COVID-19 Fashion Industry Stock Analysis

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Motivation and Research Question

The world is being hit by COVID and it's affecting world economy and it's market. And it's showing significant change in stock market. Most of the people might think that it won't affect much on Fashion industry, but it is. Not only small brands stocks are fluctuating but big fashion name like Louis Vuitton, Christian Dior, Salvatore Ferragamo and many more have shown very interesting result in before and after covid situation. According to a report issued by McKinsey & Company, more than 40 percent of the global luxury-goods production happens in Italy, and all the Italian factories have temporarily shut down.

Since the stock market has had to deal with some major changes on its own. In this project, I have built a Python script to analyze the impacts of COVID-19 on stock prices regarding the fashion industry in Europe.

Companies' stocks I have taken consideration for analysis are:

1) Brunello Cucinelli
2) Christian Dior
3) Kering group
4) louis Vuitton
5) Moncler
6) Salvatore Ferragamo
7) Tod

how you Retrieve data

I have used Bloomberg terminal excel add in to download the stock price of the above companies during the 12/31/2019 to 29/01/2021. Below are the steps I followed to download the data.

Step 1: I opened the Bloomberg Terminal and then used XLTP commend to open excel add in the terminal.

Step 2: After opening the terminal of excel I used BDH command which stands for Bloomberg Data History which Returns the historical data for your selected security between the dates that you select.

Formula Syntax: =BDH ("Security", "Field", "Start Date", "End Date", "Optional arguments")

1) For Kering group
   BDH("KER1 EU EQUITY", "PX LAST", "12/31/2019", "1/29/2021", "Fill=Not Applicable")
2) For louis Vuitton
   BDH("LVMH EU EQUITY", "PX LAST", "12/31/2019", "1/29/2021", "Fill=Not Applicable")
3) For Brunello Cucinelli
   BDH("BC EU EQUITY", "PX LAST", "12/31/2019", "1/29/2021", "Fill=Not Applicable")

4) For Christian Dior
   BDH("CD1 EU EQUITY", "PX LAST", "12/31/2019", "1/29/2021", "Fill=Not Applicable")
5) For Moncler
   BDH("MC EU EQUITY", "PX LAST", "12/31/2019", "1/29/2021", "Fill=Not Applicable")
6) For Tod
   BDH("TOD EU EQUITY", "PX LAST", "12/31/2019", "1/29/2021", "Fill=Not Applicable")
7) Salvatore Ferragamo
   BDH("SFER EU EQUITY", "PX LAST", "12/31/2019", "1/29/2021", "Fill=Not Applicable")

Step 3: After step 2 I download the data of 7 fashion brand and convert .xlsm into .csv for easy processor in python.

Data analysis and Data visualization

I have made this project on Jupyter Notebook and used Python as programming language. I have imported different libraries in Python for analysis.

```
# importing libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.pylab as pylab
import numpy as np
from sklearn import metrics
from sklearn.linear_model import LinearRegression
import numpy as np
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
%matplotlib inline
import cufflinks as cf
cf.go_offline()
sns.set(rc={'axes.facecolor':'white', 'figure.facecolor':'white'})
from pandas_datareader import data
```

I have merge CSV file of 7 different files which includes closing price of stock of each companies during the period of Dec 2019 to Jan 2021.

```python
# readind CSV files
d1 = pd.read_csv('C:/Users/Drashti Patel/OneDrive/Desktop/FE 551/Bloomberge/Brucuc.csv') # Brunello Cucinelli stocks
d2 = pd.read_csv('C:/Users/Drashti Patel/OneDrive/Desktop/FE 551/Bloomberge/CDI.csv') # Christian Dior stocks
d3 = pd.read_csv('C:/Users/Drashti Patel/OneDrive/Desktop/FE 551/Bloomberge/KER.csv') # Kering group stocks
d4 = pd.read_csv('C:/Users/Drashti Patel/OneDrive/Desktop/FE 551/Bloomberge/MCEU.csv') # louis vuitton stocks
d5 = pd.read_csv('C:/Users/Drashti Patel/OneDrive/Desktop/FE 551/Bloomberge/moncler.csv') # Moncler stocks
d6 = pd.read_csv('C:/Users/Drashti Patel/OneDrive/Desktop/FE 551/Bloomberge/SFER.csv') # Salvatore Ferragamo stocks
d7 = pd.read_csv('C:/Users/Drashti Patel/OneDrive/Desktop/FE 551/Bloomberge/tod.csv') # Tod stocks


# All the stocks price are from 12/31/2019 to 29/01/2021
```

