1. The analysis is to be performed for NASDAQ 100. Check the stock symbols of the companies to be analyzed in the 'Nasdaq 100 Market cap.xlsx'. Read only the relevant files from the folder

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

```
# To install pandas_datareader

# run the code below

# pip install pandas_datareader

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import pandas_datareader as datareader
import datetime as dt
from dateutil.relativedelta import relativedelta as rd
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tsa.stattools import adfuller
# import warnings
# warnings.filterwarnings('ignore')

address = '/content/drive/MyDrive/Capstone Job Guaranty/Capstone
2/Problem  - For Learners/'

nasdaq_symbol = pd.read_excel(address + 'Nasdaq 100 Market cap.xlsx')

nasdaq100_metrics_ratios = pd.read_excel(address +
'nasdaq100_metrics_ratios.xlsx')

os.chdir(address)

file_count = 0
list_files = []
abs_files = []
for file_name in nasdaq_symbol.Symbol:
    try :
        file_path = os.getcwd() + '/NASDAQ_DATA/' +file_name +'.csv'
        temp_file = pd.read_csv(file_path)
        temp_file.insert(loc = 0, column = 'Symbol', value =
file_name)
        temp_file.Date = pd.to_datetime(temp_file.Date,
infer_datetime_format = True)
        list_files.append(temp_file)
```

```
    except :
        abs_files.append(file_name)
        continue
```

```
len(list_files)
```

```
102
```

```
master_data = pd.concat(list_files)
```

```
master_data.columns
```

```
Index(['Symbol', 'Date', 'High', 'Low', 'Open', 'Close', 'Volume',
       'Adj Close'],
      dtype='object')
```

```
master_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 474247 entries, 0 to 1164
Data columns (total 8 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   Symbol     474247 non-null  object
 1   Date       474247 non-null  datetime64[ns]
 2   High       474247 non-null  float64
 3   Low        474247 non-null  float64
 4   Open       474247 non-null  float64
 5   Close      474247 non-null  float64
 6   Volume     474247 non-null  float64
 7   Adj Close  474247 non-null  float64
dtypes: datetime64[ns](1), float64(6), object(1)
memory usage: 32.6+ MB
```

```
min_max_date = master_data.groupby('Symbol')['Date'].agg([min, max])
min_max_date
```

```
              min        max
Symbol
AAPL   1999-12-31 2022-10-28
ABNB   2020-12-10 2022-10-28
ADBE   1999-12-31 2022-10-28
ADI    1999-12-31 2022-10-28
ADP    1999-12-31 2022-10-28
...           ...        ...
WBA    1999-12-31 2022-10-28
WDAY   2012-10-12 2022-10-28
XEL    1999-12-31 2022-10-28
ZM     2019-04-18 2022-10-28
ZS     2018-03-16 2022-10-28

[102 rows x 2 columns]
```

```python
# lets say for analysis we are using last 10 years data
start = dt.datetime(2002, 11, 1)
start
```

```
datetime.datetime(2002, 11, 1, 0, 0)
```

```python
end = dt.datetime(2022, 10, 24)
```

```python
master_data.shape
```

```
(474247, 8)
```

```python
master_data.describe(datetime_is_numeric = True)
```

```
                                Date           High            Low  \
count                         474247  474247.000000  474247.000000
mean   2012-05-02 11:42:51.118425600      78.122040      75.990176
min              1999-12-31 00:00:00       0.032000       0.025500
25%              2006-11-03 00:00:00      16.683626      16.100000
50%              2012-10-10 00:00:00      36.349998      35.389999
75%              2018-01-24 00:00:00      76.440002      74.510002
max              2022-10-28 00:00:00    2715.659912    2632.219971
std                              NaN     158.651773     154.511824

                Open          Close        Volume      Adj Close
count  474247.000000  474247.000000  4.742470e+05  474247.000000
mean       77.074417      77.076235  1.843704e+07      73.076970
min         0.027500       0.026500  0.000000e+00       0.022405
25%        16.389999      16.391222  1.581600e+06      13.235787
50%        35.880001      35.889999  3.579800e+06      29.216110
75%        75.480003      75.500000  1.046985e+07      70.079777
max      2680.000000    2703.260010  7.421641e+09    2703.260010
std       156.644407     156.581800  7.172834e+07     156.939467
```

```python
master_data[(master_data.Date >= start) & (master_data.Date <=
end)].groupby('Symbol').size().sort_values()
```

```
Symbol
CEG      193
ABNB     471
LCID     529
DDOG     781
CRWD     850
        ...
GILD    5029
FISV    5029
FAST    5029
INTU    5029
AAPL    5029
Length: 102, dtype: int64
```

```
master_data = master_data[(master_data.Date >= start) &
(master_data.Date <= end)]

master_data.reset_index(drop = True, inplace = True)

master_data.head()

  Symbol       Date      High       Low      Open     Close
Volume  \
0   AAPL 2002-11-01  0.294643  0.283750  0.284643  0.292143
189828800.0
1   AAPL 2002-11-04  0.310357  0.291964  0.294643  0.301607
376818400.0
2   AAPL 2002-11-05  0.302857  0.291964  0.299107  0.301786
210694400.0
3   AAPL 2002-11-06  0.309286  0.298214  0.305000  0.307500
216389600.0
4   AAPL 2002-11-07  0.305357  0.282321  0.302500  0.285714
336179200.0

   Adj Close
0   0.249028
1   0.257095
2   0.257248
3   0.262119
4   0.243548

master_data.tail()

       Symbol       Date        High         Low        Open
Close  \
426754     ZS 2022-10-18  152.500000  146.679993  151.100006
149.690002
426755     ZS 2022-10-19  151.210007  146.000000  147.910004
148.770004
426756     ZS 2022-10-20  154.880005  148.848999  149.279999
150.229996
426757     ZS 2022-10-21  150.919998  142.710007  148.979996
150.479996
426758     ZS 2022-10-24  151.460007  144.300003  151.360001
148.669998

           Volume   Adj Close
426754  2059400.0  149.690002
426755  1594500.0  148.770004
426756  1709500.0  150.229996
426757  2140900.0  150.479996
426758  1375200.0  148.669998

master_data.shape
```

```
(426759, 8)
```

4. Collate both the files imported in the last step to have the fields ‘Market cap’ as well as ‘Last sale’ along with the different metrics/ratios already present in ‘nasdaq100_metrics_ratios.xlsx’.

```
metrics = pd.merge(nasdaq100_metrics_ratios,
nasdaq_symbol[['Symbol','Market Cap', 'Last Sale']],
         left_on= 'symbol', right_on='Symbol').drop(columns =
'Symbol')

metrics.head()
```

```
  symbol         company                  sector  \
0   AAPL      Apple Inc.  Information Technology
1   ABNB          Airbnb  Consumer Discretionary
2   ADBE      Adobe Inc.  Information Technology
3    ADI  Analog Devices  Information Technology
4    ADP             ADP  Information Technology

                                    subsector  asset_turnover_2017  \
0  Technology Hardware, Storage & Peripherals                 0.66
1          Internet & Direct Marketing Retail                  NaN
2                        Application Software                 0.54
3                              Semiconductors                 0.36
4       Data Processing & Outsourced Services                  NaN

   asset_turnover_2018  asset_turnover_2019  asset_turnover_2020  \
0                 0.72                 0.74                 0.83
1                 0.55                 0.64                 0.36
2                 0.54                 0.57                 0.57
3                 0.30                 0.29                 0.26
4                 0.34                 0.34                 0.35

   asset_turnover_2021  asset_turnover_2022  ...
yoy_eps_growth_latest  \
0                 1.08                  NaN  ...                     -
7.69
1                 0.50                  NaN  ...
609.09
2                 0.61                  NaN  ...                     -
3.97
3                 0.20                  NaN  ...
6.67
4                 0.33                 0.29  ...
19.05

   yoy_revenue_growth_2017  yoy_revenue_growth_2018
yoy_revenue_growth_2019  \
0                    11.34                    21.69
```

```
5.36
1                       NaN                       40.08
31.58
2                     25.51                       24.45
25.21
3                     36.64                       10.91
-3.22
4                       NaN                        8.65
7.16

   yoy_revenue_growth_2020  yoy_revenue_growth_2021
yoy_revenue_growth_2022  \
0                    11.94                       38.50
NaN
1                    31.27                      -18.11
NaN
2                    16.86                       23.69
NaN
3                    -6.25                       21.07
NaN
4                     4.84                        4.95
11.87

   yoy_revenue_growth_latest     Market Cap  Last Sale
0                       5.11  2625740143000    $151.45
1                      41.00    69569944167    $116.65
2                      15.54   149144569000    $320.81
3                      26.30    75484763090    $146.76
4                      12.02    98332762096    $236.78

[5 rows x 285 columns]
```

```
metrics.columns = metrics.columns.str.lower().str.replace(' ', '_')
```

5. A variable with very small variance does not add much value in model building. List those variables which have variance less than .005. Eliminate these variables.

```
var_data = metrics.var(numeric_only= True).sort_values(ascending=
True)
cols = var_data[var_data < 0.005].index
cols
```

```
Index(['capex_to_revenue_2022', 'inventory_to_revenue_2022',
       'inventory_to_revenue_2018', 'inventory_to_revenue_2017'],
      dtype='object')
```

```
metrics.drop(columns = cols, inplace = True)
```

6. In the file ‘nasdaq100_metrics_ratios.xlsx’, there are missing values in many variables. Delete those variables which have around 30% or more values missing.

```
metrics.shape
```

```
(102, 281)
```

```
missing_perc = metrics.isna().sum() /metrics.shape[0]*100
missing_perc.sort_values(ascending = False)
```

```
goodwill_to_asset_latest            100.000000
days_inventory_2022                  88.235294
inventory_turnover_2022              88.235294
price_earnings_growth_ratio_2022     87.254902
rate_of_return_2022                  85.294118
                                       ...
enterprise_value_to_ebit_latest       0.000000
equity_to_assets_latest               0.000000
equity_to_assets_2021                 0.000000
equity_to_assets_2020                 0.000000
last_sale                             0.000000
Length: 281, dtype: float64
```

```
metrics.drop(columns = missing_perc[missing_perc >30].index, inplace =
True)
```

```
metrics.head()
```

```
  symbol         company                  sector  \
0   AAPL      Apple Inc.  Information Technology
1   ABNB          Airbnb  Consumer Discretionary
2   ADBE      Adobe Inc.  Information Technology
3    ADI  Analog Devices  Information Technology
4    ADP             ADP  Information Technology


                                subsector  asset_turnover_2017  \
0  Technology Hardware, Storage & Peripherals                 0.66
1          Internet & Direct Marketing Retail                  NaN
2                        Application Software                 0.54
3                              Semiconductors                 0.36
4       Data Processing & Outsourced Services                  NaN

   asset_turnover_2018  asset_turnover_2019  asset_turnover_2020  \
0                 0.72                 0.74                 0.83
1                 0.55                 0.64                 0.36
2                 0.54                 0.57                 0.57
3                 0.30                 0.29                 0.26
4                 0.34                 0.34                 0.35

   asset_turnover_2021  asset_turnover_latest  ...
```

```
yoy_eps_growth_2021  \
0                 1.08                     0.24  ...                     
71.04
1                 0.50                     0.12  ...                     
96.46
2                 0.61                     0.17  ...                    -
7.48
3                 0.20                     0.06  ...                     
5.49
4                 0.33                     0.06  ...                     
6.49

   yoy_eps_growth_latest  yoy_revenue_growth_2017  
yoy_revenue_growth_2018  \
0                  -7.69                    11.34                    
21.69
1                 609.09                      NaN                    
40.08
2                  -3.97                    25.51                    
24.45
3                   6.67                    36.64                    
10.91
4                  19.05                      NaN                     
8.65

   yoy_revenue_growth_2019  yoy_revenue_growth_2020  
yoy_revenue_growth_2021  \
0                     5.36                    11.94                    
38.50
1                    31.58                    31.27                   
-18.11
2                    25.21                    16.86                    
23.69
3                    -3.22                    -6.25                    
21.07
4                     7.16                     4.84                     
4.95

   yoy_revenue_growth_latest     market_cap  last_sale
0                       5.11  2625740143000    $151.45
1                      41.00    69569944167    $116.65
2                      15.54   149144569000    $320.81
3                      26.30    75484763090    $146.76
4                      12.02    98332762096    $236.78

[5 rows x 201 columns]
```

```
metrics.shape
```

```
(102, 201)
```

```
metrics.columns
```

```
Index(['symbol', 'company', 'sector', 'subsector',
'asset_turnover_2017',
       'asset_turnover_2018', 'asset_turnover_2019',
'asset_turnover_2020',
       'asset_turnover_2021', 'asset_turnover_latest',
       ...
       'yoy_eps_growth_2021', 'yoy_eps_growth_latest',
       'yoy_revenue_growth_2017', 'yoy_revenue_growth_2018',
       'yoy_revenue_growth_2019', 'yoy_revenue_growth_2020',
       'yoy_revenue_growth_2021', 'yoy_revenue_growth_latest',
'market_cap',
       'last_sale'],
      dtype='object', length=201)
```

```
metrics.isna().sum().sort_values(ascending = False)
```

```
scaled_net_operating_assets_2017      30
interest_coverage_2018                30
yoy_ebitda_growth_2017                30
price_earnings_growth_ratio_latest    30
yoy_revenue_growth_2017               30
                                      ..
enterprise_value_to_ebit_latest        0
equity_to_assets_latest                0
equity_to_assets_2021                  0
equity_to_assets_2020                  0
last_sale                              0
Length: 201, dtype: int64
```

