Financial analysis American Automobile & Tech industry - Notebook

May 15, 2020

1 Financial Analysis of the American Automobile & Tech sector

This short analysis, provides an overview of the financial behavior of the american automobile sector for the last 3 years. To do so we intend to analyze specifically the market price of Ford and General Motors.

We also want to analyze the relationship between Tesla and the two classic american automobile compagnies. Our intuition is that Tesla is perceived by investors as a tech company rather than a automobile company, we want to verify it with some corrolation analysis.

Lastely we are going to study the impact of the coronavirus crisis on the automobile and tech stock prices.

[26]:
```
import pandas as pd
import pandas_datareader.data as web
import datetime
import matplotlib.pyplot as plt
%matplotlib inline
```

[22]:
```
start = datetime.datetime(2017,1,3)
end = datetime.datetime(2020,1,3)
```

[23]:
```
df_ford = web.DataReader('F','yahoo',start,end)
df_ford.head()
```

[23]:

Date	High	Low	Open	Close	Volume	Adj Close
2017-01-03	12.60	12.13	12.20	12.59	40510800.0	10.077526
2017-01-04	13.27	12.74	12.77	13.17	77638100.0	10.541780
2017-01-05	13.22	12.63	13.21	12.77	75628400.0	10.221605
2017-01-06	12.84	12.64	12.80	12.76	40315900.0	10.213601
2017-01-09	12.86	12.63	12.79	12.63	39438400.0	10.109543

[24]:
```
df_gm = web.DataReader('GM','yahoo',start,end)
df_gm.head(3)
```

[24]:

```
                High        Low       Open      Close      Volume  Adj Close
Date
2017-01-03  35.570000  34.840000  34.980000  35.150002  10904900.0  30.431576
2017-01-04  37.240002  35.470001  35.599998  37.090000  23388500.0  32.111160
2017-01-05  37.049999  36.070000  37.009998  36.389999  15636700.0  31.505117
```

[30]:

```
df_tesla = web.DataReader('TSLA','yahoo',start,end)
df_tesla.head(3)
```

[30]:

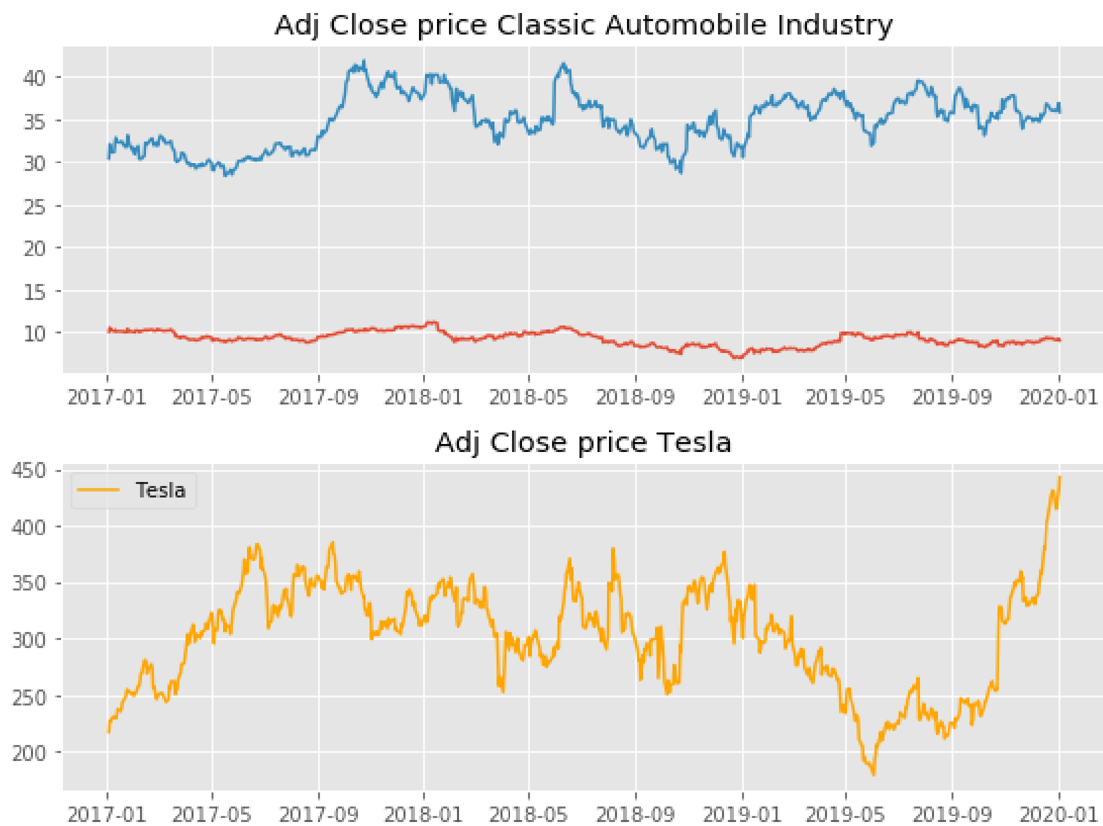
```
                  High         Low        Open       Close    Volume  \
Date
2017-01-03  220.330002  210.960007  214.860001  216.990005   5923300
2017-01-04  228.000000  214.309998  214.750000  226.990005  11213500
2017-01-05  227.479996  221.949997  226.419998  226.750000   5911700

             Adj Close
Date
2017-01-03  216.990005
2017-01-04  226.990005
2017-01-05  226.750000
```

