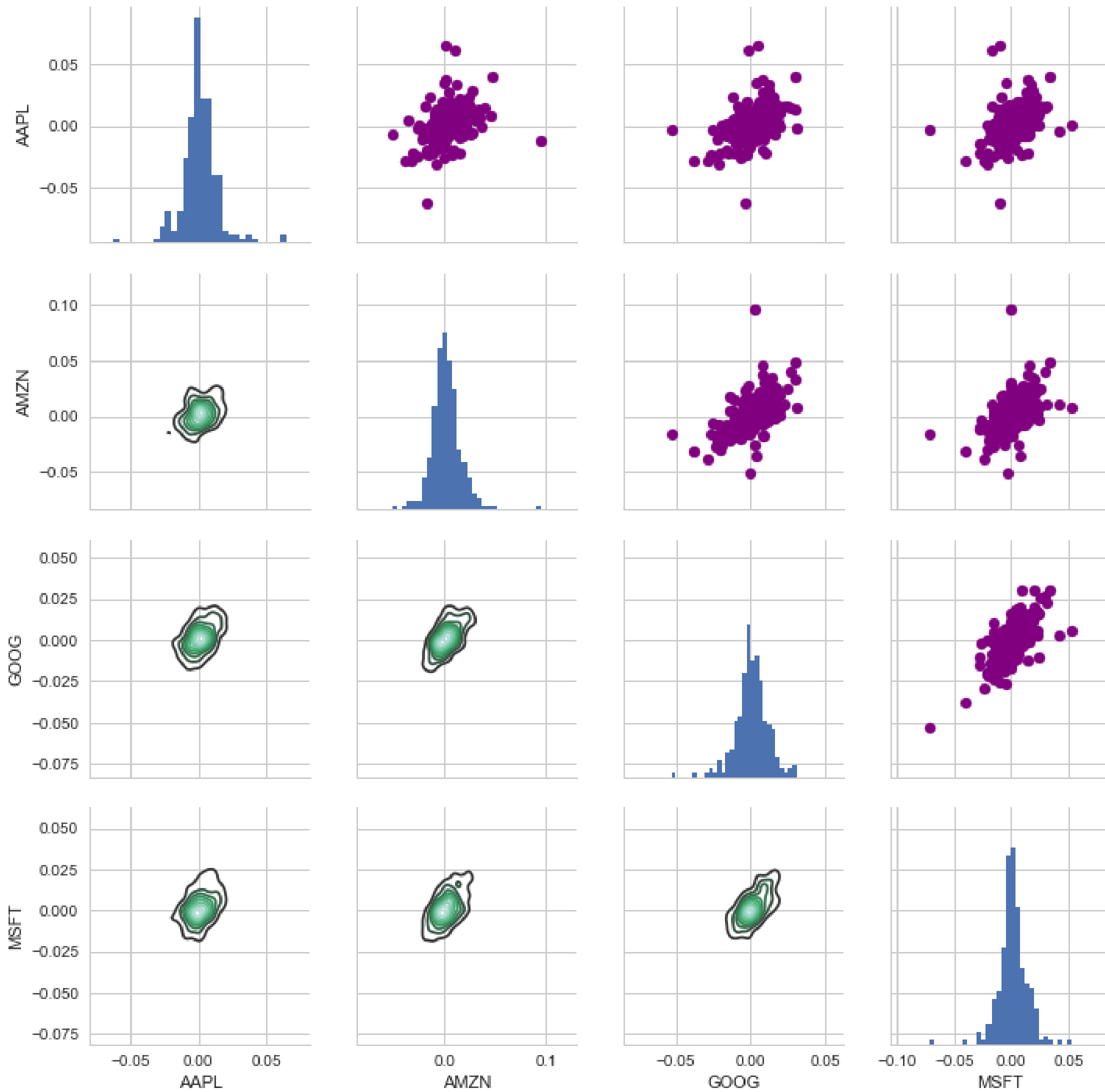
In [91]: sns.pairplot(tech_rets.dropna())

Out[91]: <seaborn.axisgrid.PairGrid at 0x11fc26510>




```
In [99]: #can make customized comparsion

         returns_fig = sns.PairGrid(tech_rets.dropna())

         returns_fig.map_upper(plt.scatter,color='purple')
         returns_fig.map_lower(sns.kdeplot,color='cool')
         returns_fig.map_diag(plt.hist,bins=30)
```

