

Industry Picking Strategy

```
In [1]: import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import openpyxl as p
import yfinance as yf
from statsmodels.formula.api import ols
import statsmodels.formula.api as smf
import pickle
import statsmodels.stats.api as sms
from statsmodels.compat import lzip
```

```
In [2]: indus = pd.read_csv('11 sectors.csv')
indus = indus.set_index('Date')
indus5 = indus.loc['201701':'201912']
x = indus5.std()
x = x.sort_values()
most_stable_indus = x.index[0:5]

print('The 1st stable industry from Jan. 2017 to Dec. 2019 is ' + most_stable_in
print('The 2nd stable industry from Jan. 2017 to Dec. 2019 is ' + most_stable_in
print('The 3rd stable industry from Jan. 2017 to Dec. 2019 is ' + most_stable_in
print('The 4th stable industry from Jan. 2017 to Dec. 2019 is ' + most_stable_in
print('The 5th stable industry from Jan. 2017 to Dec. 2019 is ' + most_stable_in
```

The 1st stable industry from Jan. 2017 to Dec. 2019 is Utilities Industry.
The 2nd stable industry from Jan. 2017 to Dec. 2019 is Communication Services Industry.
The 3rd stable industry from Jan. 2017 to Dec. 2019 is Financials Industry.
The 4th stable industry from Jan. 2017 to Dec. 2019 is Information Technology Industry.
The 5th stable industry from Jan. 2017 to Dec. 2019 is Health Care Industry.

Industry Picking Strategy

```
In [3]: # Get S&P500 stocks symbols from Wikipedia and set column 'Symbol' as tickers.
sp500url = 'https://en.wikipedia.org/wiki/List_of_S%26P_500_companies'
data_table = pd.read_html(sp500url)
tickers = data_table[0]

# Use for loop to adjust the format of the stock code in the 'Symbol' column.
for i in range(len(tickers)):
    if tickers['Symbol'][i] == 'BRK.B':
        tickers['Symbol'][i] == 'BRK-B'
    elif tickers['Symbol'][i] == 'BF.B':
        tickers['Symbol'][i] == 'BF-B'

display(tickers)
```

	Symbol	Security	SEC filings	GICS Sector	GICS Sub-Industry	Headquarters Location	Date first added	CIK
0	MMM	3M	reports	Industrials	Industrial Conglomerates	Saint Paul, Minnesota	1976-08-09	66740
1	AOS	A. O. Smith	reports	Industrials	Building Products	Milwaukee, Wisconsin	2017-07-26	91142
2	ABT	Abbott	reports	Health Care	Health Care Equipment	North Chicago, Illinois	1964-03-31	1800
3	ABBV	AbbVie	reports	Health Care	Pharmaceuticals	North Chicago, Illinois	2012-12-31	1551152
4	ACN	Accenture	reports	Information Technology	IT Consulting & Other Services	Dublin, Ireland	2011-07-06	1467373
...	...	...	...	...	...	...	...	...
498	YUM	Yum! Brands	reports	Consumer Discretionary	Restaurants	Louisville, Kentucky	1997-10-06	104106
499	ZBRA	Zebra Technologies	reports	Information Technology	Electronic Equipment & Instruments	Lincolnshire, Illinois	2019-12-23	877212
500	ZBH	Zimmer Biomet	reports	Health Care	Health Care Equipment	Warsaw, Indiana	2001-08-07	1136869
501	ZION	Zions Bancorporation	reports	Financials	Regional Banks	Salt Lake City, Utah	2001-06-22	109380
502	ZTS	Zoetis	reports	Health Care	Pharmaceuticals	Parsippany, New Jersey	2013-06-21	1555280

503 rows × 9 columns

```
In [4]: df = pd.read_csv('daily.csv')
df['Date'] = pd.to_datetime(df['Date'])
df = df.set_index('Date')
df = df.loc['2017-01-01':'2019-12-31']
```

```
In [5]: chosen_stock = []

for j in range(len(most_stable_indus)):
    sector = tickers.loc[tickers['GICS Sector'] == most_stable_indus[int('{}'.format(j))]]
    prices = yf.download(sector, start = '2017-01-01', end = '2019-12-31')['Adj Close']
    prices = prices.dropna(axis = 1)
    prices.index = pd.to_datetime(prices.index)
    sector = prices.columns.values
    result = df.merge(prices, on = ['Date'], how = 'inner')

    alphas_list = []
    std0_list = []
    beta1_list = []
    std1_list = []
    beta2_list = []
```

```

std2_list = []
beta3_list = []
std3_list = []
beta4_list = []
std4_list = []
f_test_result = []

for i in sector:
    result['ret_{}'.format(i)] = np.log(result['{}_{}'.format(i)]/result['{}_{}'.format(i)].f
    result['retrf_{}'.format(i)] = result['ret_{}'.format(i)] - np.log(result
    result = result.drop(columns = ['{}_{}'.format(i)])

    # Fama-French Model
    formula = 'retrf_{} ~ mktrf + smb + hml + mom'.format(i)
    lr = ols(formula, result).fit()
    alphas_list.append(lr.params['Intercept'])
    std0_list.append(lr.bse['Intercept'])
    beta1_list.append(lr.params['mktrf'])
    std1_list.append(lr.bse['mktrf'])
    beta2_list.append(lr.params['smb'])
    std2_list.append(lr.bse['smb'])
    beta3_list.append(lr.params['hml'])
    std3_list.append(lr.bse['smb'])
    beta4_list.append(lr.params['mom'])
    std4_list.append(lr.bse['mom'])
    hypotheses = '(smb=0), (hml=0), (mom=0)'
    f_test_result.append(lr.f_test(hypotheses))

final_result = pd.DataFrame(index=["Portfolio_{}".format(i) for i in sector]
                             data={
                                 "alpha":alphas_list,
                                 "alpha_standard_error": std0_list,
                                 "beta1":beta1_list,
                                 "beta1_standard_error": std1_list,
                                 "beta2":beta2_list,
                                 "beta2_standard_error": std2_list,
                                 "beta3":beta3_list,
                                 "beta3_standard_error": std3_list,
                                 "beta4":beta4_list,
                                 "beta4_standard_error": std4_list})

final_result['predict'] = final_result['alpha'] + final_result['beta1'] * re
final_result = final_result['predict'].sort_values()
chosen_stock.append(final_result.index[-1].split('_')[1])
chosen_stock.append(final_result.index[-2].split('_')[1])