1.1 First visualization overview - Automobile Industry

1.1.1 Price analysis

[47]:

```
#Volume plot
fig, axes = plt.subplots(2,1,figsize=(8,6))
axes[0].plot(df_ford['Adj Close'],label='Ford')
axes[0].set_title('Adj Close price Classic Automobile Industry')
axes[0].plot(df_gm['Adj Close'],label='GM')
axes[1].plot(df_tesla['Adj Close'], label='Tesla',c='orange')
axes[1].set_title('Adj Close price Tesla')
plt.legend()
plt.tight_layout()
```

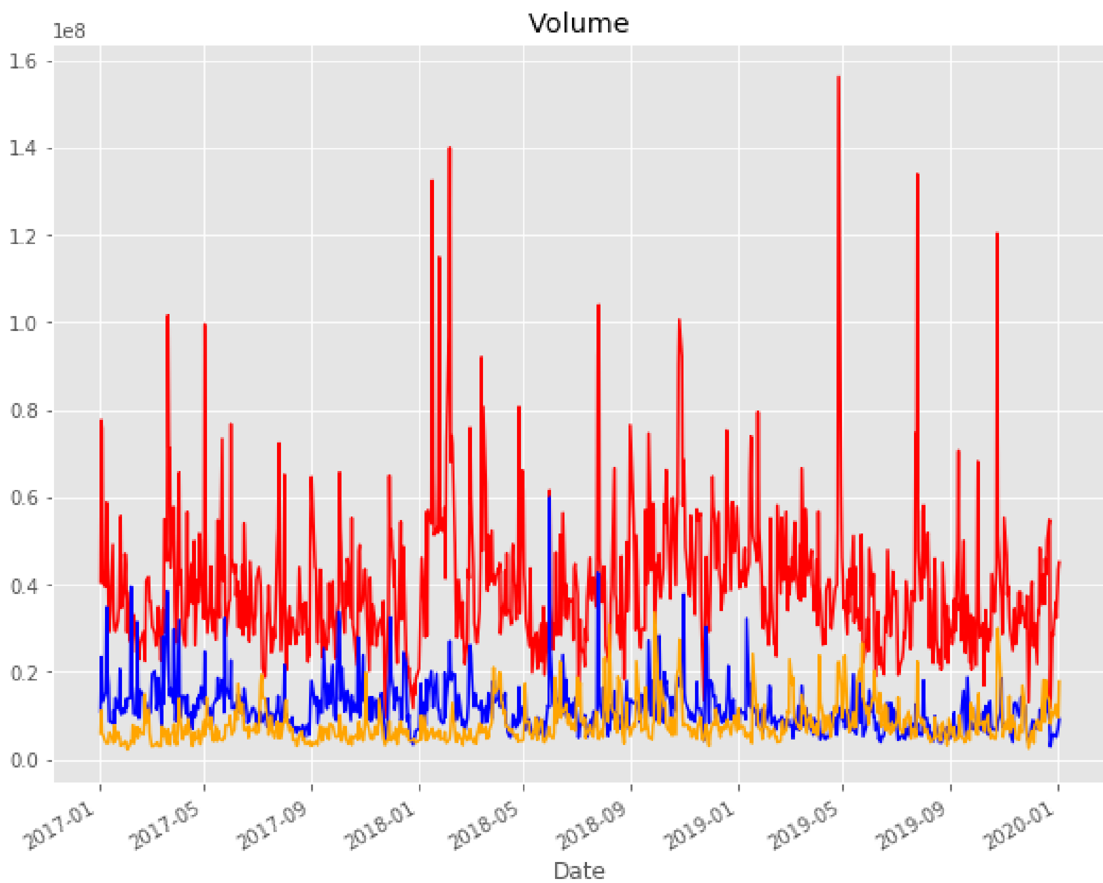


Commentary: At first sight the volatility for Tesla stock price seems higher than for Ford and GM

1.1.2 Volume analysis

[50]:
```python
df_ford['Volume'].plot(figsize=(10,8),title='Volume',label='Ford',c='r')
df_gm['Volume'].plot(label='GM',c='b')
df_tesla['Volume'].plot(label='Tesla',c='orange')
```