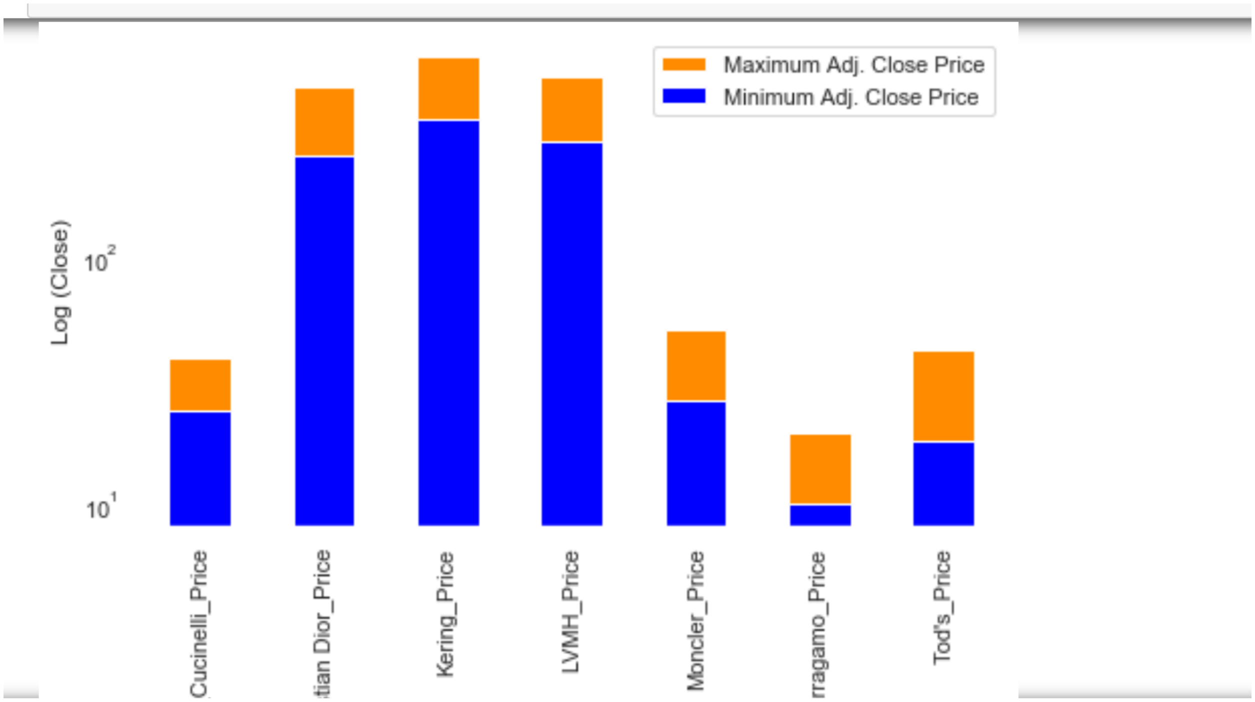
```python
# mergeing columns to make one data set using inner join

m1 = d1.merge(d2, on = "Date", how = 'inner')
m2 = m1.merge(d3, on = "Date", how = 'inner')
m3 = m2.merge(d4, on = "Date", how = 'inner')
m4 = m3.merge(d5, on = "Date", how = 'inner')
m5 = m4.merge(d6, on = "Date", how = 'inner')
df = m5.merge(d7, on = "Date", how = 'inner')
print(df)
```

```python
df =  pd.read_csv("Final Data.csv", index_col=0)
print(df)
```

```
            Brunello_Cucinelli_Price  Christian Dior_Price  Kering_Price  \
Date
12/31/2019                    31.695                456.45         588.3
1/2/2020                      32.168                463.20         600.9
1/3/2020                      32.109                461.60         600.2
1/6/2020                      31.780                460.00         592.0
1/7/2020                      34.049                461.80         595.6
...                              ...                   ...           ...
1/25/2021                     33.680                442.60         535.9
1/26/2021                     34.060                445.40         555.0
1/27/2021                     33.720                437.80         539.5
1/28/2021                     33.980                444.40         557.2
1/29/2021                     33.300                430.80         540.4

            LVMH_Price  Moncler_Price  Salvatore_Ferragamo_Price  Tod's_Price
Date
12/31/2019      412.70         40.206                     18.788       41.321
1/2/2020        422.15         40.730                     18.850       41.480
1/3/2020        417.50         40.210                     18.640       41.460
1/6/2020        418.30         40.120                     18.485       39.940
1/7/2020        415.75         40.300                     18.640       39.940
...                ...            ...                        ...          ...
1/25/2021       508.30         47.490                     15.630       26.460
1/26/2021       520.00         48.140                     15.850       26.900
1/27/2021       503.70         47.060                     16.420       27.280
1/28/2021       515.10         48.110                     16.720       26.880
1/29/2021       502.00         46.440                     16.040       25.820

[276 rows x 7 columns]
```

