Stock Market Analysis for Tech Stocks

In this project, we'll analyse data from the stock market for some technology stocks.

Again, we'll use Pandas to extract and analyse the information, visualise it, and look at different ways to analyse the risk of a stock, based on its performance history.

Here are the questions we'll try to answer:

- What was the change in a stock's price over time?
- What was the daily return average of a stock?
- What was the moving average of various stocks?
- What was the correlation between daily returns of different stocks?
- How much value do we put at risk by investing in a particular stock?
- How can we attempt to predict future stock behaviour?

In [4]:
```
#Python Data Analysis imports
import pandas as pd
from pandas import Series,DataFrame
import numpy as np

#Visualisation imports
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
%matplotlib inline

#To grab stock data
from pandas.io.data import DataReader
from datetime import datetime

#To handle floats in Python 2
from __future__ import division
```

```
/Users/sajal/Library/Enthought/Canopy_64bit/User/lib/python2.7/site-packages/pandas/io/data.p
y:35: FutureWarning:
The pandas.io.data module is moved to a separate package (pandas-datareader) and will be remo
ved from pandas in a future version.
After installing the pandas-datareader package (https://github.com/pydata/pandas-datareader),
you can change the import ``from pandas.io import data, wb`` to ``from pandas_datareader impo
rt data, wb``.
  FutureWarning)
```

We're going to analyse some tech stocks, and it seems like a good idea to look at their performance over the last year. We can create a list with the stock names, for future looping.

In [29]:
```
#We're going to analyse stock info for Apple, Google, Microsoft, and Amazon
tech_list = ['AAPL','GOOG','MSFT','AMZN','YHOO']
```

In [30]:
```
#Setting the end date to today
end = datetime.now()

#Start date set to 1 year back
start = datetime(end.year-1,end.month,end.day)
```

In [32]:
```
#Using Yahoo Finance to grab the stock data
for stock in tech_list:
    globals()[stock] = DataReader(stock,'yahoo',start,end) #The globals method sets the stoc
k name to a global variable
```

Thanks to the globals method, Apple's stock data will be stored in the AAPL global variable dataframe. Let's see if that worked.

In [33]:
```
AAPL.head()
```

Out[33]:

Date	Open	High	Low	Close	Volume	Adj Close
2015-09-23	113.629997	114.720001	113.300003	114.320000	35756700	111.926895
2015-09-24	113.250000	115.500000	112.370003	115.000000	50219500	112.592660
2015-09-25	116.440002	116.690002	114.019997	114.709999	56151900	112.308730
2015-09-28	113.849998	114.570000	112.440002	112.440002	52109000	110.086252
2015-09-29	112.830002	113.510002	107.860001	109.059998	73365400	106.777002

In [17]:
```
#Basic stats for Apple's Stock
AAPL.describe()
```

Out[17]:

	Open	High	Low	Close	Volume	Adj Close
count	253.000000	253.000000	253.000000	253.000000	2.530000e+02	253.000000
mean	104.824941	105.777510	103.881146	104.858498	4.179762e+07	103.707287
std	8.073718	8.110392	8.019398	8.075914	1.749642e+07	7.735402
min	90.000000	91.669998	89.470001	90.339996	1.304640e+07	89.853242
25%	97.320000	98.209999	96.580002	97.139999	2.944520e+07	96.348065
50%	105.519997	106.309998	104.879997	105.790001	3.695570e+07	104.701886
75%	110.629997	111.769997	109.410004	110.779999	4.896780e+07	109.220001
max	123.129997	123.820000	121.620003	122.570000	1.333697e+08	120.004194

And that easily, we can make out what the stock's minimum, maximum, and average price was for the last year.

In [20]:
```
#Some basic info about the dataframe
AAPL.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 253 entries, 2015-09-23 to 2016-09-22
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
```

No missing info in the dataframe above, so we can go about our business.

What's the change in stock's price over time?