7. For the variables which have less than 30% values missing, perform missing value imputation. Missing value imputation should be done considering the sector of the company.

```
metrics_copy = metrics.copy()
```

```
missing_cals = metrics_copy.isna().sum()
msng_cols = missing_cals[missing_cals > 0].sort_values(ascending =
False).index.tolist()
msng_cols1 = msng_cols.copy()
```

```
len(msng_cols1)
```

```
149
```

```
for col in msng_cols :
    med_values = metrics_copy.groupby('sector')[col].median()
    for sec in med_values.index:
        metrics_copy.loc[(metrics_copy[col].isna() )&
(metrics_copy.sector == sec), col] = med_values[sec]
```

```
missing_cals = metrics_copy.isna().sum()
msng_cols = missing_cals[missing_cals > 0].sort_values(ascending =
False).index.tolist()
msng_cols
```

```
['mscore_2019',
 'mscore_2020',
 'mscore_2021',
 'price_to_free_cashflow_2019',
 'price_to_free_cashflow_2020',
 'price_to_free_cashflow_2021',
 'price_to_free_cashflow_latest']
```

```
# check the rows where these values are missing
```

```
metrics_copy.isna().any()
```

```
symbol                          False
company                         False
sector                          False
subsector                       False
asset_turnover_2017             False
                                 ...
yoy_revenue_growth_2020         False
yoy_revenue_growth_2021         False
yoy_revenue_growth_latest       False
market_cap                      False
last_sale                       False
Length: 201, dtype: bool
```

```
metrics_copy[metrics_copy.isna().sum(axis =1 ) >0]
```

```
   symbol                  company     sector           subsector  \
6     AEP  American Electric Power  Utilities  Electric Utilities
21    CEG     Constellation Energy  Utilities     Multi-Utilities
37    EXC                   Exelon  Utilities     Multi-Utilities
99    XEL             Xcel Energy  Utilities     Multi-Utilities

    asset_turnover_2017  asset_turnover_2018  asset_turnover_2019  \
6                  0.24                 0.24                 0.22
21                 0.27                 0.26                 0.39
37                 0.29                 0.30                 0.28
99                 0.27                 0.26                 0.24

    asset_turnover_2020  asset_turnover_2021
asset_turnover_latest  ...  \
6                  0.19                 0.20
0.05  ...
21                 0.36                 0.41
0.12  ...
37                 0.26                 0.28
```

```
0.05  ...
99                 0.22                 0.24
0.06  ...

    yoy_eps_growth_2021  yoy_eps_growth_latest
yoy_revenue_growth_2017  \
6                  12.22                 -11.30                    -
6.01
21               -134.85                 -81.82
2.68
37                -13.43                  14.63
4.51
99                  6.09                   3.45
2.68

    yoy_revenue_growth_2018  yoy_revenue_growth_2019
yoy_revenue_growth_2020  \
6                      4.75                    -4.22
-4.50
21                     4.75                    -7.40
-6.98
37                     5.00                    -4.77
-4.36
99                     0.77                    -1.80
-1.54

    yoy_revenue_growth_2021  yoy_revenue_growth_latest   market_cap
last_sale
6                     11.54                      17.91  44807878084
$87.22
21                    11.73                      30.91  28651255316
$87.66
37                     9.68                       5.14  37299734885
$37.545
99                    13.93                      10.17  34192428038
$62.51

[4 rows x 201 columns]
```

```
metrics_copy.loc[metrics_copy.isna().sum(axis =1 )
>0,metrics_copy.isna().any()]
```

```
    mscore_2019  mscore_2020  mscore_2021  price_to_free_cashflow_2019
\
6           NaN          NaN          NaN                          NaN

21          NaN          NaN          NaN                          NaN

37          NaN          NaN          NaN                          NaN
```

```
99          NaN          NaN          NaN                         NaN


    price_to_free_cashflow_2020  price_to_free_cashflow_2021  \
6                           NaN                          NaN
21                          NaN                          NaN
37                          NaN                          NaN
99                          NaN                          NaN

    price_to_free_cashflow_latest
6                             NaN
21                            NaN
37                            NaN
99                            NaN
```

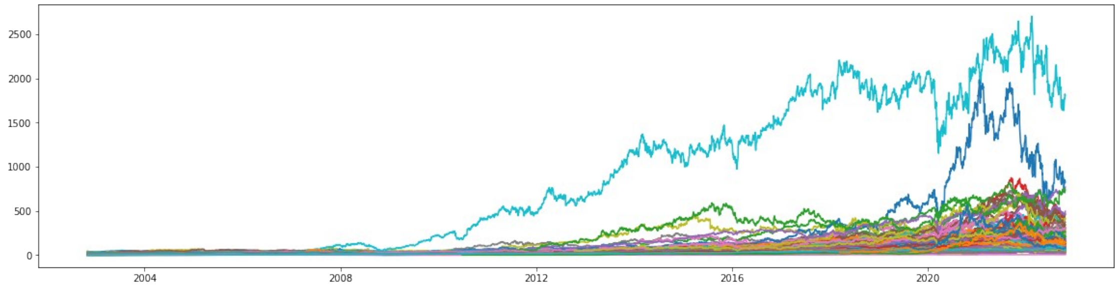
Since the values are not available for for this particular sector we will fill these values using overall median values

```
for col in msng_cols:
    med_values = metrics_copy[col].median()
    metrics_copy.loc[metrics_copy[col].isna(), col] = med_values

missing_cals = metrics_copy.isna().sum()
msng_cols = missing_cals[missing_cals > 0].sort_values(ascending = 
False).index.tolist()
msng_cols

[]
```

8. Perform in-depth analysis of COVID impact on stock prices. Create visuals to support the insights. The analysis must address the following:

```
1.   Which industries and companies observed the max and which of them observed the min impact. You may use growth/degrowth as a measure of impact. Perform week over week, MoM (month over month), QoQ, YoY analysis as appropriate.

2.   Which industries and companies recovered the fastest and which of them recovered the slowest.
```

```
y = master_data.loc[master_data.Symbol == 'AAPL','Adj Close' ]
x = master_data.loc[master_data.Symbol == 'AAPL','Date' ]

plt.figure(figsize = (20,5))
for s in master_data.Symbol.unique():
    y = master_data.loc[master_data.Symbol == s,'Adj Close' ]
    x = master_data.loc[master_data.Symbol == s,'Date' ]
    plt.plot(x,y, label = s)
    #plt.legend(loc = 'upper left')
plt.show()
```



before Covid : first case on January 20, 2020

lets take last 4 years data pre covid date : January 20, 2020

```
# pre covid dates
start = dt.datetime(2020, 1, 20) - rd(years = 4)
start

datetime.datetime(2016, 1, 20, 0, 0)

end = dt.datetime(2020, 1, 20)

aa = master_data.copy()

aa = aa[['Date', 'Symbol', 'Adj Close']]

aa['month'] = aa.Date.dt.month
aa['year'] = aa.Date.dt.year
aa['mon_yr'] = aa.month.astype(str) + '-' + aa.year.astype(str)

mon_end = aa.groupby('mon_yr').agg(max)['Date']
mon_end[:5]

mon_yr
1-2003   2003-01-31
1-2004   2004-01-30
1-2005   2005-01-31
1-2006   2006-01-31
1-2007   2007-01-31
Name: Date, dtype: datetime64[ns]

month_end_Data = aa[aa.Date.isin(mon_end.values)]
month_end_Data.sort_values('Date' , inplace = True)

/usr/local/lib/python3.7/dist-packages/pandas/util/_decorators.py:311:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  return func(*args, **kwargs)

month_end_Data
```

```
              Date Symbol   Adj Close  month  year   mon_yr
19      2002-11-29   AAPL    0.235937     11  2002  11-2002
254350  2002-11-29   MDLZ   14.948846     11  2002  11-2002
45751   2002-11-29   AMGN   35.625038     11  2002  11-2002
10548   2002-11-29    ADI   19.904331     11  2002  11-2002
102092  2002-11-29  CMCSA    5.902415     11  2002  11-2002
...            ...    ...         ...    ...   ...      ...
235404  2022-10-24   LCID   12.800000     10  2022  10-2022
240433  2022-10-24   LRCX  373.959991     10  2022  10-2022
340294  2022-10-24    PEP  177.679993     10  2022  10-2022
352193  2022-10-24   REGN  737.150024     10  2022  10-2022
426758  2022-10-24     ZS  148.669998     10  2022  10-2022

[20383 rows x 6 columns]
```

```
# #month_end_Data_formatted = month_end_Data.pivot(index = 'Symbol',
#                     columns = 'Date',
#                     values = 'Adj Close')

#month_end_Data_formatted

month_end_Data.sort_values(['Symbol', 'Date'], inplace = True)
```

```
/usr/local/lib/python3.7/dist-packages/pandas/util/_decorators.py:311:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  return func(*args, **kwargs)
```

```
import warnings
warnings.filterwarnings('ignore')

month_end_Data['lag_series'] = month_end_Data['Adj
Close'].shift(periods = 12)
month_end_Data['diff_series'] =  month_end_Data['Adj Close'] -
month_end_Data['lag_series']
month_end_Data['YOY'] = month_end_Data['diff_series']
/month_end_Data['lag_series']*100
month_end_Data[:20]
```

```
          Date Symbol  Adj Close  month  year   mon_yr  lag_series  \
19  2002-11-29   AAPL   0.235937     11  2002  11-2002         NaN
40  2002-12-31   AAPL   0.218128     12  2002  12-2002         NaN
61  2003-01-31   AAPL   0.218585      1  2003   1-2003         NaN
80  2003-02-28   AAPL   0.228479      2  2003   2-2003         NaN
101 2003-03-31   AAPL   0.215236      3  2003   3-2003         NaN
122 2003-04-30   AAPL   0.216454      4  2003   4-2003         NaN
143 2003-05-30   AAPL   0.273231      5  2003   5-2003         NaN
```

```
164 2003-06-30   AAPL   0.290126      6  2003   6-2003         NaN
186 2003-07-31   AAPL   0.320875      7  2003   7-2003         NaN
207 2003-08-29   AAPL   0.344164      8  2003   8-2003         NaN
228 2003-09-30   AAPL   0.315395      9  2003   9-2003         NaN
251 2003-10-31   AAPL   0.348426     10  2003  10-2003         NaN
270 2003-11-28   AAPL   0.318287     11  2003  11-2003    0.235937
292 2003-12-31   AAPL   0.325289     12  2003  12-2003    0.218128
312 2004-01-30   AAPL   0.343402      1  2004   1-2004    0.218585
331 2004-02-27   AAPL   0.364104      2  2004   2-2004    0.228479
354 2004-03-31   AAPL   0.411596      3  2004   3-2004    0.215236
375 2004-04-30   AAPL   0.392417      4  2004   4-2004    0.216454
395 2004-05-28   AAPL   0.427122      5  2004   5-2004    0.273231
416 2004-06-30   AAPL   0.495315      6  2004   6-2004    0.290126

     diff_series        YOY
19           NaN        NaN
40           NaN        NaN
61           NaN        NaN
80           NaN        NaN
101          NaN        NaN
122          NaN        NaN
143          NaN        NaN
164          NaN        NaN
186          NaN        NaN
207          NaN        NaN
228          NaN        NaN
251          NaN        NaN
270     0.082350  34.903158
292     0.107161  49.127621
312     0.124818  57.102746
331     0.135626  59.360352
354     0.196360  91.230493
375     0.175963  81.293637
395     0.153891  56.322866
416     0.205189  70.723958
```

```
month_end_Data = month_end_Data[['Date', 'Symbol','Adj Close', 'YOY']]
month_end_Data.head(20)
```

```
          Date Symbol  Adj Close        YOY
19  2002-11-29   AAPL   0.235937        NaN
40  2002-12-31   AAPL   0.218128        NaN
61  2003-01-31   AAPL   0.218585        NaN
80  2003-02-28   AAPL   0.228479        NaN
101 2003-03-31   AAPL   0.215236        NaN
122 2003-04-30   AAPL   0.216454        NaN
143 2003-05-30   AAPL   0.273231        NaN
164 2003-06-30   AAPL   0.290126        NaN
186 2003-07-31   AAPL   0.320875        NaN
207 2003-08-29   AAPL   0.344164        NaN
```

```
228 2003-09-30   AAPL   0.315395        NaN
251 2003-10-31   AAPL   0.348426        NaN
270 2003-11-28   AAPL   0.318287  34.903158
292 2003-12-31   AAPL   0.325289  49.127621
312 2004-01-30   AAPL   0.343402  57.102746
331 2004-02-27   AAPL   0.364104  59.360352
354 2004-03-31   AAPL   0.411596  91.230493
375 2004-04-30   AAPL   0.392417  81.293637
395 2004-05-28   AAPL   0.427122  56.322866
416 2004-06-30   AAPL   0.495315  70.723958
```

```
start = dt.datetime(2018, 1, 1)
```

```
data_2018 = month_end_Data[month_end_Data.Date >= start]
```

```
data_2018
```

```
             Date Symbol   Adj Close        YOY
3837   2018-01-31   AAPL   39.802277  40.191505
3856   2018-02-28   AAPL   42.516209  32.081005
3877   2018-03-29   AAPL   40.048103  18.637165
3898   2018-04-30   AAPL   39.446598  16.863434
3920   2018-05-31   AAPL   44.776775  24.230744
...           ...    ...         ...        ...
426678 2022-06-30     ZS  149.509995 -30.801631
426698 2022-07-29     ZS  155.059998 -34.271546
426721 2022-08-31     ZS  159.240005 -42.789392
426742 2022-09-30     ZS  164.369995 -37.315996
426758 2022-10-24     ZS  148.669998 -53.374520

[5727 rows x 4 columns]
```

```
new = pd.merge(data_2018,nasdaq100_metrics_ratios[['symbol',
'sector']], how = 'left', left_on = 'Symbol', right_on = 'symbol')
```

```
new
```

```
           Date Symbol   Adj Close        YOY symbol
sector
0    2018-01-31   AAPL   39.802277  40.191505   AAPL  Information
Technology
1    2018-02-28   AAPL   42.516209  32.081005   AAPL  Information
Technology
2    2018-03-29   AAPL   40.048103  18.637165   AAPL  Information
Technology
3    2018-04-30   AAPL   39.446598  16.863434   AAPL  Information
Technology
4    2018-05-31   AAPL   44.776775  24.230744   AAPL  Information
Technology
...         ...    ...         ...        ...    ...
...
5722 2022-06-30     ZS  149.509995 -30.801631     ZS  Information
```

```
Technology
5723 2022-07-29     ZS  155.059998 -34.271546     ZS  Information
Technology
5724 2022-08-31     ZS  159.240005 -42.789392     ZS  Information
Technology
5725 2022-09-30     ZS  164.369995 -37.315996     ZS  Information
Technology
5726 2022-10-24     ZS  148.669998 -53.374520     ZS  Information
Technology

[5727 rows x 6 columns]
```

```
data_2018
```

```
             Date Symbol   Adj Close        YOY
3837   2018-01-31   AAPL   39.802277  40.191505
3856   2018-02-28   AAPL   42.516209  32.081005
3877   2018-03-29   AAPL   40.048103  18.637165
3898   2018-04-30   AAPL   39.446598  16.863434
3920   2018-05-31   AAPL   44.776775  24.230744
...           ...    ...         ...        ...
426678 2022-06-30     ZS  149.509995 -30.801631
426698 2022-07-29     ZS  155.059998 -34.271546
426721 2022-08-31     ZS  159.240005 -42.789392
426742 2022-09-30     ZS  164.369995 -37.315996
426758 2022-10-24     ZS  148.669998 -53.374520

[5727 rows x 4 columns]
```

```
pivot_data = data_2018.pivot(index = 'Symbol', columns = 'Date',
values='YOY')
```

```
pivot_data.iloc[:,25:]
```

```
Date    2020-02-28  2020-03-31  2020-04-30  2020-05-29  2020-06-30  \
Symbol
AAPL     59.941135   35.624291   48.325846   83.774755   86.516658
ABNB           NaN         NaN         NaN         NaN         NaN
ADBE     31.474284   19.419116   22.261025   42.709492   47.737996
ADI       4.083935  -13.058934   -3.742573   19.331712   10.914997
ADP       3.196893  -12.591224   -8.843191   -6.539867   -7.904942
...            ...         ...         ...         ...         ...
WBA     -33.521123  -25.215789  -16.423805   -9.734908  -19.578660
WDAY    -12.469051  -32.476019  -25.156840  -10.136196   -8.862730
XEL      16.692413   10.119089   15.476681   16.416589    7.822315
ZM       64.062500  137.284818   86.518554  125.109731  185.550164
ZS        4.649761  -14.197095   -1.800609   42.925835   42.875784

Date    2020-07-31  2020-08-31  2020-09-30  2020-10-30  2020-11-
30  ...  \
Symbol                                                             ..
```

```
.
AAPL    101.892946  149.727523  108.883373   76.781036
79.724042  ...
ABNB           NaN         NaN         NaN         NaN
NaN  ...
ADBE     48.671629   80.447083   77.531219   60.867851
54.579525  ...
ADI      -0.189173    8.647494    6.671978   13.487851
25.712637  ...
ADP     -18.376778  -16.251249  -11.475666   -0.254558
4.301287  ...
...            ...         ...         ...         ...         ...  ..
.
WBA     -22.510775  -22.787151  -32.485768  -35.400344  -
33.408073  ...
WDAY     -9.530952   35.215483   26.576839   29.575722
25.496873  ...
XEL      18.865073   11.019586    9.128325   13.147602
12.408984  ...
ZM      165.846506  254.641663  516.942263  559.479193
542.093940  ...
ZS       54.088064  108.524877  197.693626  208.663032
198.772294  ...

Date    2022-01-31  2022-02-28  2022-03-31  2022-04-29  2022-05-31  \
Symbol
AAPL     33.265735   36.979553   43.796798   20.635162   20.127088
ABNB    -16.152046  -26.585897   -8.609135  -11.290602  -13.910251
ADBE     16.463588    1.742550   -4.154659  -22.109215  -17.460061
ADI      13.149705    4.645659    8.352702    2.537731    4.120226
ADP      27.232511   19.712341   23.005053   18.878680   15.876408
...            ...         ...         ...         ...         ...
WBA       2.806738   -0.111960  -15.291120  -17.055898  -13.273368
WDAY     11.198521   -6.578836   -3.610669  -16.315791  -31.663168
XEL      11.922518   18.149327   11.509200    5.588933    9.230243
ZM      -58.534685  -64.508442  -63.512714  -68.842508  -67.589661
ZS       28.748117   16.641465   40.548728    8.047328  -21.168899

Date    2022-06-30  2022-07-29  2022-08-31  2022-09-30  2022-10-24
Symbol
AAPL      0.395092   12.051595    4.130274   -1.784878    0.325391
ABNB    -41.831003  -22.935902  -27.014647  -37.383010  -31.800072
ADBE    -37.494026  -34.025064  -43.733615  -52.198981  -51.377697
ADI     -13.640312    4.530494   -5.306267  -15.279236  -15.167839
ADP       7.746127   17.193209   19.127568   15.249484    7.499936
...            ...         ...         ...         ...         ...
WBA     -24.935812  -12.442249  -27.870517  -30.320188  -22.970229
WDAY    -41.534725  -33.831054  -39.756921  -39.085197  -48.979243
XEL      10.437227   10.248073   11.046527    5.253815   -2.003109
ZM      -72.102937  -72.531077  -72.227979  -71.858510  -70.649917
```

```
ZS      -30.801631  -34.271546  -42.789392  -37.315996  -53.374520

[102 rows x 33 columns]
```

```
pivot_data_sect =
pd.concat([pivot_data,nasdaq100_metrics_ratios.set_index('symbol')
[['sector']]], axis = 1)
```