Out[99]: <seaborn.axisgrid.PairGrid at 0x123d40c10>



In [100]: `# Correlation of the closing price`

In [101]: `closing_df.head()`

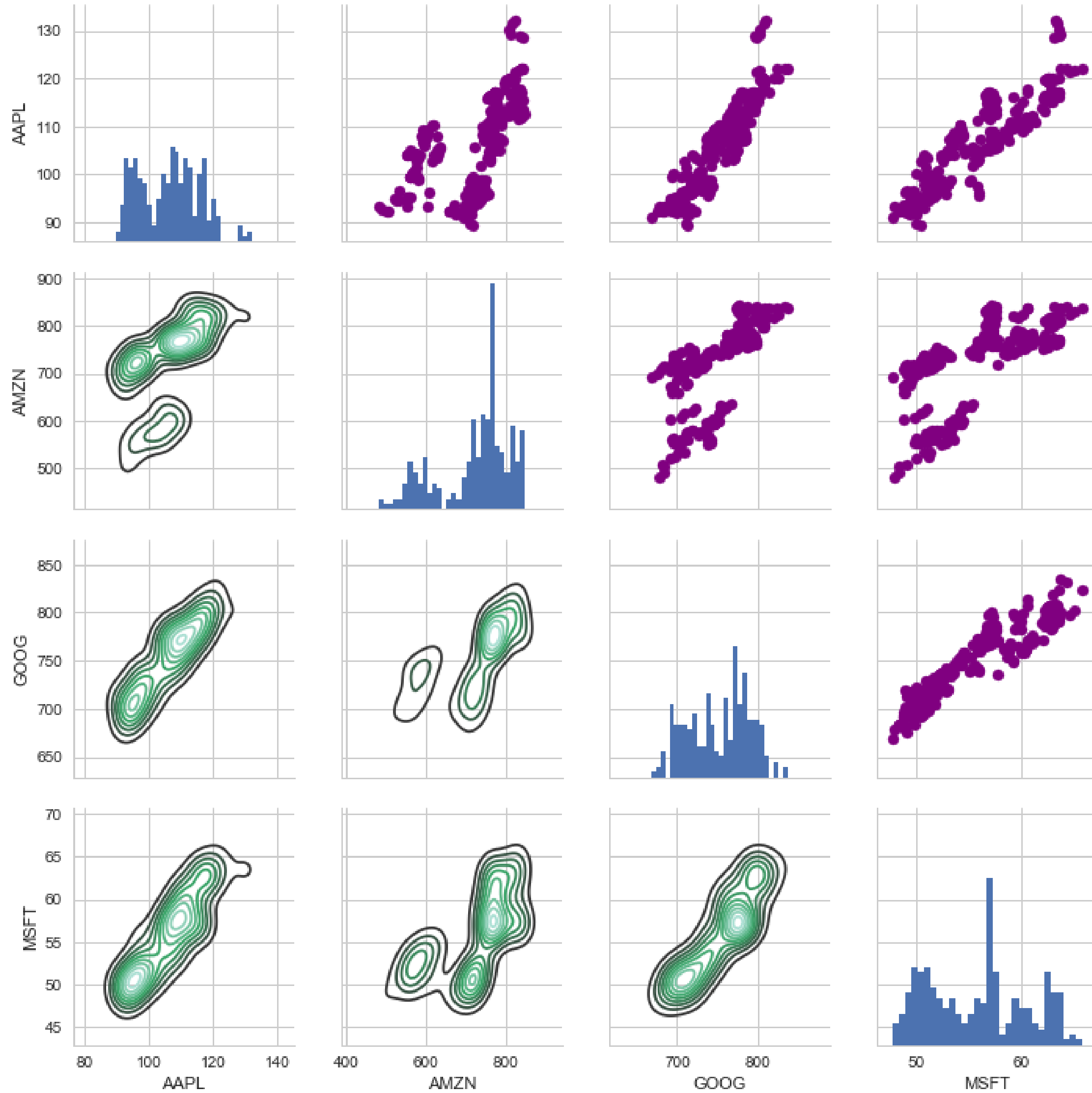
Out[101]:

Date	AAPL	AMZN	GOOG	MSFT
2016-02-09	93.426774	482.070007	678.109985	47.963861
2016-02-10	92.718621	490.480011	684.119995	48.382377
2016-02-11	92.158002	503.820007	683.109985	48.362910
2016-02-12	92.443230	507.079987	682.400024	49.151279
2016-02-16	95.049622	521.099976	691.000000	50.082544