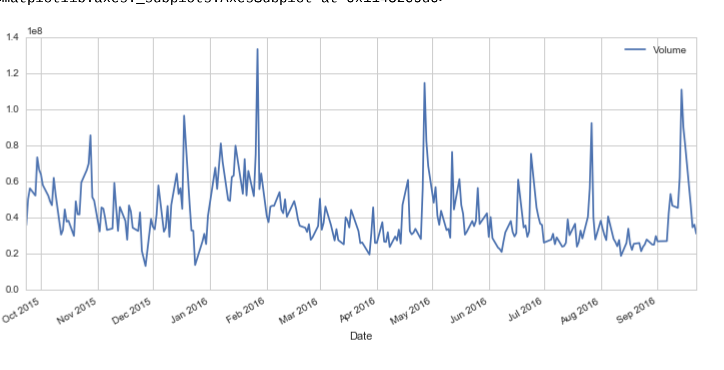
In [27]:
```
#Plotting the stock's adjusted closing price using pandas
AAPL['Adj Close'].plot(legend=True,figsize=(12,5))
```

Out[27]: `<matplotlib.axes._subplots.AxesSubplot at 0x11463ef50>`

Similarily, we can plot change in a stock's volume being traded, over time.

In [34]:
```
#Plotting the total volume being traded over time
AAPL['Volume'].plot(legend=True,figsize=(12,5))
```

Out[34]: `<matplotlib.axes._subplots.AxesSubplot at 0x1148209d0>`



What was the moving average of various stocks?

Let's check out the moving average for stocks over a 10, 20 and 50 day period of time. We'll add that information to the stock's dataframe.

In [42]:
```
ma_day = [10,20,50]

for ma in ma_day:
    column_name = "MA for %s days" %(str(ma))

    AAPL[column_name] = AAPL['Adj Close'].rolling(window=ma,center=False).mean()
```

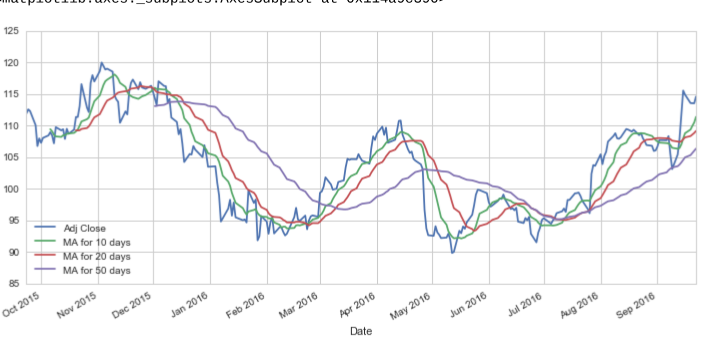
In [44]:
```
AAPL.tail()
```

Out[44]:

Date	Open	High	Low	Close	Volume	Adj Close	MA for 10 days	MA for 20 days	MA for 50 days
2016-09-16	115.120003	116.129997	114.040001	114.919998	79886900	114.919998	108.808999	108.1500	104.992706
2016-09-19	115.190002	116.180000	113.250000	113.580002	47023000	113.580002	109.393999	108.3610	105.341124
2016-09-20	113.050003	114.120003	112.510002	113.570000	34514300	113.570000	109.980999	108.6140	105.683375
2016-09-21	113.849998	113.989998	112.440002	113.550003	36003200	113.550003	110.499999	108.8490	106.016473
2016-09-22	114.349998	114.940002	114.000000	114.620003	31011700	114.620003	111.410000	109.1785	106.381911

In [45]:
```
AAPL[['Adj Close','MA for 10 days','MA for 20 days','MA for 50 days']].plot(subplots=False,f
igsize=(12,5))
```

Out[45]: `<matplotlib.axes._subplots.AxesSubplot at 0x114a9c390>`



Moving averages for more days have a smoother plot, as they're less reliable on daily fluctuations. So even though, Apple's stock has a slight dip near the start of September, it's generally been on an upward trend since mid-July.

What was the daily return average of a stock?