```

[*****100%*****] 30 of 30 completed

1 Failed download:

- CEG: Data doesn't exist for startDate = 1483246800, endDate = 1577768400

[*****100%*****] 25 of 25 completed

[*****100%*****] 67 of 67 completed

1 Failed download:

- BRK.B: No data found for this date range, symbol may be delisted

[*****100%*****] 76 of 76 completed

[*****100%*****] 63 of 63 completed

1 Failed download:

- OGN: Data doesn't exist for startDate = 1483246800, endDate = 1577768400

In [6]: chosen_stock

Out[6]: ['NRG', 'NEE', 'MTCH', 'LYV', 'MSCI', 'SPGI', 'ENPH', 'SEDG', 'DXCM', 'VRTX']

```
In [7]: download_stock = yf.download(chosen_stock, start = '2017-01-01', end = '2019-12-
chosen_result = df.merge(download_stock, on = ['Date'], how = 'inner')

for i in chosen_stock:
    chosen_result['ret_{}'.format(i)] = np.log(chosen_result['{}'.format(i)]/chc
    chosen_result['retrf_{}'.format(i)] = chosen_result['ret_{}'.format(i)] - np
    formula = 'retrf_{}~ mktrf + smb + hml + mom'.format(i)
    results = smf.ols(formula, chosen_result).fit()
    print()
    print('*****The Fama-French Model Regression of {}:*****')
    print(results.summary())
```

[*****100%*****] 10 of 10 completed

*****The Fama-French Model Regression of NRG:*****
OLS Regression Results

Dep. Variable:	retrf_NRG	R-squared:	0.115
Model:	OLS	Adj. R-squared:	0.110
Method:	Least Squares	F-statistic:	24.26
Date:	Fri, 23 Dec 2022	Prob (F-statistic):	6.78e-19
Time:	16:48:54	Log-Likelihood:	1944.8
No. Observations:	752	AIC:	-3880.
Df Residuals:	747	BIC:	-3857.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0052	0.001	-7.709	0.000	-0.006	-0.004
mktrf	0.0074	0.001	9.049	0.000	0.006	0.009
smb	0.0009	0.001	0.655	0.513	-0.002	0.004
hml	-0.0017	0.001	-1.267	0.205	-0.004	0.001
mom	0.0006	0.001	0.508	0.612	-0.002	0.003

Omnibus:	699.180	Durbin-Watson:	1.658
Prob(Omnibus):	0.000	Jarque-Bera (JB):	74765.471
Skew:	3.727	Prob(JB):	0.00
Kurtosis:	51.276	Cond. No.	2.42

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama-French Model Regression of NEE:*****
OLS Regression Results

Dep. Variable:	retrf_NEE	R-squared:	0.117
Model:	OLS	Adj. R-squared:	0.112
Method:	Least Squares	F-statistic:	24.69
Date:	Fri, 23 Dec 2022	Prob (F-statistic):	3.20e-19
Time:	16:48:54	Log-Likelihood:	2484.5

No. Observations: 752 AIC: -4959.
 Df Residuals: 747 BIC: -4936.
 Df Model: 4
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0055	0.000	-16.868	0.000	-0.006	-0.005
mktrf	0.0015	0.000	3.673	0.000	0.001	0.002
smb	-0.0044	0.001	-6.508	0.000	-0.006	-0.003
hml	-0.0031	0.001	-4.656	0.000	-0.004	-0.002
mom	0.0008	0.001	1.370	0.171	-0.000	0.002
Omnibus:	46.382		Durbin-Watson:		1.889	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		86.415	
Skew:	-0.415		Prob(JB):		1.72e-19	
Kurtosis:	4.439		Cond. No.		2.42	

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama-French Model Regression of MTCH:*****
 OLS Regression Results

Dep. Variable:	retrf_MTCH	R-squared:	0.197			
Model:	OLS	Adj. R-squared:	0.192			
Method:	Least Squares	F-statistic:	45.69			
Date:	Fri, 23 Dec 2022	Prob (F-statistic):	2.34e-34			
Time:	16:48:54	Log-Likelihood:	1686.9			
No. Observations:	752	AIC:	-3364.			
Df Residuals:	747	BIC:	-3341.			
Df Model:	4					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	-0.0051	0.001	-5.415	0.000	-0.007	-0.003
mktrf	0.0097	0.001	8.369	0.000	0.007	0.012
smb	0.0040	0.002	2.046	0.041	0.000	0.008
hml	-0.0096	0.002	-4.937	0.000	-0.013	-0.006
mom	0.0064	0.002	4.051	0.000	0.003	0.010
=====						
Omnibus:	343.976	Durbin-Watson:	2.085			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	26666.858			
Skew:	-1.153	Prob(JB):	0.00			
Kurtosis:	32.082	Cond. No.	2.42			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama-French Model Regression of LYV:*****
 OLS Regression Results

Dep. Variable:	retrf_LYV	R-squared:	0.302
Model:	OLS	Adj. R-squared:	0.299
Method:	Least Squares	F-statistic:	80.98

Date: Fri, 23 Dec 2022 Prob (F-statistic): 4.25e-57
 Time: 16:48:54 Log-Likelihood: 2110.1
 No. Observations: 752 AIC: -4210.
 Df Residuals: 747 BIC: -4187.
 Df Model: 4
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0057	0.001	-10.578	0.000	-0.007	-0.005
mktrf	0.0102	0.001	15.380	0.000	0.009	0.011
smb	0.0026	0.001	2.324	0.020	0.000	0.005
hml	-0.0038	0.001	-3.444	0.001	-0.006	-0.002
mom	0.0020	0.001	2.258	0.024	0.000	0.004
=====						
Omnibus:		161.098	Durbin-Watson:		1.819	
Prob(Omnibus):		0.000	Jarque-Bera (JB):		3199.846	
Skew:		0.379	Prob(JB):		0.00	
Kurtosis:		13.077	Cond. No.		2.42	

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama-French Model Regression of MSCI:*****
 OLS Regression Results