In [102]: `returns_fig = sns.PairGrid(closing_df)`

```
returns_fig.map_upper(plt.scatter,color='purple')
returns_fig.map_lower(sns.kdeplot,color='cool')
returns_fig.map_diag(plt.hist,bins=30)
```

Out[102]: <seaborn.axisgrid.PairGrid at 0x124fb6250>



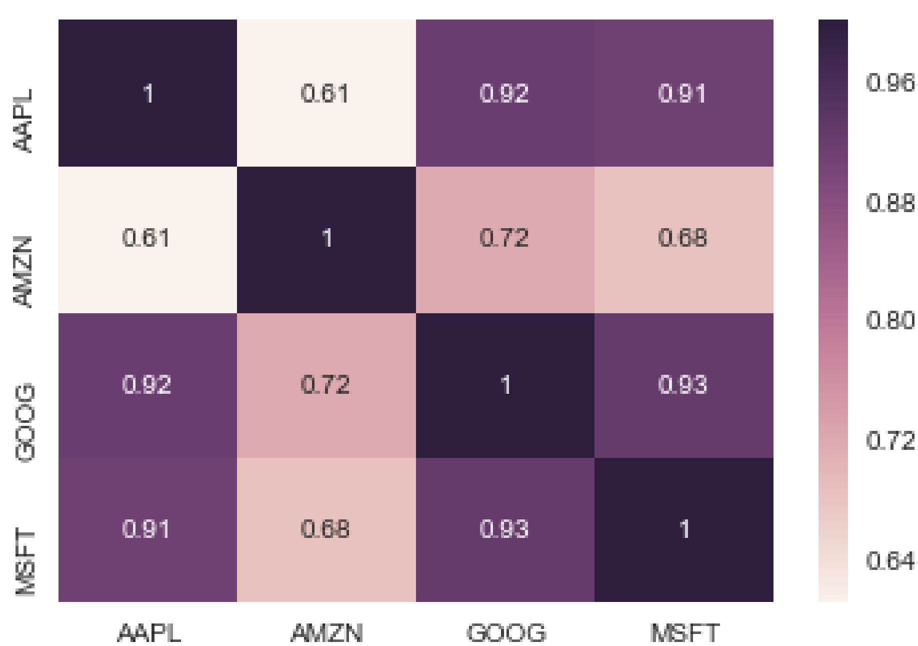
In [103]: # Correlation plot

In [115]:
```
corrmat = tech_rets.corr()
sns.heatmap(corrmat,annot=True)
```

Out[115]: <matplotlib.axes._subplots.AxesSubplot at 0x12824b550>


```
In [116]: corrmat1 = closing_df.corr()
          sns.heatmap(corrmat1,annot=True)
```

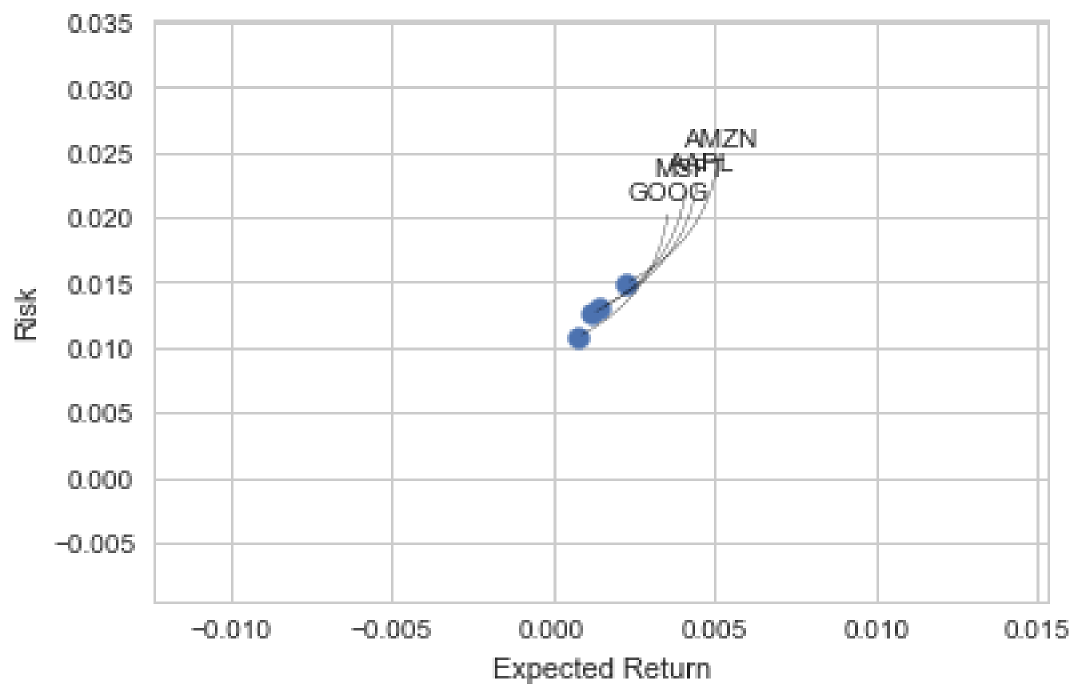
Out[116]: <matplotlib.axes._subplots.AxesSubplot at 0x1271bfb90>



```
In [118]: # RISK ANALYSIS
```