[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x172d7778248>
```

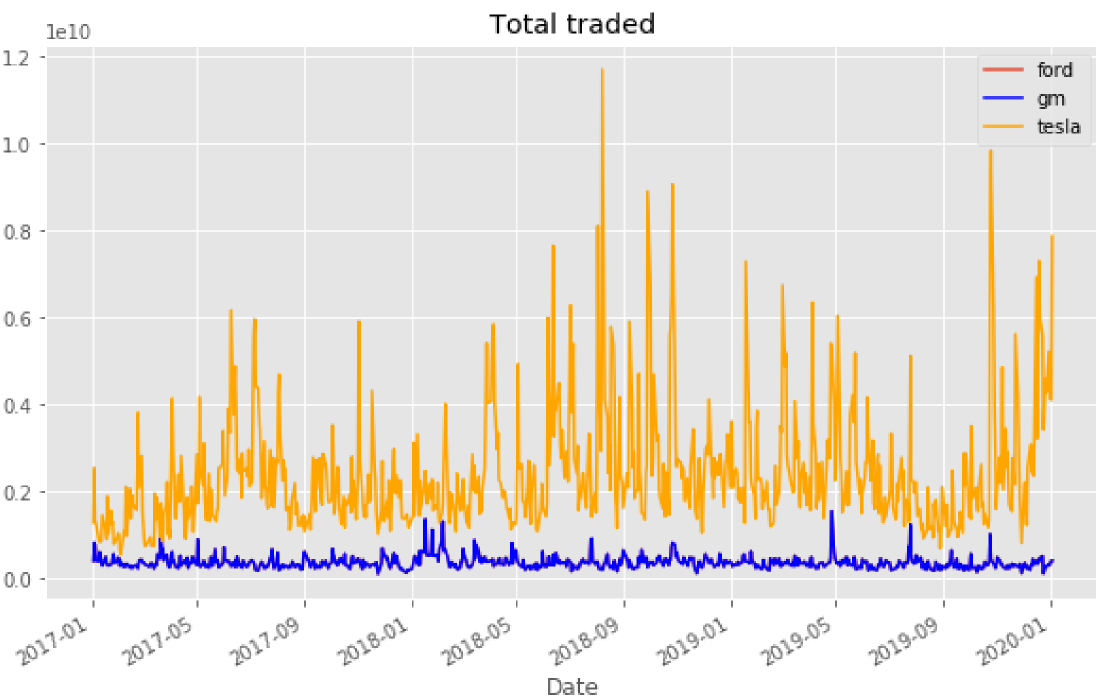


1.1.3 Estimation of total traded

[51]:
```
df_ford['Total traded'] = df_ford['Adj Close'] * df_ford['Volume']
df_gm['Total traded'] = df_ford['Adj Close'] * df_ford['Volume']
df_tesla['Total traded'] = df_tesla['Adj Close'] * df_tesla['Volume']
```

[53]:
```
df_ford['Total traded'].plot(figsize=(10,6),title='Total traded',label='ford')
df_gm['Total traded'].plot(label='gm',c='b')
df_tesla['Total traded'].plot(label='tesla',c='orange')
plt.legend()
```

[53]: <matplotlib.legend.Legend at 0x172e02de948>

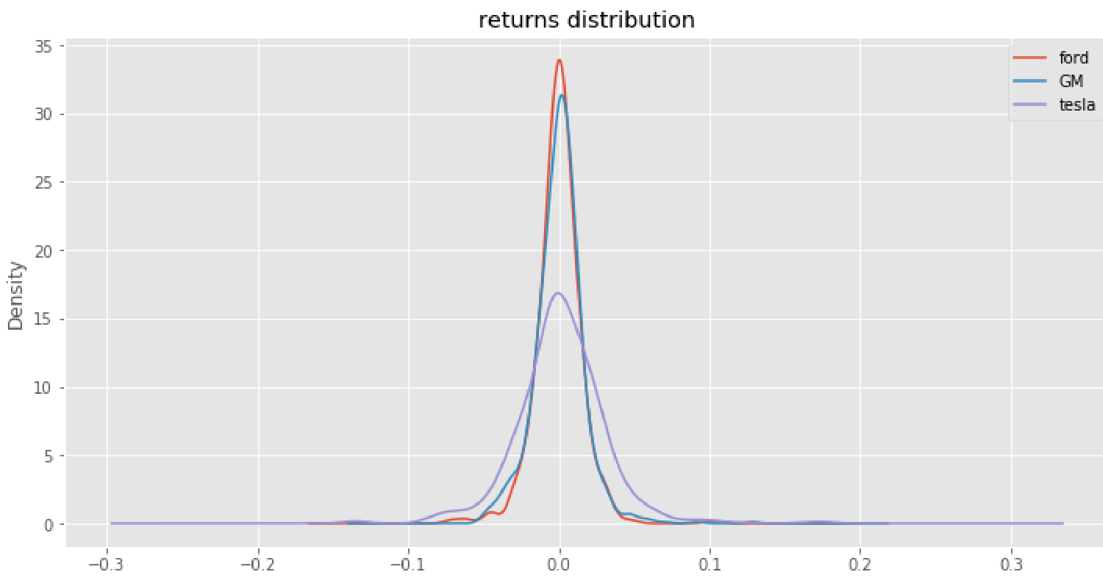


1.2 Returns and Volatility analysis

[55]:
```
df_ford['returns'] = (df_ford['Adj Close'] / df_ford['Adj Close'].shift(1)) -1
df_gm['returns'] = (df_gm['Adj Close'] / df_gm['Adj Close'].shift(1)) -1
df_tesla['returns'] = (df_tesla['Adj Close'] / df_tesla['Adj Close'].shift(1))␣
↪-1
```

[66]:
```
df_ford["returns"].plot(kind='kde',title='returns distribution',figsize=(12,6),␣
↪label='ford')
df_gm['returns'].plot(kind='kde',label='GM')
df_tesla['returns'].plot(kind='kde',label='tesla')
plt.legend()
```

[66]: <matplotlib.legend.Legend at 0x172e4c87a48>



Commentary: Visualy we notice immediatly that the kurtosis of ford and GM returns are very similar, whereas Tesla's kurtosis is much bigger. Tesla's volatility is higher.

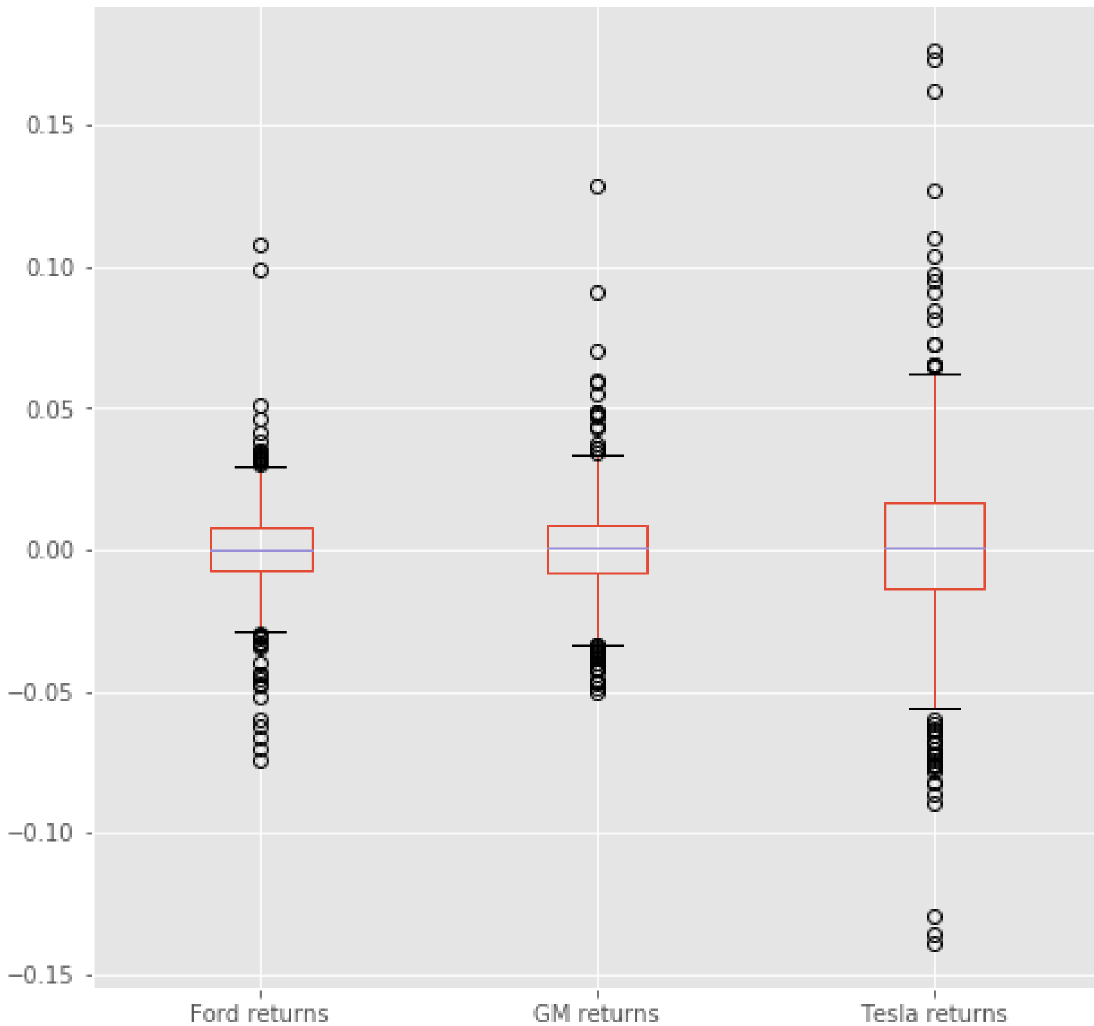
