Time Series Assignment - Financial Time series Model

Install pandas-datareader library

In a command window: conda install pandas-datareader if you have not installed it yet.

Download data

Download the adjusted close price for Facebook (FB.US), 3M (MMM.US), IBM (IBM.US), and Amazon (AMZN.US) using the following code:

In [42]:
```
#Importing libraries necessary for analysis
import pandas as pd
import numpy as np
import seaborn as sns
pd.core.common.is_list_like = pd.api.types.is_list_like
import pandas_datareader.data as web
import datetime
from matplotlib import pyplot
from pandas.plotting import lag_plot
from pandas.plotting import scatter_matrix
from pylab import pcolor, show, colorbar, xticks, yticks
```

In [2]:
```
#importing stock data from yahoo
start = datetime.datetime(2013, 2, 28)
end = datetime.datetime(2018, 2, 27)
aapl = web.DataReader('AAPL', 'yahoo', start, end)
intc = web.DataReader('INTC', 'yahoo', start, end)
ebay = web.DataReader('EBAY', 'yahoo', start, end)
amzn = web.DataReader('AMZN', 'yahoo', start, end)
```

In [3]:
```
#Formating closing prices columns to be easily identified
aapl = aapl.rename(columns={'Adj Close' : 'AAPLClosingPrice'})
intc = intc.rename(columns={'Adj Close' : 'INTCClosingPrice'})
ebay = ebay.rename(columns={'Adj Close' : 'EBAYClosingPrice'})
amzn = amzn.rename(columns={'Adj Close' : 'AMZNClosingPrice'})
```

In [4]:
```
#Concatenating all closing prices (for 4 stocks) as one table
Table = pd.concat([aapl.AAPLClosingPrice,intc.INTCClosingPrice,ebay.EBAYC]
                  axis=1, ignore_index=False)
```

In [5]:
```
#Filtering out closing prices based on End of Month time points
TableEoM = Table.groupby(pd.Grouper(freq='BM'))['AAPLClosingPrice','INTCC
                                                 'EBAYClosingPrice','AMZNC
```

In [6]:
```
TableEoM.head(5)
```

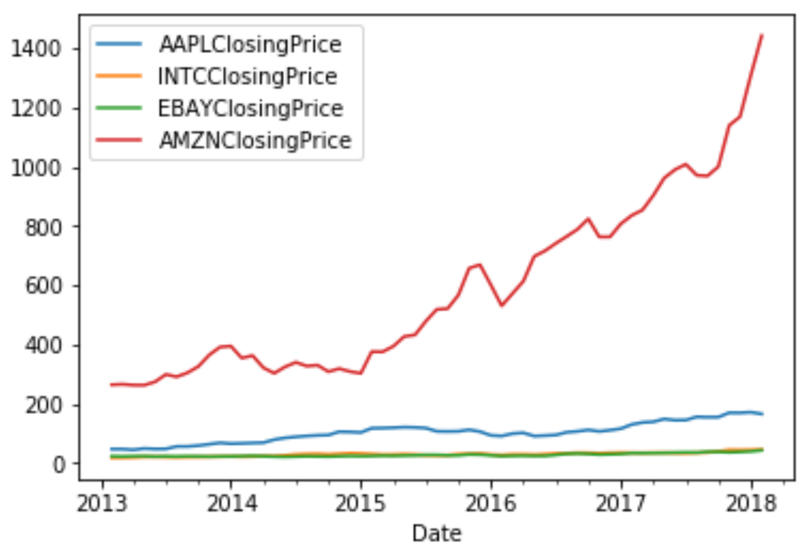
Out[6]:

Date	AAPLClosingPrice	INTCClosingPrice	EBAYClosingPrice	AMZNClosingPrice
2013-02-28	46.861313	17.537090	23.026094	264.269989
2013-03-29	46.908136	18.040610	22.174663	265.758498
2013-04-30	44.564433	18.666755	23.040825	263.072273
2013-05-31	49.051813	20.424195	23.127678	262.727725
2013-06-28	47.357114	20.870562	21.791456	274.102000

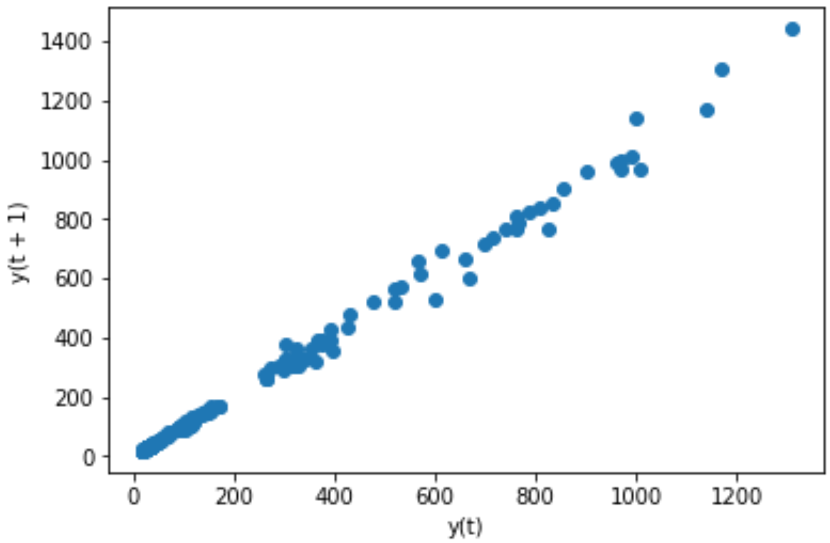
Plotting Autocorrelations

(2 marks) Correctly plot data and identify whether or not it is autocorrelated? Write it your interpretation as a commnet in the code section

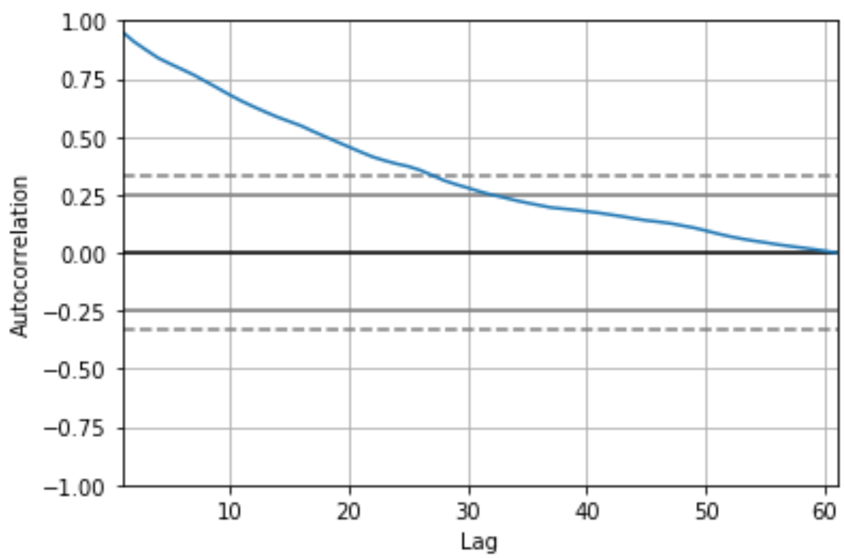
In [7]:
```
#Time series plot showing end of month closing prices by stock
TableEoM.plot()
pyplot.show()
```