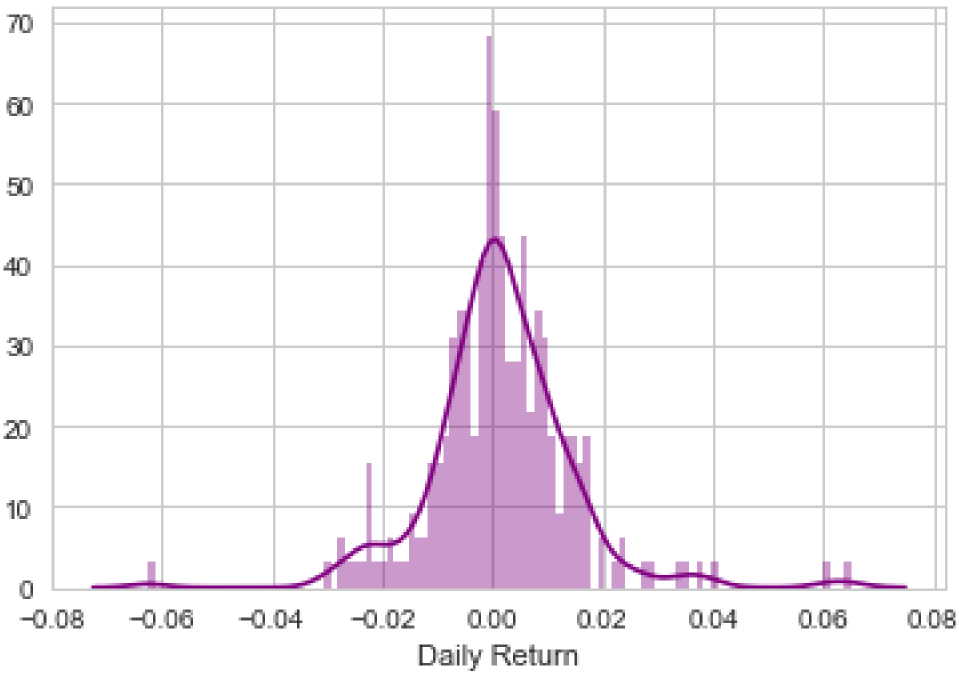
```
In [119]: rets = tech_rets.dropna()
```

```
In [128]: area = np.pi*20 # Area of the circles of the scatterplot

          plt.scatter(rets.mean(),rets.std(),s=area)

          plt.xlabel('Expected Return')
          plt.ylabel('Risk')

          for label, x, y in zip(rets.columns,rets.mean(),rets.std()):   #every co
              plt.annotate(
              label,
              xy = (x,y), xytext = (50,50),
              textcoords = 'offset points', ha = 'right', va = 'bottom',
              arrowprops = dict(arrowstyle = '-', connectionstyle = 'arc3,rad=-0.3'
```




```
In [126]: # Value at Risk using
          #   1. Bootstrap method with Quantiles
          #   2. Monte Carlo
```

```
In [129]: sns.distplot(AAPL['Daily Return'].dropna(),bins=100,color='purple')

Out[129]: <matplotlib.axes._subplots.AxesSubplot at 0x128c984d0>
```




```
In [136]: # Bootstrap
          # Quantile to get the risk value
          rets.head()
```

```
Out[136]:                 AAPL      AMZN      GOOG      MSFT
          Date
          2016-02-10 -0.007580  0.017446  0.008863  0.008726
          2016-02-11 -0.006046  0.027198 -0.001476 -0.000402
          2016-02-12  0.003095  0.006471 -0.001039  0.016301
          2016-02-16  0.028195  0.027648  0.012603  0.018947
          2016-02-17  0.015315  0.024947  0.025181  0.026032
```

```
In [137]: rets.tail()
```

```
Out[137]:                 AAPL      AMZN      GOOG      MSFT
          Date
          2017-02-02 -0.001709  0.009131  0.003563 -0.006449
          2017-02-03  0.004279 -0.035419  0.003707  0.008073
          2017-02-06  0.009374 -0.003160 -0.000187 -0.000628
          2017-02-07  0.009517  0.006018  0.007026 -0.003300
          2017-02-08  0.003877  0.008874  0.001747 -0.001419
```