[68]:
```
df_box = pd.
↪concat([df_ford['returns'],df_gm['returns'],df_tesla['returns']],axis=1)
df_box.columns = ['Ford returns','GM returns','Tesla returns']
df_box.head()
```

[68]:

	Ford returns	GM returns	Tesla returns
Date			
2017-01-03	NaN	NaN	NaN
2017-01-04	0.046068	0.055192	0.046085
2017-01-05	-0.030372	-0.018873	-0.001057
2017-01-06	-0.000783	-0.010992	0.009967
2017-01-09	-0.010188	0.000556	0.009912

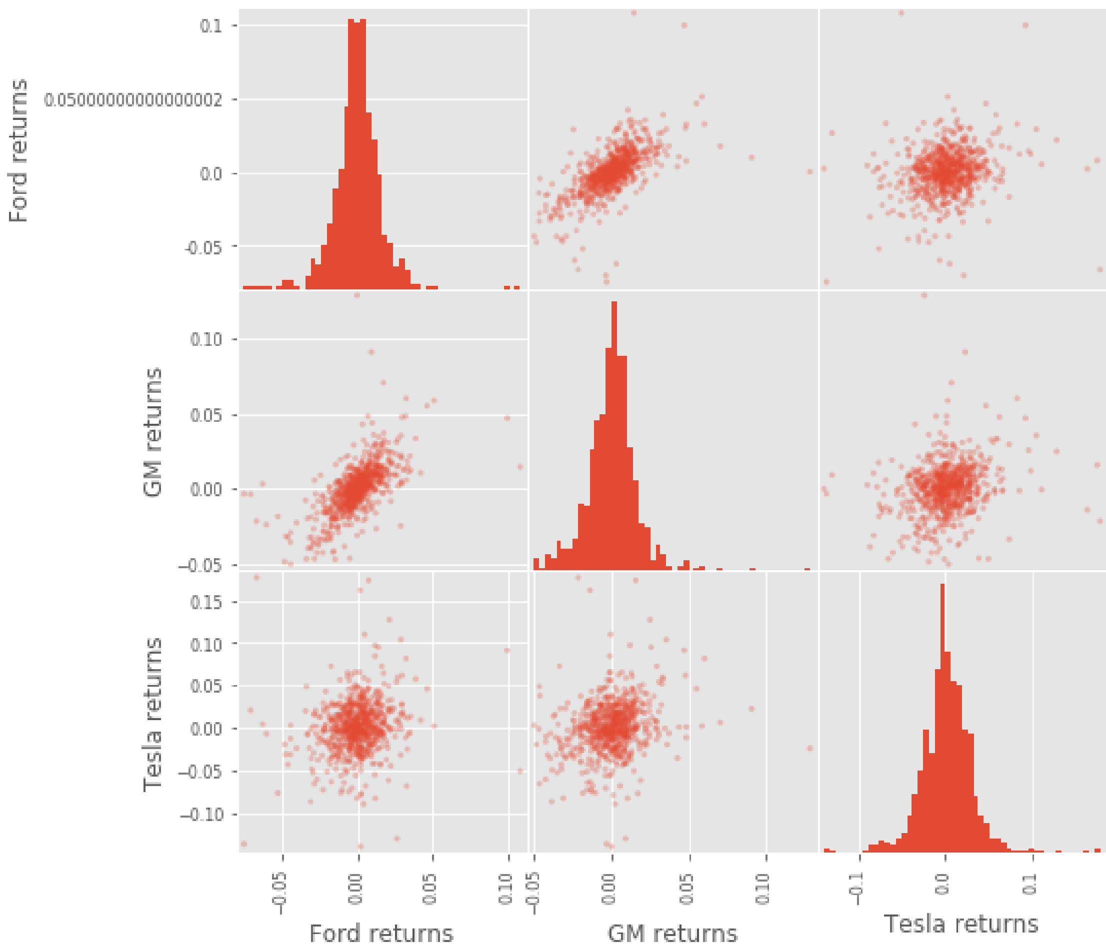
[72]:
```
df_box.plot(kind='box',figsize=(8,8))
```

[72]: <matplotlib.axes._subplots.AxesSubplot at 0x172de306288>



[73]:
```
from pandas.plotting import scatter_matrix
```

[76]:
```
scatter_matrix(df_box,figsize=(8,8),alpha=0.3,hist_kwds={'bins':50});
```



[77]:
```
df_box.corr()
```

[77]:

	Ford returns	GM returns	Tesla returns
Ford returns	1.000000	0.624726	0.172857
GM returns	0.624726	1.000000	0.220504
Tesla returns	0.172857	0.220504	1.000000

Commentary: Our graphic analysis and the calculation of the correlations show that Tesla's financial evolution is poorely linked to the evolution of Ford and GM. On the other hand Ford and GM share a fairly consistent correlation, some statiscal test could maybe confirm our view with more precision.

[84]:
```
# the Pearson's Correlation test
from scipy.stats import pearsonr
data1 = df_ford['Adj Close'].dropna()
data2 = df_gm['Adj Close'].dropna()
stat, p = pearsonr(data1, data2)
```