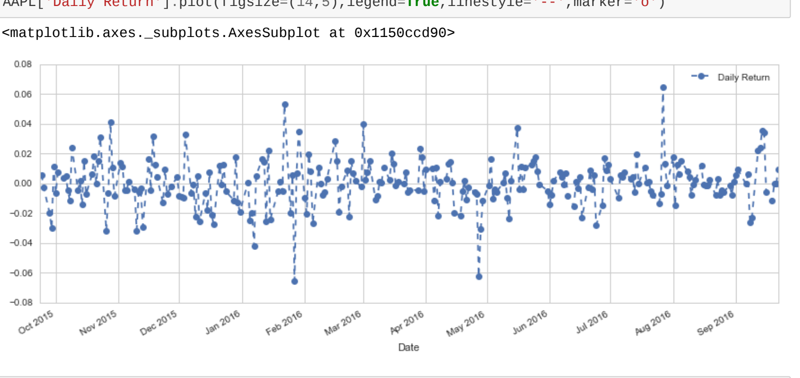
In [46]:
```
#The daily return column can be created by using the percentage change over the adjusted clo
sing price
AAPL['Daily Return'] = AAPL['Adj Close'].pct_change()
```

In [49]:
```
AAPL['Daily Return'].tail()
```

Out[49]:
```
Date
2016-09-16   -0.005624
2016-09-19   -0.011660
2016-09-20   -0.000088
2016-09-21   -0.000176
2016-09-22    0.009423
Name: Daily Return, dtype: float64
```

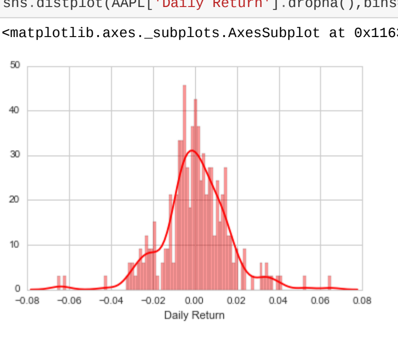
In [50]:
```
#Plotting the daily return
AAPL['Daily Return'].plot(figsize=(14,5),legend=True,linestyle='--',marker='o')
```

Out[50]: `<matplotlib.axes._subplots.AxesSubplot at 0x1150ccd90>`



In [56]:
```
sns.distplot(AAPL['Daily Return'].dropna(),bins=100,color='red')
```

Out[56]: `<matplotlib.axes._subplots.AxesSubplot at 0x1163caad0>`



Positive daily returns seem to be slightly more frequent than negative returns for Apple.

What was the correlation between daily returns of different stocks?

In [60]:
```
#Reading just the 'Adj Close' column this time
close_df = DataReader(tech_list,'yahoo',start,end)['Adj Close']
```

In [69]:
```
close_df.tail()
```

Out[69]:

Date	AAPL	AMZN	GOOG	MSFT	YHOO
2016-09-16	114.919998	778.520020	768.880005	57.250000	43.669998
2016-09-19	113.580002	775.099976	765.700012	56.930000	43.189999
2016-09-20	113.570000	780.219971	771.409973	56.810001	42.790001
2016-09-21	113.550003	789.739990	776.219971	57.759998	44.139999
2016-09-22	114.620003	804.700012	787.210022	57.820000	44.150002

Everything works as expected.

Just as we did earlier, we can use Pandas' pct_change method to get the daily returns of our stocks.

In [66]:
```
rets_df = close_df.pct_change()
```

In [68]:
```
rets_df.tail()
```

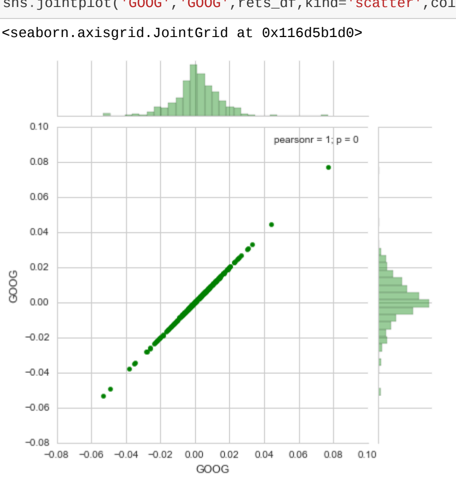
Out[68]:

Date	AAPL	AMZN	GOOG	MSFT	YHOO
2016-09-16	-0.005624	0.011472	-0.003732	0.001049	-0.007274
2016-09-19	-0.011660	-0.004393	-0.004136	-0.005590	-0.010992
2016-09-20	-0.000088	0.006606	0.007457	-0.002108	-0.009261
2016-09-21	-0.000176	0.012202	0.006235	0.016722	0.031549
2016-09-22	0.009423	0.018943	0.014158	0.001039	0.000227

Let's try creating a scatterplot to visualise any correlations between different stocks. First we'll visualise a scatterplot for the relationship between the daily return of a stock to itself.