And I have converted all the numeric data into float. Because float values can easily be plot on graph.

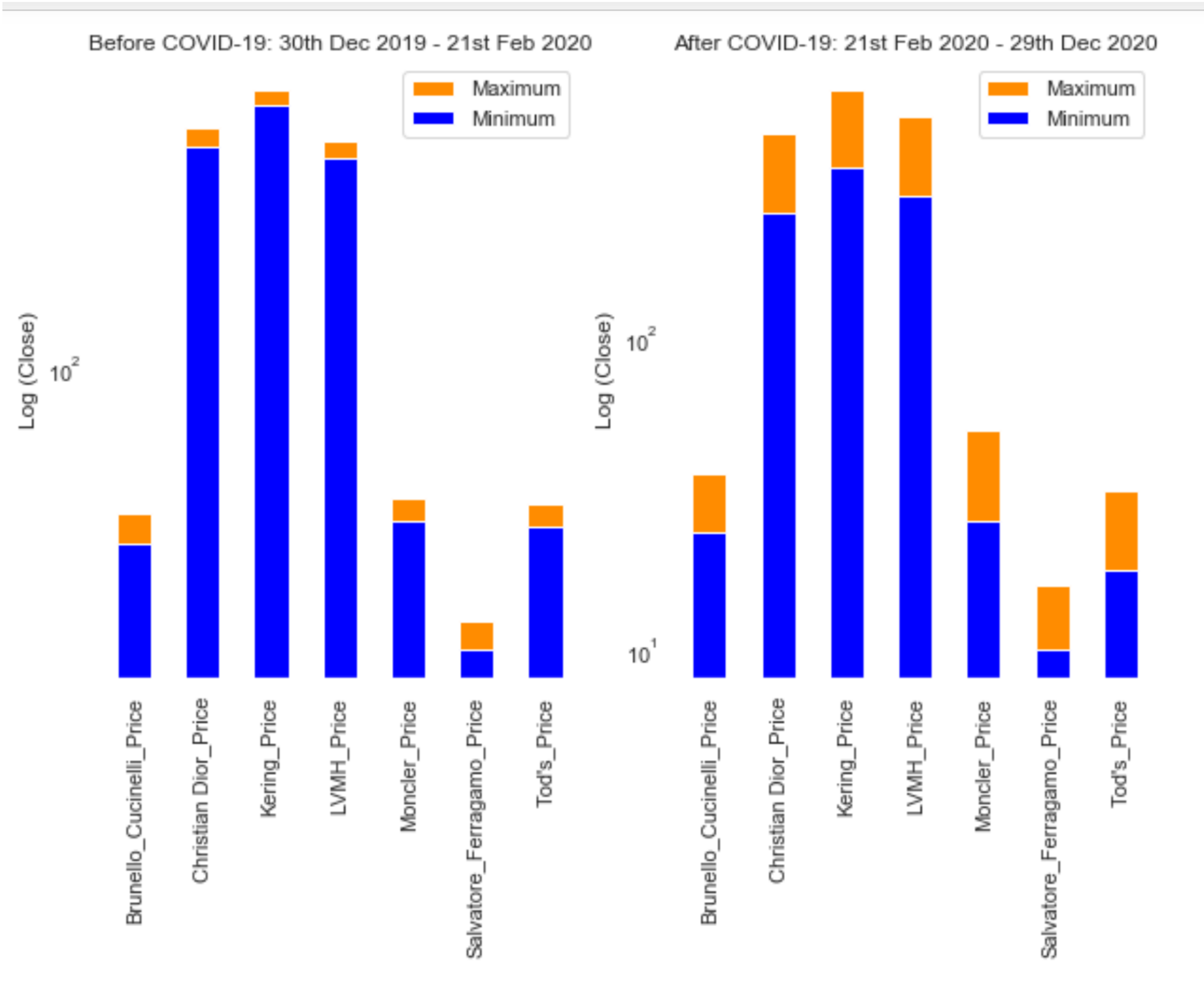
Firstly I have investigate the maximum and minimum adjusted close price price for each company's stock throughout the time period. I have used a bar plot to visualize the data, and also used a log scale for close price to normalize the values to a uniform scale.