```
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
        print('Probably independent')
else:
        print('Probably dependent')
```

```
stat=0.314, p=0.000
Probably dependent
```

The Person Correlation test confirms a significative correlation between ford and Gm.

[83]:
```
# the Pearson's Correlation test
from scipy.stats import pearsonr
data1 = df_ford['Adj Close'].dropna()
data2 = df_tesla['Adj Close'].dropna()
stat, p = pearsonr(data1, data2)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
        print('Probably independent')
else:
        print('Probably dependent')
```

```
stat=-0.028, p=0.447
Probably independent
```

Whereas the relationship between the classical automobile constructors and Tesla seems unsignificent

1.3 Second visualization overview : Tesla & Tech compagnies

Can we determine a significent correlation between the evolution of Tesla's stock price and the other Tech compagnies stock prices(Facebook and Google)?

[88]:
```
df_goog = web.DataReader('GOOGL','yahoo',start,end)
df_goog.head()
```

[88]:
```
                  High         Low        Open       Close   Volume  \
Date
2017-01-03  811.440002  796.890015  800.619995  808.010010  1959000
2017-01-04  813.429993  804.109985  809.890015  807.770020  1515300
2017-01-05  813.739990  805.919983  807.500000  813.020020  1340500
2017-01-06  828.960022  811.500000  814.989990  825.210022  2017100
2017-01-09  830.429993  821.619995  826.369995  827.179993  1408900

             Adj Close
Date
2017-01-03  808.010010
2017-01-04  807.770020
2017-01-05  813.020020
```