In [71]:
```
sns.jointplot('GOOG','GOOG',rets_df,kind='scatter',color='green')
```

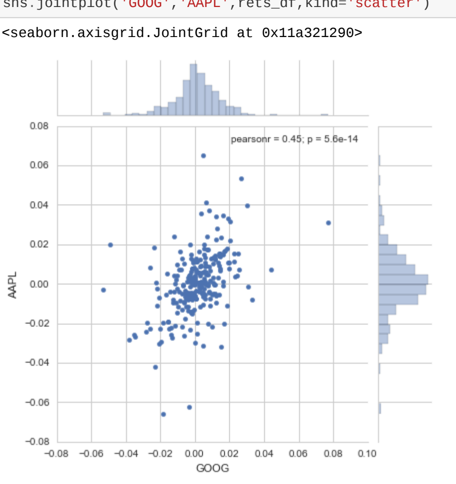
Out[71]: `<seaborn.axisgrid.JointGrid at 0x116d5b1d0>`



As expected, the relationship is perfectly linear because we're trying to correlate something with itself. Now, let's check out the relationship between Google and Apple's daily returns.

In [78]:
```
sns.jointplot('GOOG','AAPL',rets_df,kind='scatter')
```

Out[78]: `<seaborn.axisgrid.JointGrid at 0x11a321290>`

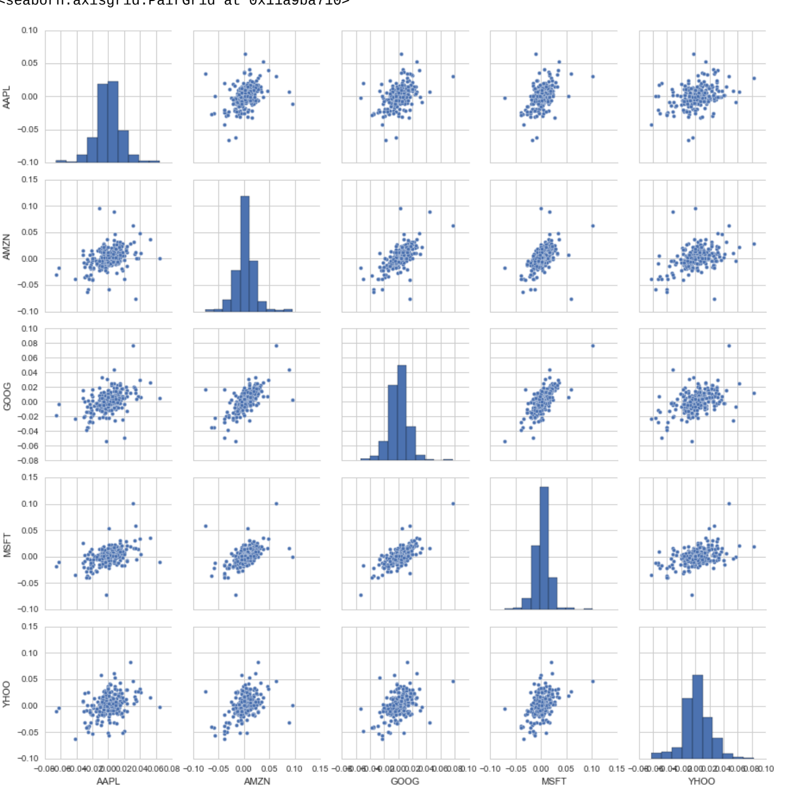


There seems to be a minor correlation between the two stocks, looking at the figure above. The Pearson R Correlation Coefficient value of 0.45 echoes that sentiment.

But what about other combinations of stocks?