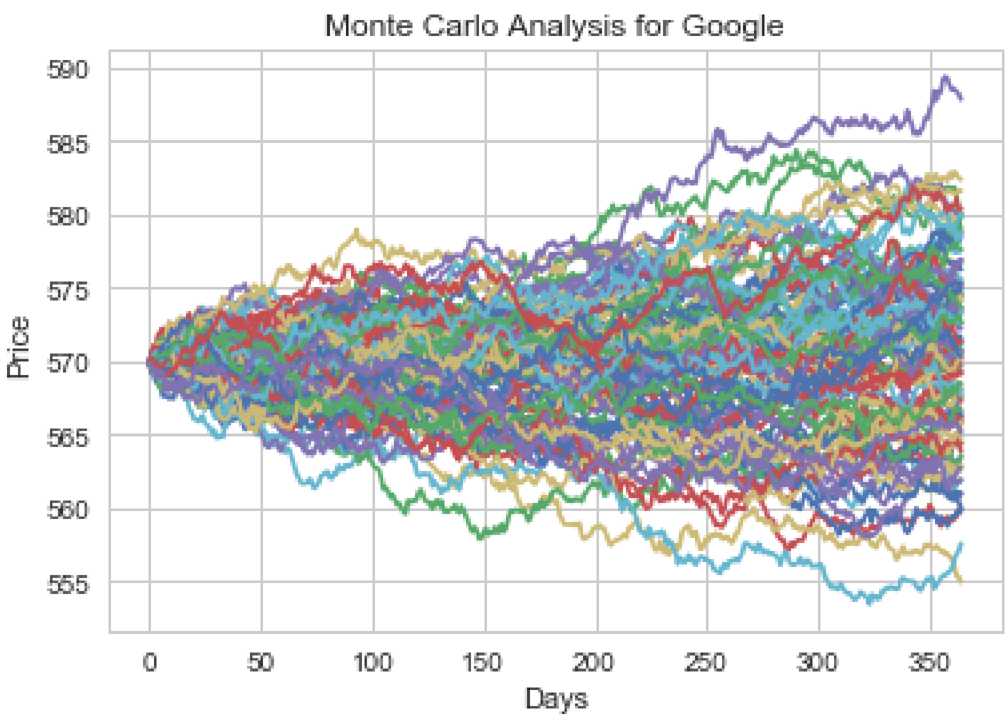
```
In [138]: rets['AAPL'].quantile(0.05)
```

```
Out[138]: -0.020747924597211573
```

```
In [139]: # MONTE CARLO

In [141]: days = 365
          dt=1/days
          mu=rets.mean()['GOOG']
          sigma = rets.std()['GOOG']

In [162]: def stock_monte_carlo(start_price,days,mu,sigma):
              ''' This function takes in starting stock price, days of simulation,m

              # Define a price array
              price = np.zeros(days)
              price[0] = start_price
              # Schok and Drift
              shock = np.zeros(days)
              drift = np.zeros(days)

              # Run price array for number of days
              for x in xrange(1,days):

                  # Calculate Schock
                  shock[x] = np.random.normal(loc=mu * dt, scale=sigma * np.sqrt(dt
                  # Calculate Drift
                  drift[x] = mu * dt
                  # Calculate Price
                  price[x] = price[x-1] + (price[x-1] * (drift[x] + shock[x]))

              return price

In [159]: GOOG.head()

Out[159]:                   Open        High         Low       Close   Volume  \
          Date
          2016-02-09  672.320007  699.900024  668.770020  678.109985  3608900
          2016-02-10  686.859985  701.309998  682.130005  684.119995  2638000
          2016-02-11  675.000000  689.349976  668.867981  683.109985  3024000
          2016-02-12  690.260010  693.750000  678.599976  682.400024  2141400
          2016-02-16  692.979980  698.000000  685.049988  691.000000  2520000

                       Adj Close
          Date
          2016-02-09  678.109985
          2016-02-10  684.119995
          2016-02-11  683.109985
          2016-02-12  682.400024
          2016-02-16  691.000000

In [163]: # Get start price from GOOG.head()
          start_price = 569.85
```

```
for run in xrange(100):
    plt.plot(stock_monte_carlo(start_price,days,mu,sigma))
plt.xlabel("Days")
plt.ylabel("Price")
plt.title('Monte Carlo Analysis for Google')
```