```
2017-01-06  825.210022
2017-01-09  827.179993
```

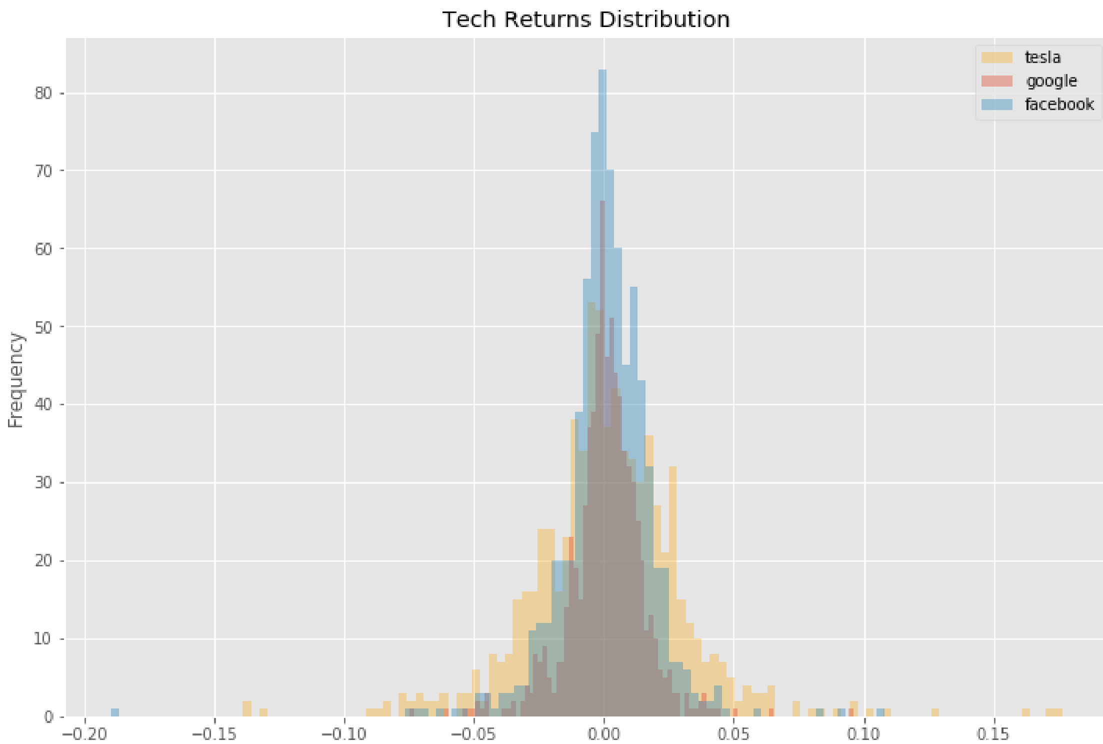
[90]:
```
df_fb = web.DataReader('FB','yahoo',start,end)
df_fb.head()
```

[90]:
```
                  High         Low        Open       Close    Volume  \
Date
2017-01-03  117.839996  115.510002  116.029999  116.860001  20663900
2017-01-04  119.660004  117.290001  117.550003  118.690002  19630900
2017-01-05  120.949997  118.320000  118.860001  120.669998  19492200
2017-01-06  123.879997  120.029999  120.980003  123.410004  28545300
2017-01-09  125.430000  123.040001  123.550003  124.900002  22880400

             Adj Close
Date
2017-01-03  116.860001
2017-01-04  118.690002
2017-01-05  120.669998
2017-01-06  123.410004
2017-01-09  124.900002
```

[93]:
```
df_fb['returns'] = df_fb['Adj Close'].pct_change(1)
df_goog['returns'] = df_goog['Adj Close'].pct_change(1)
```

[104]:
```
df_tesla['returns'].plot.hist(bins=100, alpha=0.3,label='tesla',color='orange')
df_goog['returns'].plot.hist(figsize=(12,8),bins=100,label='google',title='Tech␣
 ↪Returns Distribution',alpha=0.4)
df_fb['returns'].plot.hist(bins=100,alpha=0.4, label='facebook')

plt.legend()
```

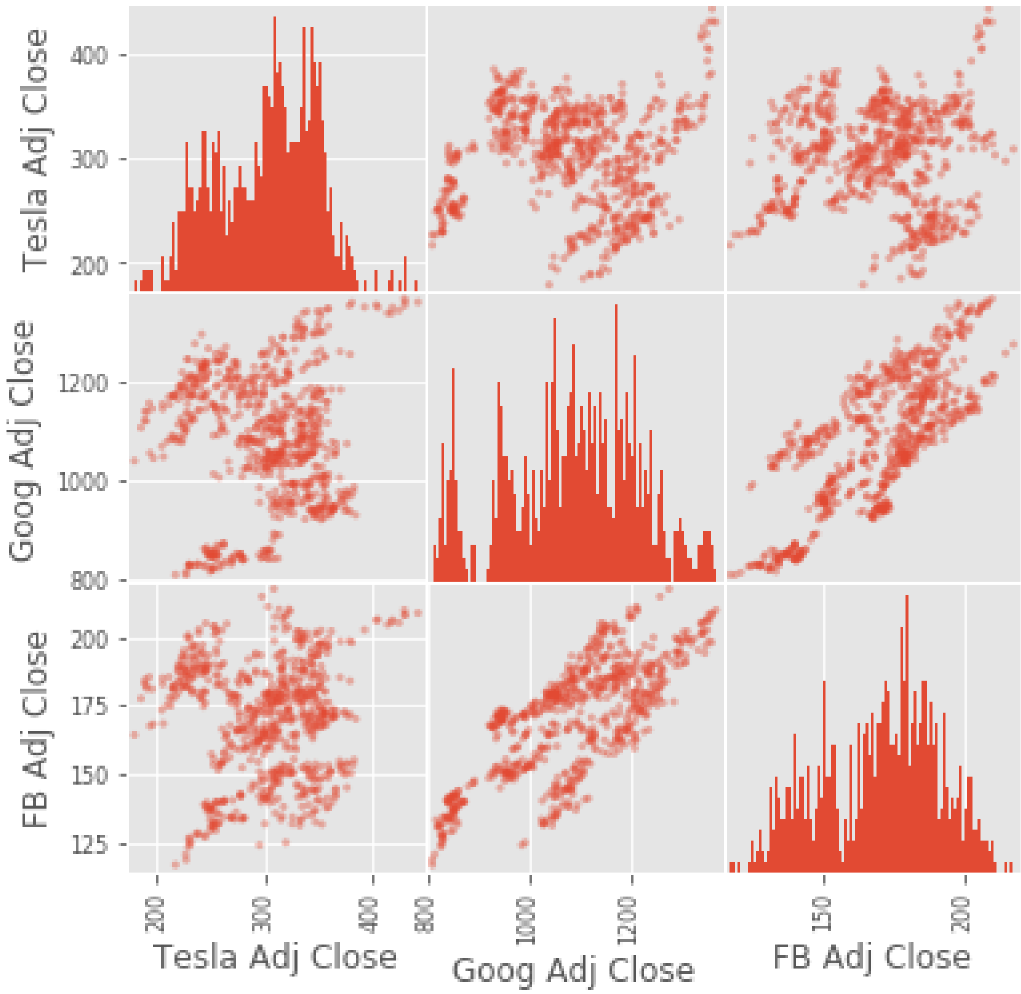
[104]:
```
<matplotlib.legend.Legend at 0x172e80c6c08>
```



[111]:
```
df_tech_box = pd.concat([df_tesla['Adj Close'],df_goog['Adj Close'],df_fb['Adj␣
↪Close']],axis=1)
df_tech_box.columns = ['Tesla Adj Close','Goog Adj Close','FB Adj Close']
```

[112]:
```
scatter_matrix(df_tech_box,alpha=0.4,figsize=(6,6),hist_kwds={'bins':100})
```

[112]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000172E861E4C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000172E8669548>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000172E865F448>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000172E87B9C88>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000172E87FD988>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000172E8A64148>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000172E8A98A48>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000172E8AD6F88>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000172E8ADD088>]],
      dtype=object)
```