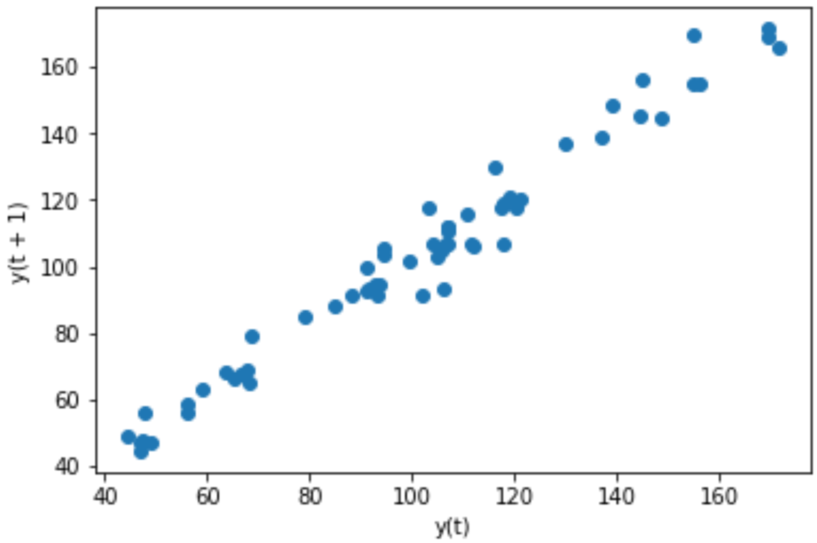
In [8]:
```
#The lag plot displaying closing price by day, exhibits a linear pattern,
#strongly non-random and further suggests that an autoregressive model is
lag_plot(TableEoM)
pyplot.show()
```



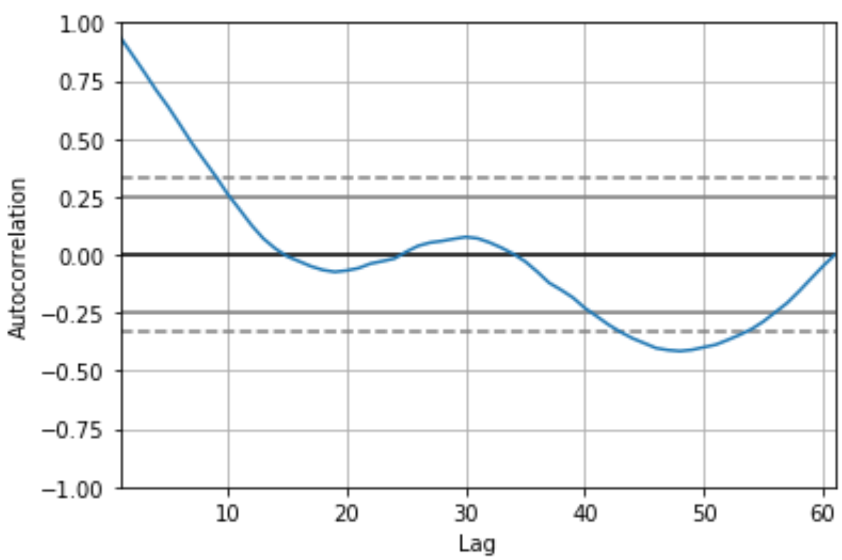
In [47]:
```
#When all stocks are grouped together, the autocorrelation plot below ex
#that from periods 0 to 30 are correlated and significant.The datapoints
pd.plotting.autocorrelation_plot(TableEoM)
pyplot.show()
```



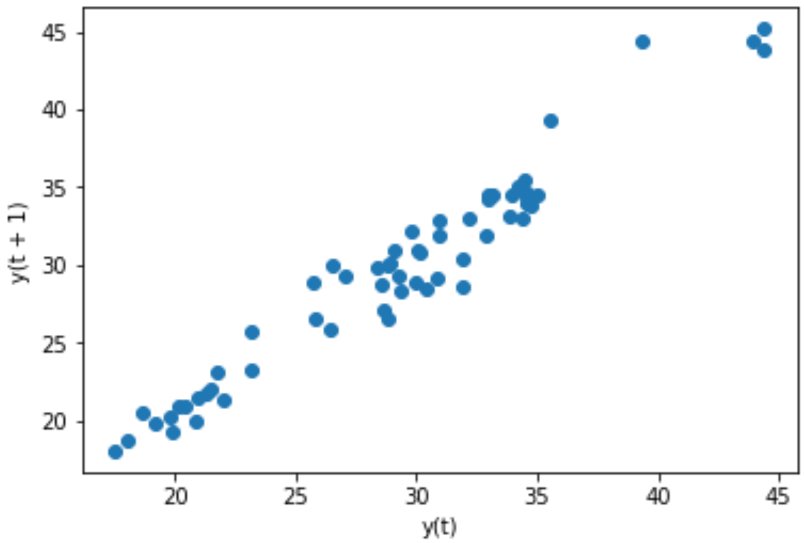
In [10]:
```
#AAPL stock lag plot exhibits a linear pattern,thus, confirming the data
#strongly non-random and further suggests that an autoregressive model i:
lag_plot(TableEoM.AAPLClosingPrice)
pyplot.show()
```



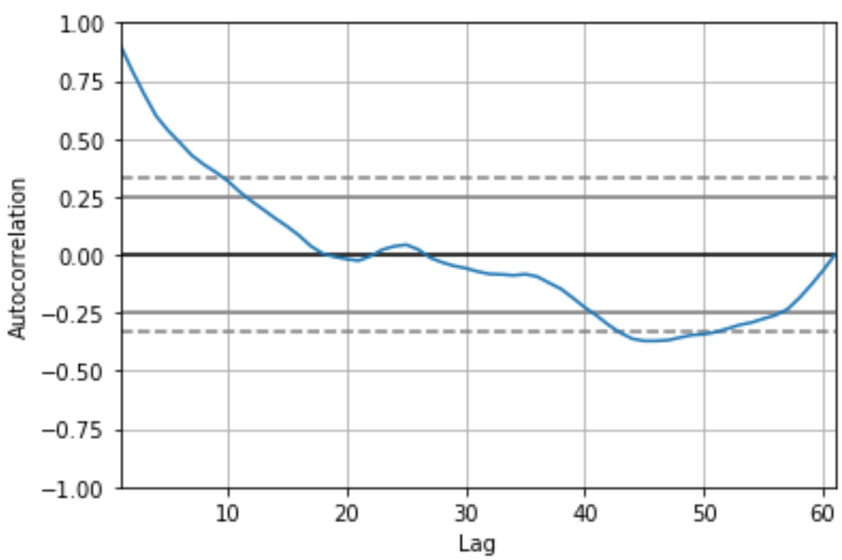
In [11]:
```
#AAPL closing prices are correlated and significant between lags 1 to 9 
pd.plotting.autocorrelation_plot(TableEoM.AAPLClosingPrice)
pyplot.show()
```