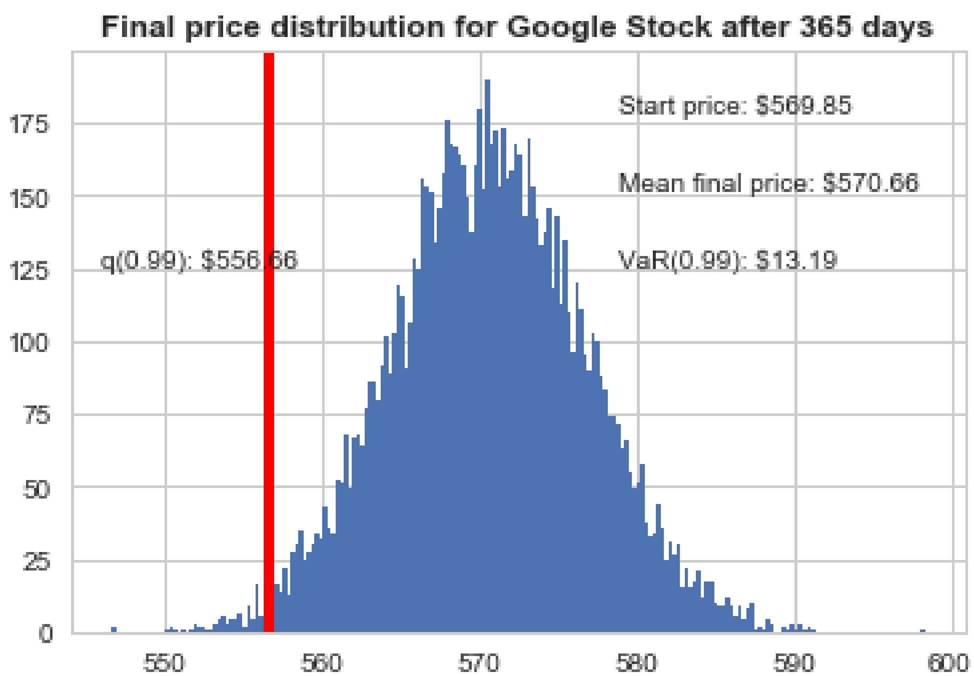
Out[163]: <matplotlib.text.Text at 0x1291c6c10>



In [171]:
```
runs = 10000

simulations = np.zeros(runs)

for run in xrange(runs):
    simulations[run]= stock_monte_carlo(start_price,days,mu,sigma)[days-1
```

In [173]:
```
# Now we'lll define q as the 1% empirical qunatile, this basically means
q = np.percentile(simulations, 1)

# Now let's plot the distribution of the end prices
plt.hist(simulations,bins=200)

# Using plt.figtext to fill in some additional information onto the plot
```

```
# Starting Price
plt.figtext(0.6, 0.8, s="Start price: $%.2f" %start_price)
# Mean ending price
plt.figtext(0.6, 0.7, "Mean final price: $%.2f" % simulations.mean())

# Variance of the price (within 99% confidence interval)
plt.figtext(0.6, 0.6, "VaR(0.99): $%.2f" % (start_price - q,))

# Display 1% quantile
plt.figtext(0.15, 0.6, "q(0.99): $%.2f" % q)

# Plot a line at the 1% quantile result
plt.axvline(x=q, linewidth=4, color='r')

# Title
plt.title(u"Final price distribution for Google Stock after %s days" % da
```




```
In [ ]:
```