[113]:
```
df_tech_box.corr()
```

[113]:

	Tesla Adj Close	Goog Adj Close	FB Adj Close
Tesla Adj Close	1.000000	0.018457	0.034168
Goog Adj Close	0.018457	1.000000	0.741292
FB Adj Close	0.034168	0.741292	1.000000

Our intuition was partially right. Tesla isn't considered by investors as a regular car company. However there is no evidence that Tesla is financially considered as a tech company since the correlation is poor between Tesla's market price evolution and other tech compagnies. This is fairly understandable, since the economic structure on which rely Tesla and digital compagnies such as facebook are completly different.

1.4 Third Visualization overview : the Impact of coronavirus on automobile and tech compagnies

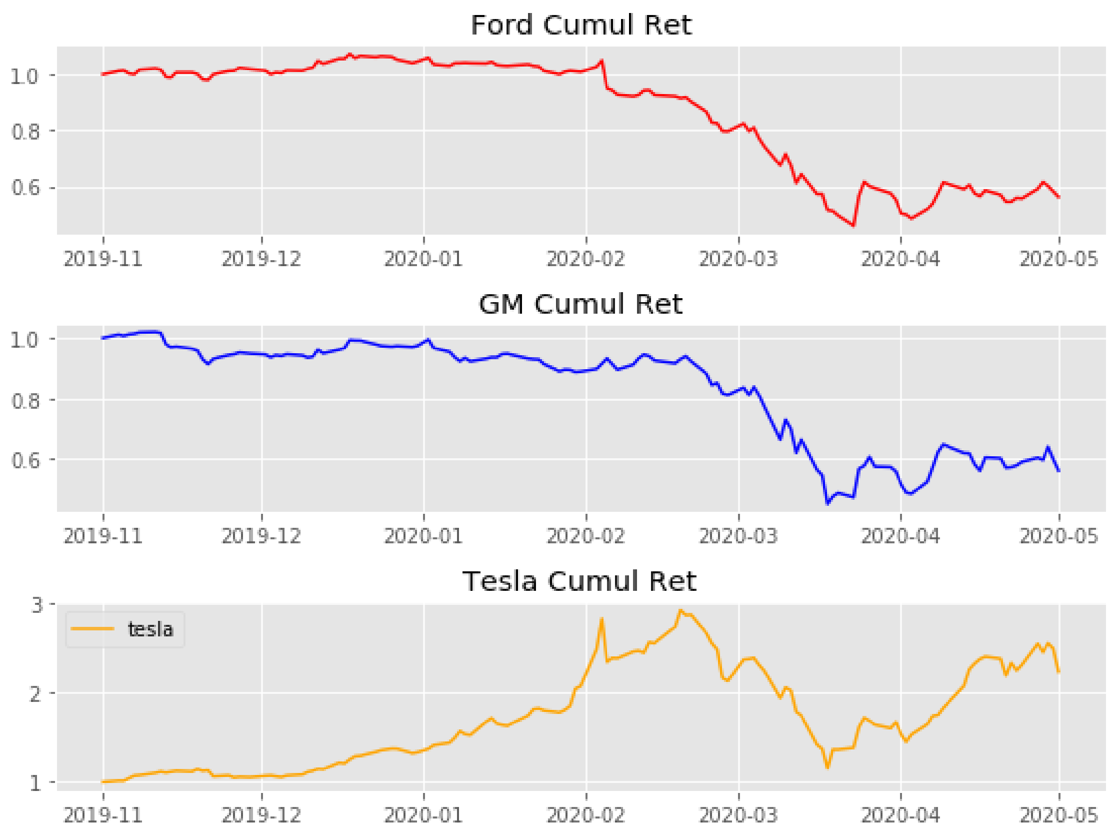
[122]:
```
start = datetime.datetime(2019,11,1)
end = datetime.datetime(2020,5,3)
```