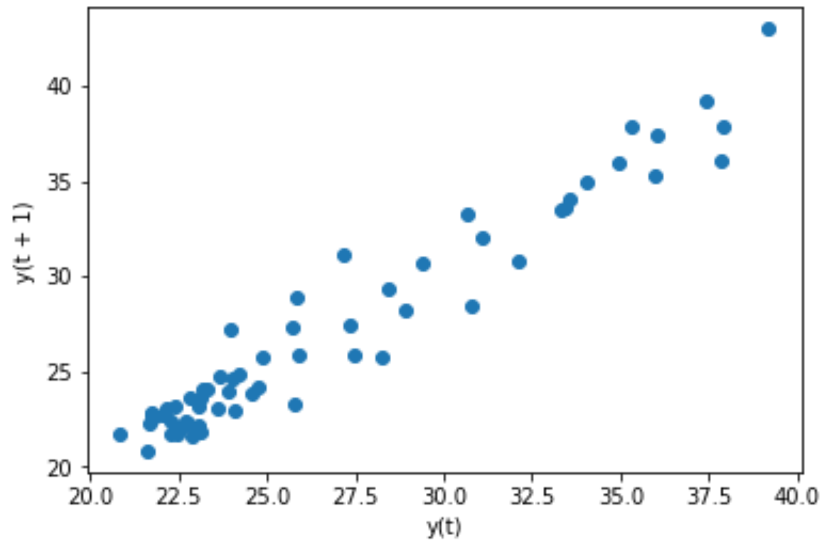
In [12]:
```
#INTC stock lag plot exhibits a linear pattern,thus, confirming the data
#strongly non-random and further suggests that an autoregressive model i:
lag_plot(TableEoM.INTCClosingPrice)
pyplot.show()
```



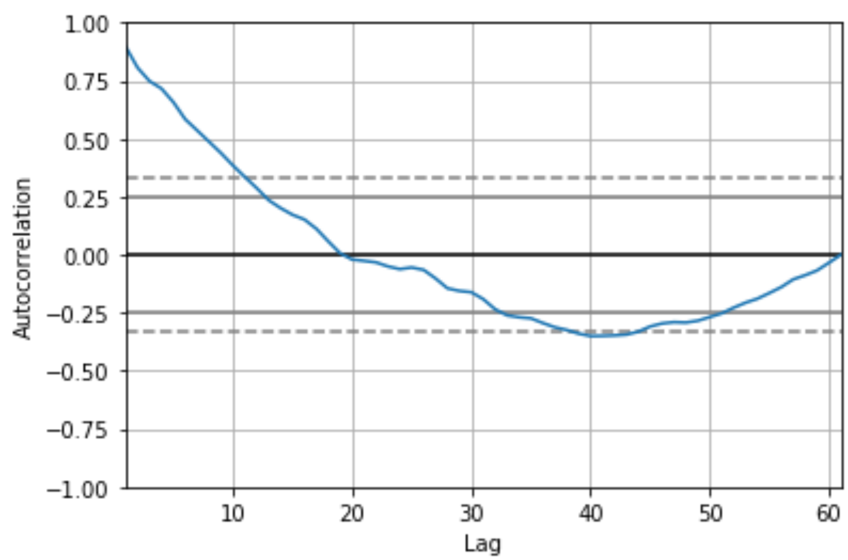
In [13]:
```
#INTC Closing price is correlated between lags 1 to 11 and 45 to 46(albe.
pd.plotting.autocorrelation_plot(TableEoM.INTCClosingPrice)
pyplot.show()
```



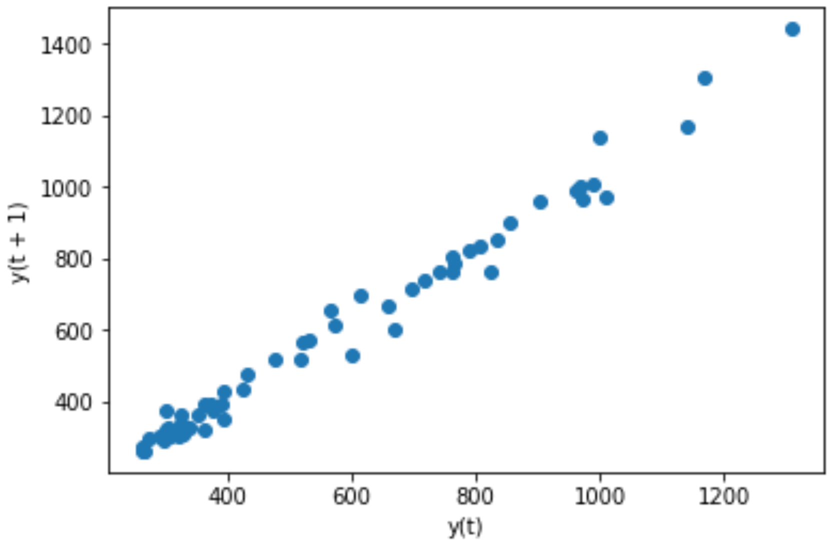
In [14]:
```
#EBAY stock lag plot exhibits a linear pattern,thus, confirming the data
#strongly non-random and further suggests that an autoregressive model i:
lag_plot(TableEoM.EBAYClosingPrice)
pyplot.show()
```



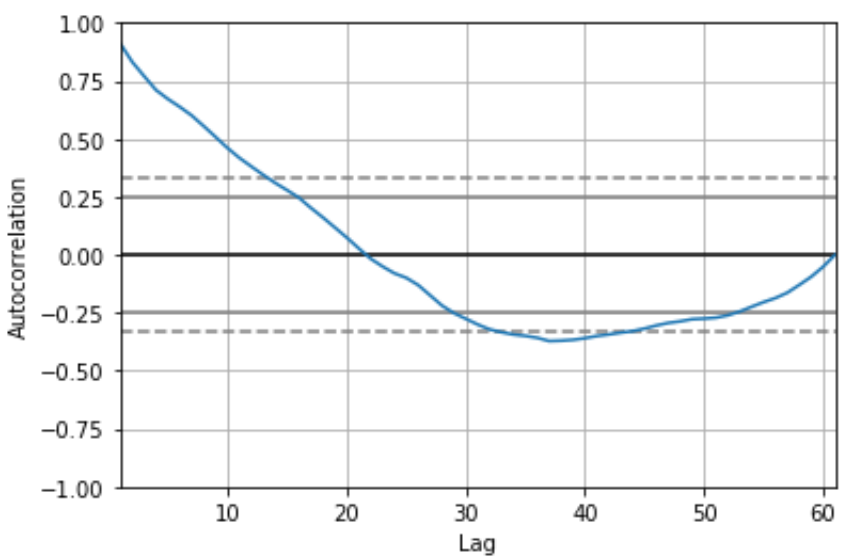
In [15]:
```
#EBAY closing prices are autocorrelated from lag 1 till lag 10
pd.plotting.autocorrelation_plot(TableEoM.EBAYClosingPrice)
pyplot.show()
```



In [16]:
```
#AMZN stock lag plot exhibits a linear pattern,thus, confirming the data
#strongly non-random and further suggests that an autoregressive model i
lag_plot(TableEoM.AMZNClosingPrice)
pyplot.show()
```



In [17]:
```
#AMZN closing prices are autocorrelated from lag 1 till lag 12 as well a
pd.plotting.autocorrelation_plot(TableEoM.AMZNClosingPrice)
pyplot.show()
```