Using the graph above, stocks can be classified into two groups: Reliable stocks and Volatile stocks.

Reliable stocks are the ones that didn't show much difference between the minimum adj. close price and the maximum adj. close price in the time period specified. e.g.: Tod'sand Moncler. Volatile stocks are the ones that varied the most between the minimum and maximum adj. closing price of stocks. e.g.: frragamo

Now, I have divided the data into two parts: Before Covid and After Covid for further analysis.



It is clear that most of the stocks pre COVID-19 period saw a change in volatility in their closing prices once the COVID-19 storm hit.

In the next step I have find the returns. A return is define as the change in price of stocks over time, which can be called as price of change or percentage change. A positive return shows profit and negative return will show loss.

1]:

Date	Brunello_Cucinelli_Price	Christian Dior_Price	Kering_Price	LVMH_Price	Moncler_Price	Salvatore_Ferragamo_Price	Tod's_Price
1/2/2020	0.014923	0.014788	0.021418	0.022898	0.013033	0.003300	0.003848
1/3/2020	-0.001834	-0.003454	-0.001165	-0.011015	-0.012767	-0.011141	-0.000482
1/6/2020	-0.010246	-0.003466	-0.013662	0.001916	-0.002238	-0.008315	-0.036662
1/7/2020	0.071397	0.003913	0.006081	-0.006096	0.004487	0.008385	0.000000
1/8/2020	0.012570	0.005197	0.002686	0.017198	0.026551	0.010193	0.007511
...	...	...	...	...	...	...	...
1/25/2021	-0.012896	-0.005840	-0.015794	-0.013010	-0.025846	-0.016981	-0.032187
1/26/2021	0.011283	0.006326	0.035641	0.023018	0.013687	0.014075	0.016629
1/27/2021	-0.009982	-0.017063	-0.027928	-0.031346	-0.022435	0.035962	0.014126
1/28/2021	0.007711	0.015075	0.032808	0.022633	0.022312	0.018270	-0.014663
1/29/2021	-0.020012	-0.030603	-0.030151	-0.025432	-0.034712	-0.040670	-0.039435

275 rows × 7 columns

```
returns.idxmin()

# findind when stock prices are minimum
```

]:

```
Brunello_Cucinelli_Price      3/23/2020
Christian Dior_Price          3/16/2020
Kering_Price                  3/16/2020
LVMH_Price                    3/16/2020
Moncler_Price                 3/16/2020
Salvatore_Ferragamo_Price     3/12/2020
Tod's_Price                   2/24/2020
dtype: object
```

From the above value we can say that most of these stocks had their lowest return in 12th March 2020. In that date the USA declared a national emergency, while italy had the highest number of deaths per day in the world (including China at its peak).