[132]:
```
covid_ford = web.DataReader('F','yahoo',start,end)
covid_gm = web.DataReader('GM','yahoo',start,end)
covid_goog = web.DataReader('GOOGL','yahoo',start,end)
covid_fb = web.DataReader('FB','yahoo',start,end)
covid_tesla = web.DataReader('TSLA','yahoo',start,end)
```

[133]:
```
covid_ford['Cumul Return'] = covid_ford['Adj Close'] / covid_ford.iloc[0]['Adj␣
↪Close']
covid_gm['Cumul Return'] = covid_gm['Adj Close'] / covid_gm.iloc[0]['Adj Close']
covid_tesla['Cumul Return'] = covid_tesla['Adj Close'] / covid_tesla.
↪iloc[0]['Adj Close']
```

[159]:
```
fig,axes= plt.subplots(3,1,figsize=(8,6))
axes[0].plot(covid_ford['Cumul Return'],label='ford',c='r')
axes[0].set_title("Ford Cumul Ret")

axes[1].plot(covid_gm['Cumul Return'],label='gm',c='b')
axes[1].set_title("GM Cumul Ret")

axes[2].plot(covid_tesla['Cumul Return'],label='tesla',c='orange')
axes[2].set_title("Tesla Cumul Ret")
plt.tight_layout()
plt.legend()
```

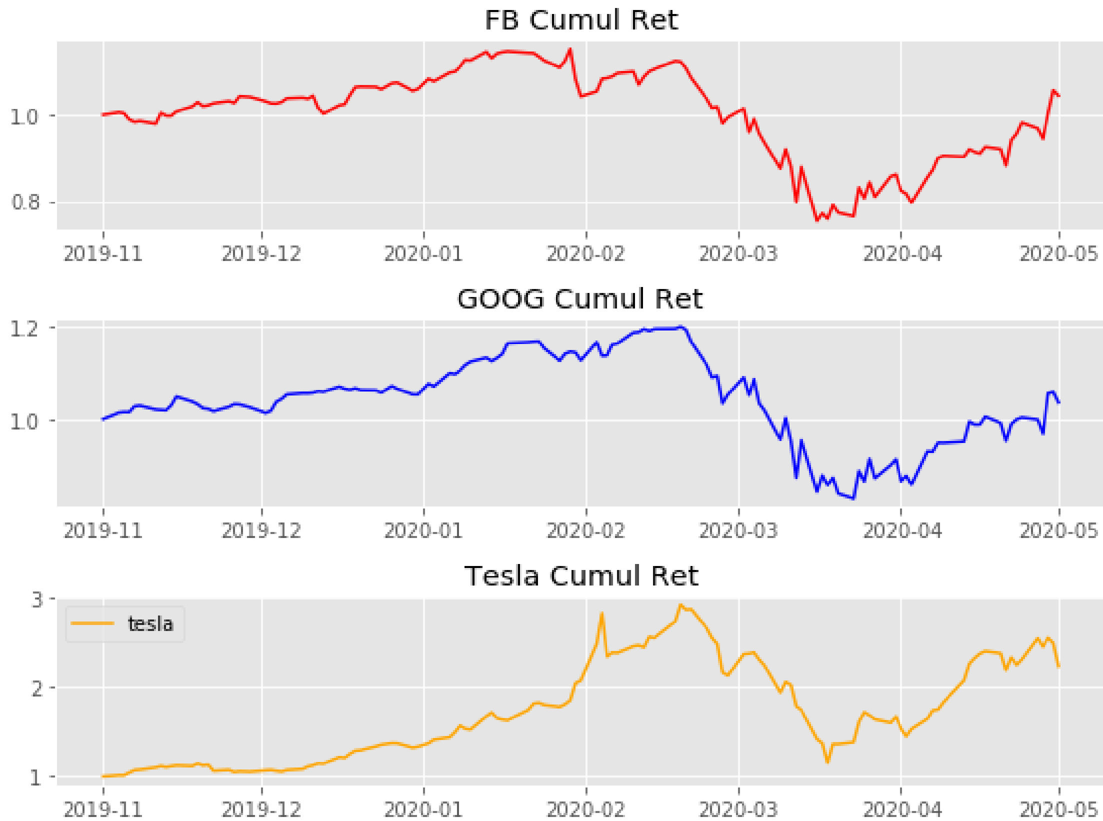
[159]:
```
<matplotlib.legend.Legend at 0x172ec80c7c8>
```



[160]:
```
covid_fb['Cumul Return'] = covid_fb['Adj Close'] / covid_fb.iloc[0]['Adj Close']
covid_goog['Cumul Return'] = covid_goog['Adj Close'] / covid_goog.iloc[0]['Adj␣
↪Close']
```

[161]:
```
fig,axes= plt.subplots(3,1,figsize=(8,6))
axes[0].plot(covid_fb['Cumul Return'],label='fb',c='r')
axes[0].set_title("FB Cumul Ret")

axes[1].plot(covid_goog['Cumul Return'],label='goog',c='b')
axes[1].set_title("GOOG Cumul Ret")

axes[2].plot(covid_tesla['Cumul Return'],label='tesla',c='orange')
axes[2].set_title("Tesla Cumul Ret")
plt.tight_layout()
plt.legend()
```

[161]:
```
<matplotlib.legend.Legend at 0x172ed971c48>
```



Commentary: The analysis of the daily cumulative returns shows how badly the coranivrus impacted the performance of Ford and GM, whereas the tech compagnies and Tesla seem to have quickly recovered from the market crash.