immediate impact

```
dd = pivot_data_sect.loc[:,(pivot_data_sect.columns ==
dt.datetime(2020,3, 31)) | (pivot_data_sect.columns =='sector')]
dd.columns = ['march_end', 'sector']
dd.sort_values('march_end', ascending= True, inplace = True)
```

```
dd.sector.unique()
```

```
array(['Information Technology', 'Consumer Discretionary',
       'Communication Services', 'Health Care', 'Consumer Staples',
       'Utilities', 'Industrials'], dtype=object)
```

```
dd
```

```
       march_end                  sector
DDOG  -51.644512  Information Technology
MAR   -39.291536  Consumer Discretionary
BIDU  -38.859571  Communication Services
ALGN  -38.821086             Health Care
CTSH  -35.025225  Information Technology
...          ...                     ...
DXCM  126.087315             Health Care
ZM    137.284818  Information Technology
ABNB         NaN  Consumer Discretionary
CEG          NaN               Utilities
LCID         NaN  Consumer Discretionary

[102 rows x 2 columns]
```

```
(dd[dd.march_end <0].sector.value_counts() / dd.sector.value_counts()
* 100).sort_values()
```

```
Health Care               23.076923
Information Technology    40.476190
Consumer Staples          42.857143
Communication Services    46.153846
Utilities                 50.000000
Consumer Discretionary    53.333333
Industrials               62.500000
Name: sector, dtype: float64
```

- Industrials faced the maximum immediate impact

- Healthcare faced the minimum

considering March as baseline study the data for June to check impact

```
dd = pivot_data_sect.loc[:,
(pivot_data_sect.columns.isin([dt.datetime(2020,3, 31),

dt.datetime(2020,6, 30),

dt.datetime(2020,10, 30)])) | (pivot_data_sect.columns =='sector')]
dd.columns = ['march_end', 'june_end', 'oct_end','sector']
#dd.sort_values('march_end', ascending= True, inplace = True)
```

March vs June

2. Which industries and companies recovered the fastest and which of them recovered the slowest.

```
month_end_Data['lag'] = month_end_Data['Adj Close'].shift(periods=1)
month_end_Data['diff'] = month_end_Data['Adj Close'] -
month_end_Data['lag']

month_end_Data['MOM'] = month_end_Data['diff']/month_end_Data['lag'] *
100

month_end_Data = month_end_Data[['Date', 'Symbol', 'Adj Close',
'YOY','MOM']]

xx = month_end_Data[month_end_Data.Date >= dt.datetime(2020,
3,31)].sort_values(['Symbol', 'Date'])

#xx[xx.Symbol == 'DDOG']
```

9. Perform PCA to reduce the number of variables in the data.

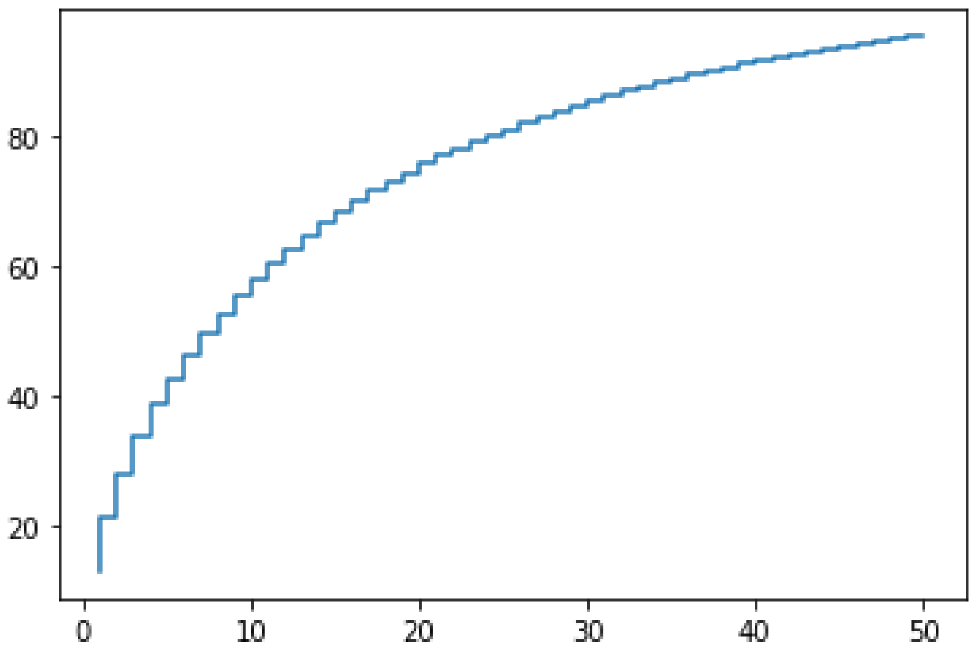
```
mod_data = metrics_copy.set_index('symbol').select_dtypes(exclude =
'object')
mod_data.shape

(102, 196)

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
std_data = sc.fit_transform(mod_data)
```

```python
var_exp = {}
for n in range(1,51):
    pca = PCA (n_components= n)
    pca.fit(std_data)
    var_exp.update({n : pca.explained_variance_ratio_.sum()*100})

list(var_exp.keys())
list(var_exp.values())
```

```
[13.160229885722183,
 21.269969144292443,
 28.13388457235746,
 34.036185403567984,
 38.71647621751884,
 42.63350594925897,
 46.304336571938435,
 49.57536063489103,
 52.60674504530451,
 55.45531015227352,
 57.986412225995565,
 60.434104058039416,
 62.612170059311644,
 64.72049657810041,
 66.59770453833696,
 68.34014225404069,
 69.97750400780752,
 71.54038769046986,
 73.05851600255387,
 74.37508892327918,
 75.66255519821267,
 76.88347113648712,
 77.97348671457311,
 79.03024066004023,
 80.04311989165339,
 81.01158557699438,
 81.93068277898777,
 82.83831294708516,
 83.72567693562144,
 84.5926721764121,
 85.37696819594103,
 86.15970551808073,
 86.89613264891648,
 87.60505740041084,
 88.27082658303719,
 88.86444837782241,
 89.45232135253548,
 90.02221312980049,
 90.5604645549915,
 91.0799036959897,
 91.58735338308456,
 92.08355198530812,
```

```
 92.56043946307251,
 93.02347230902193,
 93.43821553295501,
 93.84328420345241,
 94.21750917371847,
 94.57541629534616,
 94.92144833256181,
 95.24950917338444]
```

```
plt.step(list(var_exp.keys()),list(var_exp.values()))
plt.show()
```




```
pca = PCA (n_components= 38)
pca.fit(std_data)
(pca.explained_variance_ratio_*100).round(2).cumsum()
```

```
array([13.16, 21.27, 28.13, 34.03, 38.71, 42.63, 46.3 , 49.57, 52.6 ,
       55.45, 57.98, 60.43, 62.61, 64.72, 66.6 , 68.34, 69.98, 71.54,
       73.06, 74.38, 75.67, 76.89, 77.98, 79.04, 80.05, 81.02, 81.94,
       82.85, 83.74, 84.61, 85.39, 86.17, 86.91, 87.62, 88.29, 88.88,
       89.47, 90.04])
```

```
pca.transform(std_data).shape
```

```
(102, 38)
```

```
data_clus = pd.DataFrame(pca.transform(std_data), columns =
['PC{}'.format(i+1) for i in range(38)])
data_clus.index = mod_data.index
```

```
data_clus.head()
```