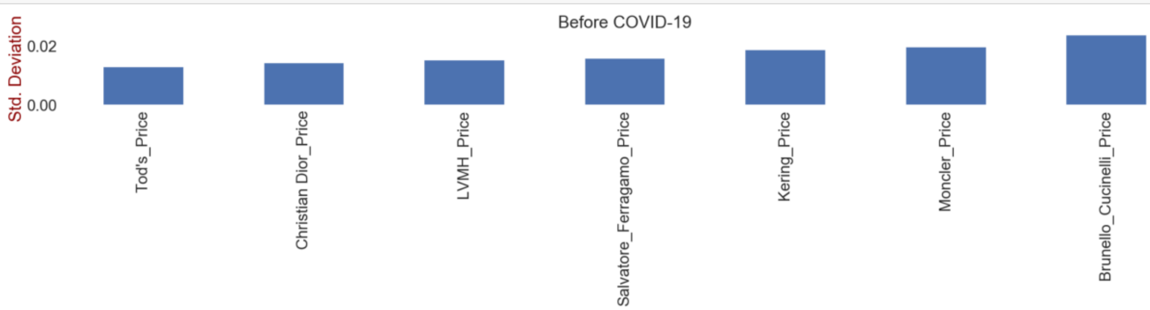
```
returns.idxmax()

# finding when stock prices are maximum
```

```
]: Brunello_Cucinelli_Price      3/24/2020
   Christian Dior_Price          3/24/2020
   Kering_Price                  3/17/2020
   LVMH_Price                    3/17/2020
   Moncler_Price                 3/13/2020
   Salvatore_Ferragamo_Price     5/28/2020
   Tod's_Price                   3/18/2020
   dtype: object
```

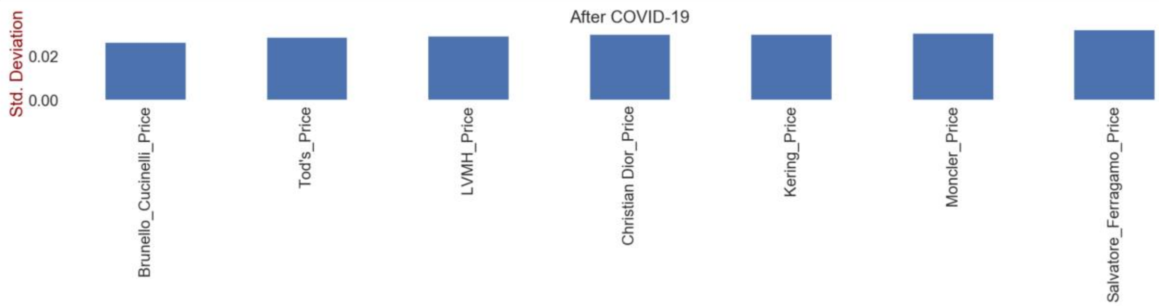
From the above value we can say that all the companies had their highest stock price in March as well and on 24th May Trump announced that USA will be Open for Business very soon.

Now, It's time to try to divide the returns to two datasets, before and after COVID-19, then I have apply the standard deviation on the stock returns. In the next graphs, if the stocks occur at the right end of the chart, they are considered volatile with significant values of standard deviation while if they occur on the left they should be considered reliable.

```
# applying standard deviation for before COVID
stdb = returnsB.std()
stda = returnsA.std()
plt.figure(figsize=(30,8))
sns.set(font_scale=2.5)
ax = stdb.sort_values().plot.bar(title="Before COVID-19")
plt.ylabel("Std. Deviation", color = 'darkred')
plt.tight_layout()
ax.set_facecolor('w')
```



```
# applying standard deviation for after COVID
stda = returnsA.std()
plt.figure(figsize=(30,8))
sns.set(font_scale=2.5)
ax = stda.sort_values().plot.bar(title="After COVID-19")
plt.ylabel("Std. Deviation", color='darkred')
plt.tight_layout()
ax.set_facecolor('w')
```



Comparing the two graphs, we can say that Brunello Cucinelli has shown most change in before and after covid situation as it comes as reliable after covid. And on other hand Tod's stock mange to become stable in the pandemic.

To elaborate more on the impact of the COVID-19 on each of the stock prices, divide each of the stock daily prices by the row of reference.