In [ ]:

Monthly Returns

(2 marks) Use shift trick to correctly calculate monthly returns

In [18]:
```
#Shifting on time period runs a loop on available data to calculate mont
(TableEoM/TableEoM.shift(1)-1).dropna().head(5)
```

Out[18]:

Date	AAPLClosingPrice	INTCClosingPrice	EBAYClosingPrice	AMZNClosingPrice
2013-03-29	0.000999	0.028712	-0.036977	0.005633
2013-04-30	-0.049964	0.034708	0.039061	-0.010108
2013-05-31	0.100694	0.094148	0.003770	-0.001310
2013-06-28	-0.034549	0.021855	-0.057776	0.043293
2013-07-31	0.008505	-0.046760	0.036544	0.090750

In [19]:
```
#AAPL stock lag plot exhibits a linear pattern,thus, confirming the data
TableReturn = (TableEoM/TableEoM.shift(1)-1).dropna()
```

In [20]:
```
TableReturn.sample(5)
```

Out[20]:

Date	AAPLClosingPrice	INTCClosingPrice	EBAYClosingPrice	AMZNClosingPrice
2016-01-29	-0.119021	-0.102843	-0.087669	-0.101904
2014-06-30	0.076133	0.110778	-0.036046	0.071362
2016-12-30	0.038471	0.038027	0.033547	-0.000013
2015-02-27	0.137485	-0.048011	0.023062	0.241118
2017-03-31	0.053026	-0.018615	0.004044	0.022130

In [21]:
```
#Absolute change in prices
def parser(x):
    return datetime.strptime('190'+x, '%Y-%m')

df = TableEoM.diff()[1:].dropna()
df.head(5)
```

Out[21]:

Date	AAPLClosingPrice	INTCClosingPrice	EBAYClosingPrice	AMZNClosingPrice
2013-03-29	0.046824	0.503520	-0.851431	1.488509
2013-04-30	-2.343703	0.626145	0.866162	-2.686226
2013-05-31	4.487379	1.757439	0.086853	-0.344548
2013-06-28	-1.694698	0.446368	-1.336222	11.374275
2013-07-31	0.402779	-0.975907	0.796354	24.874819

In [22]:
```
df.head(5)
```

Out[22]:

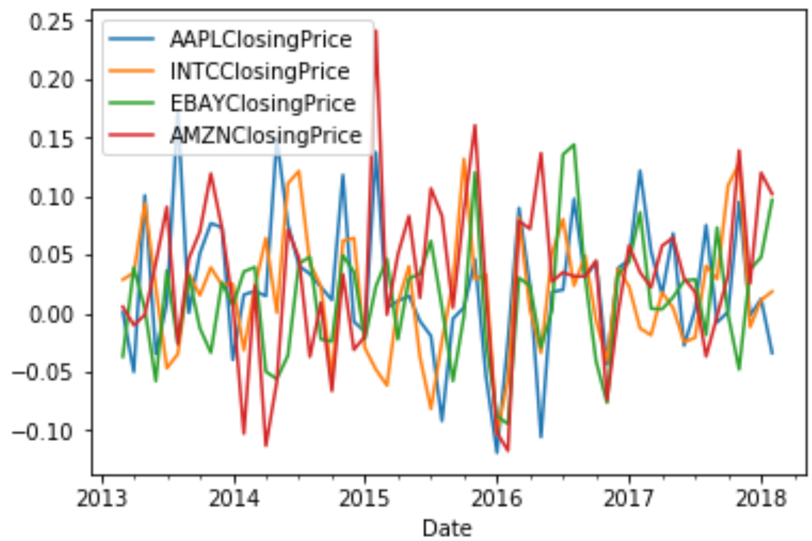
Date	AAPLClosingPrice	INTCClosingPrice	EBAYClosingPrice	AMZNClosingPrice
2013-03-29	0.046824	0.503520	-0.851431	1.488509
2013-04-30	-2.343703	0.626145	0.866162	-2.686226
2013-05-31	4.487379	1.757439	0.086853	-0.344548
2013-06-28	-1.694698	0.446368	-1.336222	11.374275
2013-07-31	0.402779	-0.975907	0.796354	24.874819

In [ ]:

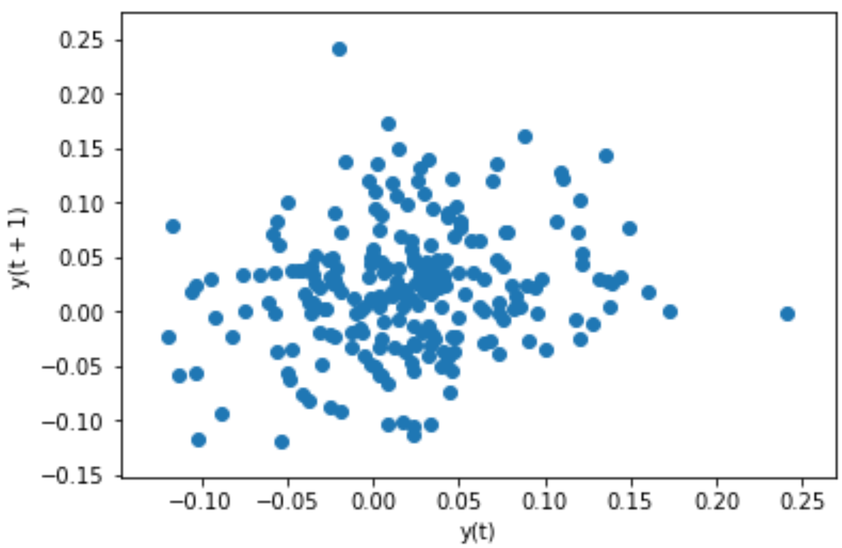
Plotting Return Correlations

(3 marks) Correctly draw autocorrelation plots, state whether or not they are autocorrelated. In addition, state whether or not monthly returns are correlated among companies (you may use scatter matrix) and find out which companies are the most and the least correlated in terms of their monthly returns. You may use **matplotlib.pyplot.pcolor** for better visualization of the correlation coefficients.

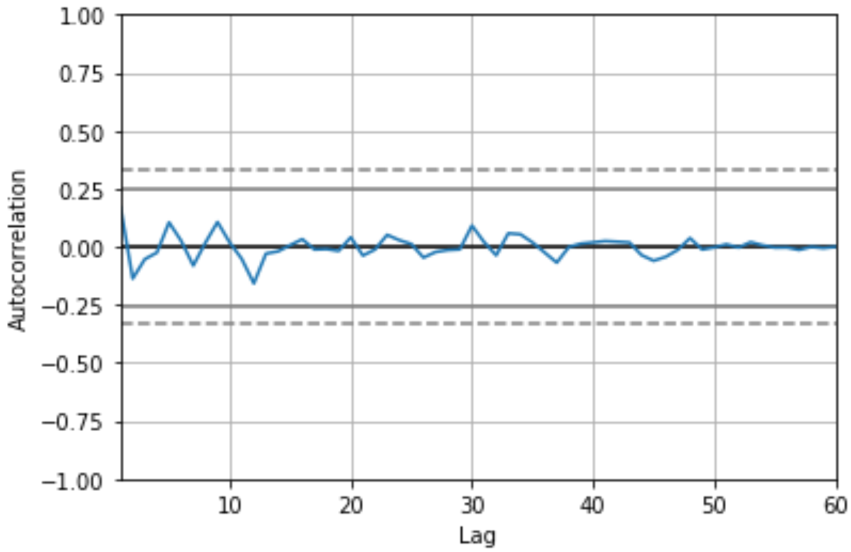
In [23]:
```
#Time series plot showing monthly returns by stock
TableReturn.plot()
pyplot.show()
```