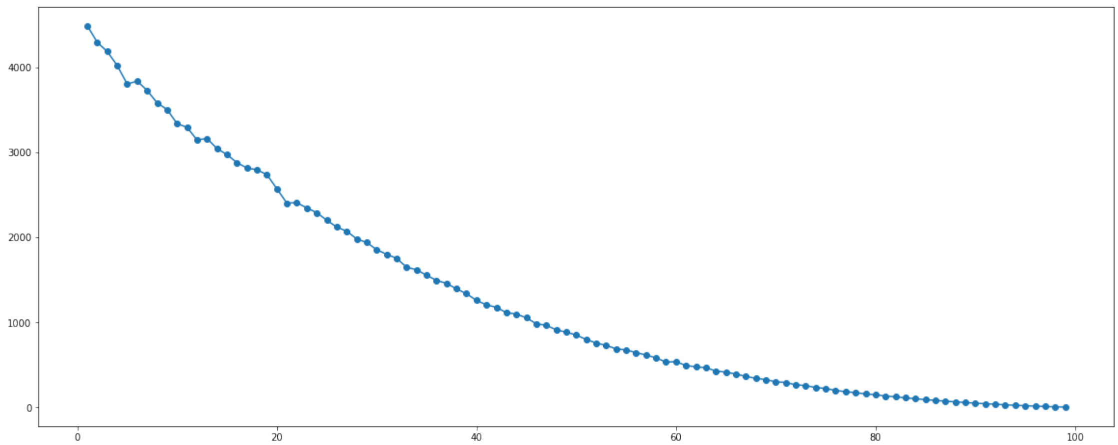
```
             PC1       PC2       PC3       PC4       PC5       PC6
PC7  \
symbol

AAPL    2.508779 -2.059098 -1.584418 -2.088492 -0.202303  2.629262
0.141312
ABNB    1.052795  4.444473  0.234520 -0.237378 -1.833663  0.127684
1.311946
ADBE   -3.219014  1.080023 -2.194774 -0.717679  0.892588 -1.634878
0.885902
ADI    -0.123312 -3.613646 -0.204188  3.208105 -0.300550 -2.749567
1.852539
ADP     1.776947 -1.366474 -0.636562  0.379961 -2.531387  1.956196
1.958174

             PC8       PC9      PC10  ...      PC29      PC30
PC31  \
symbol                                ...

AAPL   -0.258179 -0.969263 -0.072883  ...  0.274594 -1.289807 -
1.301752
ABNB   -0.479320  2.976805 -6.345660  ...  1.919134  3.899206
0.412855
ADBE    0.496283 -1.697916 -1.381777  ...  0.206993  1.186022 -
0.721061
ADI    -0.441778 -0.112619  0.349087  ...  0.492689  0.854499
0.081958
ADP    -0.545353 -0.077636 -1.944790  ...  0.062147 -0.777171 -
0.343856

            PC32      PC33      PC34      PC35      PC36      PC37
PC38
symbol

AAPL   -2.640428 -0.747464  0.069812 -0.729245 -0.289137 -0.265812
0.071802
ABNB    1.220387 -2.933663 -1.467199 -2.187527  1.745256 -1.023764 -
0.492250
ADBE   -0.830476  1.005554  0.872081  0.284651  0.039153 -0.530643
0.063841
ADI     0.306140 -0.308680  0.343213  0.726728  0.819607 -0.168936
1.666022
ADP     0.262265  0.699786  1.321764  1.120539 -0.376106  0.542871 -
0.414144

[5 rows x 38 columns]
```

```
data_clus1 = data_clus.merge(nasdaq100_metrics_ratios,left_index=True,
right_index=False, right_on='symbol')[['PC'+str(i) for i in
range(1,39)]+['sector']]
```

```
data_clus12 = pd.get_dummies(data_clus1, columns =
['sector'],drop_first=True)
```

10. After PCA, perform cluster analysis to identify cohorts. Define cohorts (cluster profiling) and share the insights.

```
from sklearn.cluster import KMeans
clus_std = sc.fit_transform(data_clus12)

errors = {}
for i in range(1,100):
    kmm = KMeans(n_clusters=i, random_state = 12)
    kmm.fit(clus_std)
    errors.update({i :round(kmm.inertia_,2)})
err = pd.Series(errors)

plt.figure(figsize = (20, 8))
plt.plot(err.index, err.values)
plt.scatter(err.index, err.values)
plt.show()
```



elbow curve apprears inconclusive from business perspective. we will create 7 clusters because there are 7 sectors

```
kmm = KMeans(n_clusters=7, random_state = 12)
kmm.fit(clus_std)
clus_labs = kmm.labels_

#metrics_copy.drop(columns='cluster_label',inplace=True)

metrics_copy.insert(loc = 0, column='cluster_label', value=clus_labs)

metrics_copy.head(2)

   cluster_label symbol     company                   sector  \
0              6   AAPL  Apple Inc.  Information Technology
1              4   ABNB      Airbnb  Consumer Discretionary
```

```
                                     subsector  asset_turnover_2017  \
0  Technology Hardware, Storage & Peripherals                0.660
1          Internet & Direct Marketing Retail                0.825

   asset_turnover_2018  asset_turnover_2019  asset_turnover_2020  \
0                 0.72                 0.74                 0.83
1                 0.55                 0.64                 0.36

   asset_turnover_2021  ...  yoy_eps_growth_2021
yoy_eps_growth_latest  \
0                 1.08  ...                71.04                  -
7.69
1                 0.50  ...                96.46
609.09

   yoy_revenue_growth_2017  yoy_revenue_growth_2018
yoy_revenue_growth_2019  \
0                   11.340                    21.69
5.36
1                   23.355                    40.08
31.58

   yoy_revenue_growth_2020  yoy_revenue_growth_2021  \
0                    11.94                    38.50
1                    31.27                   -18.11

   yoy_revenue_growth_latest     market_cap  last_sale
0                       5.11  2625740143000    $151.45
1                      41.00    69569944167    $116.65

[2 rows x 202 columns]
```

1. Highlight companies from different sectors falling in the same cohort. Share your findings.

```
metrics_copy.groupby('cluster_label').size()
```

```
cluster_label
0     2
1    25
2     4
3     7
4    35
5     9
6    20
dtype: int64
```

```
metrics_copy[['symbol','cluster_label','sector']].sort_values(by='clus
ter_label')
```

```
    symbol  cluster_label                  sector
49    ISRG              0             Health Care
70    NVDA              0  Information Technology
67      MU              1  Information Technology
30    CTSH              1  Information Technology
86    SIRI              1  Communication Services
..     ...            ...                     ...
48    INTU              6  Information Technology
100     ZM              6  Information Technology
65    MSFT              6  Information Technology
33    DOCU              6  Information Technology
101     ZS              6  Information Technology

[102 rows x 3 columns]
```

```python
for i in range(7):

print(metrics_copy[['symbol','cluster_label','sector']].sort_values(by
='cluster_label')[metrics_copy.cluster_label      == i],'\n\n')
```

```
   symbol  cluster_label                  sector
49   ISRG              0             Health Care
70   NVDA              0  Information Technology


   symbol  cluster_label                  sector
67     MU              1  Information Technology
30   CTSH              1  Information Technology
86   SIRI              1  Communication Services
66   MTCH              1  Communication Services
93    TXN              1  Information Technology
26   CRWD              1  Information Technology
23  CMCSA              1  Communication Services
58   MCHP              1  Information Technology
39   FISV              1  Information Technology
71   NXPI              1  Information Technology
73   OKTA              1  Information Technology
64   MRVL              1  Information Technology
15   AVGO              1  Information Technology
55   LRCX              1  Information Technology
95   VRSN              1  Information Technology
12   ANSS              1  Information Technology
76   PAYX              1  Information Technology
89   SWKS              1  Information Technology
53   KLAC              1  Information Technology
88   SPLK              1  Information Technology
8    AMAT              1  Information Technology
75   PANW              1  Information Technology
3     ADI              1  Information Technology
47   INTC              1  Information Technology
```

98	WDAY	1	Information Technology

	symbol	cluster_label	sector
99	XEL	2	Utilities
37	EXC	2	Utilities
21	CEG	2	Utilities
6	AEP	2	Utilities

	symbol	cluster_label	sector
52	KHC	3	Consumer Staples
59	MDLZ	3	Consumer Staples
51	KDP	3	Consumer Staples
97	WBA	3	Consumer Staples
24	COST	3	Consumer Staples
79	PEP	3	Consumer Staples
62	MNST	3	Consumer Staples

	symbol	cluster_label	sector
61	META	4	Communication Services
84	SBUX	4	Consumer Discretionary
85	SGEN	4	Health Care
54	LCID	4	Consumer Discretionary
78	PDD	4	Consumer Discretionary
74	ORLY	4	Consumer Discretionary
57	MAR	4	Consumer Discretionary
69	NTES	4	Communication Services
68	NFLX	4	Communication Services
63	MRNA	4	Health Care
60	MELI	4	Consumer Discretionary
56	LULU	4	Consumer Discretionary
50	JD	4	Consumer Discretionary
41	GILD	4	Health Care
46	ILMN	4	Health Care
1	ABNB	4	Consumer Discretionary
7	ALGN	4	Health Care
96	VRTX	4	Health Care
10	AMGN	4	Health Care
11	AMZN	4	Consumer Discretionary
14	ATVI	4	Communication Services
16	AZN	4	Health Care
17	BIDU	4	Communication Services
18	BIIB	4	Health Care
19	BKNG	4	Consumer Discretionary
22	CHTR	4	Communication Services
83	ROST	4	Consumer Discretionary
36	EBAY	4	Consumer Discretionary
32	DLTR	4	Consumer Discretionary

```
82   REGN              4             Health Care
92   TSLA              4  Consumer Discretionary
34   DXCM              4             Health Care
35     EA              4  Communication Services
31   DDOG              4  Information Technology
91   TMUS              4  Communication Services
```

```
   symbol  cluster_label       sector
45   IDXX              5  Health Care
44    HON              5  Industrials
77   PCAR              5  Industrials
29   CTAS              5  Industrials
72   ODFL              5  Industrials
94   VRSK              5  Industrials
28    CSX              5  Industrials
38   FAST              5  Industrials
25   CPRT              5  Industrials
```

```
    symbol  cluster_label                  sector
90    TEAM              6  Information Technology
87    SNPS              6  Information Technology
0     AAPL              6  Information Technology
80    PYPL              6  Information Technology
2     ADBE              6  Information Technology
4      ADP              6  Information Technology
5     ADSK              6  Information Technology
9      AMD              6  Information Technology
13    ASML              6  Information Technology
20    CDNS              6  Information Technology
81    QCOM              6  Information Technology
27    CSCO              6  Information Technology
40    FTNT              6  Information Technology
42    GOOG              6  Communication Services
43   GOOGL              6  Communication Services
48    INTU              6  Information Technology
100     ZM              6  Information Technology
65    MSFT              6  Information Technology
33    DOCU              6  Information Technology
101     ZS              6  Information Technology
```

```
# This is formatted as code
```

1. Plot seasonality, trend, and irregular components over time for the historical stock prices of apple.

2. Based on trend and seasonality, choose appropriate exponential smoothing method to forecast for week-end share price value for next 12.

3. Perform augmented Dickey–Fuller test (ADF) to check for stationary for apple stock.

4. For the historical stock prices of apple, look at the ACF and PACF plots and strategize for ARIMA modeling. Find appropriate values of p, d and q and forecast for month-end share price value for next 12 months. For model validation, find out MAPE of 12 months.

5. Pick up the top 2 companies from each sector based on market capitalization. Create trend charts for the last 5 years for month-end share price (use variable - 'Adjusted close'). Showcase 12 months rolling mean and standard deviation within the same chart. Share your observations regarding the stationarity for all the companies.

