

Capstone Project on Finance and Risk Analytics

Prepared by:
Durgesh Chaubey



Problem Statement

Consider yourself working for an associate at an investment firm that manages accounts for private clients. Your role requires you to analyze a portfolio of stocks to provide consultation on investment management based on client requirements.

Your task is to provide consultation to two different investors, Mr. Patrick Jyenger and Mr. Peter Jyenger based on their requirements and financial objectives. You can refer to the elements mentioned in the video to develop the investor persona.

Investors Profile

1. MR. PATRICK JYENGER:

- Age 55 years
- Successful first generation entrepreneur
- Owner of Jyenger Water Works (JWW)
- Considering business succession plan and retirement
- Conservative investor
- Wants to maintain descent style of living
- Wants to invest 500k USD in equities
- Wants to make it 1 mn in five years duration

2. MR. PETER JYENGER:

- Age 32 years
- Son of Mr. Patrick Jyenger
- Risk taker
- Feels financial secured
- Aggressive investor
- Preferes high return investment
- Wants to invest 1 million USD
- Wants to invest in most high margin stocks for inorganic expansion of JWW in future
- Duration of investment: Less than or upto 5 years

Codes Used for Representing S&P500 Index and 24 Given Stocks

1. SP500: S&P500 index
2. AAL_Avi: American Airlines Group Inc, Travel/Aviation/Hospitality Sector
3. ALGT_Avi: Allegiant Travel Company, Travel/Aviation/Hospitality Sector
4. ALK_Avi: Alaska Air Group Inc, Travel/Aviation/Hospitality Sector
5. DAL_Avi: Delta Air Lines Inc, Travel/Aviation/Hospitality Sector
6. HA_Avi: Hawaiian Holdings Inc, Travel/Aviation/Hospitality Sector
7. LUV_Avi: Southwest Airlines Co, Travel/Aviation/Hospitality Sector
8. BCS_Fin: Barclays, Banking/Financial Services and Insurance Sector
9. CS_Fin: Credit Suisse, Banking/Financial Services and Insurance Sector
10. DB_Fin: Deutsche Bank, Banking/Financial Services and Insurance Sector
11. GS_Fin: Goldman Sachs, Banking/Financial Services and Insurance Sector
12. MS_Fin: Morgan Stanley, Banking/Financial Services and Insurance Sector
13. WFC_Fin: Wells Fargo, Banking/Financial Services and Insurance Sector
14. JNJ_Ph: Johnson & Johnson, Pharmaceuticals/Healthcare/Life Sciences Sector
15. MRK_Ph: Merck and Co inc., Pharmaceuticals/Healthcare/Life Sciences Sector
16. PFE_Ph: Pfizer inc, Pharmaceuticals/Healthcare/Life Sciences Sector
17. UNH_Ph: United Health Group Inc, Pharmaceuticals/Healthcare/Life Sciences Sector
18. BHC_Ph: Bausch Health Companies inc, Pharmaceuticals/Healthcare/Life Sciences Sector
19. RHHBY_Ph: Roche Holding AG, Pharmaceuticals/Healthcare/Life Sciences Sector
20. AAPL_Tech: Apple Inc, Technology/IT Sector
21. AMZN_Tech: Amazon, Technology/IT Sector
22. FB_Tech: Facebook, Technology/IT Sector
23. GOOG_Tech: Alphabet (Google), Technology/IT Sector
24. IBM_Tech: IBM, Technology/IT Sector
25. MSFT_Tech: Microsoft, Technology/IT Sector

Single Dataframe Containing Stock Prices of All 25 Entities

```
# Setting 'Date' column as index  
stocks_price_df = stocks_price_df.set_index('Date')
```

```
In [85]: # Inspecting the dataframe  
stocks_price_df
```

Out[85]:

	SP500	AAL_Avi	ALGT_Avi	ALK_Avi	DAL_Avi	HA_Avi	LUV_Avi	BCS_Fin	CS_Fin	DB_Fin	GS_Fin	MS_Fin	WFC_Fin	BI
Date														
2010-10-01	1146.239990	8.758067	36.766212	10.972344	10.668407	5.742526	12.018754	13.351167	30.167257	44.981487	127.147858	20.962959	19.105776	24.7
2010-10-04	1137.030029	8.597802	35.371429	10.703489	10.224259	5.540189	11.907295	13.274275	29.943998	44.263348	126.175117	20.703226	18.971230	24.8
2010-10-06	1160.750000	8.701504	35.805168	10.767396	10.508514	5.636539	12.093060	13.770571	30.830046	46.140301	128.757706	21.339991	19.621542	25.2
2010-10-06	1159.969971	8.701504	35.677608	10.743157	10.464101	5.752162	12.018754	13.609801	31.032362	46.703384	129.850906	21.264584	19.658911	25.6
2010-10-07	1158.060059	8.710930	35.464993	10.247319	10.455217	5.925593	11.963027	13.085538	31.199810	46.213741	130.083435	21.004854	19.434673	25.8
...
2020-09-24	3246.590088	11.770000	121.500000	35.700001	29.010000	12.400000	36.860001	4.750000	9.620000	8.110000	195.110001	46.610001	23.320000	15.2
2020-09-25	3298.459961	12.290000	123.760002	36.700001	29.780001	12.800000	37.099998	4.700000	9.480000	8.000000	194.949997	47.040001	23.639999	15.3
2020-09-28	3351.600098	12.760000	127.110001	37.540001	31.340000	13.380000	38.240002	4.990000	9.900000	8.430000	199.070007	48.380001	23.820000	15.2
2020-09-29	3335.469971	12.250000	121.089996	36.669998	30.610001	12.860000	37.610001	4.960000	9.830000	8.270000	196.789993	47.240002	23.260000	14.8
2020-09-30	3363.000000	12.290000	119.800003	36.630001	30.580000	12.890000	37.500000	5.010000	9.970000	8.400000	200.970001	48.349998	23.510000	15.8

2517 rows × 25 columns

```
In [86]: # Creating a single dataframe containing volume data of all the stocks  
stocks_volume_df = sp500_volume_df.merge(aviation_volume_df, on='Date', how='inner').merge(finance_volume_df, on='Date', how='inner')
```

Single Dataframe Containing Volumes of All 25 Entities

```
In [88]: # Inspecting the dataframe  
stocks_volume_df
```

```
Out[88]:
```

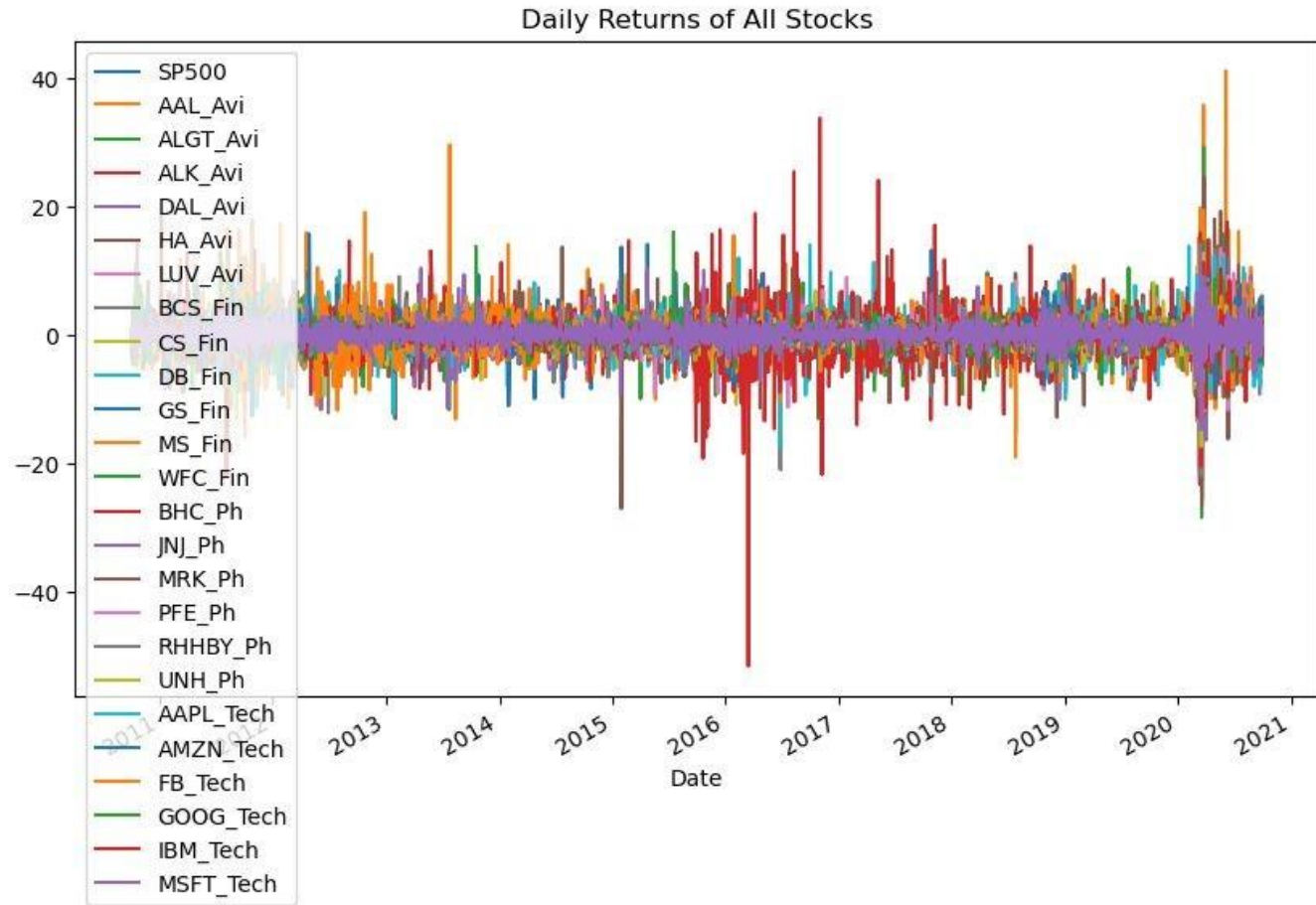
	SP500	AAL_Avi	ALGT_Avi	ALK_Avi	DAL_Avi	HA_Avi	LUV_Avi	BCS_Fin	CS_Fin	DB_Fin	GS_Fin	MS_Fin	WFC_Fin
Date													
2010-10-01	4298910000	3603800.0	159100.0	1663600.0	9094900.0	645400.0	5722500.0	3083200.0	1814900.0	2010600.0	7439800.0	16292200.0	32117900.0
2010-10-04	3604110000	3856800.0	189700.0	1512400.0	7916400.0	618900.0	6537700.0	1362300.0	1085600.0	1245600.0	5866700.0	11955800.0	25645400.0
2010-10-05	4068840000	3896600.0	175000.0	2567200.0	12624100.0	534800.0	8060000.0	3028000.0	1025300.0	2270900.0	8724700.0	19234700.0	42788700.0
2010-10-06	4073160000	3230200.0	187200.0	1043600.0	10124100.0	2563900.0	7457000.0	1934500.0	871300.0	1887400.0	6330600.0	15158700.0	31852900.0
2010-10-07	3910550000	3877700.0	162700.0	7682400.0	7162500.0	1115200.0	3413900.0	8002200.0	1377000.0	1191000.0	4471500.0	11649500.0	27293900.0
...
2020-09-24	4599470000	49163200.0	172300.0	3326000.0	22257800.0	879700.0	10798800.0	5312400.0	2347300.0	3842200.0	5114600.0	9832700.0	43329100.0
2020-09-25	3792220000	43764000.0	115100.0	1767600.0	21831500.0	923400.0	9297300.0	3185200.0	2241100.0	5570900.0	3106000.0	9816000.0	30229900.0
2020-09-28	3946060000	63558200.0	188400.0	2922800.0	22098400.0	1076800.0	9235200.0	3486300.0	2165500.0	4359600.0	3280100.0	9466200.0	41103500.0
2020-09-29	3651880000	46994300.0	187800.0	1743500.0	14785600.0	953100.0	5232400.0	3701800.0	1767800.0	4034000.0	2400000.0	11355600.0	38416300.0
2020-09-30	4722530000	65055100.0	263000.0	1921600.0	16602100.0	916700.0	10100500.0	3001400.0	2495600.0	4516300.0	3073900.0	15045200.0	43058500.0