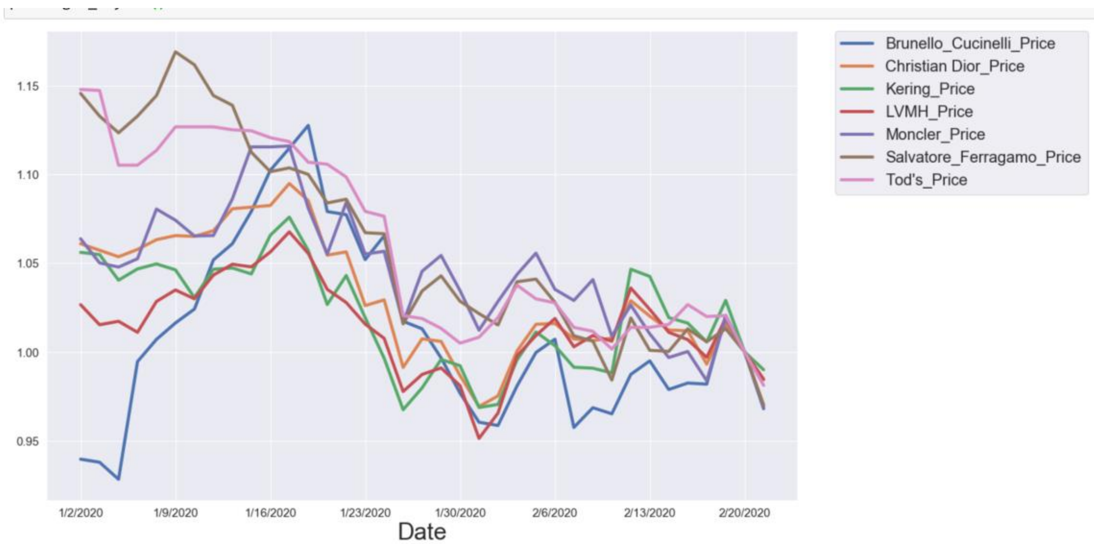
```
dfb= df.loc['1/2/2020':'2/21/2020']
dfa = df.loc['2/24/2020':'12/29/2020']
dfa = dfa/dfa.iloc[0]
```

```
dfa.head()
```

]:

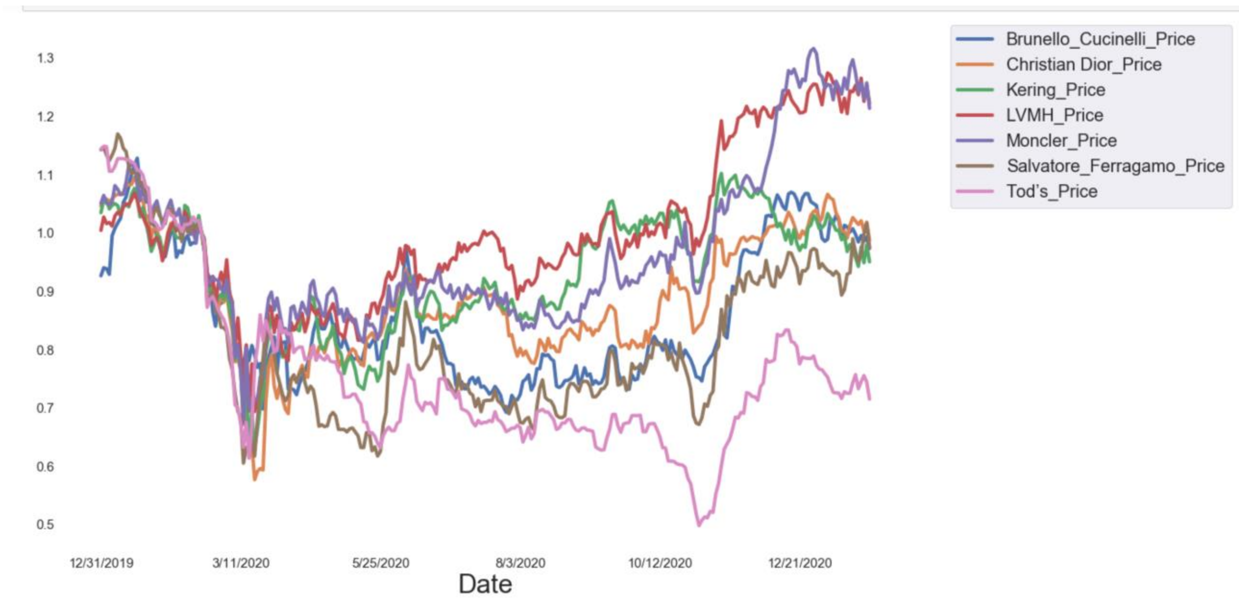
Date	Brunello_Cucinelli_Price	Christian Dior_Price	Kering_Price	LVMH_Price	Moncler_Price	Salvatore_Ferragamo_Price	Tod's_Price
2/24/2020	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
2/25/2020	0.992802	0.974422	0.978503	0.974720	0.996010	1.014879	1.015238
2/26/2020	0.930280	0.988687	1.001152	0.991009	1.009119	1.024913	1.021587
2/27/2020	0.903153	0.946877	0.957006	0.941491	1.002565	0.985121	1.009524
2/28/2020	0.944268	0.933596	0.971209	0.977326	1.001995	0.980277	0.994921