Dep. Variable:	retrf_MSCI	R-squared:	0.463			
Model:	OLS	Adj. R-squared:	0.460			
Method:	Least Squares	F-statistic:	161.2			
Date:	Fri, 23 Dec 2022	Prob (F-statistic):	2.06e-99			
Time:	16:48:54	Log-Likelihood:	2305.1			
No. Observations:	752	AIC:	-4600.			
Df Residuals:	747	BIC:	-4577.			
Df Model:	4					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0054	0.000	-13.104	0.000	-0.006	-0.005
mktrf	0.0117	0.001	22.950	0.000	0.011	0.013
smb	-0.0004	0.001	-0.459	0.646	-0.002	0.001
hml	-0.0029	0.001	-3.436	0.001	-0.005	-0.001
mom	0.0025	0.001	3.597	0.000	0.001	0.004
=====						
Omnibus:	82.733	Durbin-Watson:	1.934			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	412.817			
Skew:	0.348	Prob(JB):	2.28e-90			
Kurtosis:	6.563	Cond. No.	2.42			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama-French Model Regression of SPGI:*****
 OLS Regression Results

Dep. Variable:	retrf_SPGI	R-squared:	0.507
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Model:                                OLS      Adj. R-squared:      0.505
Method:                             Least Squares      F-statistic:      192.4
Date:                               Fri, 23 Dec 2022      Prob (F-statistic):      2.51e-113
Time:                               16:48:54      Log-Likelihood:      2484.0
No. Observations:                    752      AIC:      -4958.
Df Residuals:                        747      BIC:      -4935.
Df Model:                            4
Covariance Type:                     nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0057	0.000	-17.433	0.000	-0.006	-0.005
mktrf	0.0103	0.000	25.595	0.000	0.009	0.011
smb	-0.0031	0.001	-4.594	0.000	-0.004	-0.002
hml	-0.0013	0.001	-1.979	0.048	-0.003	-1.07e-05
mom	0.0027	0.001	4.835	0.000	0.002	0.004
Omnibus:		90.309	Durbin-Watson:			1.806
Prob(Omnibus):		0.000	Jarque-Bera (JB):			710.661
Skew:		0.168	Prob(JB):			4.81e-155
Kurtosis:		7.751	Cond. No.			2.42

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama-French Model Regression of ENPH:*****
 OLS Regression Results

```

Dep. Variable:      retrf_ENPH      R-squared:      0.092
Model:              OLS      Adj. R-squared:      0.088
Method:             Least Squares      F-statistic:      19.02
Date:               Fri, 23 Dec 2022      Prob (F-statistic):      6.59e-15
Time:               16:48:54      Log-Likelihood:      1223.0
No. Observations:   752      AIC:      -2436.
Df Residuals:       747      BIC:      -2413.
Df Model:            4
Covariance Type:    nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0025	0.002	-1.456	0.146	-0.006	0.001
mktrf	0.0098	0.002	4.556	0.000	0.006	0.014
smb	0.0208	0.004	5.699	0.000	0.014	0.028
hml	-0.0033	0.004	-0.906	0.365	-0.010	0.004
mom	0.0074	0.003	2.523	0.012	0.002	0.013
Omnibus:		180.307	Durbin-Watson:			1.944
Prob(Omnibus):		0.000	Jarque-Bera (JB):			1685.577
Skew:		0.793	Prob(JB):			0.00
Kurtosis:		10.161	Cond. No.			2.42

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama-French Model Regression of SEDG:*****
 OLS Regression Results

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=====
Dep. Variable:          retrf_SEDG      R-squared:                0.099
Model:                  OLS             Adj. R-squared:           0.094
Method:                 Least Squares   F-statistic:             20.46
Date:                   Fri, 23 Dec 2022 Prob (F-statistic):      5.22e-16
Time:                   16:48:54        Log-Likelihood:          1552.2
No. Observations:      752             AIC:                    -3094.
Df Residuals:          747             BIC:                    -3071.
Df Model:               4
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0043	0.001	-3.807	0.000	-0.007	-0.002
mktrf	0.0096	0.001	6.908	0.000	0.007	0.012
smb	0.0067	0.002	2.857	0.004	0.002	0.011
hml	-0.0050	0.002	-2.162	0.031	-0.010	-0.000
mom	0.0018	0.002	0.964	0.335	-0.002	0.006

```

=====
Omnibus:                368.674      Durbin-Watson:           2.185
Prob(Omnibus):           0.000      Jarque-Bera (JB):        6003.694
Skew:                    1.795      Prob(JB):                0.00
Kurtosis:                16.369      Cond. No.                2.42
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama-French Model Regression of DXCM:*****
 OLS Regression Results

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=====
Dep. Variable:          retrf_DXCM      R-squared:                0.129
Model:                  OLS             Adj. R-squared:           0.125
Method:                 Least Squares   F-statistic:             27.73
Date:                   Fri, 23 Dec 2022 Prob (F-statistic):      1.71e-21
Time:                   16:48:54        Log-Likelihood:          1564.5
No. Observations:      752             AIC:                    -3119.
Df Residuals:          747             BIC:                    -3096.
Df Model:               4
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0053	0.001	-4.749	0.000	-0.007	-0.003
mktrf	0.0094	0.001	6.892	0.000	0.007	0.012
smb	0.0088	0.002	3.814	0.000	0.004	0.013
hml	-0.0080	0.002	-3.516	0.000	-0.013	-0.004
mom	0.0029	0.002	1.576	0.116	-0.001	0.007

```

=====
Omnibus:                381.261      Durbin-Watson:           2.007
Prob(Omnibus):           0.000      Jarque-Bera (JB):        96692.664
Skew:                    -1.060      Prob(JB):                0.00
Kurtosis:                58.511      Cond. No.                2.42
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*****The Fama–French Model Regression of VRTX:*****
 OLS Regression Results

Dep. Variable:	retrf_VRTX	R-squared:	0.290
Model:	OLS	Adj. R-squared:	0.286
Method:	Least Squares	F-statistic:	76.34
Date:	Fri, 23 Dec 2022	Prob (F-statistic):	2.81e-54
Time:	16:48:54	Log-Likelihood:	1970.6
No. Observations:	752	AIC:	-3931.
Df Residuals:	747	BIC:	-3908.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0057	0.001	-8.839	0.000	-0.007	-0.004
mktrf	0.0111	0.001	13.982	0.000	0.010	0.013
smb	0.0021	0.001	1.584	0.114	-0.001	0.005
hml	-0.0086	0.001	-6.433	0.000	-0.011	-0.006
mom	-0.0001	0.001	-0.136	0.892	-0.002	0.002

Omnibus:	689.767	Durbin-Watson:	1.948
Prob(Omnibus):	0.000	Jarque-Bera (JB):	43975.765
Skew:	3.844	Prob(JB):	0.00
Kurtosis:	39.666	Cond. No.	2.42

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Portfolio Chosen