6. Perform ADF test to check for stationary for all the companies selected in the last step.

7. Perform batch forecasting for top 2 companies from each sector based on market capitalization for week-end share price value for next 12 months using auto-arima. You may want to leverage the library 'pmdarima' for auto-arima. Use your discretion. For model validation, find out MAPE of 12 months.

```
## Plot seasonality, trend, and irregular components over time for the
historical stock prices of apple.

master_data_AAPL = master_data[master_data.Symbol == 'AAPL']
[['Date','Adj Close']]

master_data_AAPL.columns

Index(['Date', 'Adj Close'], dtype='object')

master_data.tail(2)

       Symbol        Date        High         Low        Open
Close  \
426757     ZS 2022-10-21  150.919998  142.710007  148.979996
150.479996
426758     ZS 2022-10-24  151.460007  144.300003  151.360001
148.669998

           Volume   Adj Close
426757  2140900.0  150.479996
426758  1375200.0  148.669998

start = dt.datetime(2015, 1, 1)
start

datetime.datetime(2015, 1, 1, 0, 0)
```

```python
data_AAPL_2015 = master_data_AAPL[master_data_AAPL.Date>=start]
```

```python
apple_ts = data_AAPL_2015.set_index('Date')
```

```python
apple_ts.index
```

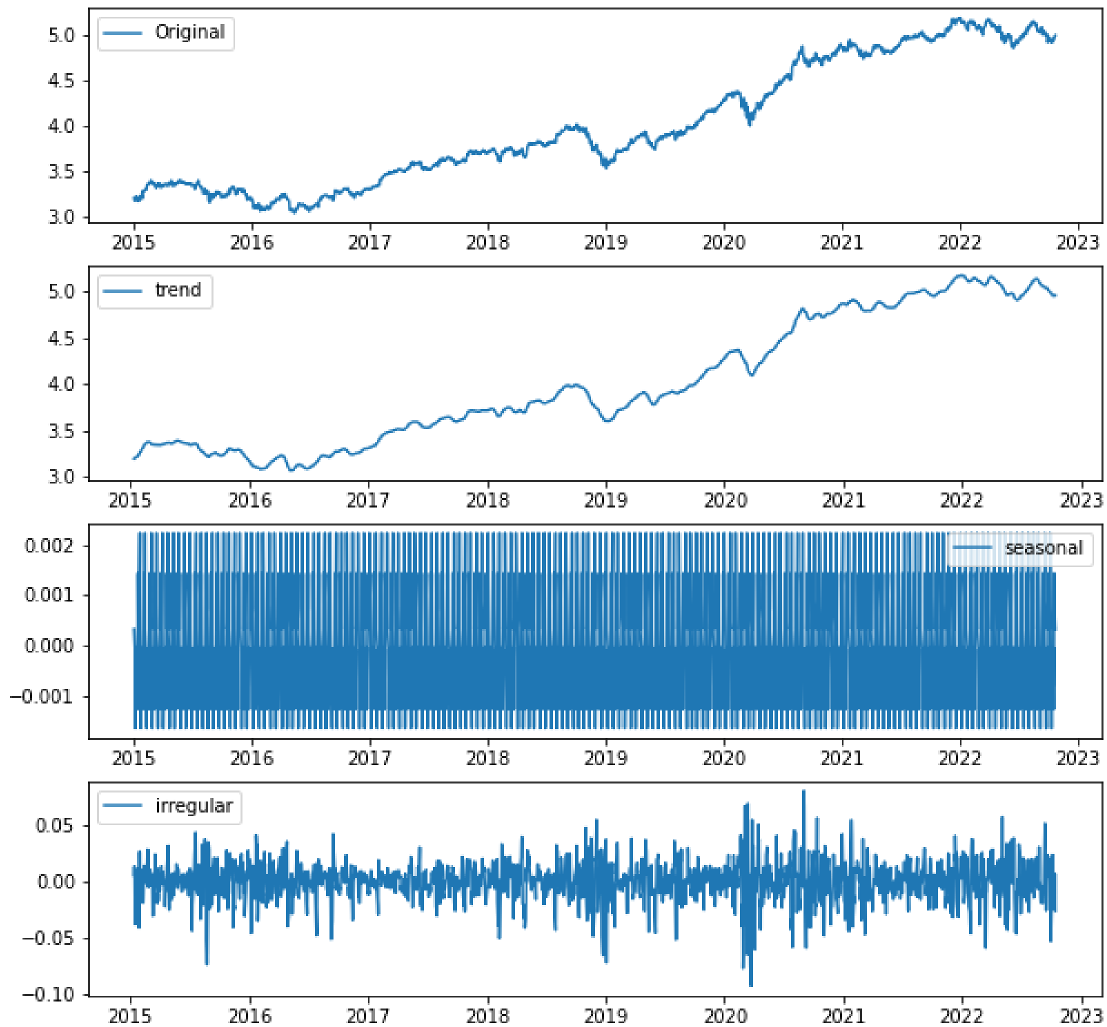
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06', '2015-01-07',
               '2015-01-08', '2015-01-09', '2015-01-12', '2015-01-13',
               '2015-01-14', '2015-01-15',
               ...
               '2022-10-11', '2022-10-12', '2022-10-13', '2022-10-14',
               '2022-10-17', '2022-10-18', '2022-10-19', '2022-10-20',
               '2022-10-21', '2022-10-24'],
              dtype='datetime64[ns]', name='Date', length=1967,
freq=None)
```

```python
apple_ts.sort_index(inplace=True)
```

```python
def decompose(time_series):
    ts_log = np.log(time_series)
    decompose = seasonal_decompose(ts_log, period = 12)
    trend = decompose.trend
    seasonal = decompose.seasonal
    irregular = decompose.resid
    f,ax = plt.subplots(4,1,figsize = (10,10))
    ax[0].plot(ts_log, label = 'Original')
    ax[0].legend(loc ='best')
    ax[1].plot(trend, label = 'trend')
    ax[1].legend(loc ='best')
    ax[2].plot(seasonal, label = 'seasonal')
    ax[2].legend(loc ='best')
    ax[3].plot(irregular, label = 'irregular')
    ax[3].legend(loc ='best')
    plt.show()
    return irregular
```

```python
plt.figure(figsize=(25,8))
ts_decomposed = decompose(apple_ts)
plt.show()
```

```
<Figure size 1800x576 with 0 Axes>
```




```
apple_ts.squeeze()[1:10]
```

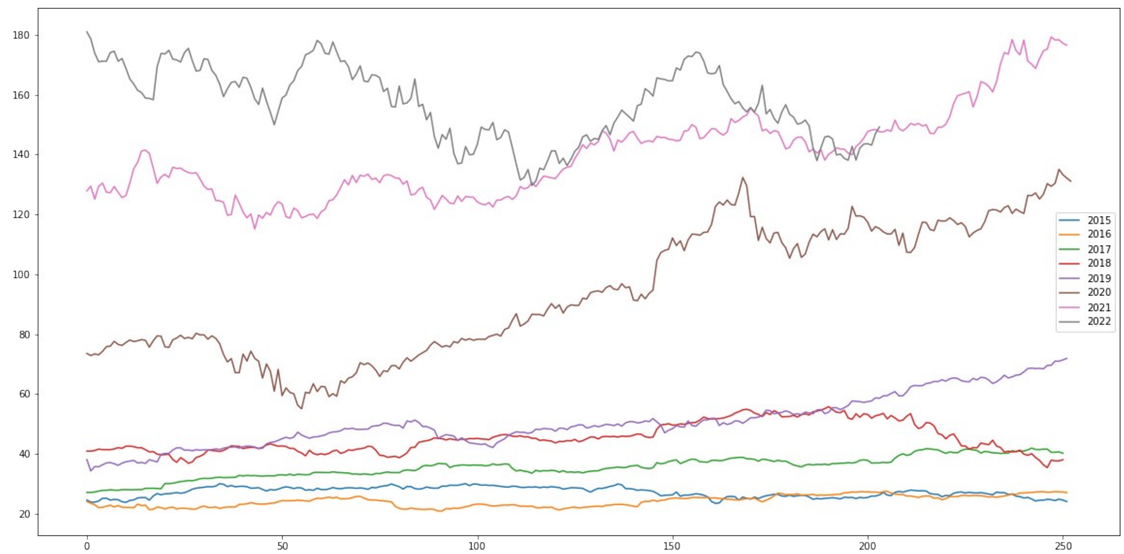
```
Date
2015-01-05    23.910093
2015-01-06    23.912338
2015-01-07    24.247652
2015-01-08    25.179300
2015-01-09    25.206299
2015-01-12    24.585203
2015-01-13    24.803484
2015-01-14    24.708967
2015-01-15    24.038361
Name: Adj Close, dtype: float64
```

```
apple_ts.index
```

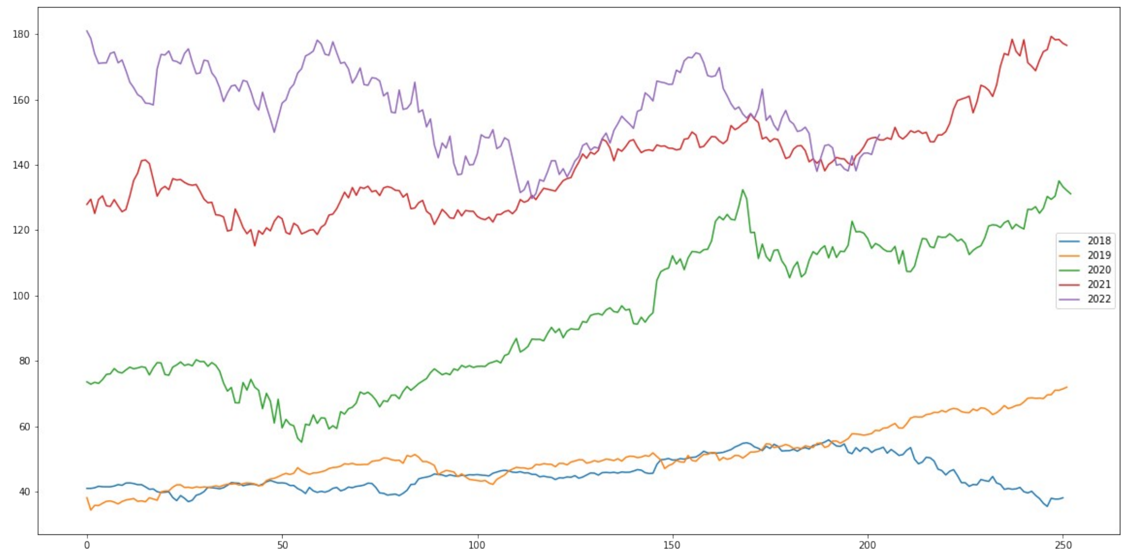
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06', '2015-01-07',
               '2015-01-08', '2015-01-09', '2015-01-12', '2015-01-13',
               '2015-01-14', '2015-01-15',
               ...
```

```
                 '2022-10-11', '2022-10-12', '2022-10-13', '2022-10-14',
                 '2022-10-17', '2022-10-18', '2022-10-19', '2022-10-20',
                 '2022-10-21', '2022-10-24'],
                dtype='datetime64[ns]', name='Date', length=1967,
freq=None)
```

```
# Checking for seasonality again
plt.figure(figsize=(20,10))
for i in (range(2015,2023)):
    x = list(apple_ts.squeeze()[str(i)])
    plt.plot(x,label=i)


plt.legend()
plt.show()
```




```
# Checking for trend again
plt.figure(figsize=(20,10))
for i in (range(2018,2023)):
    x = list(apple_ts.squeeze()[str(i)])
    plt.plot(x,label=i)

plt.legend()
plt.show()
```




```
bb = apple_ts.copy()

bb.reset_index(inplace=True)

# bb['month'] = bb.Date.dt.month
# bb['year'] = bb.Date.dt.year
bb['weekday'] = bb.Date.dt.weekday

bb
```

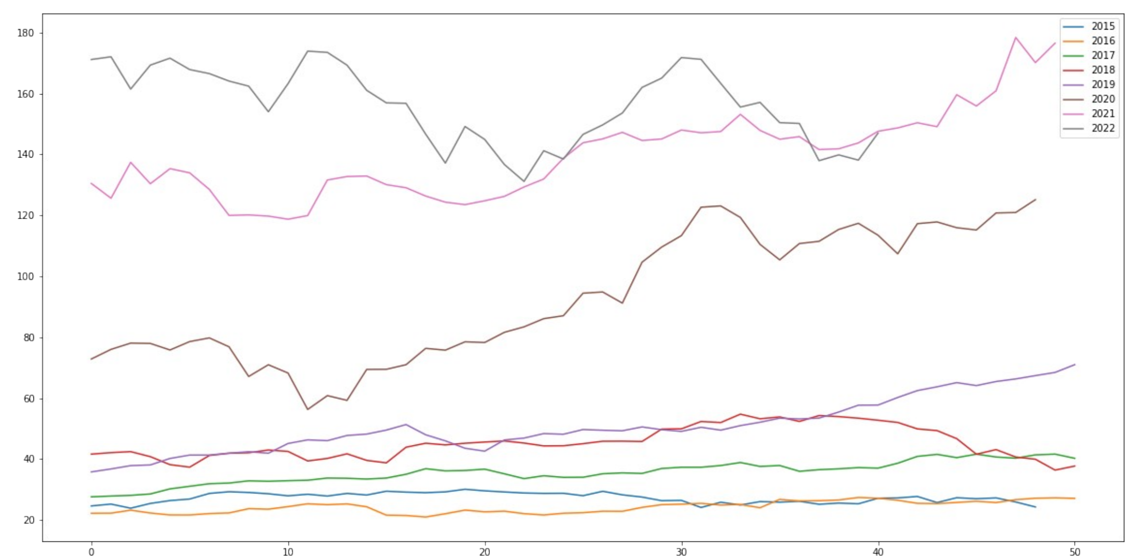
```
            Date   Adj Close  weekday
0    2015-01-02   24.603207        4
1    2015-01-05   23.910093        0
2    2015-01-06   23.912338        1
3    2015-01-07   24.247652        2
4    2015-01-08   25.179300        3
...         ...         ...      ...
1962 2022-10-18  143.511932        1
1963 2022-10-19  143.621750        2
1964 2022-10-20  143.152527        3
1965 2022-10-21  147.026108        4
1966 2022-10-24  149.202484        0

[1967 rows x 3 columns]
```

```
week_end_data = bb[bb.weekday == 4]
week_end_data.tail(10)
```