2517 rows × 25 columns

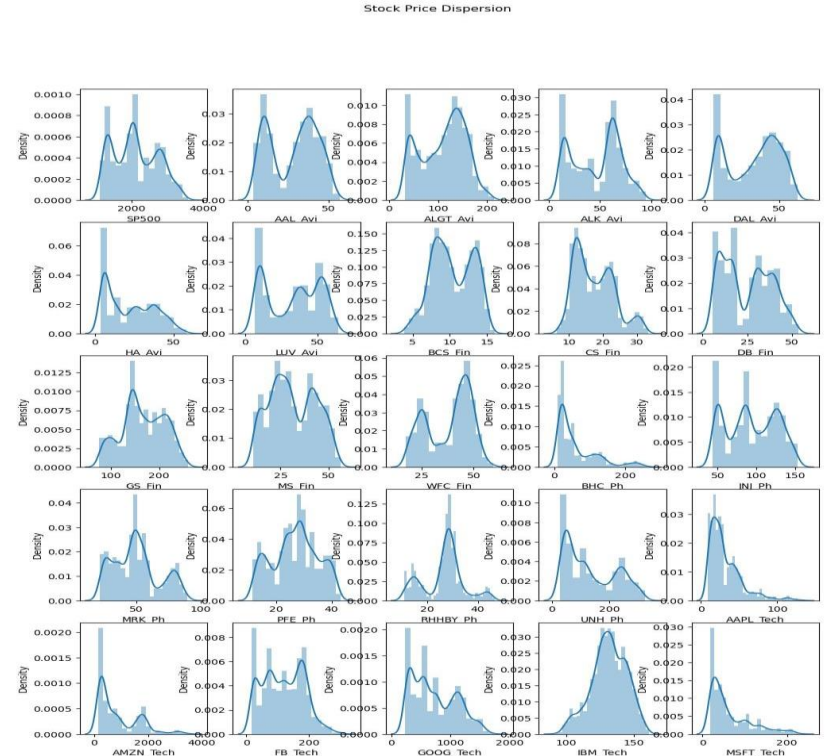
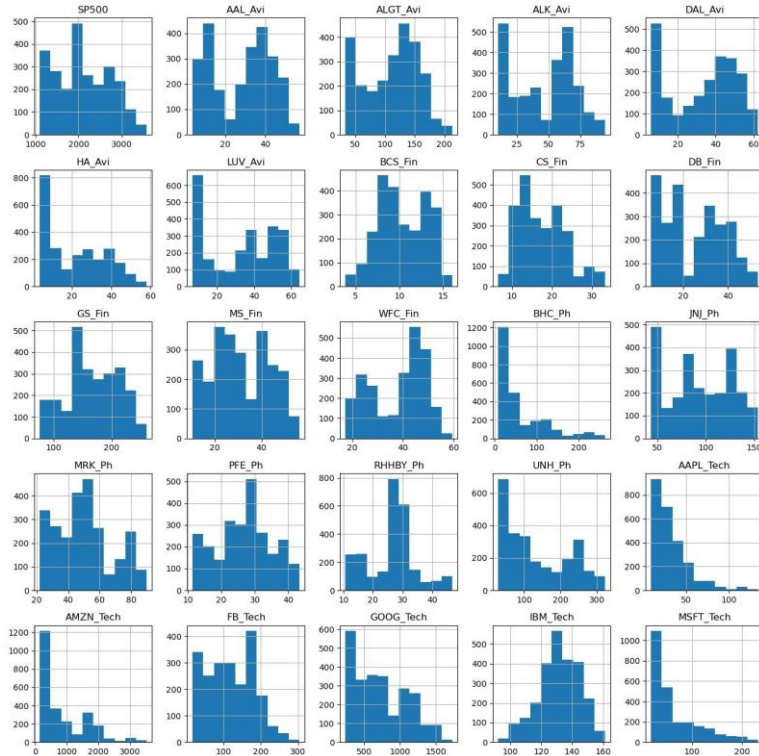
Task: Inspecting the combined dataframes for missing values

```
In [89]: # Checking for missing values
```

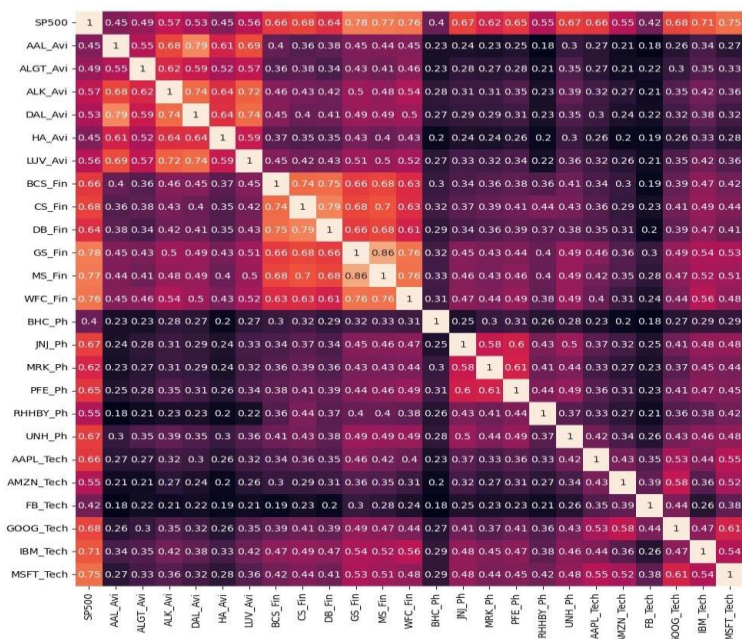
Daily Returns of all Stocks



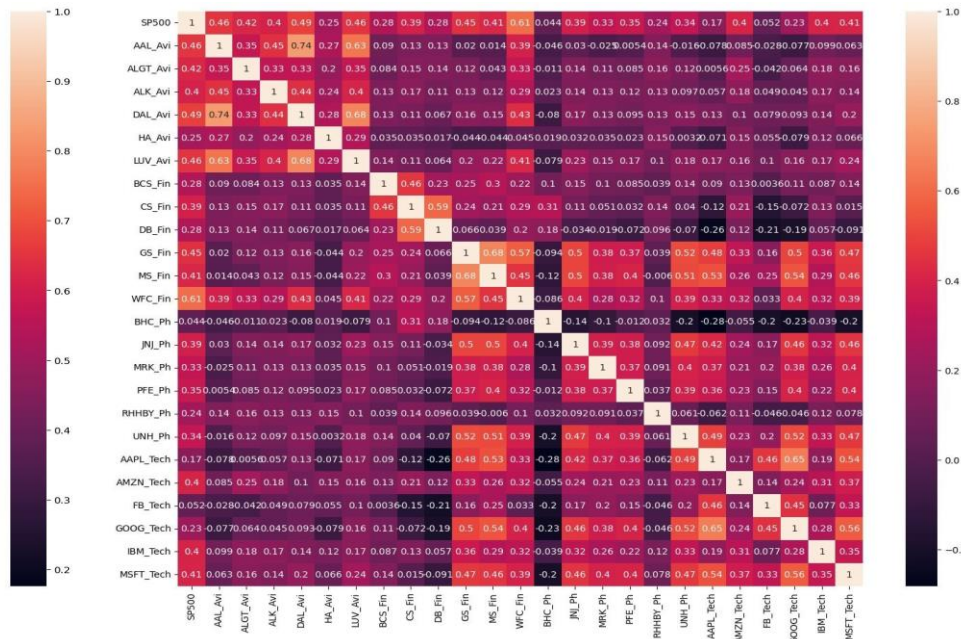
Plot showing Stock Price Dispersion



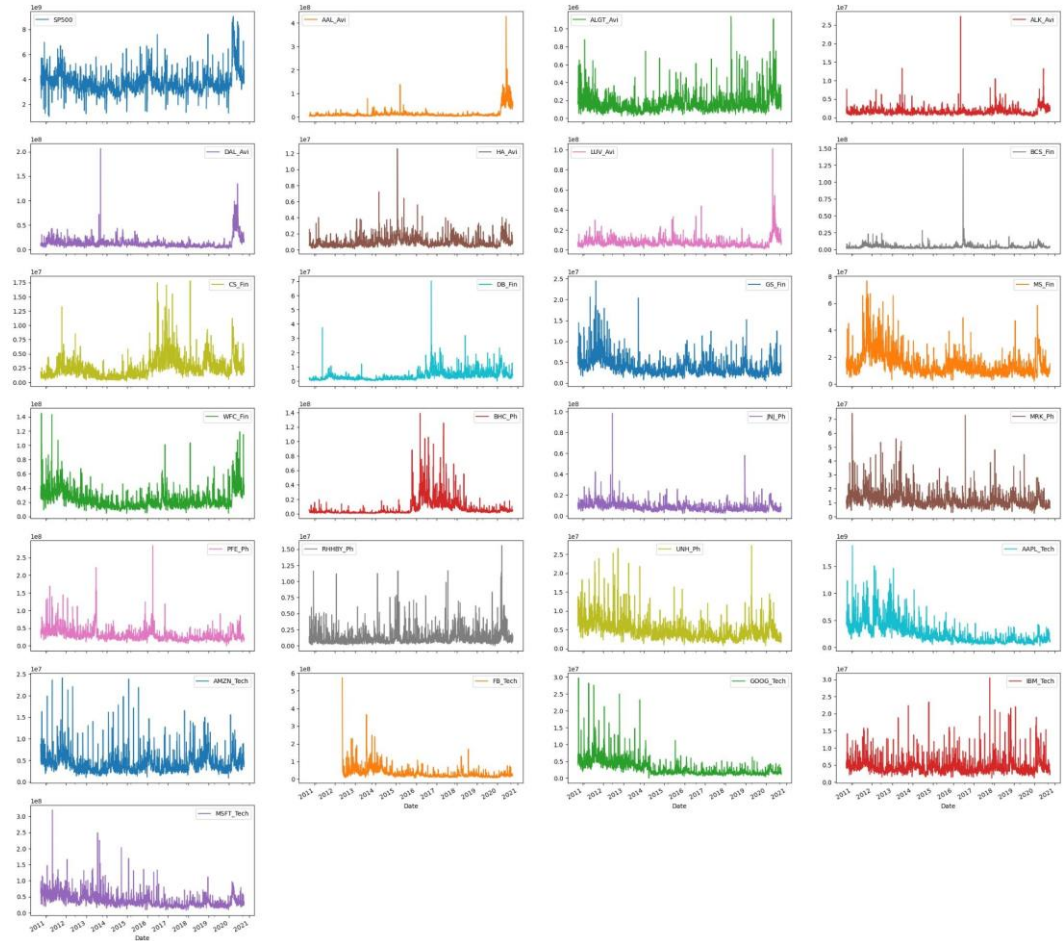
Plots showing Correlation of Prices and Volume