In [80]:
```
sns.pairplot(rets_df.dropna())
```

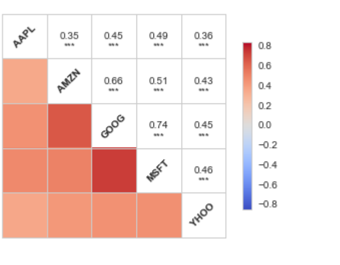
Out[80]: `<seaborn.axisgrid.PairGrid at 0x11a9ba710>`



Quick and dirty overarching visualisation of the scatterplots and histograms of daily returns of our stocks. To see the actual numbers for the correlation coefficients, we can use seaborn's corrplot method.

In [87]:
```
sns.corrplot(rets_df.dropna(),annot=True)
```

Out[87]: `<matplotlib.axes._subplots.AxesSubplot at 0x127a07690>`



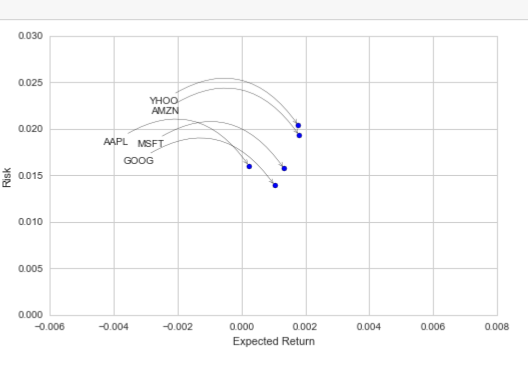
Google and Microsoft seem to have the highest correlation. But another interesting thing to note is that all tech companies that we explored are positively correlated.

How much value do we put at risk by investing in a particular stock?

A basic way to quantify risk is to compare the expected return (which can be the mean of the stock's daily returns) with the standard deviation of the daily returns.

In [90]:
```
rets = rets_df.dropna()
```

In [181]:
```
plt.figure(figsize=(8,5))

plt.scatter(rets.mean(),rets.std(),s=25)

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


#For adding annotatios in the scatterplot
for label,x,y in zip(rets.columns,rets.mean(),rets.std()):
    plt.annotate(
    label,
    xy=(x,y),xytext=(-120,20),
    textcoords = 'offset points', ha = 'right', va = 'bottom',
    arrowprops = dict(arrowstyle='->',connectionstyle = 'arc3,rad=-0.5'))
```



We'd want a stock to have a high expected return and a low risk; Google and Microsoft seem to be the safe options for that. Meanwhile, Yahoo and Amazon stocks have higher expected returns, but also have a higher risk

Value at Risk

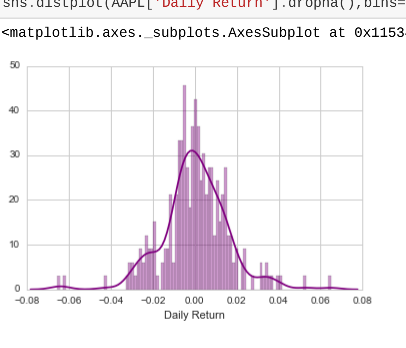
We can treat *Value at risk* as the amount of money we could expect to lose for a given confidence interval. We'll use the 'Bootstrap' method and the 'Monte Carlo Method' to extract this value.

Bootstrap Method

Using this method, we calculate the empirical quantiles from a histogram of daily returns. The quantiles help us define our confidence interval.

In [182]:
```
sns.distplot(AAPL['Daily Return'].dropna(),bins=100,color='purple')
```

Out[182]: `<matplotlib.axes._subplots.AxesSubplot at 0x11534fdd0>`



To recap, our histogram for Apple's stock looked like the above. And our daily returns dataframe looked like:

In [183]:
```
rets.head()
```

Out[183]:

Date	AAPL	AMZN	GOOG	MSFT	YHOO
2015-09-24	0.005948	-0.004328	0.005527	0.000912	-0.013450
2015-09-25	-0.002522	-0.017799	-0.022100	0.000683	-0.007157
2015-09-28	-0.019789	-0.038512	-0.027910	-0.014793	-0.052523
2015-09-29	-0.030061	-0.015851	0.000134	0.003465	0.023913
2015-09-30	0.011370	0.031891	0.022606	0.018877	0.023001

In [187]:
```
#Using Pandas built in qualtile method
rets['AAPL'].quantile(0.05)
```

Out[187]: `-0.025722813451247724`

The 0.05 empirical quantile of daily returns is at -0.019. This means that with 95% confidence, the worst daily loss will not exceed 2.57% (of the investment).