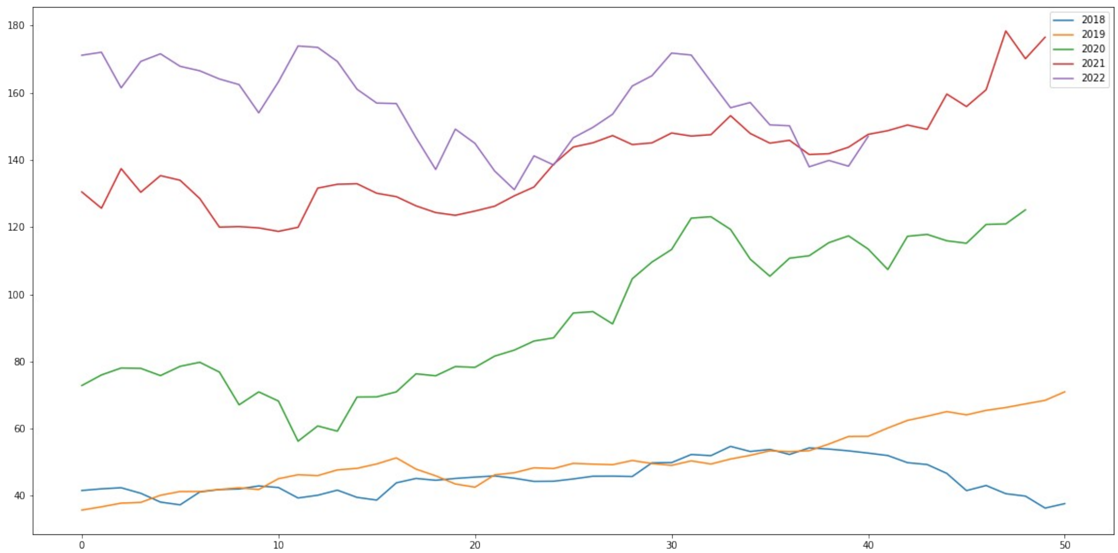
```
            Date   Adj Close  weekday
1921 2022-08-19  171.235947        4
1926 2022-08-26  163.349014        4
1931 2022-09-02  155.551956        4
1935 2022-09-09  157.109375        4
1940 2022-09-16  150.450424        4
```

```
1945 2022-09-23  150.180862        4
1950 2022-09-30  137.971115        4
1955 2022-10-07  139.857986        4
1960 2022-10-14  138.150833        4
1965 2022-10-21  147.026108        4
```

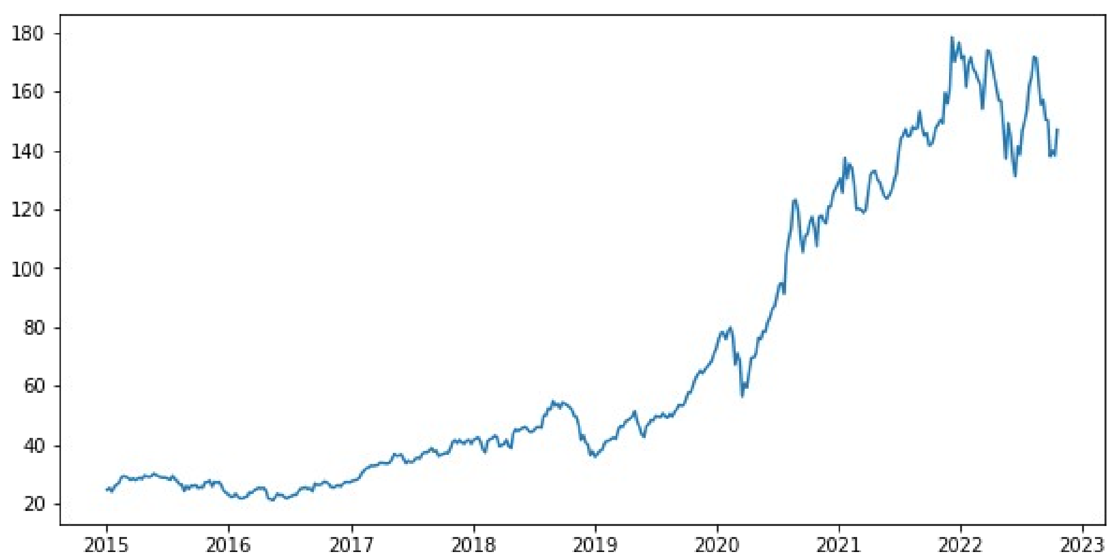
```
week_end_data.drop(columns='weekday', inplace=True)

week_end_data.set_index('Date', inplace=True)

apple_weekend = week_end_data.squeeze()

# Checking for seasonality
plt.figure(figsize=(20,10))
for i in (range(2015,2023)):
    x = list(apple_weekend[str(i)])
    plt.plot(x,label=i)


plt.legend()
plt.show()
```




```
# Checking for trend
plt.figure(figsize=(20,10))
for i in (range(2018,2023)):
    x = list(apple_weekend[str(i)])
    plt.plot(x,label=i)

plt.legend()
plt.show()
```




```
plt.figure(figsize = (10,5))
plt.plot(apple_weekend)
plt.show()
```



```
# Trend and seasonality observed. Hence triple exponential Smoothing

from statsmodels.tsa.holtwinters import ExponentialSmoothing

len(apple_weekend)
```

```
393
```

```
apple_weekend
```

```
Date
2015-01-02     24.603207
2015-01-09     25.206299
```

```
2015-01-16     23.851587
2015-01-23     25.424585
2015-01-30     26.365240
                 ...
2022-09-23    150.180862
2022-09-30    137.971115
2022-10-07    139.857986
2022-10-14    138.150833
2022-10-21    147.026108
Name: Adj Close, Length: 393, dtype: float64
```

```
train = apple_weekend[:-12]
test = apple_weekend[-12:]
```

```
train
```

```
Date
2015-01-02     24.603207
2015-01-09     25.206299
2015-01-16     23.851587
2015-01-23     25.424585
2015-01-30     26.365240
                 ...
2022-07-01    138.507507
2022-07-08    146.592850
2022-07-15    149.713348
2022-07-22    153.621414
2022-07-29    162.015808
Name: Adj Close, Length: 381, dtype: float64
```

```
train.to_excel('exp_sm.xlsx')
```

```
model=ExponentialSmoothing(train,trend='mul', seasonal='add',
seasonal_periods=7).fit()
```

```
forecast = model.forecast(12)
```

```
forecast
```

```
381    162.455159
382    162.669776
383    163.556725
384    164.992826
385    164.976000
386    165.641069
387    165.669904
388    166.449082
389    166.672209
390    167.567686
391    169.012333
392    169.004072
dtype: float64
```

```python
from sklearn.metrics import mean_absolute_percentage_error
```

```python
mean_absolute_percentage_error(test,forecast)
```

```
0.10228410324411297
```

```python
model_final = ExponentialSmoothing(apple_weekend,trend='mul',
seasonal='add', seasonal_periods=12).fit()
```

```python
model_final.forecast(12)
```

```
393    146.087249
394    146.433423
395    146.885425
396    146.489184
397    146.947246
398    148.090287
399    149.152870
400    149.193321
401    149.095874
402    148.965698
403    149.622787
404    150.876156
dtype: float64
```

```python
# Perform augmented Dickey–Fuller test (ADF) to check for stationary
for apple stock.

# For the historical stock prices of apple, look at the ACF and PACF
plots and strategize for ARIMA modeling.

#Find appropriate values of p, d and q and forecast for month-end
share price value for next 12 months. For model validation, find out
MAPE of 12 months.
```

```python
def test_stationarity(ts, title=""):
    # mean and variance for the series
    f , ax = plt.subplots(1,2, figsize = (25,5))
    ax[0].plot(ts, label = 'Original')
    ax[0].set_title(title, size = 30)

    # rolling stats
    rolling_mean = ts.rolling(window = 12).mean()
    rolling_std = ts.rolling(window = 12).std()

    ax[0].plot(rolling_mean, color = 'red', label = 'Rolling Mean')
    ax[0].plot(rolling_std, color = 'black', label = 'Rolling STD')
    ax[0].legend(loc = 'best')

    # Adfuller test
    dftest = adfuller(ts)
```

```python
    df = pd.Series(dftest[:4], index = ['Test Statistics', 'p-value',
'# Lags Used', '# Obs used'])

    if (df['p-value'] >= 0.05):
        ax[1].annotate('Fail to Reject the Null'.center(35), xy =
(0.25, 0.8), size = 25)
        ax[1].annotate('Non Stationary'.center(35), xy = (0.25, 0.7),
size = 25)
    else :
        ax[1].annotate('Reject the Null'.center(35), xy = (0.25, 0.8),
size = 25)
        ax[1].annotate('Stationary'.center(35), xy = (0.25, 0.7), size
= 25)

    c = 0.4
    for i in range(4):
        text = '{}    : {:.4f}'.format(df.index[i], df[i])
        ax[1].annotate(text, xy = (0.1, c), size = 15)
        c -= 0.1
    c = 0.4
    for i in dftest[4].keys():
        text = 'Critical Value {}    : {:.4f}'.format(i, dftest[4][i])
        ax[1].annotate(text, xy = (0.5, c), size = 15)
        c -= 0.1
    ax[1].get_xaxis().set_visible(False)
    ax[1].get_yaxis().set_visible(False)
    ax[1].axis('off')
    plt.show()

apple_all = master_data[master_data.Symbol == 'AAPL'][['Date','Adj
Close']]

cc = apple_all.copy()
cc
```

```
           Date   Adj Close
0    2002-11-01    0.249028
1    2002-11-04    0.257095
2    2002-11-05    0.257248
3    2002-11-06    0.262119
4    2002-11-07    0.243548
...         ...         ...
5024 2022-10-18  143.511932
5025 2022-10-19  143.621750
5026 2022-10-20  143.152527
5027 2022-10-21  147.026108
5028 2022-10-24  149.202484

[5029 rows x 2 columns]
```

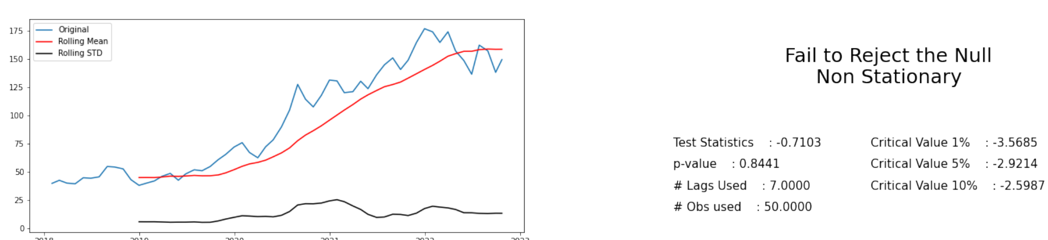
```
cc['month'] = cc.Date.dt.month
cc['year'] = cc.Date.dt.year
cc['mon_yr'] = cc.month.astype(str) + '-' + cc.year.astype(str)

mon_end = cc.groupby('mon_yr').agg(max)['Date']

month_end_Data_apl = cc[cc.Date.isin(mon_end.values)]
month_end_Data_apl.sort_values('Date' , inplace = True)

month_end_Data_apl
```

```
           Date   Adj Close  month  year   mon_yr
19   2002-11-29    0.235937     11  2002  11-2002
40   2002-12-31    0.218128     12  2002  12-2002
61   2003-01-31    0.218585      1  2003   1-2003
80   2003-02-28    0.228479      2  2003   2-2003
101  2003-03-31    0.215236      3  2003   3-2003
...         ...         ...    ...   ...      ...
4948 2022-06-30  136.304245      6  2022   6-2022
4968 2022-07-29  162.015808      7  2022   7-2022
4991 2022-08-31  156.959625      8  2022   8-2022
5012 2022-09-30  137.971115      9  2022   9-2022
5028 2022-10-24  149.202484     10  2022  10-2022

[240 rows x 5 columns]
```

```
st_date = dt.datetime(2018,1,1)

apple_monthy2018 = month_end_Data_apl.loc[month_end_Data_apl.Date >=
st_date, ['Date', 'Adj Close']].set_index('Date').squeeze()
apple_monthy2018[:5]
```

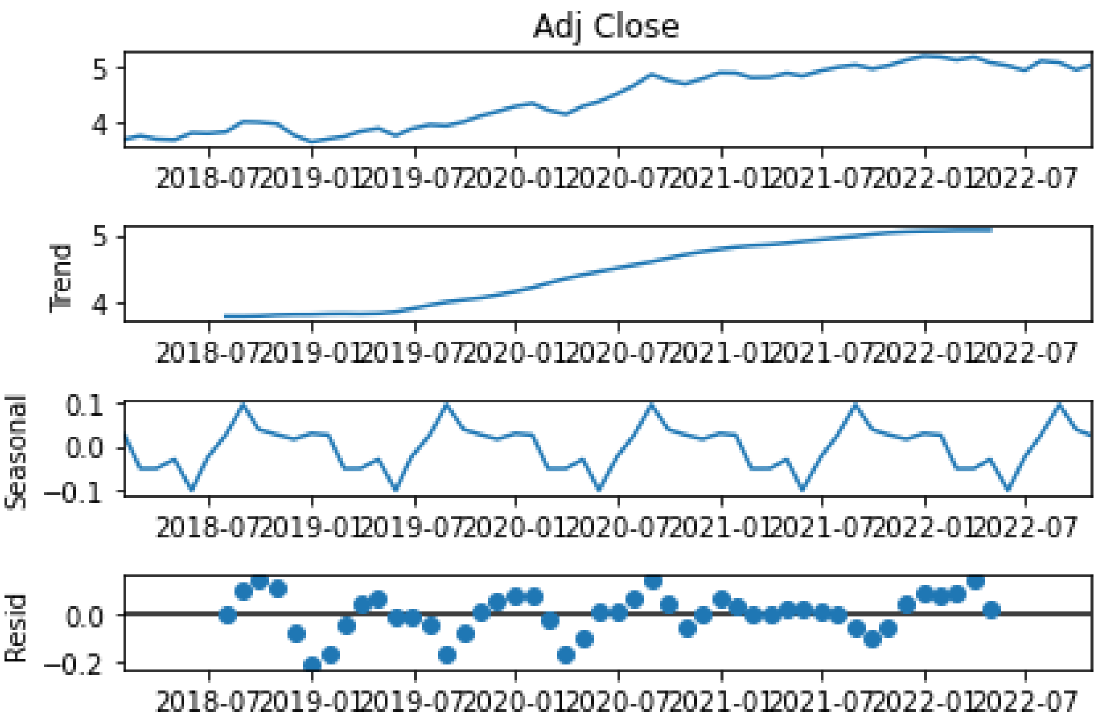
```
Date
2018-01-31    39.802277
2018-02-28    42.516209
2018-03-29    40.048103
2018-04-30    39.446598
2018-05-31    44.776775
Name: Adj Close, dtype: float64
```