Now we can easily see the impact of COVID-19 on stock prices in percentage terms.

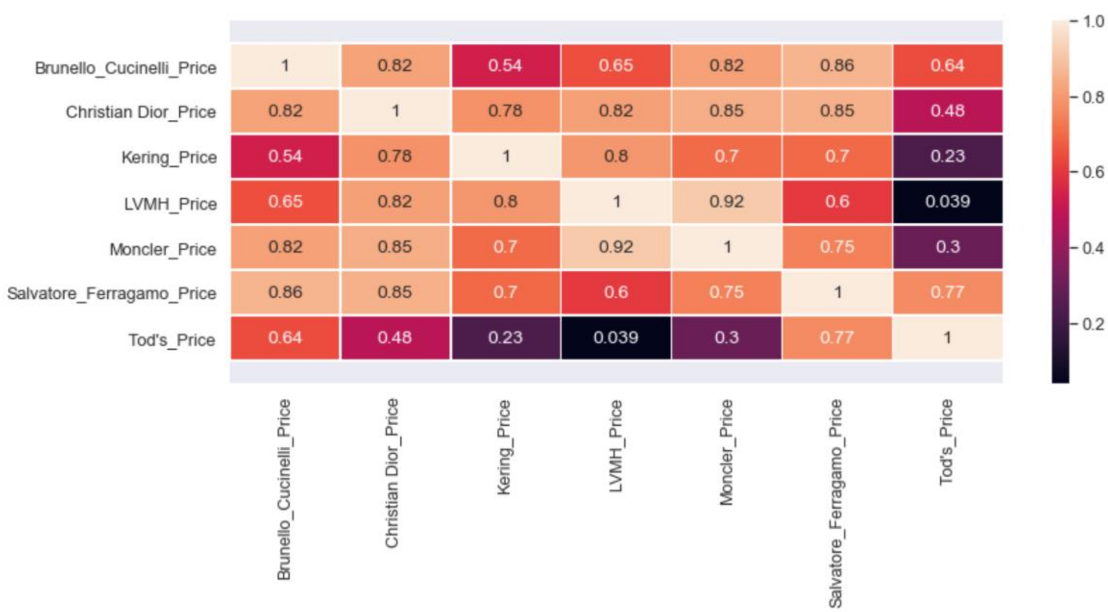


It seems that for the majority of the stocks, the outbreak of the virus did not have an impact on stock prices when there were almost no cases in Europe while thousands were in China.

Now, I have visualized the whole period.



From the above graph, we can say that during high cases of covid 19 in Europe stocks price of these companies comes at the lowest of the all time and when situation comes under control, stock prices goes up.



From above heat map, we can say that some of the companies have major effect of covid and some mange to sustain their stock price.

Conclusion and future work

The data collected showed that the stock market has drifted hard due to COVID-19, The impact is increased by the fact that many companies have limited visibility into their risk exposure or supply chain.

many brands have responded with bold approaches to give stakeholders a reason to believe that they will get through this crisis and move forward together.

For the future analysis, we can include the COVID-19 data into our analysis. We will add data related to daily new infected cases in italy for the time period of 24th Feb until 21st Apr (since there was no data about the daily numbers on the 21st,22nd,23rd). And we can also include daily cases in all over Europe to show how stock is effecting exactly according to daily cases. We can also compare this situation in USA, how USA is affecting the stock market of Fashion industry.