```
In [8]: def total_return(weights, calculated_stocks):
        return np.sum((weights * calculated_stocks.mean())*252)

        def total_vol(weights, calculated_stocks):
            return math.sqrt(np.dot(weights.T, np.dot(calculated_stocks.cov()*252, weights)))
```

```
In [9]: for i in chosen_stock:
        download_stock['ret_{}'.format(i)] = np.log(download_stock['{}'.format(i)]/c
        download_stock = download_stock.drop(columns = ['{}'.format(i)])
```

```
In [10]: rfrate = chosen_result['rf'].mean()

        best_weight = []
        best_sharpe = 0
        stock_return = []
        stock_vol = []

        for j in range(0,100000):
            # Generate 10 weights for 10 stocks randomly
            weight = np.random.random(10)
            weight /= np.sum(weight)

            # Calculate the expected return and standard deviation of the portfolio
```

```

stock_return.append(total_return(weight, download_stock))
stock_vol.append(total_vol(weight, download_stock))

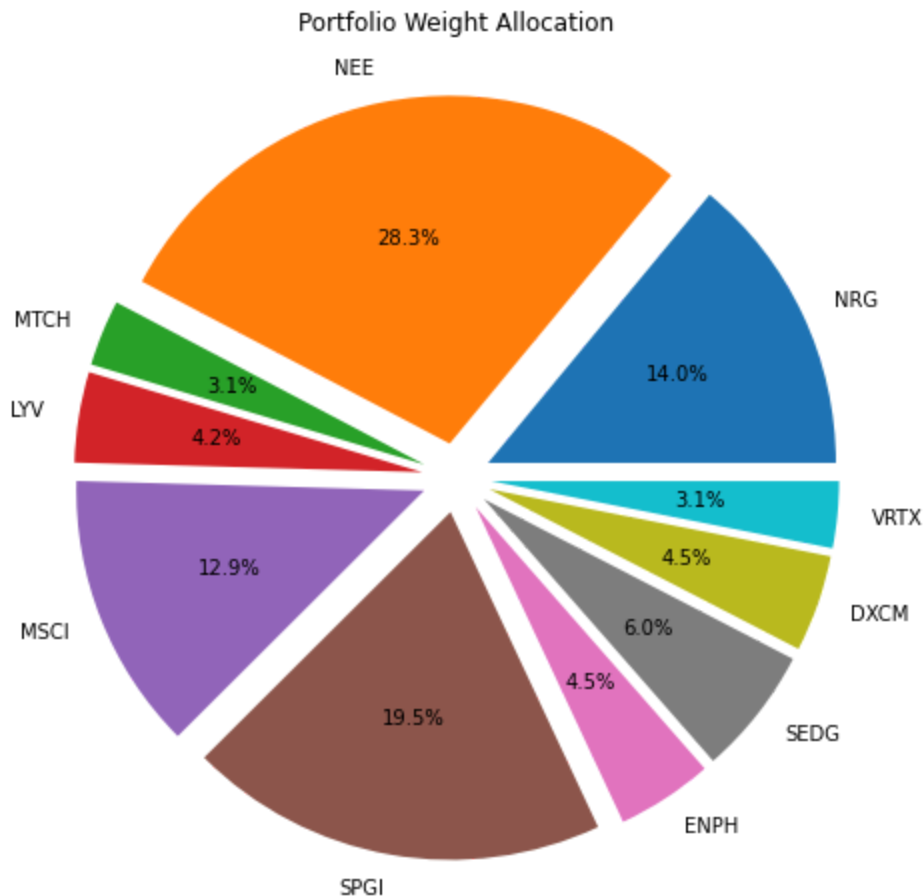
# Calculate the sharpe ratio of each stock and find the highest portfolio
sharpe_ratio = (total_return(weight, download_stock) - rfrate) / total_vol(w
if sharpe_ratio >= best_sharpe:
    best_sharpe = sharpe_ratio
    best_weight = weight

best_return = total_return(best_weight, download_stock)
best_vol = total_vol(best_weight, download_stock)
best_sharpe_ratio = (best_return - rfrate) / best_vol

# Plot the pie charts
plt.rcParams['figure.figsize'] = [12,8]
plt.pie(best_weight, explode = np.ones(10)*0.1, labels = chosen_stock, autopct =
plt.title('Portfolio Weight Allocation')
plt.show()