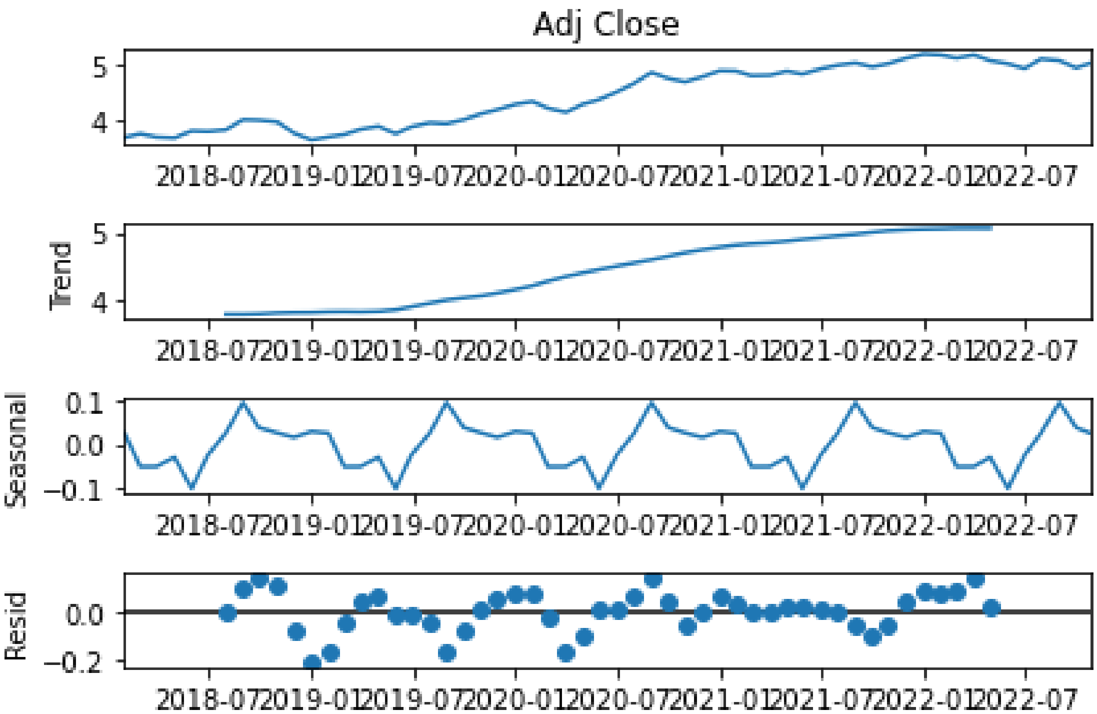
```
test_stationarity(apple_monthy2018)
```



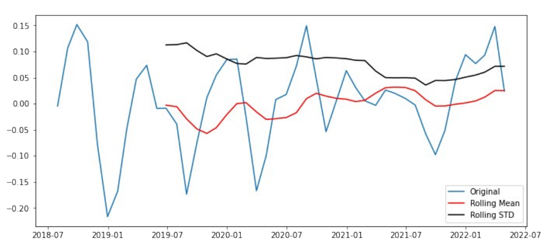

```
# The series is non-stationary

ts_log = np.log(apple_monthy2018)
```

```python
from statsmodels.tsa.seasonal import seasonal_decompose

decomposition = seasonal_decompose(ts_log, period = 12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

decomposition.plot()
```





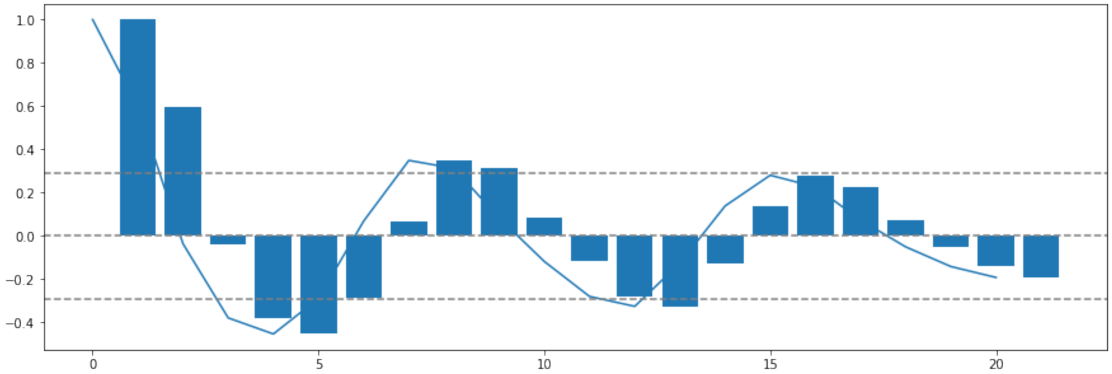

```
test_stationarity(residual.dropna())
```



Reject the Null
Stationary

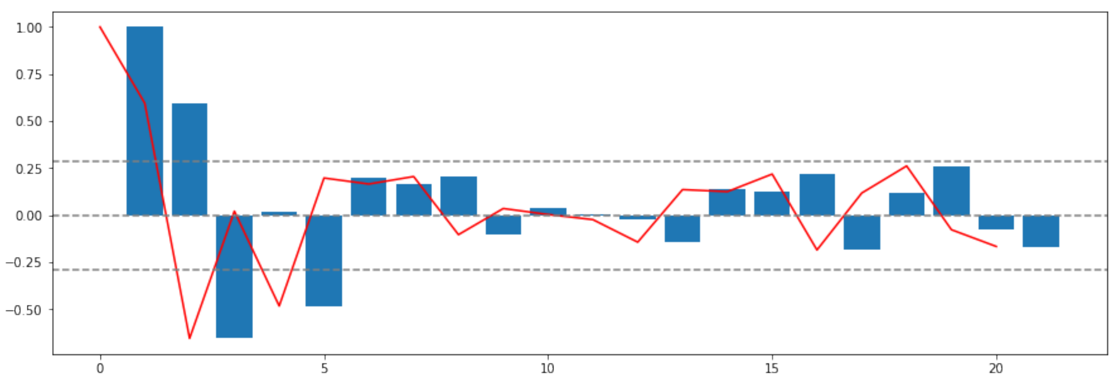
Test Statistics	: -5.8774	Critical Value 1%	: -3.5966
p-value	: 0.0000	Critical Value 5%	: -2.9333
# Lags Used	: 3.0000	Critical Value 10%	: -2.6050
# Obs used	: 42.0000		

```
residual.dropna(inplace = True)

from statsmodels.tsa.stattools import acf, pacf

lag_acf = acf(residual, nlags = 20)
plt.figure(figsize = (15,5))
plt.bar(range(1, 22),lag_acf)
plt.plot(lag_acf)
plt.axhline(y = 0, linestyle = '--', color = 'gray')
plt.axhline(y = -1.96/np.sqrt(len(residual)), linestyle = '--', color
= 'gray')
plt.axhline(y = 1.96/np.sqrt(len(residual)), linestyle = '--', color =
'gray')
plt.show()
```



ACF : q term = lag = 2

```
lag_pacf = pacf(residual, nlags = 20, method= 'ols')
plt.figure(figsize = (15,5))
plt.bar(range(1, 22),lag_pacf)
plt.plot(lag_pacf, color = 'red')
plt.axhline(y = 0, linestyle = '--', color = 'gray')
plt.axhline(y = -1.96/np.sqrt(len(residual)), linestyle = '--', color
= 'gray')
plt.axhline(y = 1.96/np.sqrt(len(residual)), linestyle = '--', color =
'gray')
plt.show()
```



PACF p term = 4

```
from statsmodels.tsa.arima.model import ARIMA

train= apple_monthy2018[:-6]
test = apple_monthy2018[-6:]

len(apple_monthy2018), train.size, test.size

(58, 52, 6)

#ARIMA
model = ARIMA(train, order=(4, 2, 2))
results_ARIMA = model.fit()
train_pred = results_ARIMA.fittedvalues
```

```
test.index
```

```
DatetimeIndex(['2022-05-31', '2022-06-30', '2022-07-29', '2022-08-31',
               '2022-09-30', '2022-10-24'],
              dtype='datetime64[ns]', name='Date', freq=None)
```

```
forecast = results_ARIMA.forecast(6)
```

```
plt.figure(figsize = (10,5))
plt.plot(train, color = 'black', label = 'train')
plt.plot(train_pred, color = 'blue', label = 'train-fit')
plt.plot(test, color = 'red', label = 'test- actual')
plt.plot(test.index, forecast,color = 'green', label = 'test-
forecast')
plt.legend()
plt.show()
```


```
mean_absolute_percentage_error(y_true = test, y_pred = forecast)
```

```
0.10274216821748973
```

Pick up the top 2 companies from each sector based on market capitalization. Create trend charts for the last 5 years for month-end share price (use variable - 'Adjusted close'). Showcase 12 months rolling mean and standard deviation within the same chart. Share your observations regarding the stationarity for all the companies.

```
sorted_metrics = metrics_copy.sort_values(['sector', 'market_cap'],
ascending = False)
```

```
sector_market_cap = sorted_metrics.groupby('sector').head(2)
[['sector','symbol', 'market_cap']]
```

```
month_end_Data
```

```
              Date Symbol   Adj Close        YOY       MOM
19      2002-11-29   AAPL    0.235937        NaN       NaN
40      2002-12-31   AAPL    0.218128        NaN -7.548445
61      2003-01-31   AAPL    0.218585        NaN  0.209464
80      2003-02-28   AAPL    0.228479        NaN  4.526399
101     2003-03-31   AAPL    0.215236        NaN -5.796232
...            ...    ...         ...        ...       ...
426678 2022-06-30     ZS  149.509995 -30.801631 -2.338495
426698 2022-07-29     ZS  155.059998 -34.271546  3.712128
426721 2022-08-31     ZS  159.240005 -42.789392  2.695736
426742 2022-09-30     ZS  164.369995 -37.315996  3.221546
426758 2022-10-24     ZS  148.669998 -53.374520 -9.551620

[20383 rows x 5 columns]
```

```
trend_data =
month_end_Data[month_end_Data.Symbol.isin(sector_market_cap.symbol)].c
opy()
```

```
trend_data.Symbol.nunique()
```

```
14
```

```
last_5_start = dt.datetime.today() - rd(years = 5, day = 1)
last_5_start
```

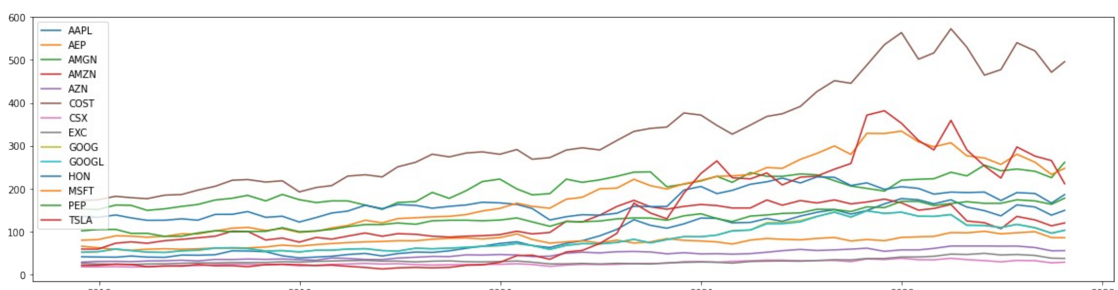
```
datetime.datetime(2017, 11, 1, 13, 19, 27, 39787)
```

```
data_last_5 = trend_data[trend_data.Date > last_5_start].copy()
```

```
data_last_5.Symbol.nunique()
```

```
14
```