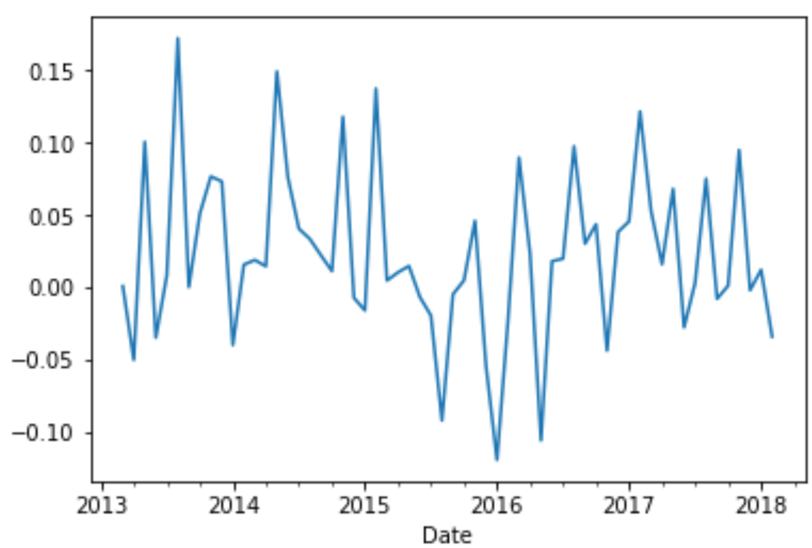
In [24]:
```
lag_plot(TableReturn)
pyplot.show()
```



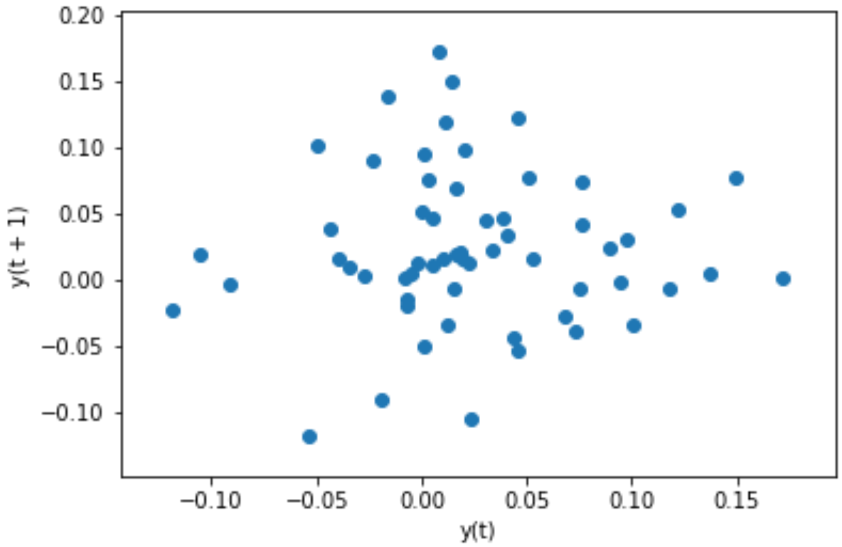
In [25]:
```
#Autocorrelation of returns grouped as one shows no autocorrelation sinc
pd.plotting.autocorrelation_plot(TableReturn)
pyplot.show()
```



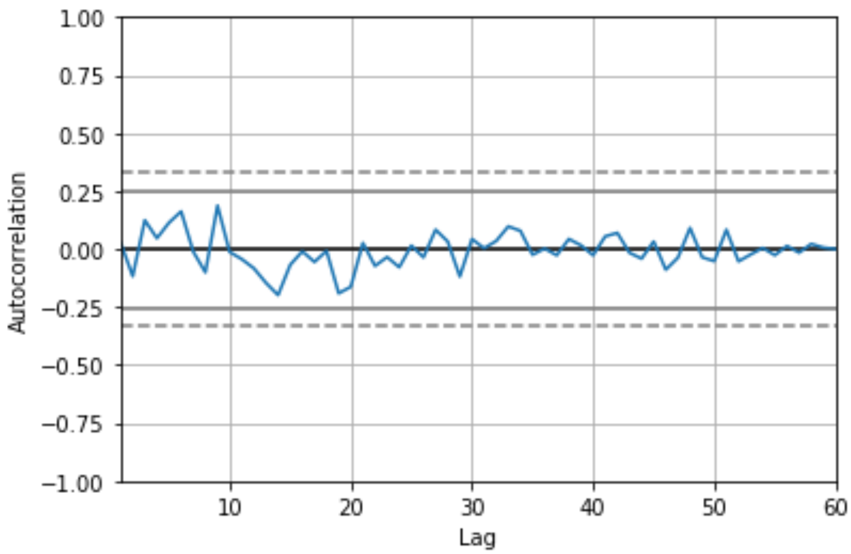
In [26]:
```
TableReturn.AAPLClosingPrice.plot()
pyplot.show()
```



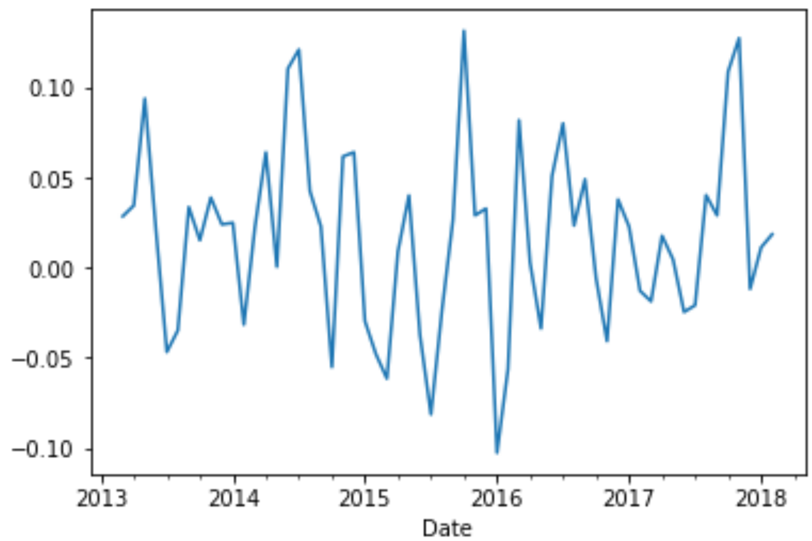
In [27]:
```
lag_plot(TableReturn.AAPLClosingPrice)
pyplot.show()
```