How can we attempt to predict future stock behaviour?

Monte Carlo Method

Check out this link for more info on the Monte Carlo method. In short: in this method, we run simulations to predict the future many times, and aggregate the results in the end for some quantifiable value.

In [188]:
```
days = 365

#delta t
dt = 1/365

mu = rets.mean()['GOOG']

sigma = rets.std()['GOOG']
```

In [194]:
```
#Function takes in stock price, number of days to run, mean and standard deviation values
def stock_monte_carlo(start_price,days,mu,sigma):

    price = np.zeros(days)
    price[0] = start_price

    shock = np.zeros(days)
    drift = np.zeros(days)

    for x in xrange(1,days):

        #Shock and drift formulas taken from the Monte Carlo formula
        shock[x] = np.random.normal(loc=mu*dt,scale=sigma*np.sqrt(dt))

        drift[x] = mu * dt

        #New price = Old price + Old price*(shock+drift)
        price[x] = price[x-1] + (price[x-1] * (drift[x]+shock[x]))

    return price
```

We're going to run the simulation of Google stocks. Let's check out the opening value of the stock.

In [190]:
```
GOOG.head()
```

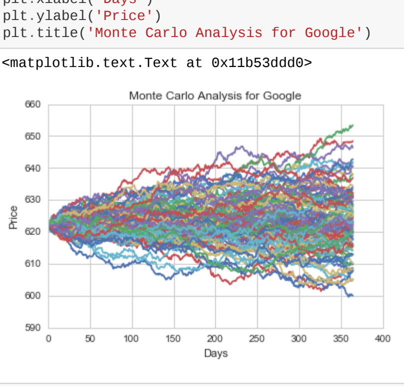
Out[190]:

Date	Open	High	Low	Close	Volume	Adj Close
2015-09-23	622.049988	628.929993	620.000000	622.359985	1470900	622.359985
2015-09-24	616.640015	627.320007	612.400024	625.799988	2240100	625.799988
2015-09-25	629.770020	629.770020	611.000000	611.969971	2174000	611.969971
2015-09-28	610.340027	614.604980	589.380005	594.890015	3127700	594.890015
2015-09-29	597.280029	605.000000	590.219971	594.969971	2309500	594.969971

Let's do a simulation of 100 runs, and plot them.

In [197]:
```
start_price = 622.049 #Taken from above

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')
```

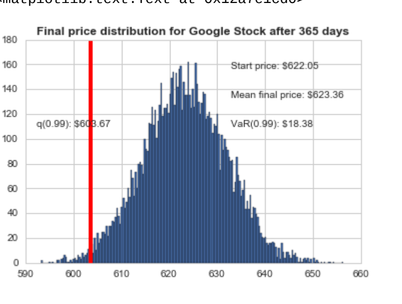
Out[197]: `<matplotlib.text.Text at 0x11b53ddd0>`



In [199]:
```
runs = 10000

simulations = np.zeros(runs)

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

In [203]:
```
q = np.percentile(simulations,1)

plt.hist(simulations,bins=200)

plt.figtext(0.6,0.8,s="Start price: $%.2f" %start_price)

plt.figtext(0.6,0.7,"Mean final price: $%.2f" % simulations.mean())

plt.figtext(0.6,0.6,"VaR(0.99): $%.2f" % (start_price -q,))

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

plt.axvline(x=q, linewidth=4, color='r')

plt.title(u"Final price distribution for Google Stock after %s days" %days, weight='bold')
```

Out[203]: `<matplotlib.text.Text at 0x12a7e1cd0>`



We can infer from this that, Google's stock is pretty stable. The starting price that we had was USD622.05, and the average final price over 10,000 runs was USD623.36.

The red line indicates the value of stock at risk at the desired confidence interval. For every stock, we'd be risking USD18.38, 99% of the time.