# Print out the final result
print(f'The tangency portfolio invests {best_weight[0]:.1%} into {chosen_stock[0]

```



The tangency portfolio invests 14.0% into NRG, 28.3% into NEE, 3.1% into MTCH, 4.2% into LYV, 12.9% into MSCI, 19.5% into SPGI, 4.5% into ENPH, 6.0% into SEDG, 4.5% into DXCM, and 3.1% into VRTX achieving a volatility 14.83% and expected return of 39.25% for a Sharpe Ratio of 2.604.

In [11]:

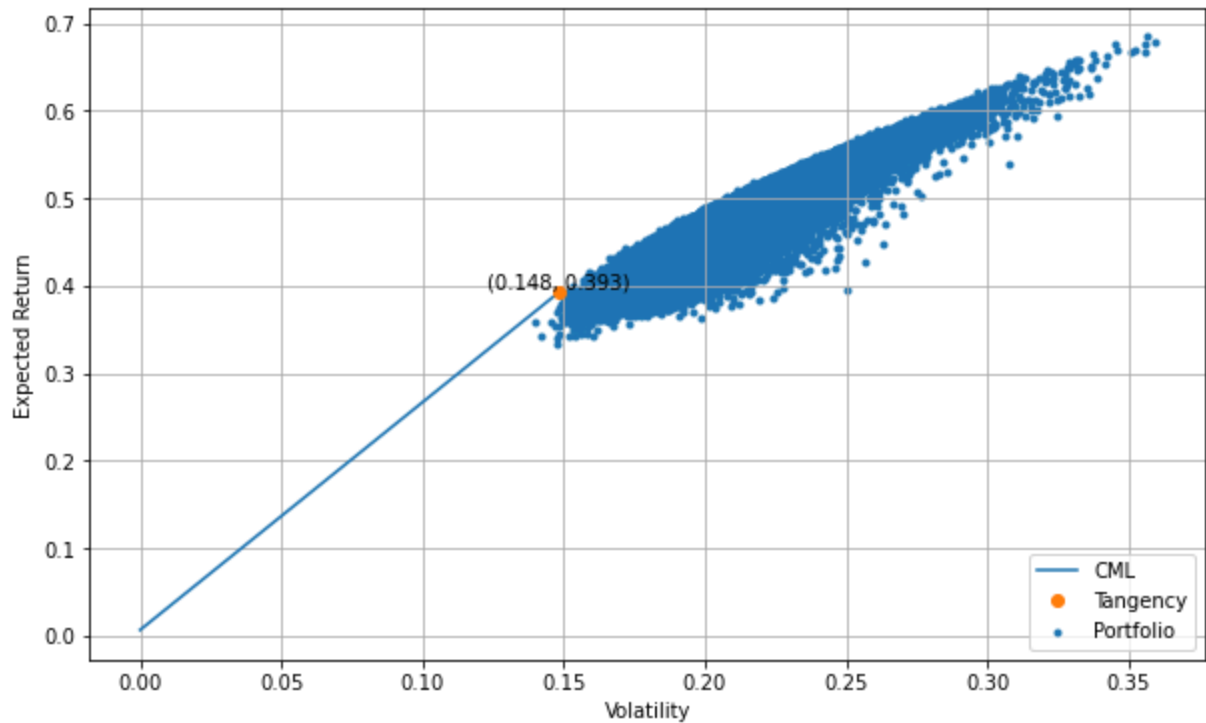
```

result_shown = pd.DataFrame([[best_return, best_vol, best_sharpe_ratio]], columns
result_shown.index = ['Result']
display(result_shown)

```

```
plt.rcParams['figure.figsize'] = [10,6]
plt.scatter(stock_vol , stock_return, marker = '.', label='Portfolio')
plt.plot(np.array([0, best_vol]), np.array([rfrate, best_return]), label='CML')
plt.plot(best_vol,best_return,'o',label='Tangency')
plt.text(best_vol,best_return,(round(best_vol,3),round(best_return,3)), ha = 'center')
plt.grid('on')
plt.legend(loc='lower right')
plt.xlabel('Volatility')
plt.ylabel('Expected Return')
plt.show()
```

	Return	Volatility	Sharpe Ratio
Result	0.392534	0.148322	2.604093



Fama_French Regression

```
In [12]: a = pd.DataFrame(np.sum(download_stock*best_weight, axis = 1), columns = ['total', 'fama'])
final_fama = chosen_result.merge(a, on = ['Date'], how = 'inner')
final_fama.head()
```

	mktrf	smb	hml	rf	mom	DXCM	ENPH	LYV	MSCI	MTCH	...	ret
Date												
2017-01-03	0.83	-0.13	0.05	0.002	-0.61	14.5625	1.05	27.400000	74.041428	16.494013	...	
2017-01-04	0.79	0.95	-0.16	0.002	-0.37	15.1800	1.15	27.629999	75.922829	16.455944	...	

	mktrf	smb	hml	rf	mom	DXCM	ENPH	LYV	MSCI	MTCH	...	ret
Date												
2017-01-05	-0.21	-0.88	-0.79	0.002	-0.60	15.6650	1.12	27.500000	76.797646	17.122175	...	0
2017-01-06	0.29	-0.66	-0.31	0.002	-0.18	15.8075	1.11	27.680000	78.453247	17.160246	...	(
2017-01-09	-0.37	-0.29	-1.04	0.002	-0.37	15.6225	1.11	27.290001	77.775955	17.274456	...	-(

5 rows x 36 columns

```
In [13]: final_fama['total_returnrf'] = final_fama['total_return'] - np.log(final_fama['r
formula = 'total_returnrf~ mktrf + smb + hml + mom'
results = smf.ols(formula, final_fama).fit()
print(results.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          total_returnrf      R-squared:                0.534
Model:                  OLS                Adj. R-squared:            0.532
Method:                 Least Squares       F-statistic:              214.5
Date:                  Fri, 23 Dec 2022     Prob (F-statistic):      1.61e-122
Time:                  16:52:13             Log-Likelihood:          2702.1
No. Observations:      753                 AIC:                    -5394.
Df Residuals:          748                 BIC:                    -5371.
Df Model:               4
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0053	0.000	-21.481	0.000	-0.006	-0.005
mktrf	0.0075	0.000	24.763	0.000	0.007	0.008
smb	0.0002	0.001	0.472	0.637	-0.001	0.001
hml	-0.0033	0.001	-6.512	0.000	-0.004	-0.002
mom	0.0020	0.000	4.819	0.000	0.001	0.003

```
=====
Omnibus:                56.390      Durbin-Watson:              1.640
Prob(Omnibus):           0.000      Jarque-Bera (JB):           100.853
Skew:                    0.507      Prob(JB):                  1.26e-22
Kurtosis:                 4.479      Cond. No.                   2.42
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
In [14]: alphas_listfama = []
beta_listfama = []
formula = 'total_returnrf ~ mktrf'
lr = ols(formula, final_fama).fit()
alphas_listfama.append(lr.params['Intercept'])
beta_listfama.append(lr.params['mktrf'])
```

```
resultfama = pd.DataFrame(index=['resultfama'],
                           data={
                               "alpha": alphas_listfama,
                               "beta": beta_listfama})
resultfama
```

```
Out[14]:
```

	alpha	beta
resultfama	-0.005126	0.007972

```
In [15]: TIfama = final_fama['total_returnrf'].mean() / resultfama['beta']
Jafama = final_fama['total_returnrf'].mean() - resultfama['beta'] * final_fama['total_returnrf'].mean()
print(TIfama)
print(Jafama)
```

```
resultfama    -0.590952
Name: beta, dtype: float64
resultfama    -0.005126
Name: beta, dtype: float64
```