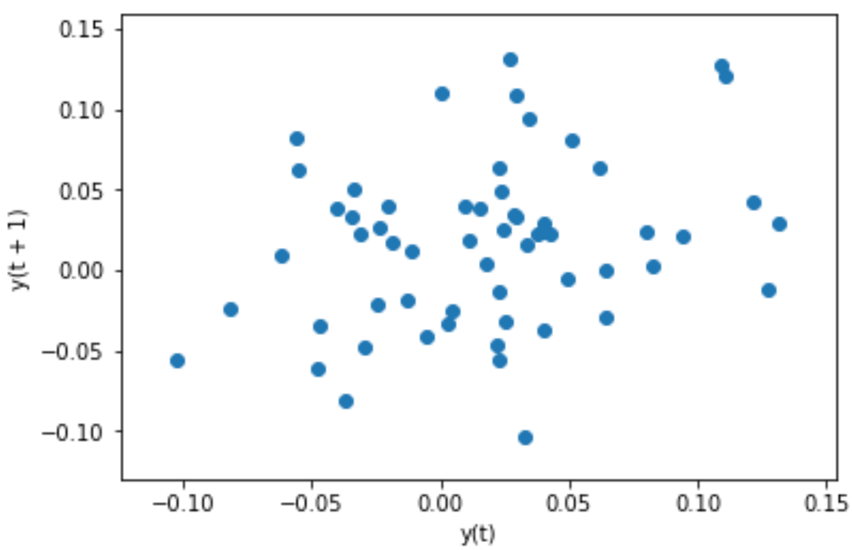
In [28]:
```
#Autocorrelation ghaphs suggests Apple stock returns are not autocorrela
pd.plotting.autocorrelation_plot(TableReturn.AAPLClosingPrice)
pyplot.show()
```



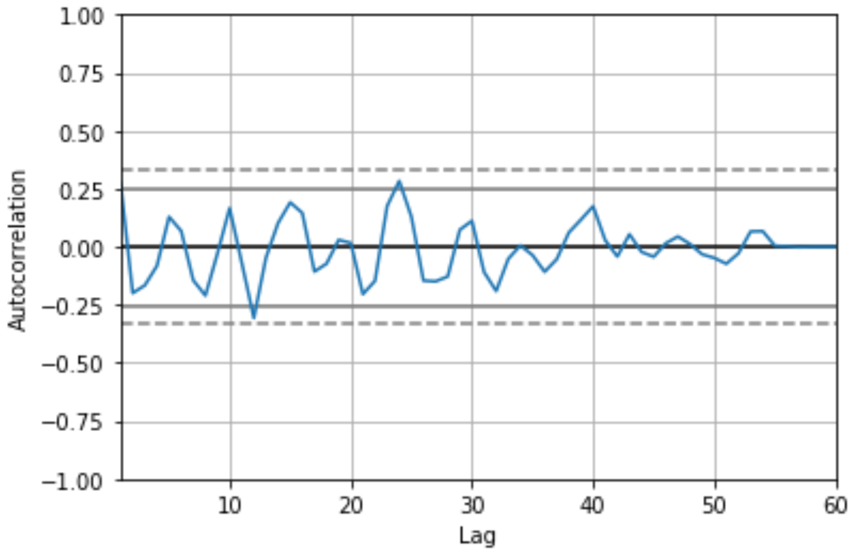
In [29]:
```
TableReturn.INTCClosingPrice.plot()
pyplot.show()
```



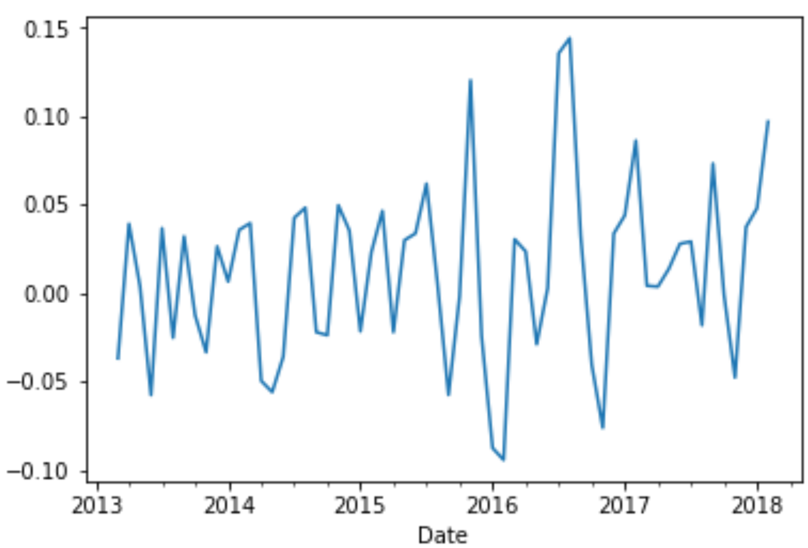
In [30]:
```
lag_plot(TableReturn.INTCClosingPrice)
pyplot.show()
```



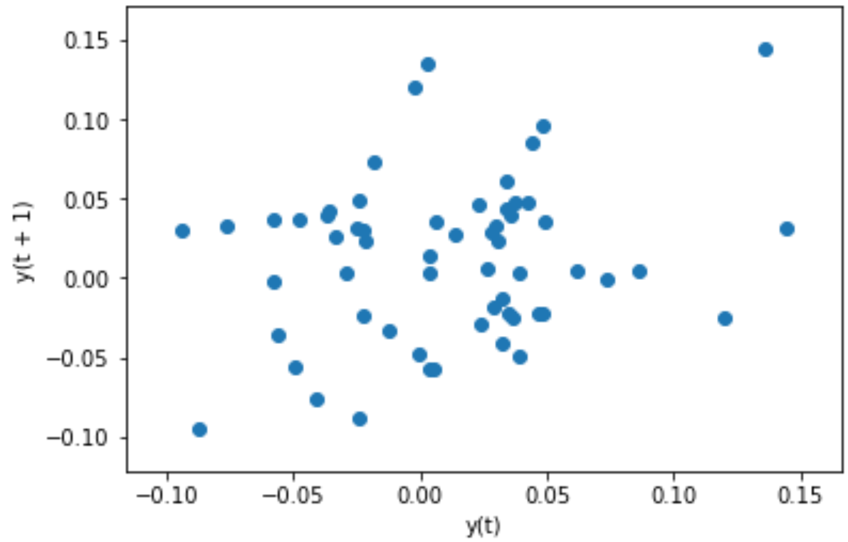
In [31]:
```
#Autocorrelation ghaphs suggests Apple stock returns are not autocorrela
pd.plotting.autocorrelation_plot(TableReturn.INTCClosingPrice)
pyplot.show()
```