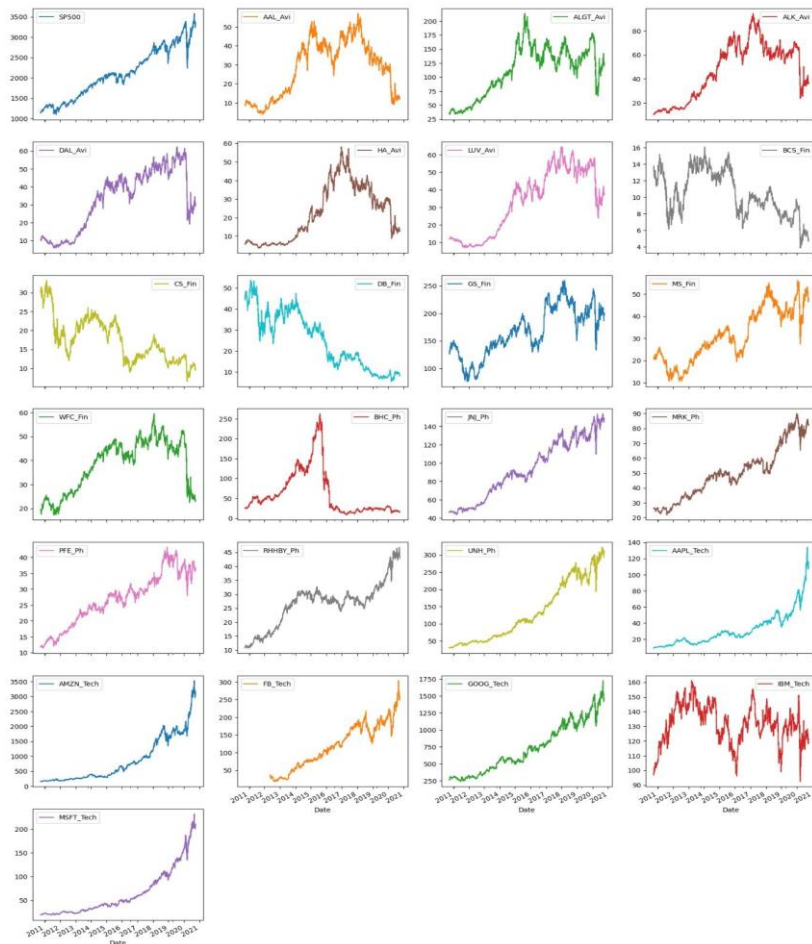
Prices



Charts Showing Volume Movement of Stocks



Charts Showing Price Movement of Stocks



Non-Normalized Prices of All Stocks

Non-Normalized Prices of All The Stocks

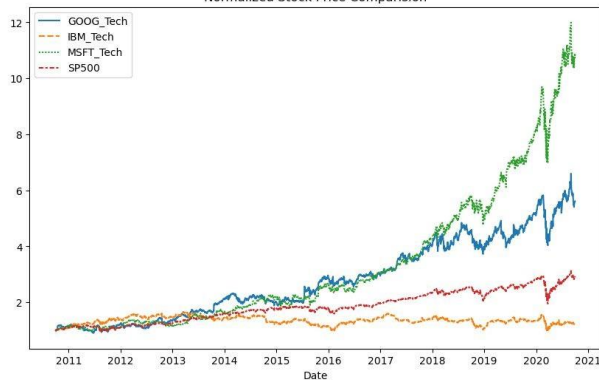


Comparison Between Normalized Stock Prices

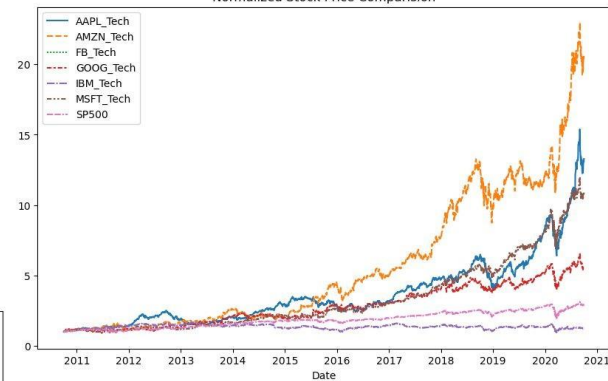
Normalized Stock Price Comparison



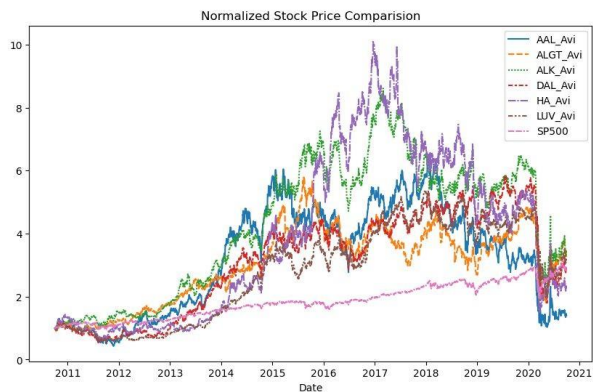
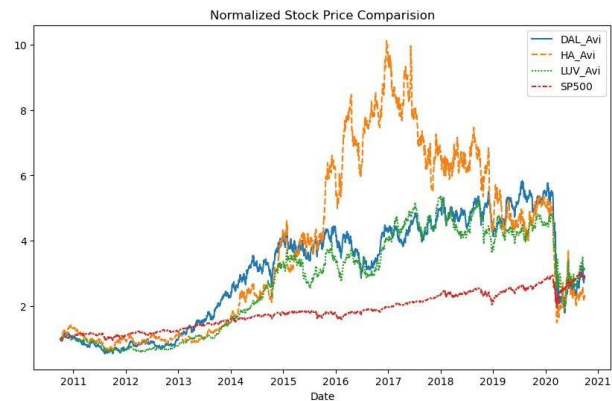
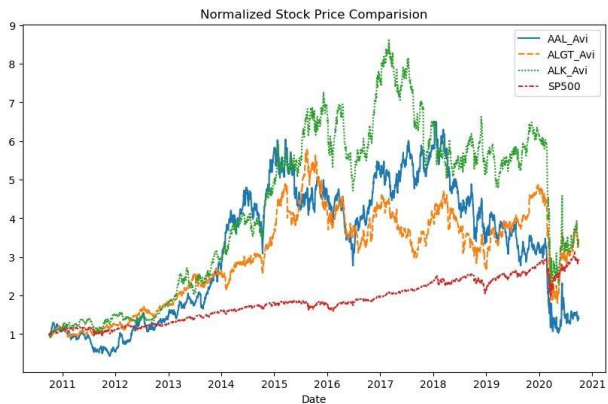
Normalized Stock Price Comparison