Test

```
In [16]: # breusch-pagan heteroskedasticity test
name = ['Lagrange multiplier statistic', 'p-value',
        'f-value', 'f p-value']
test = sms.het_breuschpagan(results.resid, results.model.exog)
lzip(name, test)
```

```
Out[16]: [('Lagrange multiplier statistic', 5.165879301311405),
          ('p-value', 0.27069675883162475),
          ('f-value', 1.2917562900749995),
          ('f p-value', 0.27164885209296025)]
```

```
In [17]: #White Standard Errors
formula = 'total_returnrf~ mktrf + smb + hml + mom'
WSE_results = smf.ols(formula, final_fama).fit(cov_type='HC1')
print(results.summary())
```

OLS Regression Results						
=====						
Dep. Variable:	total_returnrf		R-squared:	0.534		
Model:	OLS		Adj. R-squared:	0.532		
Method:	Least Squares		F-statistic:	214.5		
Date:	Fri, 23 Dec 2022		Prob (F-statistic):	1.61e-122		
Time:	16:52:13		Log-Likelihood:	2702.1		
No. Observations:	753		AIC:	-5394.		
Df Residuals:	748		BIC:	-5371.		
Df Model:	4					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	-0.0053	0.000	-21.481	0.000	-0.006	-0.005
mktrf	0.0075	0.000	24.763	0.000	0.007	0.008
smb	0.0002	0.001	0.472	0.637	-0.001	0.001

Daily						
hml	-0.0033	0.001	-6.512	0.000	-0.004	-0.002
mom	0.0020	0.000	4.819	0.000	0.001	0.003
=====						
Omnibus:	56.390		Durbin-Watson:		1.640	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		100.853	
Skew:	0.507		Prob(JB):		1.26e-22	
Kurtosis:	4.479		Cond. No.		2.42	
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [18]:

```
#Newey West Standard Errors
formula = 'total_returnrf~ mktrf + smb + hml + mom'
NWSE_results = smf.ols(formula, final_fama).fit(cov_type='HAC',
                                                cov_kwds={'maxlags':6, 'use_correction':True})
print(results.summary())
```

OLS Regression Results

Dep. Variable:	total_returnrf	R-squared:	0.534			
Model:	OLS	Adj. R-squared:	0.532			
Method:	Least Squares	F-statistic:	214.5			
Date:	Fri, 23 Dec 2022	Prob (F-statistic):	1.61e-122			
Time:	16:52:13	Log-Likelihood:	2702.1			
No. Observations:	753	AIC:	-5394.			
Df Residuals:	748	BIC:	-5371.			
Df Model:	4					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0053	0.000	-21.481	0.000	-0.006	-0.005
mktrf	0.0075	0.000	24.763	0.000	0.007	0.008
smb	0.0002	0.001	0.472	0.637	-0.001	0.001
hml	-0.0033	0.001	-6.512	0.000	-0.004	-0.002
mom	0.0020	0.000	4.819	0.000	0.001	0.003
=====						
Omnibus:	56.390	Durbin-Watson:	1.640			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	100.853			
Skew:	0.507	Prob(JB):	1.26e-22			
Kurtosis:	4.479	Cond. No.	2.42			
=====						

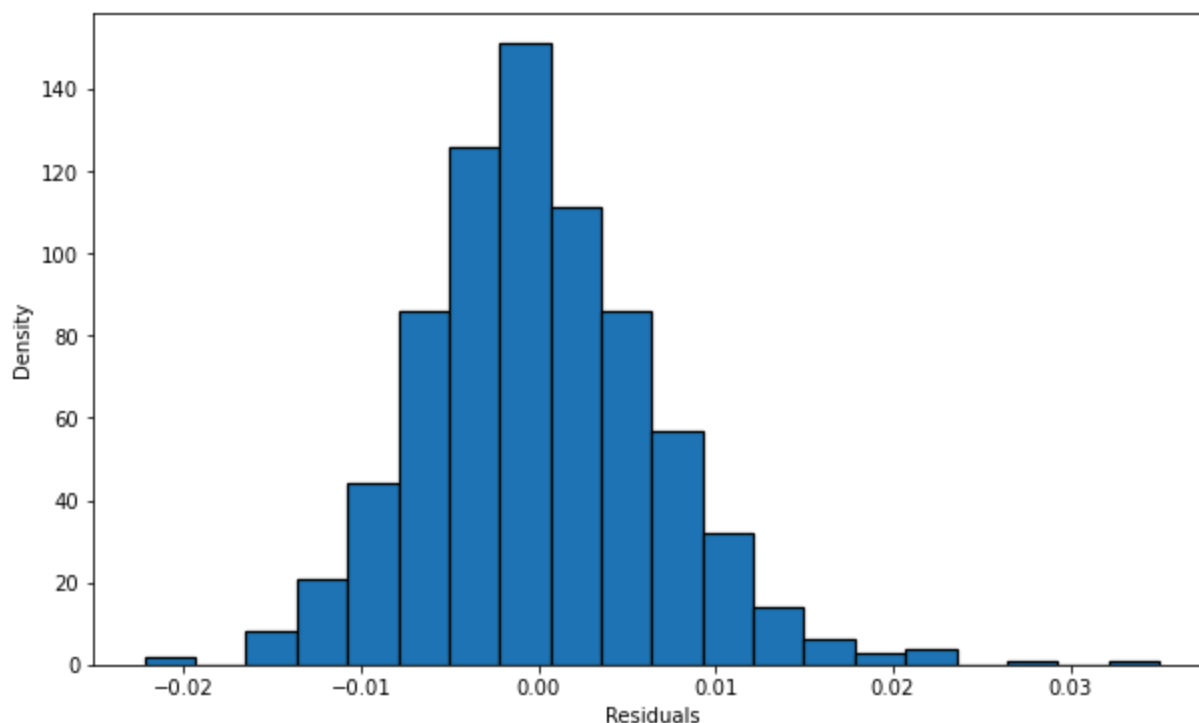
Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [19]:

```
#Testing for Normality
residuals = results.resid

plt.figure(1)
plt.hist(residuals,20,edgecolor='black',linewidth=1.2)
plt.xlabel('Residuals')
plt.ylabel('Density')
plt.show()
```



```
In [20]: #Testing for Normality
name = ['Jarque-Bera', 'Chi^2 two-tail prob.', 'Skew', 'Kurtosis']
test = sms.jarque_bera(residuals)
lzip(name, test)
```

```
Out[20]: [('Jarque-Bera', 100.8526200607653),
('Chi^2 two-tail prob.', 1.2593075614350123e-22),
('Skew', 0.5070054528850473),
('Kurtosis', 4.478583112433732)]
```

```
In [21]: #Testing for autocorrelation
sms.durbin_watson(residuals)
```

```
Out[21]: 1.6401397179974317
```

```
In [22]: #Autocorrelation Test: Breusch Godfrey
name = ['Lagrange multiplier statistic', 'p-value',
'f-value', 'f p-value']
results1 = sms.acorr_breusch_godfrey(results, 10)
lzip(name, results1)
```

```
Out[22]: [('Lagrange multiplier statistic', 96.91687594897245),
('p-value', 2.252222955239477e-16),
('f-value', 10.90176714327113),
('f p-value', 1.953717904688144e-17)]
```

```
In [23]: #F-test
hypotheses = 'mktrf = smb = hml = mom = 0'
f_test = results.f_test(hypotheses)
print(f_test)
```