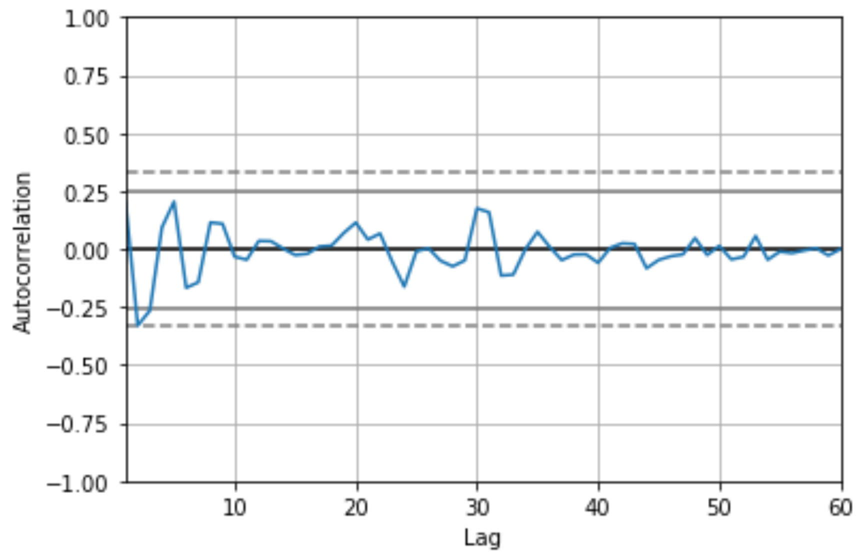
In [32]:
```
TableReturn.EBAYClosingPrice.plot()
pyplot.show()
```



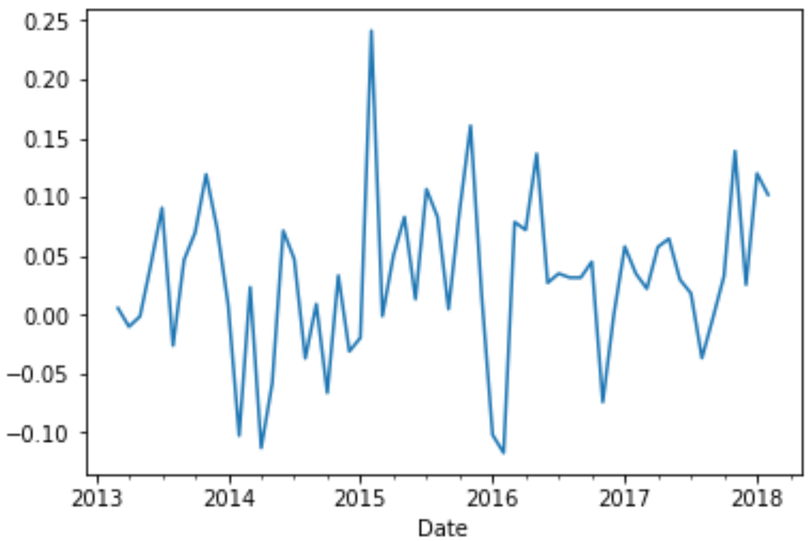
In [33]:
```
lag_plot(TableReturn.EBAYClosingPrice)
pyplot.show()
```



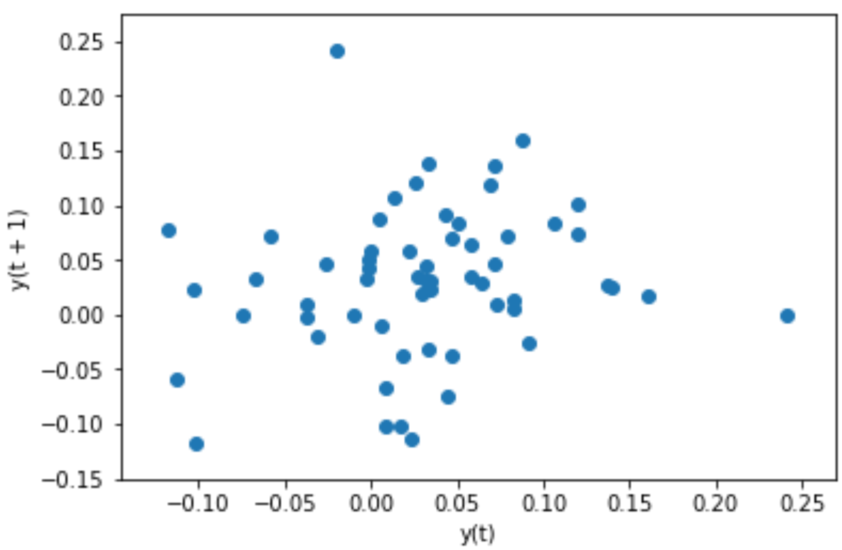
In [34]:
```
#Autocorrelation ghaphs suggests Apple stock returns are not autocorrela
pd.plotting.autocorrelation_plot(TableReturn.EBAYClosingPrice)
pyplot.show()
```



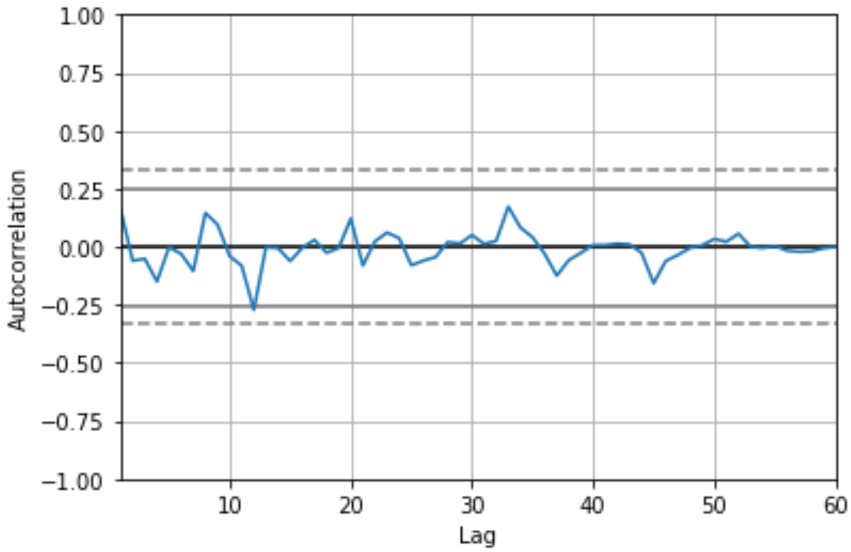
In [35]:
```
TableReturn.AMZNClosingPrice.plot()
pyplot.show()
```



In [36]:
```
lag_plot(TableReturn.AMZNClosingPrice)
pyplot.show()
```



In [37]:
```
#Autocorrelation ghaphs suggests Apple stock returns are not autocorrela
pd.plotting.autocorrelation_plot(TableReturn.AMZNClosingPrice)
pyplot.show()
```