Normalized Stock Price Comparison

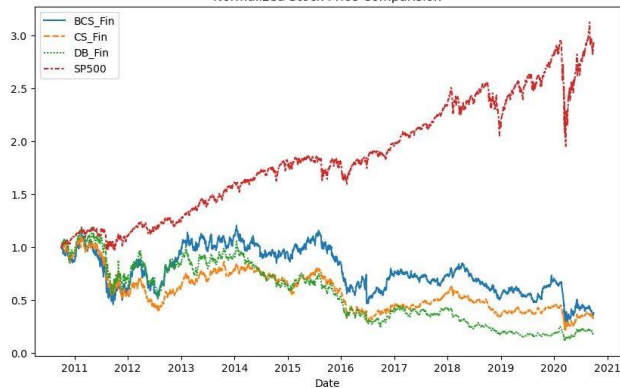


Comparison Between Normalized Stock Price

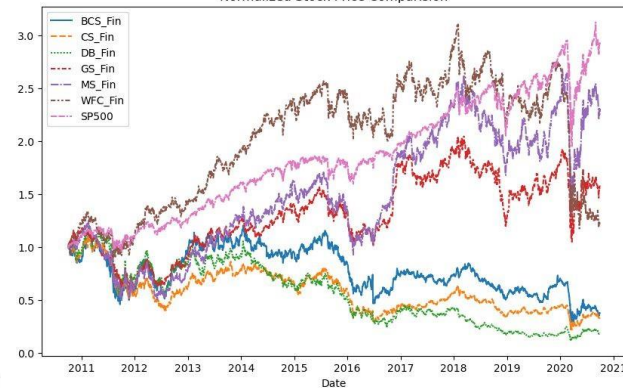


Comparison Between Normalized Stock Price

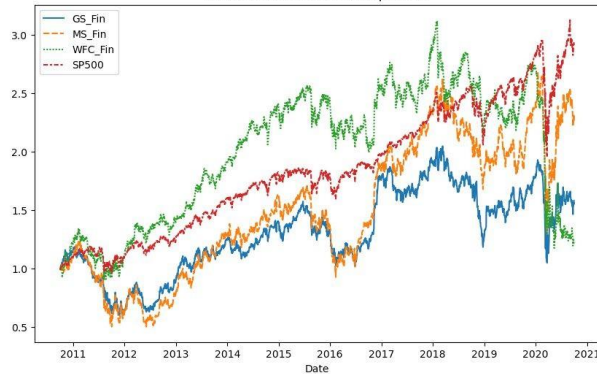
Normalized Stock Price Comparison



Normalized Stock Price Comparison

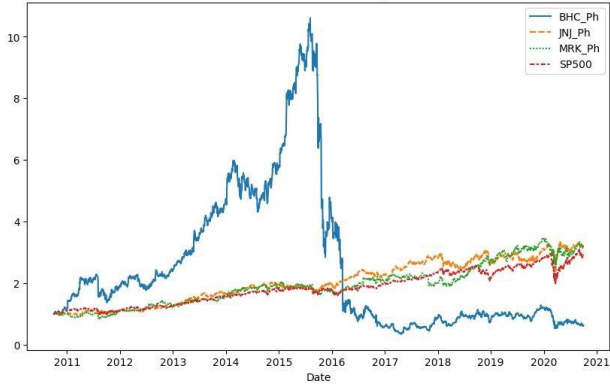


Normalized Stock Price Comparison

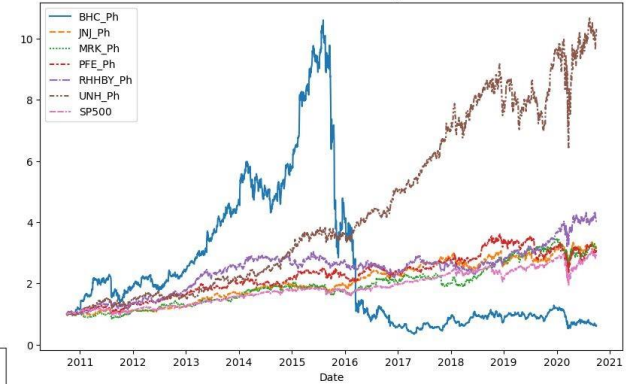


Comparison Between Normalized Stock Price

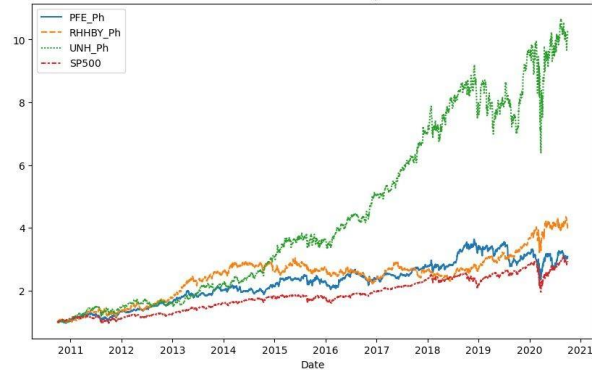
Normalized Stock Price Comparison



Normalized Stock Price Comparison

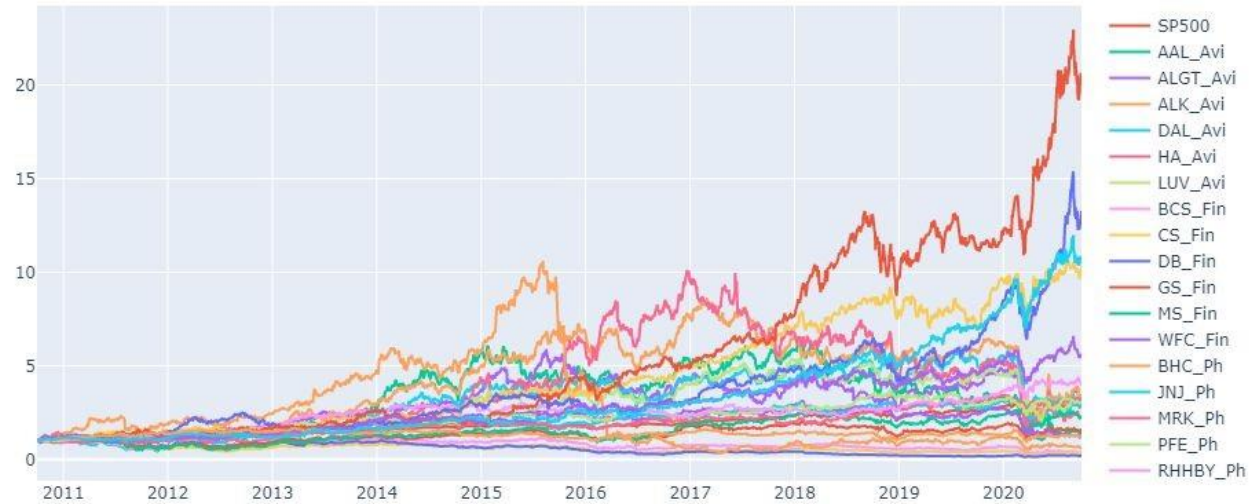


Normalized Stock Price Comparison

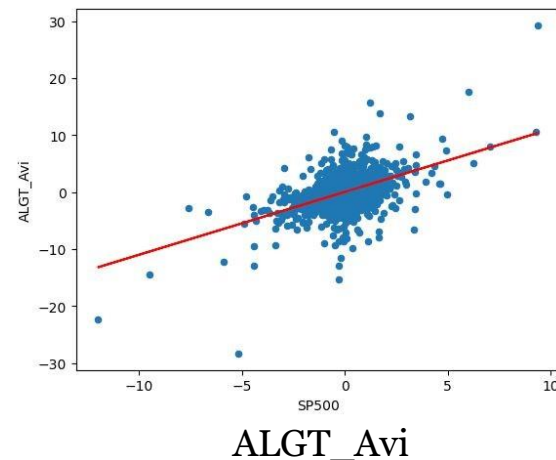
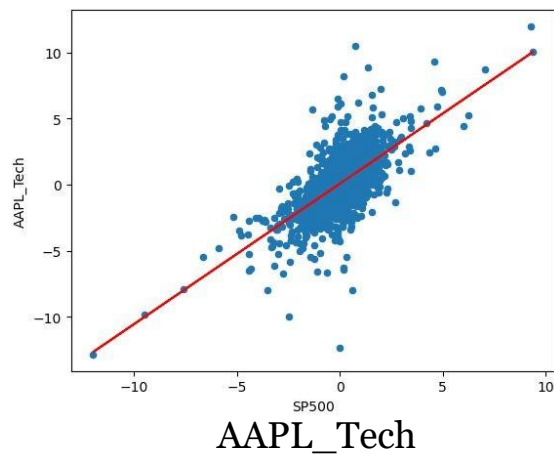
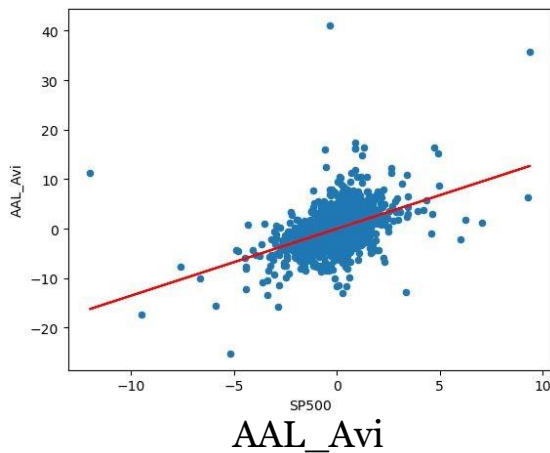


Normalized Prices of All the Stocks

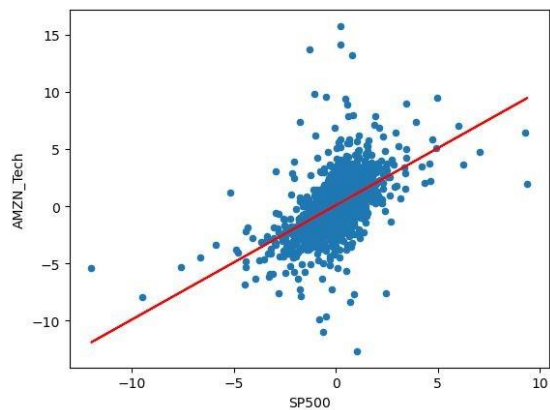
Normalized Prices of All The Stocks



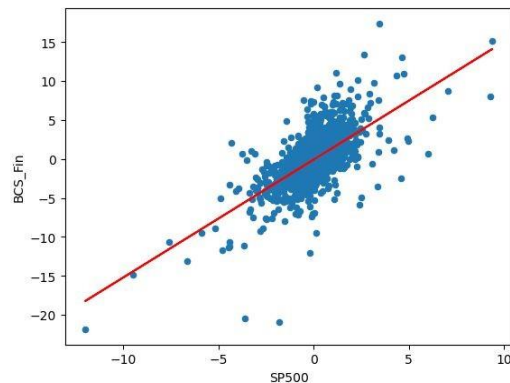
Daily Returns of Each Stock Vis-A-Vis Market Returns



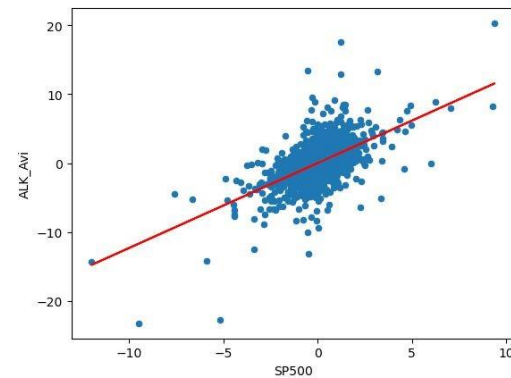
Daily Returns of Each Stock Vis-A-Vis Market Returns



AMZN_Tech

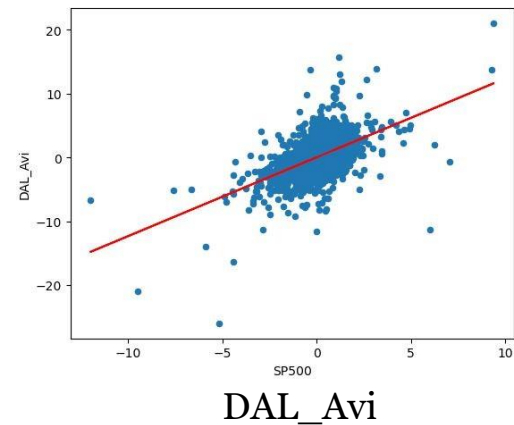
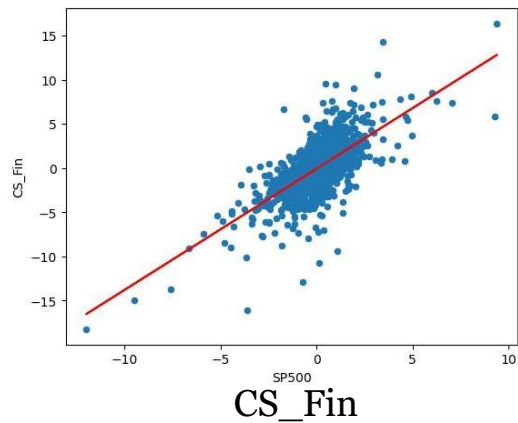
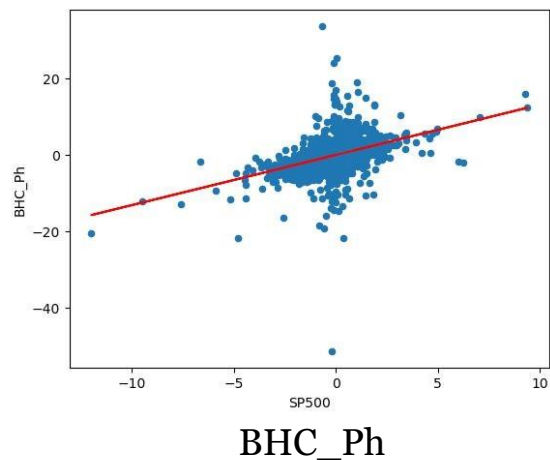


BCS_Fin

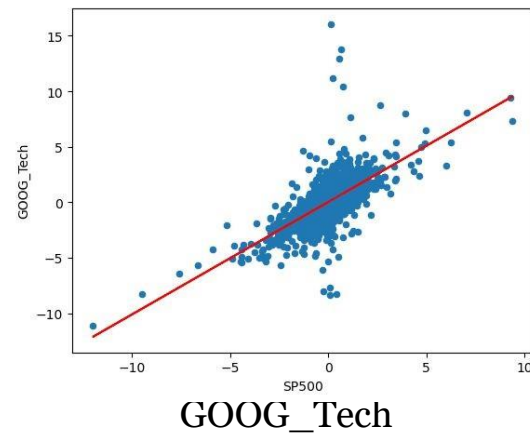
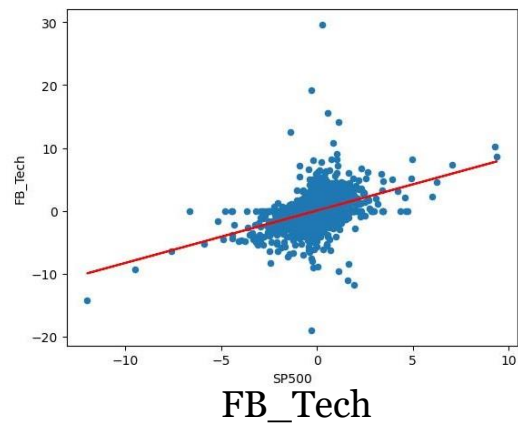
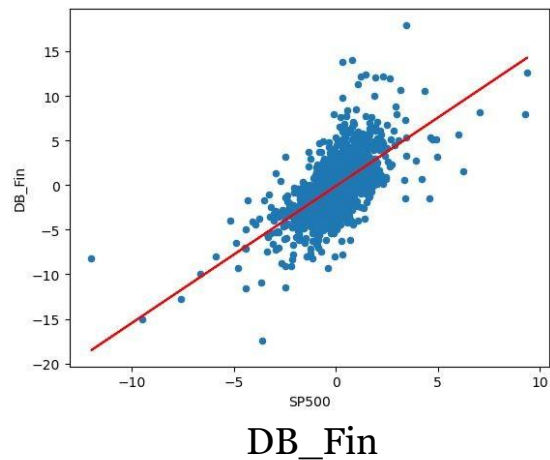


ALK_Avi

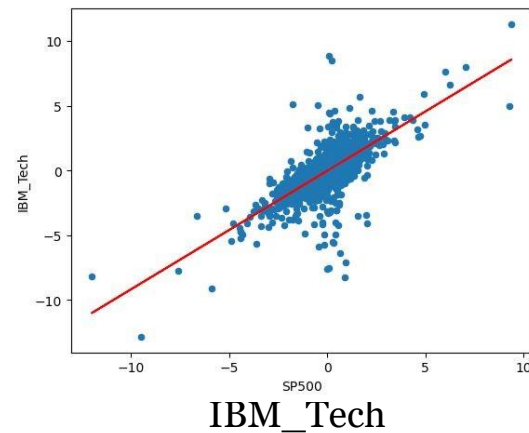
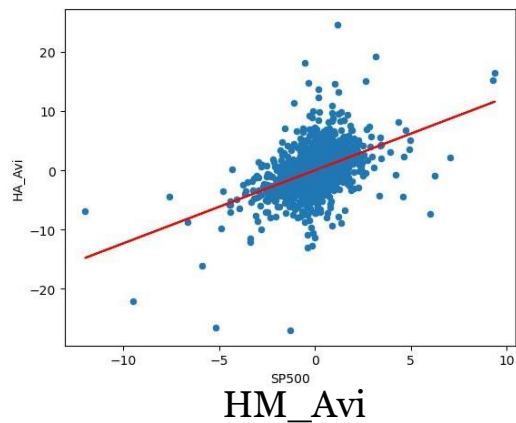
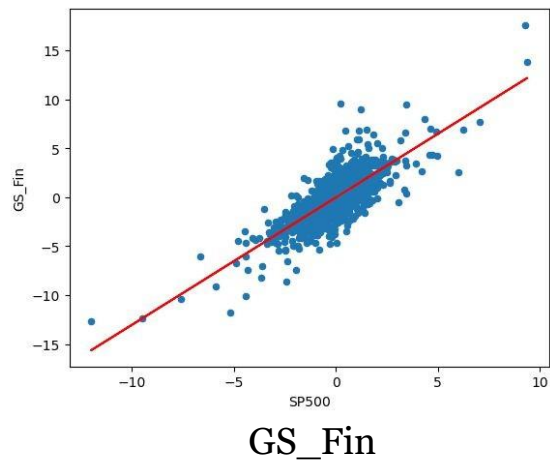
Daily Returns of Each Stock Vis-A-Vis Market Returns



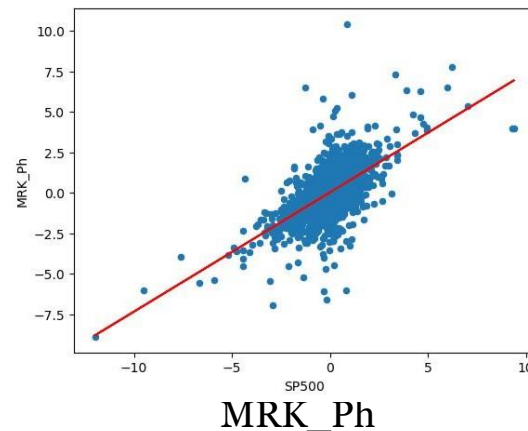
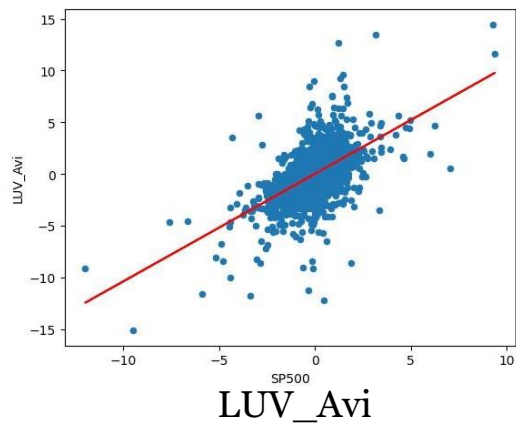
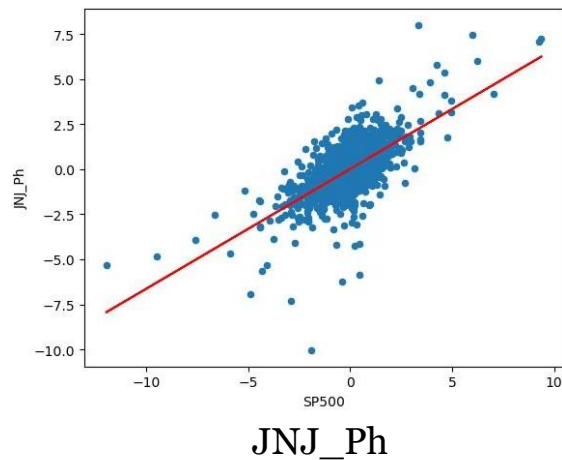
Daily Returns of Each Stock Vis-A-Vis Market Returns



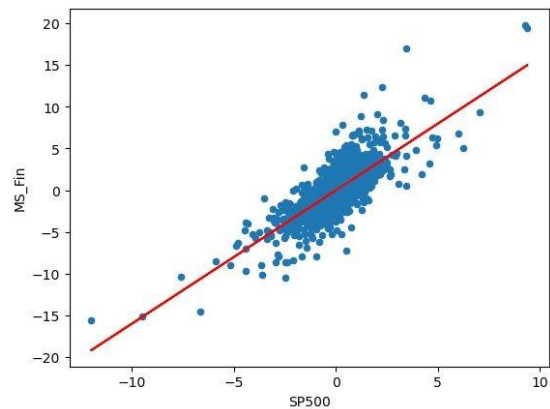
Daily Returns of Each Stock Vis-A-Vis Market Returns



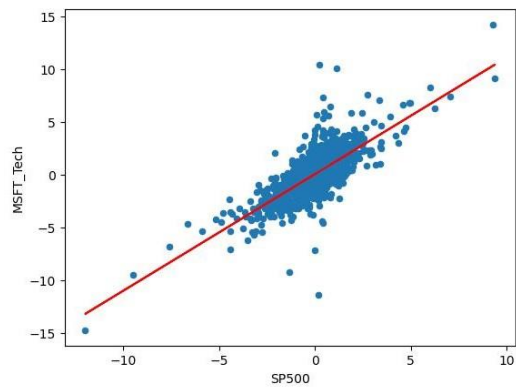
Daily Returns of Each Stock Vis-A-Vis Market Returns



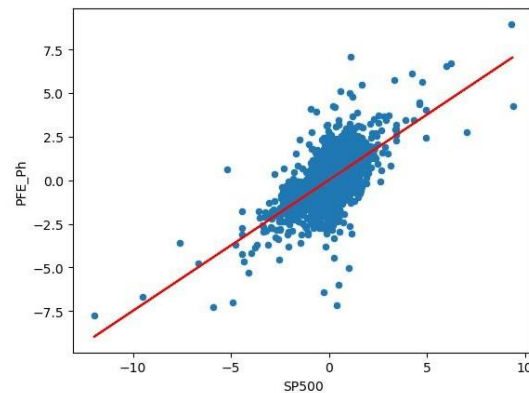
Daily Returns of Each Stock Vis-A-Vis Market Returns



MS_Fin

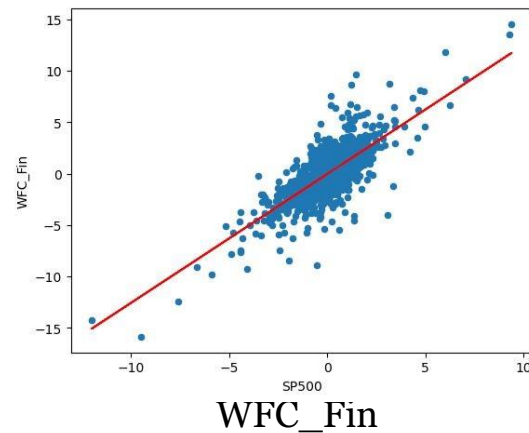
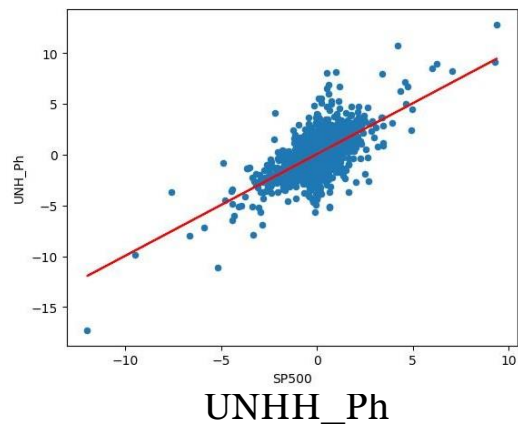
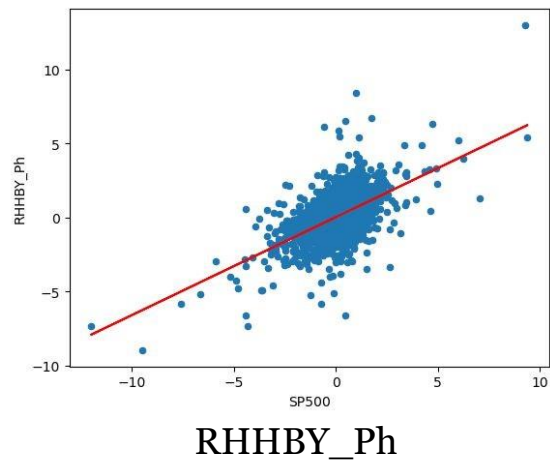


MSFT_Tech



PFE_Ph

Daily Returns of Each Stock Vis-A-Vis Market Returns



Expected Returns Based on CAPM Model

```
for i in keys:
    # Calculate return for every security using CAPM
    ER[i] = rf + ( beta[i] * (rm - rf) )

In [144]: # Printing expected returns based on CAPM
for i in keys:
    print('Expected Return Based on CAPM for {} over the given 10 years duration is {}'.format(i, ER[i]))

Expected Return Based on CAPM for AAL_Avi over the given 10 years duration is 16.369559193357873%
Expected Return Based on CAPM for ALGT_Avi over the given 10 years duration is 13.478462737676459%
Expected Return Based on CAPM for ALK_Avi over the given 10 years duration is 14.969009703190423%
Expected Return Based on CAPM for DAL_Avi over the given 10 years duration is 15.002111941260177%
Expected Return Based on CAPM for HA_Avi over the given 10 years duration is 14.99158927448274%
Expected Return Based on CAPM for LUV_Avi over the given 10 years duration is 12.757576631317734%
Expected Return Based on CAPM for BCS_Fin over the given 10 years duration is 18.216290414620914%
Expected Return Based on CAPM for CS_Fin over the given 10 years duration is 16.5933742493674%
Expected Return Based on CAPM for DB_Fin over the given 10 years duration is 18.47606456075601%
Expected Return Based on CAPM for GS_Fin over the given 10 years duration is 15.771241493550566%
Expected Return Based on CAPM for MS_Fin over the given 10 years duration is 19.193006123577085%
Expected Return Based on CAPM for WFC_Fin over the given 10 years duration is 15.22042668273112%
Expected Return Based on CAPM for BHC_Ph over the given 10 years duration is 15.944459835975147%
Expected Return Based on CAPM for JNJ_Ph over the given 10 years duration is 8.413181439920042%
Expected Return Based on CAPM for MRK_Ph over the given 10 years duration is 9.252043566584573%
Expected Return Based on CAPM for PFE_Ph over the given 10 years duration is 9.414145657619608%
Expected Return Based on CAPM for RHHBY_Ph over the given 10 years duration is 8.395399029449964%
Expected Return Based on CAPM for UNH_Ph over the given 10 years duration is 12.300778904366732%
Expected Return Based on CAPM for AAPL_Tech over the given 10 years duration is 13.020129900837842%
Expected Return Based on CAPM for AMZN_Tech over the given 10 years duration is 12.27790283625745%
Expected Return Based on CAPM for FB_Tech over the given 10 years duration is 10.360697156080095%
Expected Return Based on CAPM for GOOG_Tech over the given 10 years duration is 12.445658749314392%
Expected Return Based on CAPM for IBM_Tech over the given 10 years duration is 11.325665274609849%
Expected Return Based on CAPM for MSFT_Tech over the given 10 years duration is 13.506502746959987%

In [145]: # Stocks having negative returns
negative_return_stocks = []
for i in keys:
    if (ER[i] < 0):
        negative_return_stocks.append(i)
```

Table showing Annualized Returns, Risk/Volatility, Expected Returns as per CAPM and Sharpe Ratio

Annual_details_df['Sharpe_Ratio'] = (Annual_details_df['Annualized Returns(%)']-0.75)/Annual_details_df['Annualized Risk/Volatility']

In [159]: Annual_details_df.head(25)

Out[159]:

	Stocks	Annualized Returns(%)	Annualized Risk/Volatility	Expected Returns(%) as per CAPM	Sharpe_Ratio
0	SP500	12.29	17.35	NaN	0.665130
1	AAL_Avi	16.63	51.94	16.37	0.305737
2	ALGT_Avi	19.52	39.01	13.48	0.481159
3	ALK_Avi	19.14	37.40	14.97	0.491711
4	DAL_Avi	18.82	40.52	15.00	0.445953
5	HA_Avi	19.65	47.85	14.99	0.394984
6	LUV_Avi	16.69	32.50	12.76	0.490462
7	BCS_Fin	-1.70	40.04	18.22	-0.061189
8	CS_Fin	-4.86	35.13	16.59	-0.159693
9	DB_Fin	-8.07	41.80	18.48	-0.211005
10	GS_Fin	8.82	29.09	15.77	0.277415
11	MS_Fin	14.83	35.99	19.19	0.391220
12	WFC_Fin	6.19	28.64	15.22	0.189944
13	BHC_Ph	12.09	56.67	15.94	0.200106
14	JNJ_Ph	13.24	17.16	8.41	0.727855
15	MRK_Ph	13.73	20.85	9.25	0.628571
16	PFE_Ph	13.27	19.94	9.41	0.627884
17	RHHBY_Ph	16.03	21.07	8.40	0.725202
18	UNH_Ph	26.78	26.07	12.30	0.998466
19	AAPL_Tech	29.86	28.10	13.02	1.035943
20	AMZN_Tech	35.21	31.57	12.28	1.091543
21	FB_Tech	25.06	34.22	10.36	0.710403
22	GOOG_Tech	20.59	25.85	12.45	0.767505
23	IBM_Tech	4.77	22.39	11.33	0.179544
24	MSFT_Tech	27.17	25.53	13.51	1.034861

Portfolio Suggestions

Mr. Patrick Jyenger:

Stocks suggested:

1. AMZN
2. AAPL
3. MSFT
4. ALK
5. HA
6. MS
7. WFC

Expected Return as per CAPM:
14.74%

Mr. Peter Jyenger:

Stocks suggested:

1. AAL
2. MS
3. DAL
4. ALK
5. BHC
6. GS
7. WFC

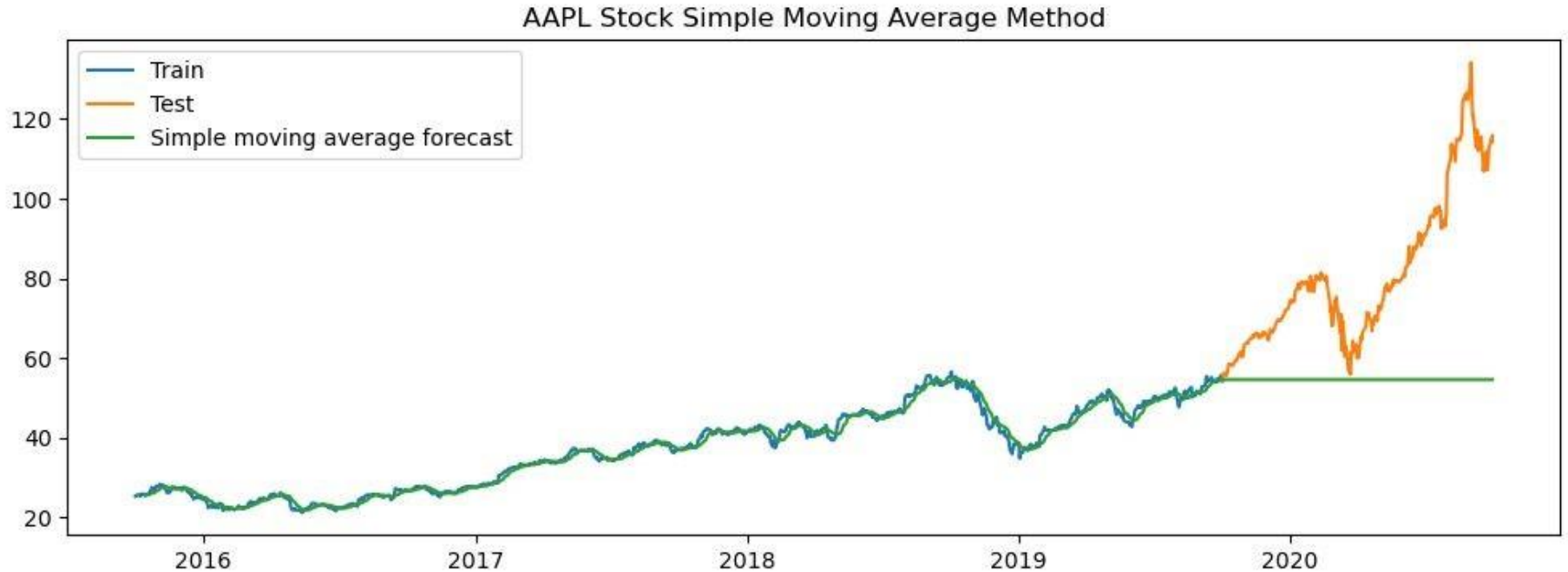
Expected Return as per CAPM:
18.21%



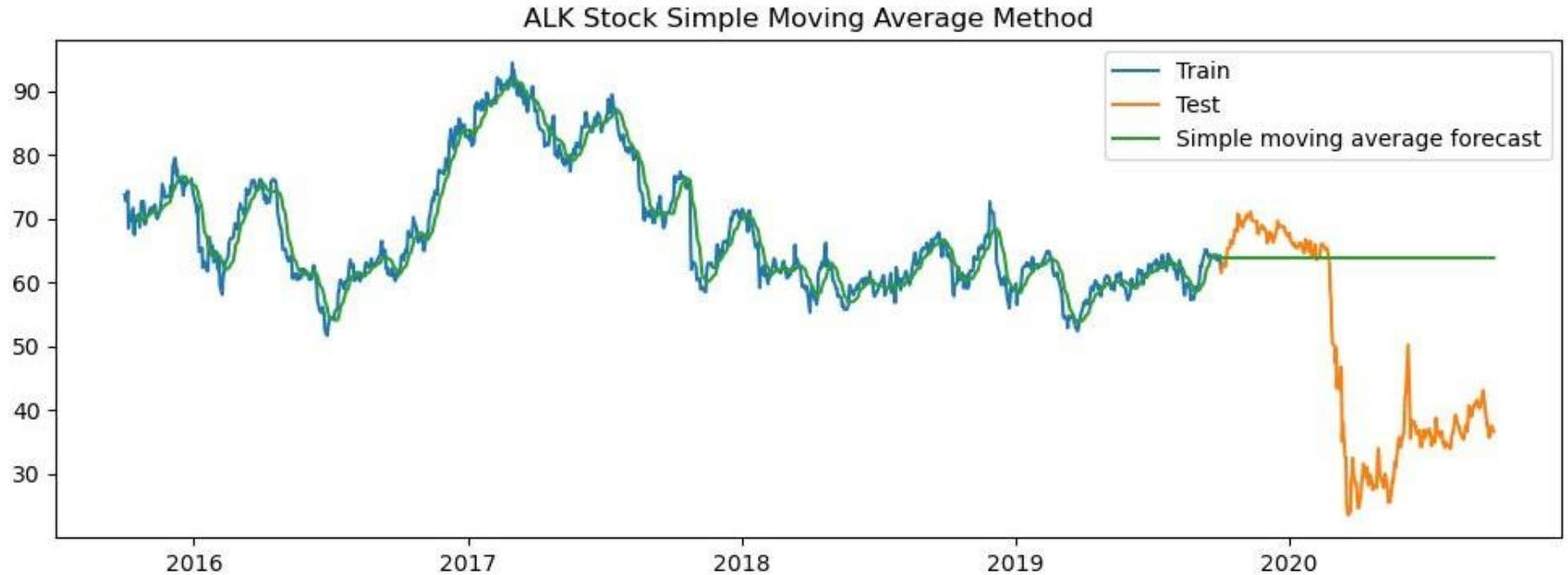
Simple Moving Average Model



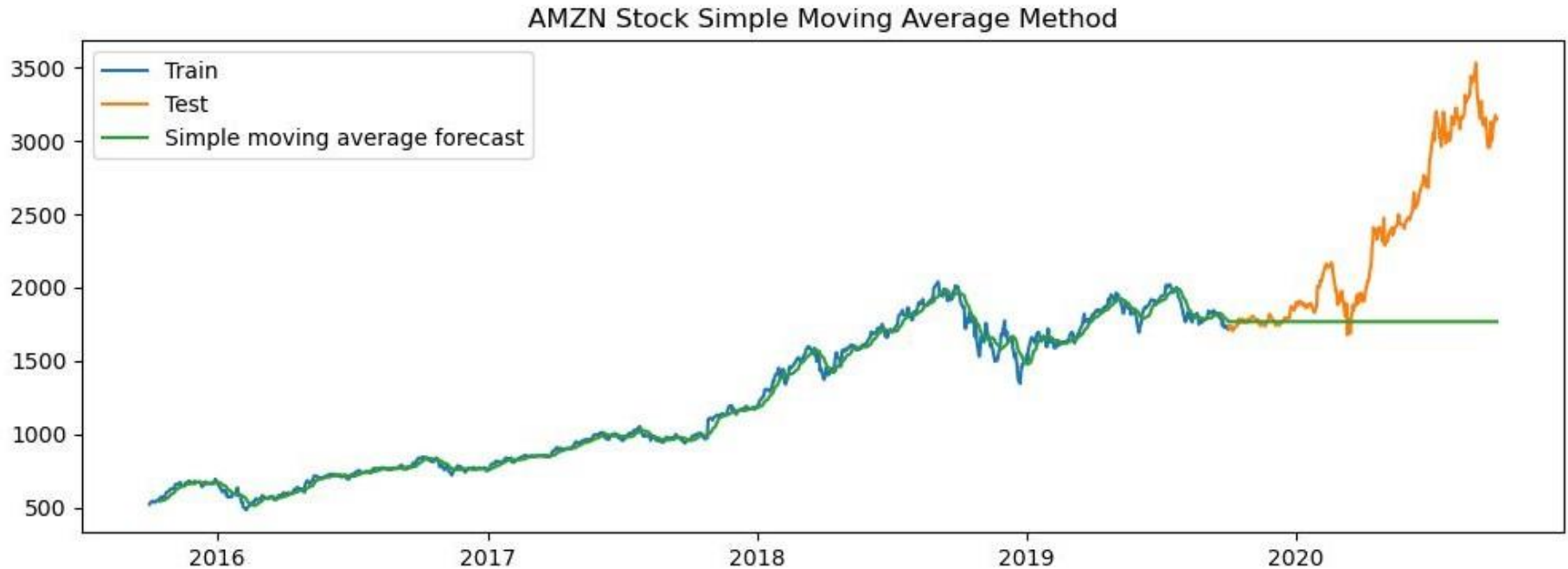
AAPL Stock Simple Moving Average Method



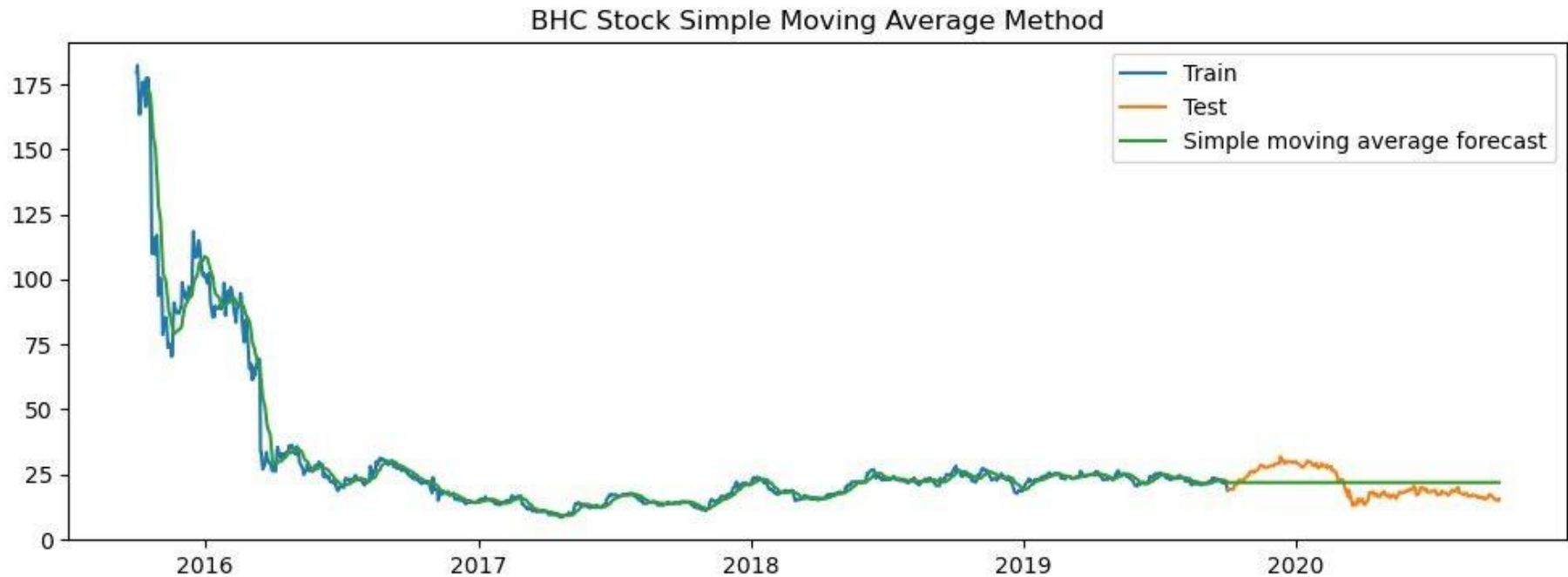
ALK Stock Simple Moving Average Method



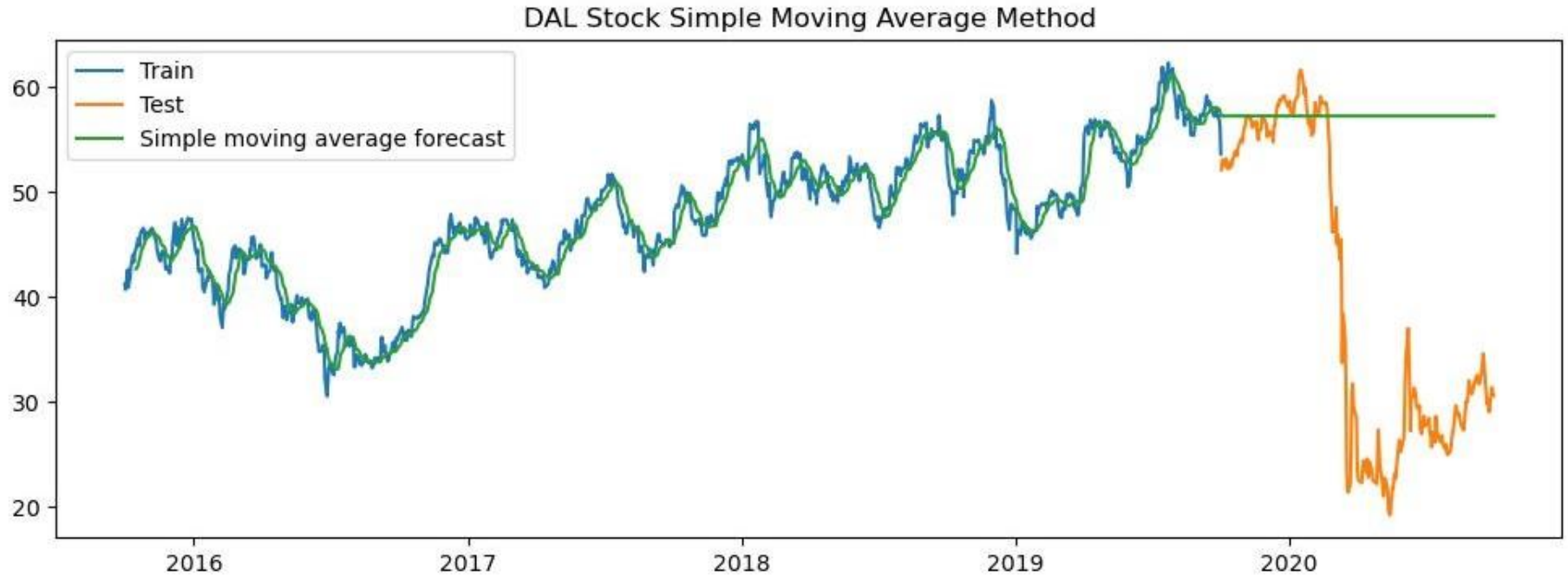
AMZN Stock Simple Moving Average Method



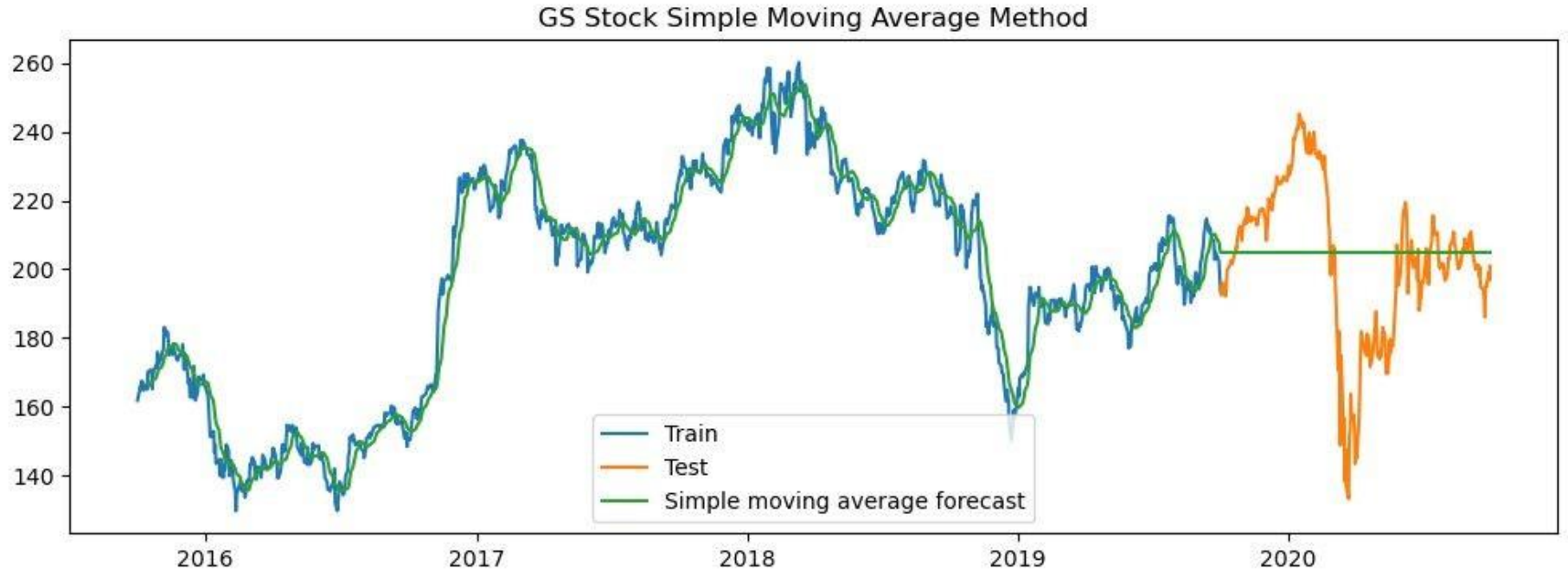
BHC Stock Simple Moving Average Method



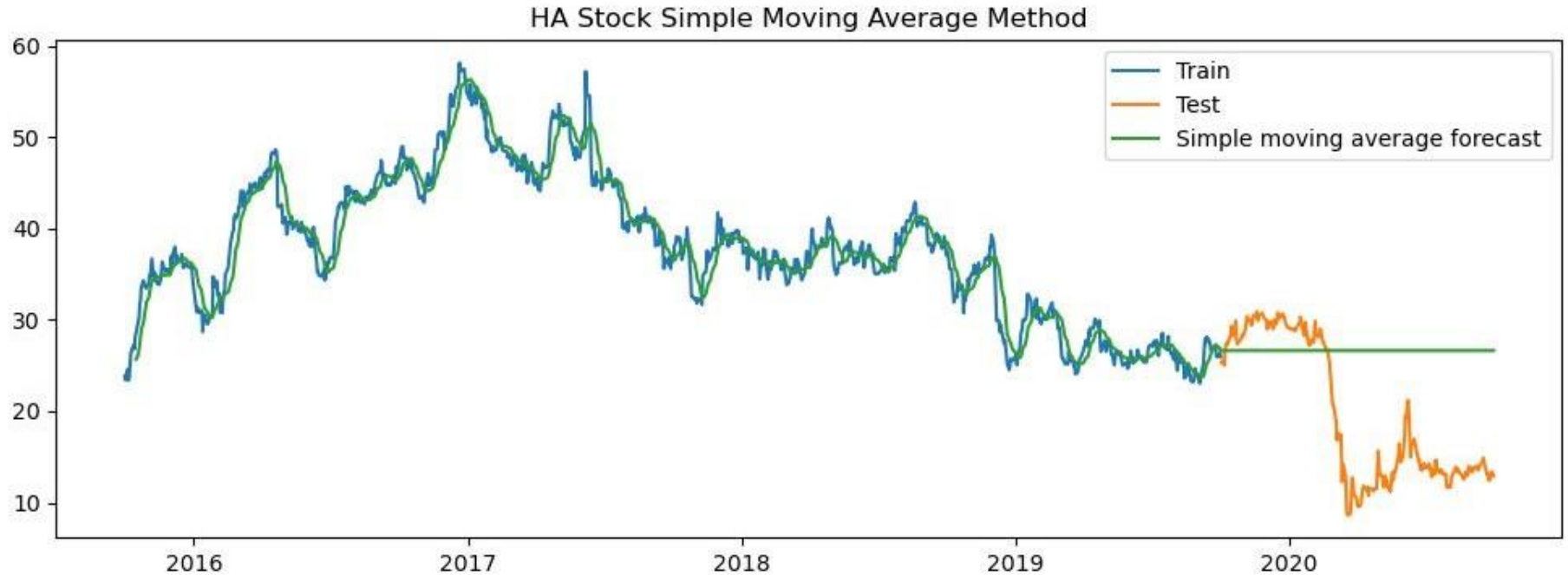
DAL Stock Simple Moving Average Method



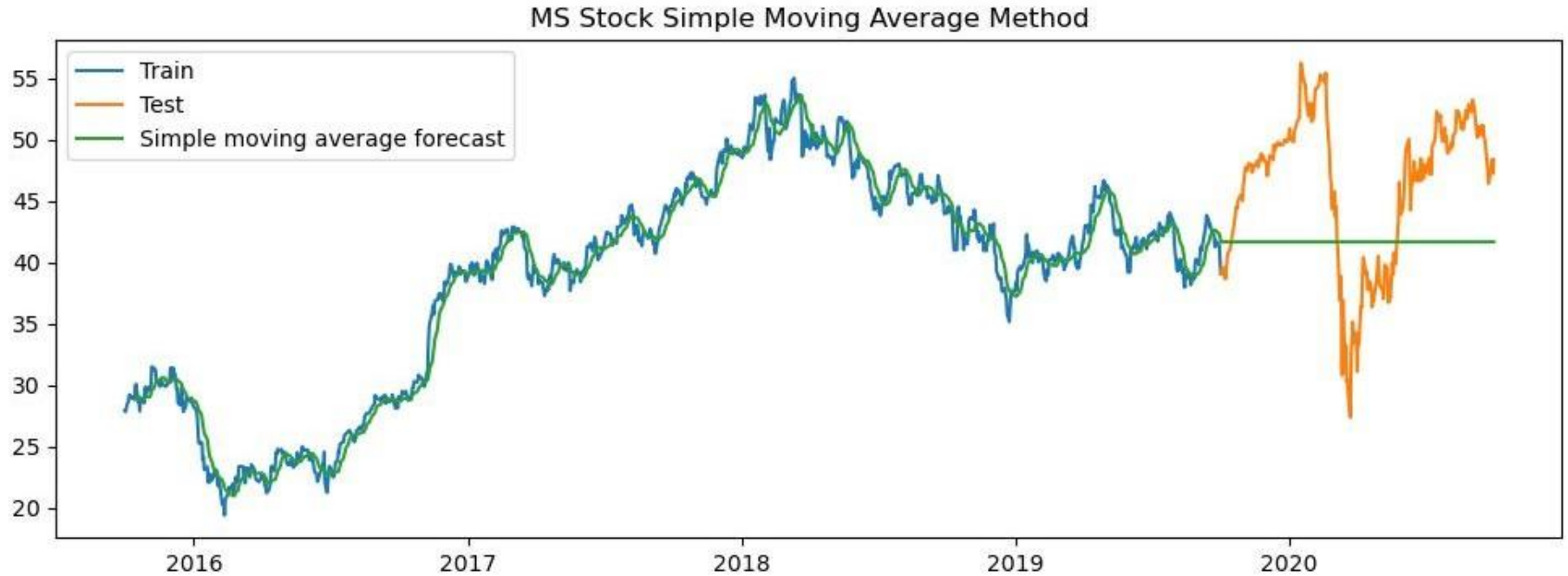
GS Stock Simple Moving Average Method



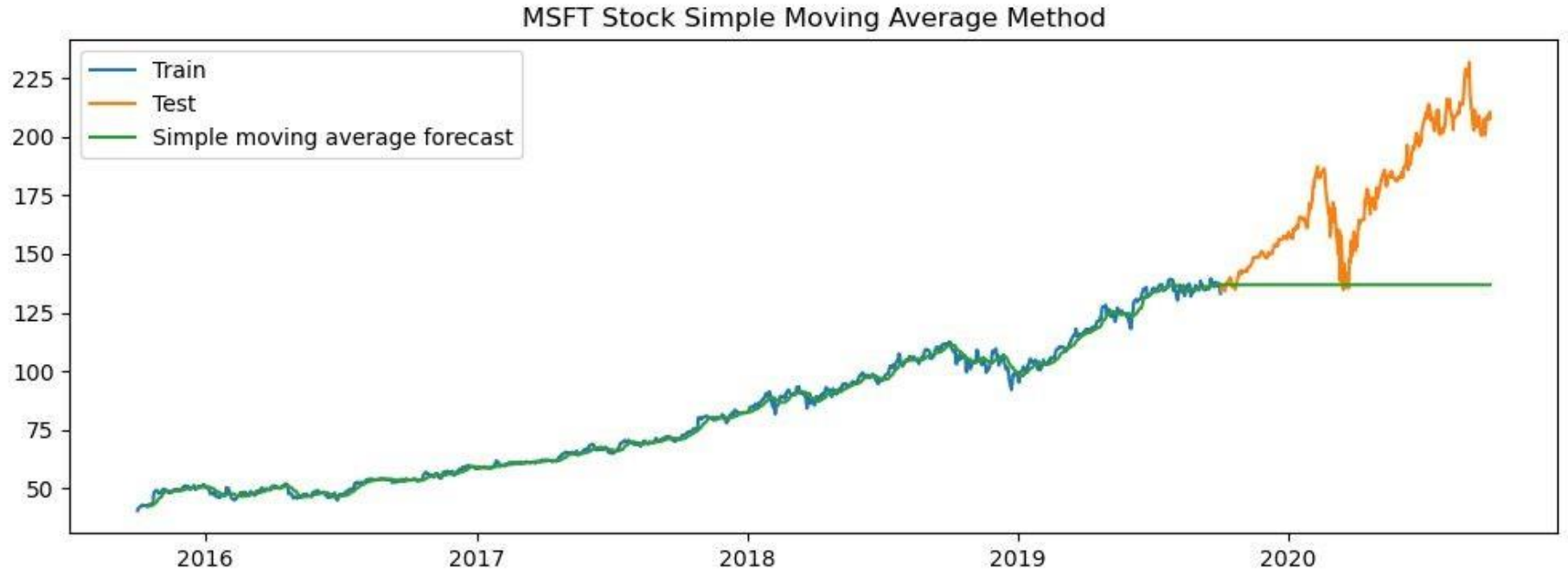
HA Stock Simple Moving Average Method



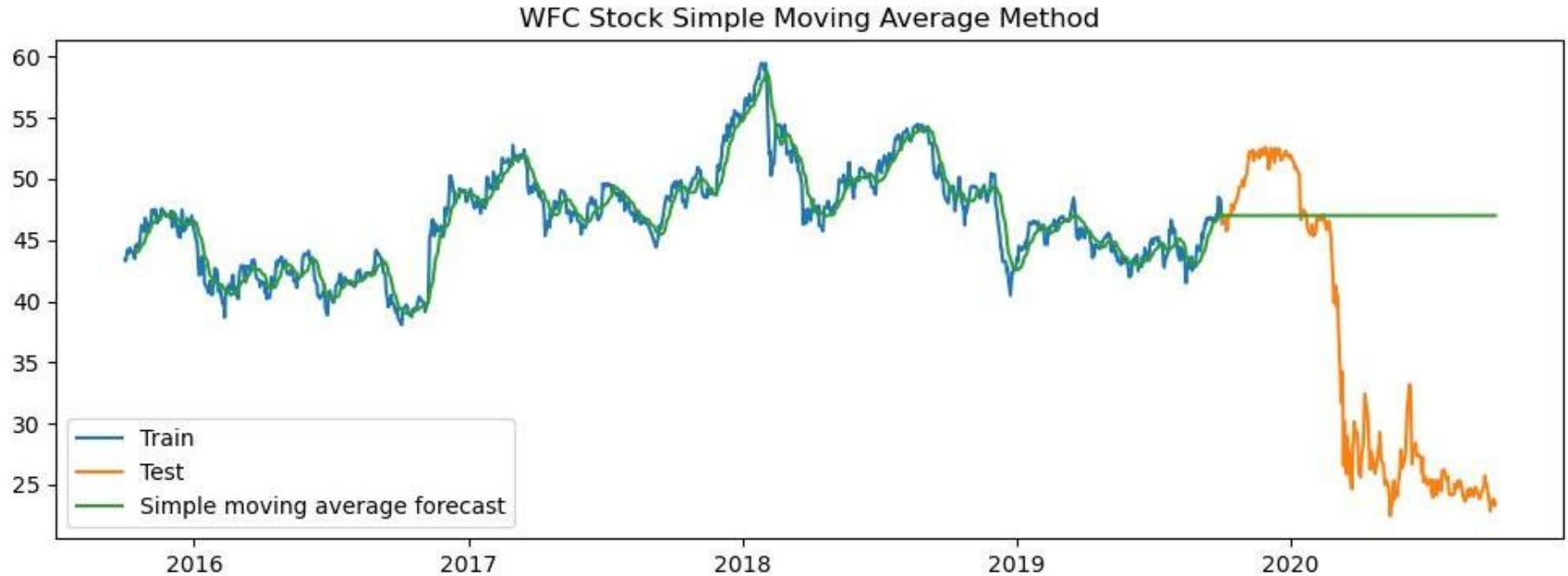
MS Stock Simple Moving Average Method



MSFT Stock Simple Moving Average Method



WFC Stock Simple Moving Average Method



THANK YOU !