<F test: F=array([[214.46791597]]), p=1.6072991762046611e-122, df_denom=748, df_num=4>

In [24]: `#Assumption 1
residuals.mean()`

Out[24]: -2.8336120523923942e-18

Analysis

In [25]: `# Analysis1: 2021
df_2021 = pd.read_csv('daily.csv')
df_2021['Date'] = pd.to_datetime(df_2021['Date'])
df_2021 = df_2021.set_index('Date')
df_2021 = df_2021.loc['2021-01-01':'2021-12-31']

stock_21 = yf.download(chosen_stock, start = '2021-01-01', end = '2021-12-31')

for i in chosen_stock:
 stock_21['ret_{}'.format(i)] = np.log(stock_21['{}'.format(i)] / stock_21['{
 stock_21 = stock_21.drop(columns = ['{}'.format(i)])

return_21 = total_return(best_weight, stock_21)
vol_21 = total_vol(best_weight, stock_21)
sharpe_ratio_21 = (return_21 - df_2021['rf'].mean()) / vol_21
print(f'The portfolio return from Jan. 2021 to Dec. 2021 is {return_21:.2%}.')
print(f'The portfolio volatility from Jan. 2021 to Dec. 2021 is {vol_21:.2f}.')
print(f'The portfolio sharpe ratio from Jan. 2021 to Dec. 2021 is {sharpe_ratio_21:.2f}.')`

[*****100%*****] 10 of 10 completed
The portfolio return from Jan. 2021 to Dec. 2021 is 24.55%.
The portfolio volatility from Jan. 2021 to Dec. 2021 is 0.19.
The portfolio sharpe ratio from Jan. 2021 to Dec. 2021 is 1.28.

In [26]: `# Analysis2: Compare 2021
df_2021 = pd.read_csv('daily.csv')
df_2021['Date'] = pd.to_datetime(df_2021['Date'])
df_2021 = df_2021.set_index('Date')
df_2021 = df_2021.loc['2021-01-01':'2021-12-31']

stock_2021 = yf.download(chosen_stock, start = '2021-01-01', end = '2021-12-31')

for i in chosen_stock:
 stock_2021['ret_{}'.format(i)] = np.log(stock_2021['{}'.format(i)] / stock_2021['{
 stock_2021 = stock_2021.drop(columns = ['{}'.format(i)])

total_return_2021 = pd.DataFrame(np.sum(stock_2021*best_weight, axis = 1), columns = chosen_stock)
capm_2021 = df_2021.merge(total_return_2021, on = ['Date'], how = 'inner')
capm_2021['total_returnrf'] = capm_2021['total_return'] - np.log(capm_2021['rf'])

alphas_list2021 = []
betas_list2021 = []
formula = 'total_returnrf ~ mktrf'
lr = ols(formula, capm_2021).fit()
alphas_list2021.append(lr.params['Intercept'])
betas_list2021.append(lr.params['mktrf'])`


```
result2021 = pd.DataFrame(index=['result2021'],
                           data={
                               "alpha": alphas_list2021,
                               "beta": beta_list2021})
result2021
```

[*****100%*****] 10 of 10 completed

Out[26]:

	alpha	beta
--	-------	------

result2021	0.000057	0.010258
------------	----------	----------

In [27]:

```
TI2021 = capm_2021['total_returnrf'].mean() / result2021['beta']
JA2021 = capm_2021['total_returnrf'].mean() - result2021['beta'] * capm_2021['mk']
print(TI2021)
print(JA2021)
```

```
result2021    0.094599
Name: beta, dtype: float64
result2021    0.000057
Name: beta, dtype: float64
```

In [28]:

```
# SP500
sp500 = pd.read_csv('HistoricalPrices.csv')
sp500 = sp500.set_index('Date')
sp500.index = pd.to_datetime(sp500.index)
sp500['return'] = np.log(sp500['close'] / sp500['close'].shift(1))*252
sp500.head()
```

Out[28]:

	close	return
--	-------	--------

Date		
2021-01-04	3700.65	NaN
2021-01-05	3726.86	1.778509
2021-01-06	3748.14	1.434803
2021-01-07	3803.79	3.714032
2021-01-08	3824.68	1.380170

In [29]:

```
sp500_vol = sp500['return'].std()
sp500_er = sp500['return'].mean()
sp500_sharpe = (sp500_er - np.log(df_2021['rf'].mean()+1)) / sp500_vol

print(f'The return of S&P500 from Jan. 2021 to Dec. 2021 is {sp500_er:.2%}.')
print(f'The volatility of S&P500 from Jan. 2021 to Dec. 2021 is {sp500_vol:.2f}.')
print(f'The Sharpe ratio of S&P500 from Jan. 2021 to Dec. 2021 is {sp500_sharpe:.2f}.')
```

```
The return of S&P500 from Jan. 2021 to Dec. 2021 is 25.40%.
The volatility of S&P500 from Jan. 2021 to Dec. 2021 is 2.07.
The Sharpe ratio of S&P500 from Jan. 2021 to Dec. 2021 is 0.12.
```

In [30]:

```
capm_sp500 = df_2021.merge(sp500, on = ['Date'], how = 'inner')
capm_sp500['total_returnrf'] = capm_sp500['return'] - np.log(capm_2021['rf']+1)
```

```

alphas_listsp500 = []
beta_listsp500 = []
formula = 'total_returnrf ~ mktrf'
lr = ols(formula, capm_sp500).fit()
alphas_listsp500.append(lr.params['Intercept'])
beta_listsp500.append(lr.params['mktrf'])

resultsp500 = pd.DataFrame(index=['resultsp500'],
                             data={
                                 "alpha": alphas_listsp500,
                                 "beta": beta_listsp500})

resultsp500

```

```

Out[30]:

```

	alpha	beta
resultsp500	0.038618	2.305282

```

In [31]:
TIsP500 = capm_sp500['total_returnrf'].mean() / resultsp500['beta']
JAsP500 = capm_sp500['total_returnrf'].mean() - resultsp500['beta'] * capm_sp500
print(TIsP500)
print(JAsP500)

resultsp500    0.111792
Name: beta, dtype: float64
resultsp500    0.056091
Name: beta, dtype: float64

```

```

In [32]:
# Analysis3: Covid 19
stock_1719 = yf.download(chosen_stock, start = '2017-03-01', end = '2019-03-31')
stock_2022 = yf.download(chosen_stock, start = '2020-03-01', end = '2022-03-31')

[*****100%*****] 10 of 10 completed
[*****100%*****] 10 of 10 completed

```

```

In [33]:
for i in chosen_stock:
    stock_1719['ret_{}'.format(i)] = np.log(stock_1719['{}'.format(i)] / stock_1
    stock_1719 = stock_1719.drop(columns = ['{}'.format(i)])

for i in chosen_stock:
    stock_2022['ret_{}'.format(i)] = np.log(stock_2022['{}'.format(i)] / stock_2
    stock_2022 = stock_2022.drop(columns = ['{}'.format(i)])

return_1719 = total_return(best_weight, stock_1719)
return_2022 = total_return(best_weight, stock_2022)
vol_1719 = total_vol(best_weight, stock_1719)
vol_2022 = total_vol(best_weight, stock_2022)
sharpe_ratio_1719 = (return_1719 - rfrate) / vol_1719
sharpe_ratio_2022 = (return_2022 - rfrate) / vol_2022

print(f'The portfolio actual return from Mar. 2017 to Mar. 2019 is {return_1719:}
print(f'The portfolio actual return from Mar. 2020 to Mar. 2022 is {return_2022:}
print(f'The portfolio volatility from Mar. 2017 to Mar. 2019 is {vol_1719:.2f}.'
print(f'The portfolio volatility from Mar. 2020 to Mar. 2022 is {vol_2022:.2f}.'
print(f'The portfolio sharpe ratio from Mar. 2017 to Mar. 2019 is {sharpe_ratio_}
print(f'The portfolio sharpe ratio from Mar. 2020 to Mar. 2022 is {sharpe_ratio_}

```

The portfolio actual return from Mar. 2017 to Mar. 2019 is 33.89%.
 The portfolio actual return from Mar. 2020 to Mar. 2022 is 20.72%.
 The portfolio volatility from Mar. 2017 to Mar. 2019 is 0.15.
 The portfolio volatility from Mar. 2020 to Mar. 2022 is 0.32.
 The portfolio sharpe ratio from Mar. 2017 to Mar. 2019 is 2.21.
 The portfolio sharpe ratio from Mar. 2020 to Mar. 2022 is 0.64.

In [34]:

```
df_1719 = pd.read_csv('daily.csv')
df_1719['Date'] = pd.to_datetime(df_1719['Date'])
df_1719 = df_1719.set_index('Date')
df_1719 = df_1719.loc['2017-03-01':'2019-3-31']

total_return_1719 = pd.DataFrame(np.sum(stock_1719 * best_weight, axis = 1), col
capm_1719 = df_1719.merge(total_return_1719, on = ['Date'], how = 'inner')
capm_1719['total_returnrf'] = capm_1719['total_return'] - np.log(capm_1719['rf'])

alphas_list1719 = []
beta_list1719 = []
formula = 'total_returnrf ~ mktrf'
lr = ols(formula, capm_1719).fit()
alphas_list1719.append(lr.params['Intercept'])
beta_list1719.append(lr.params['mktrf'])

result1719 = pd.DataFrame(index=['result1719'],
                           data={
                               "alpha":alphas_list1719,
                               "beta":beta_list1719})

result1719
```

Out[34]:

	alpha	beta
result1719	-0.004923	0.008268

In [35]:

```
df_2022 = pd.read_csv('daily.csv')
df_2022['Date'] = pd.to_datetime(df_2022['Date'])
df_2022 = df_2022.set_index('Date')
df_2022 = df_2022.loc['2020-03-01':'2022-3-31']

total_return_2022 = pd.DataFrame(np.sum(stock_2022 * best_weight, axis = 1), col
capm_2022 = df_2022.merge(total_return_2022, on = ['Date'], how = 'inner')
capm_2022['total_returnrf'] = capm_2022['total_return'] - np.log(capm_2022['rf'])

alphas_list2022 = []
beta_list2022 = []
formula = 'total_returnrf ~ mktrf'
lr = ols(formula, capm_2022).fit()
alphas_list2022.append(lr.params['Intercept'])
beta_list2022.append(lr.params['mktrf'])

result2022 = pd.DataFrame(index=['result2022'],
                           data={
                               "alpha":alphas_list2022,
                               "beta":beta_list2022})

result2022
```

Out [35]:

	alpha	beta
result2022	-0.000557	0.010574

In [36]:

```
TI1719 = capm_1719['total_returnrf'].mean() / result1719['beta']
JA1719 = capm_1719['total_returnrf'].mean() - result1719['beta'] * capm_1719['mk
print(TI1719)
print(JA1719)
```

```
result1719    -0.55465
Name: beta, dtype: float64
result1719    -0.004923
Name: beta, dtype: float64
```

In [37]:

```
TI2022 = capm_2022['total_returnrf'].mean() / result2022['beta']
JA2022 = capm_2022['total_returnrf'].mean() - result2022['beta'] * capm_2022['mk
print(TI2022)
print(JA2022)
```

```
result2022     0.049991
Name: beta, dtype: float64
result2022    -0.000557
Name: beta, dtype: float64
```