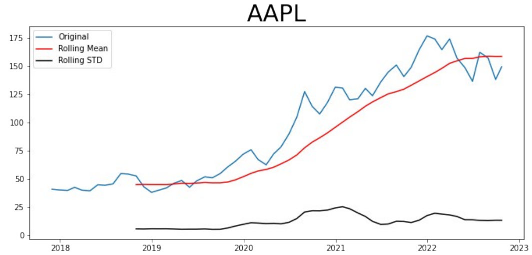
```
plt.figure(figsize = (20,5))
for comp in data_last_5.Symbol.unique():
  temp_ts = data_last_5.loc[data_last_5.Symbol == comp, ['Date','Adj
Close']].set_index('Date').squeeze()
  plt.plot(temp_ts, label = comp)
  plt.legend()
plt.show()
```



```
plt.figure(figsize = (20,5))
for comp in data_last_5.Symbol.unique():
  temp_ts = data_last_5.loc[data_last_5.Symbol == comp, ['Date','Adj Close']].set_index('Date').squeeze()
  test_stationarity(temp_ts, comp)
```

```
<Figure size 1440x360 with 0 Axes>
```

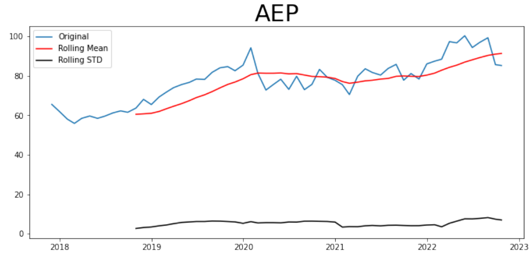
AAPL



Fail to Reject the Null
Non Stationary

Test Statistics : -0.8725	Critical Value 1% : -3.5629
p-value : 0.7969	Critical Value 5% : -2.9190
# Lags Used : 7.0000	Critical Value 10% : -2.5974
# Obs used : 52.0000	

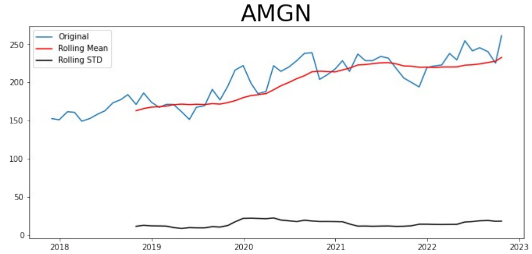
AEP



Fail to Reject the Null
Non Stationary

Test Statistics : -1.7043	Critical Value 1% : -3.5464
p-value : 0.4289	Critical Value 5% : -2.9119
# Lags Used : 0.0000	Critical Value 10% : -2.5937
# Obs used : 59.0000	

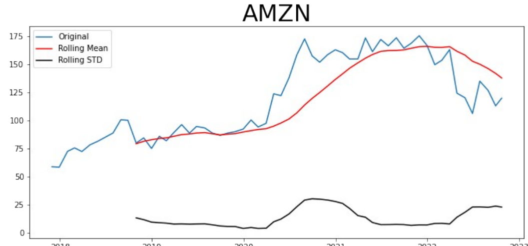
AMGN



Fail to Reject the Null
Non Stationary

Test Statistics : -1.5303	Critical Value 1% : -3.5464
p-value : 0.5185	Critical Value 5% : -2.9119
# Lags Used : 0.0000	Critical Value 10% : -2.5937
# Obs used : 59.0000	

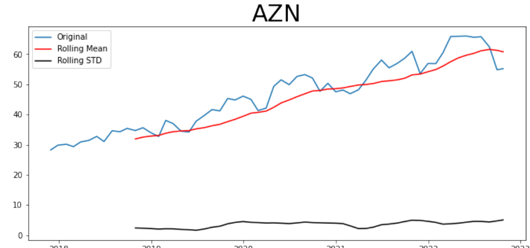
AMZN



Fail to Reject the Null
Non Stationary

Test Statistics : -1.7843	Critical Value 1% : -3.5464
p-value : 0.3883	Critical Value 5% : -2.9119
# Lags Used : 0.0000	Critical Value 10% : -2.5937
# Obs used : 59.0000	

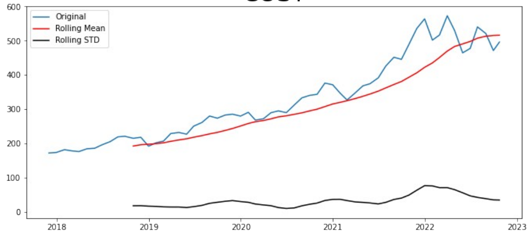
AZN



Fail to Reject the Null
Non Stationary

Test Statistics : -1.4726	Critical Value 1% : -3.5464
p-value : 0.5470	Critical Value 5% : -2.9119
# Lags Used : 0.0000	Critical Value 10% : -2.5937
# Obs used : 59.0000	

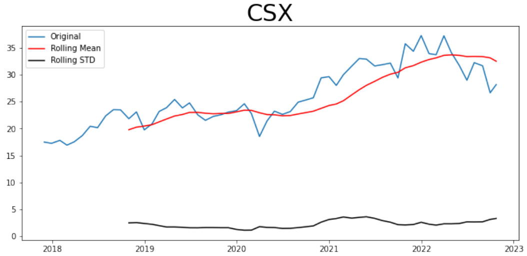
COST



Fail to Reject the Null
Non Stationary

Test Statistics : 0.0150	Critical Value 1% : -3.5602
p-value : 0.9598	Critical Value 5% : -2.9179
# Lags Used : 6.0000	Critical Value 10% : -2.5968
# Obs used : 53.0000	

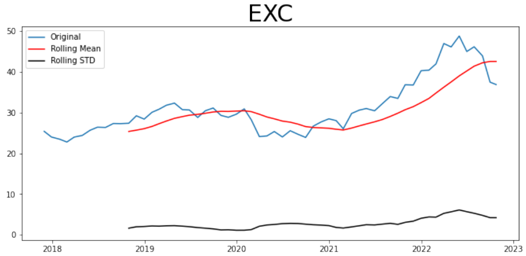
CSX



Fail to Reject the Null
Non Stationary

Test Statistics : -1.6968	Critical Value 1% : -3.5485
p-value : 0.4328	Critical Value 5% : -2.9128
# Lags Used : 1.0000	Critical Value 10% : -2.5941
# Obs used : 58.0000	

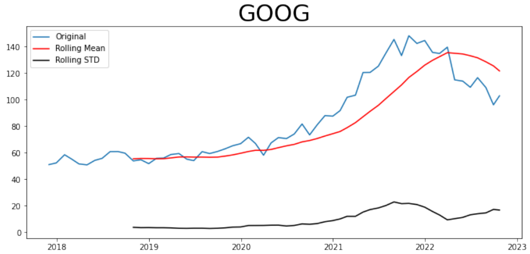
EXC



Reject the Null
Stationary

Test Statistics : -3.7748	Critical Value 1% : -3.5577
p-value : 0.0032	Critical Value 5% : -2.9168
# Lags Used : 5.0000	Critical Value 10% : -2.5962
# Obs used : 54.0000	

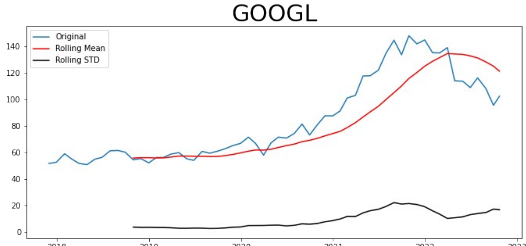
GOOG



Fail to Reject the Null
Non Stationary

Test Statistics : -1.8840	Critical Value 1% : -3.5577
p-value : 0.3396	Critical Value 5% : -2.9168
# Lags Used : 5.0000	Critical Value 10% : -2.5962
# Obs used : 54.0000	

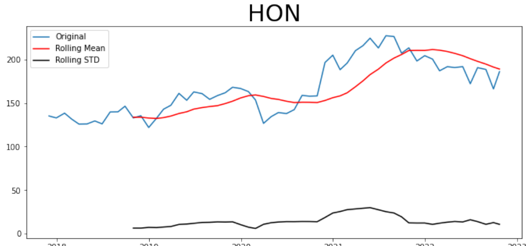
GOOGL



Fail to Reject the Null
Non Stationary

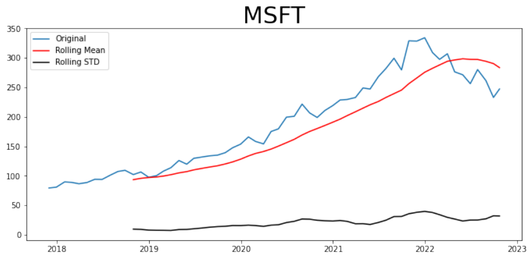
Test Statistics : -1.9062	Critical Value 1% : -3.5577
p-value : 0.3291	Critical Value 5% : -2.9168
# Lags Used : 5.0000	Critical Value 10% : -2.5962
# Obs used : 54.0000	

HON



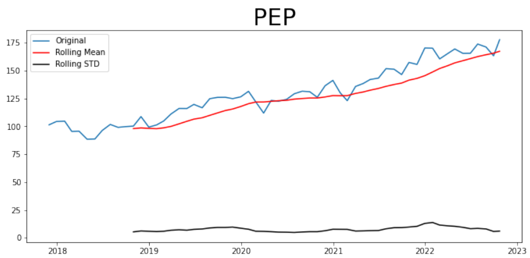
Fail to Reject the Null
Non Stationary

Test Statistics : -1.5396	Critical Value 1% : -3.5464
p-value : 0.5138	Critical Value 5% : -2.9119
# Lags Used : 0.0000	Critical Value 10% : -2.5937
# Obs used : 59.0000	



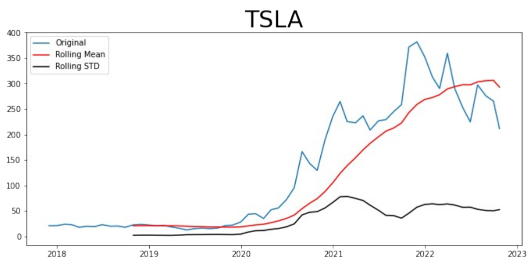
Fail to Reject the Null
Non Stationary

Test Statistics	: -1.1971	Critical Value 1%	: -3.5602
p-value	: 0.6749	Critical Value 5%	: -2.9179
# Lags Used	: 6.0000	Critical Value 10%	: -2.5968
# Obs used	: 53.0000		



Fail to Reject the Null
Non Stationary

Test Statistics	: 0.4989	Critical Value 1%	: -3.5507
p-value	: 0.9848	Critical Value 5%	: -2.9138
# Lags Used	: 2.0000	Critical Value 10%	: -2.5946
# Obs used	: 57.0000		



Reject the Null
Stationary

Test Statistics	: -2.9501	Critical Value 1%	: -3.5746
p-value	: 0.0398	Critical Value 5%	: -2.9240
# Lags Used	: 11.0000	Critical Value 10%	: -2.6000
# Obs used	: 48.0000		

Perform batch forecasting for top 2 companies from each sector based on market capitalization for week-end share price value for next 12 months using auto-arima. You may want to leverage the library 'pmdarima' for auto-arima. Use your discretion. For model validation, find out MAPE of 12 months.

```
#! pip install pmdarima

from pmdarima.arima import auto_arima

def auto_arima_foo(ts, company ):
  train = ts[:-12]
  test = ts [-12:]
  model = auto_arima(train, trace = False )
  model.fit(train)
  fit = model.predict_in_sample(train)
  forecast = model.predict(n_periods=len(test))
  mape = mean_absolute_percentage_error(y_true = test, y_pred =
forecast )
  print('Best model parameters for {} is {}'.format(company, model ))
  return mape

result = {}
for comp in data_last_5.Symbol.unique():
  temp_ts = data_last_5.loc[data_last_5.Symbol == comp, ['Date','Adj
Close']].set_index('Date').squeeze()
  result.update({comp : auto_arima_foo(temp_ts, comp)})
```

```
Best model parameters for AAPL is  ARIMA(2,1,2)(0,0,0)[0] intercept
Best model parameters for AEP is  ARIMA(0,1,0)(0,0,0)[0]
Best model parameters for AMGN is  ARIMA(0,1,0)(0,0,0)[0]
Best model parameters for AMZN is  ARIMA(0,1,0)(0,0,0)[0] intercept
Best model parameters for AZN is  ARIMA(0,1,0)(0,0,0)[0] intercept
Best model parameters for COST is  ARIMA(0,1,0)(0,0,0)[0] intercept
Best model parameters for CSX is  ARIMA(0,1,1)(0,0,0)[0] intercept
Best model parameters for EXC is  ARIMA(1,0,0)(0,0,0)[0] intercept
Best model parameters for GOOG is  ARIMA(5,2,0)(0,0,0)[0]
Best model parameters for GOOGL is  ARIMA(5,2,0)(0,0,0)[0]
Best model parameters for HON is  ARIMA(0,1,0)(0,0,0)[0]
Best model parameters for MSFT is  ARIMA(1,2,1)(0,0,0)[0]
Best model parameters for PEP is  ARIMA(0,1,2)(0,0,0)[0] intercept
Best model parameters for TSLA is  ARIMA(0,2,1)(0,0,0)[0]
```

```
result
```

```
{'AAPL': 0.11775373111272631,
 'AEP': 0.1123880349353218,
 'AMGN': 0.14019654107330873,
 'AMZN': 0.37967862152464305,
 'AZN': 0.08965947180498778,
 'COST': 0.08353647184611956,
 'CSX': 0.15452682078476707,
 'EXC': 0.1920377525225365,
 'GOOG': 0.4968724906879114,
 'GOOGL': 0.5439989480364388,
 'HON': 0.13248488401394368,
 'MSFT': 0.34833083682058286,
 'PEP': 0.040708116510733715,
 'TSLA': 0.7817791435177378}
```