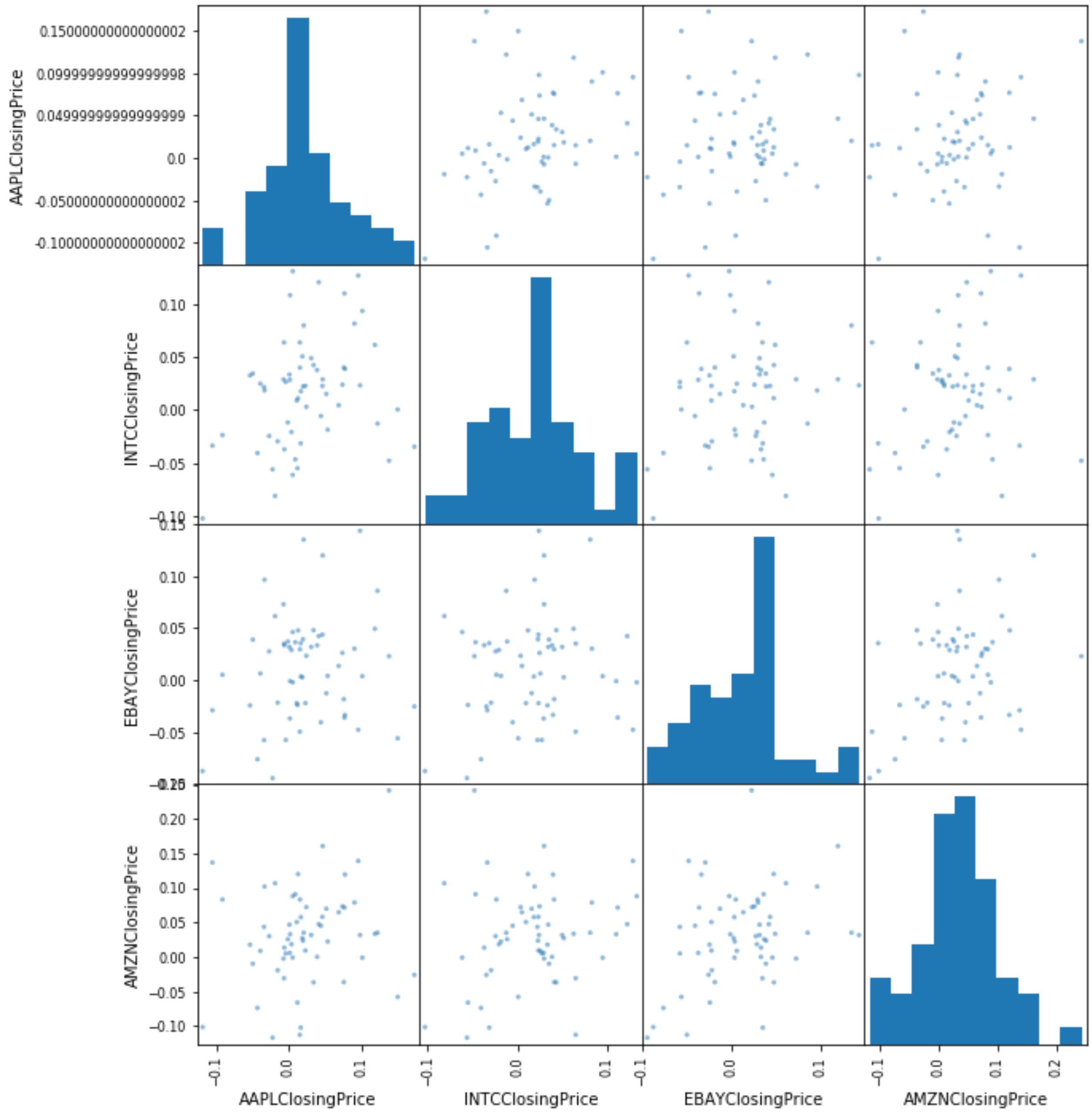


In [ ]:

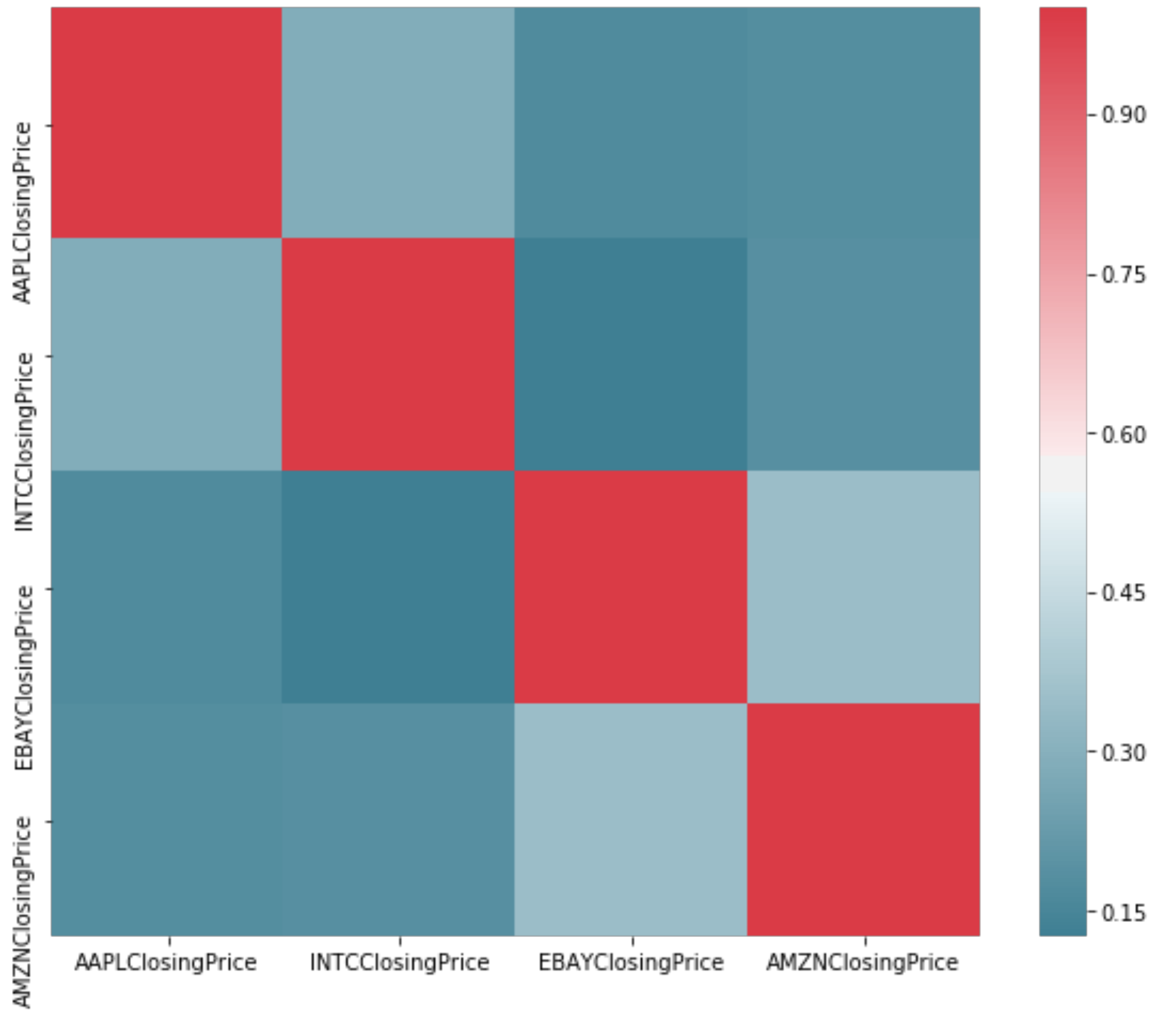
In [ ]:

Bonus

In [38]:
```
#Data visualization between return of all pairs of stock using scatterpl
scatter_matrix(TableReturn, figsize = (10,12))
pyplot.show()
```



In [48]:
```
#correlation of the returns of all pairs of stocks
f, ax = pyplot.subplots(figsize=(10, 8))
corr = TableReturn.corr()
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.dive
            square=True, ax=ax)
pyplot.show()
```



In [ ]: