Financial Instruments Coursework

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Q1

a

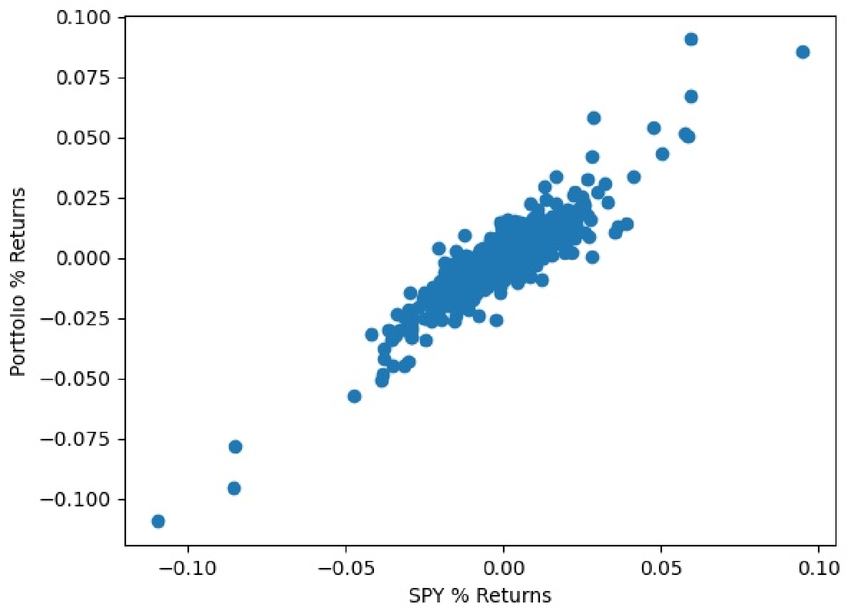


Figure 1: Scatter plot of Portfolio Returns against S&P 500

We see that there seems to be a linear relationship between returns of S&P500 and the returns of the portfolio.Also, the alpha of this portfolio seems to be zero as the intercept seems to be 0. The code written to do the calculations can be found in appendix.

b

Table 1: Mean of all Stock Returns

	ln_ret_DBE_mean	ln_ret_JPM_mean	ln_ret_MA_mean	ln_ret_NFLX_mean	ln_ret_SPY_mean	ln_ret_WMT_mean	portfolio_log_returns_mean
0	0.000209	0.000648	0.001037	0.001297	0.000622	0.000681	0.000774

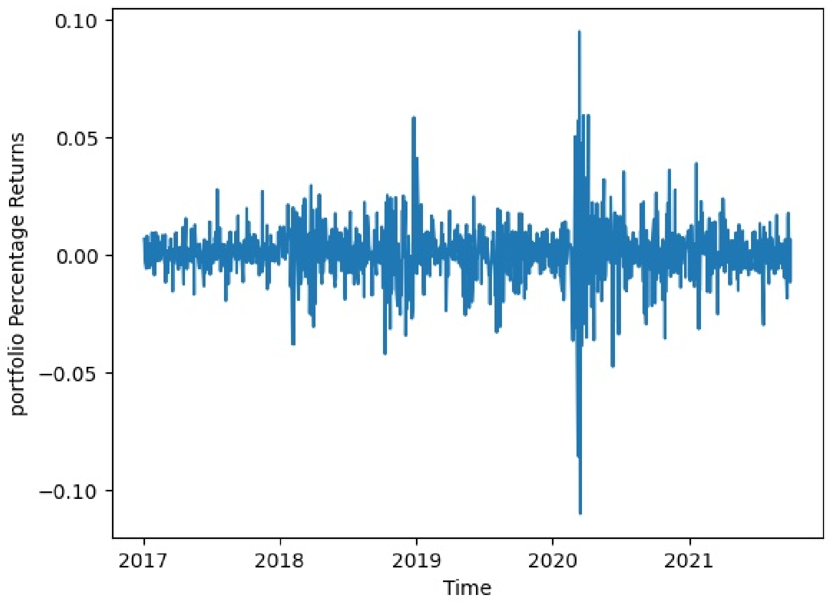


Figure 2: Portfolio Returns

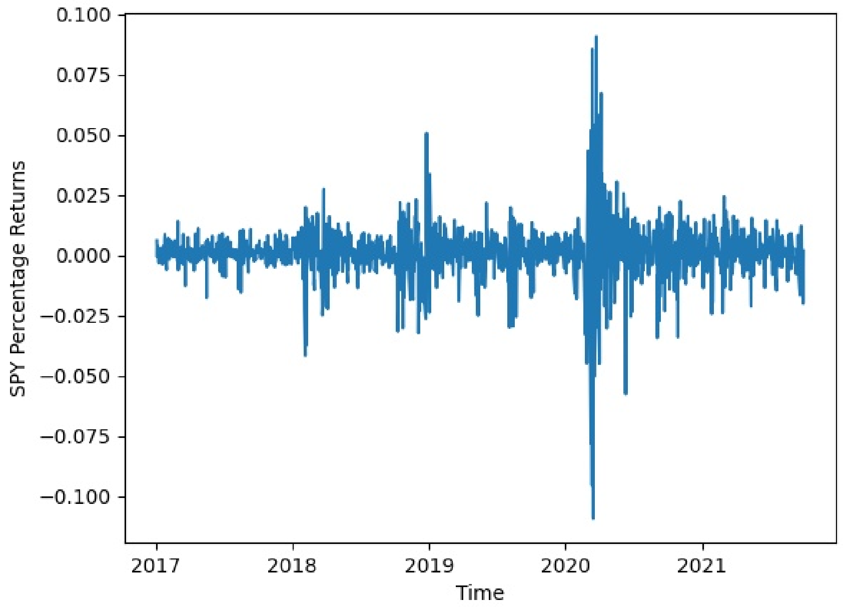


Figure 3: S&P 500

Table 2: Covariance Matrix

	ln_ret_DBE	ln_ret_JPM	ln_ret_MA	ln_ret_NFLX	ln_ret_SPY	ln_ret_WMT	portfolio_log_returns
ln_ret_DBE	0.000294	0.000128	0.000115	0.000069	0.000090	0.000030	0.000127
ln_ret_JPM	0.000128	0.000369	0.000224	0.000098	0.000177	0.000073	0.000178
ln_ret_MA	0.000115	0.000224	0.000360	0.000185	0.000187	0.000083	0.000193
ln_ret_NFLX	0.000069	0.000098	0.000185	0.000588	0.000145	0.000089	0.000206
ln_ret_SPY	0.000090	0.000177	0.000187	0.000145	0.000146	0.000080	0.000136
ln_ret_WMT	0.000030	0.000073	0.000083	0.000089	0.000080	0.000191	0.000093
portfolio_log_returns	0.000127	0.000178	0.000193	0.000206	0.000136	0.000093	0.000160

Table 3: Beta Calculated from Covariance Matrix

	DBE_beta	JPM_beta	MA_beta	NFLX_beta	SPY_beta	WMT_beta	portfolio_returns_beta
0	0.614786	1.213279	1.278208	0.990475	1.0	0.547793	0.928908

$\beta_s = \frac{\text{Cov}[R_m, R_s]}{\text{Var}[R_m]}$

where β_s is Beta of the stock, $\text{Cov}[R_m, R_s]$ is the covariance of the stock and market index, $\text{Var}[R_m]$ is the variance of the market index.

c

Table 4: Portfolio Return Info

	portfolio_annual_mean_returns	portfolio_std_returns
0	0.193622	0.19971

$\mu_{1y} = \mu_{1d} * 250$

$\sigma_{1y} = \sigma_{1d} * \sqrt{250}$

where,

μ_{1y} and μ_{1d} are annual and daily log-returns respectively and

σ_{1y} and σ_{1d} are annual and daily standard deviation of log-returns respectively

d

Given below are the regression results for the stocks and Portfolio,

Table 5: DBE Beta obtained from OLS

Model:	OLS	Adj. R-squared:	0.180
Dependent Variable:	%ret_DBE	AIC:	-6571.1406
Date:	2021-12-06 17:57	BIC:	-6560.9722
No. Observations:	1193	Log-Likelihood:	3287.6
Df Model:	1	F-statistic:	262.7
Df Residuals:	1191	Prob (F-statistic):	1.54e-53
R-squared:	0.181	Scale:	0.00023696

	Coef.	Std.Err.	t	P> |t|	[0.025	0.975]
const	-0.0001	0.0004	-0.1760	0.8603	-0.0010	0.0008
%ret_SPY	0.6008	0.0371	16.2076	0.0000	0.5281	0.6735

Omnibus:	144.633	Durbin-Watson:	2.080
Prob(Omnibus):	0.000	Jarque-Bera (JB):	873.041
Skew:	-0.371	Prob(JB):	0.000
Kurtosis:	7.125	Condition No.:	83

Table 6: JPM Beta obtained from OLS

Model:	OLS	Adj. R-squared:	0.577
Dependent Variable:	%ret_JPM	AIC:	-7066.2687
Date:	2021-12-06 17:57	BIC:	-7056.1002
No. Observations:	1193	Log-Likelihood:	3535.1
Df Model:	1	F-statistic:	1627.
Df Residuals:	1191	Prob (F-statistic):	5.92e-225
R-squared:	0.577	Scale:	0.00015647

	Coef.	Std.Err.	t	P> |t|	[0.025	0.975]
const	-0.0000	0.0004	-0.0076	0.9939	-0.0007	0.0007
%ret_SPY	1.2149	0.0301	40.3329	0.0000	1.1558	1.2740

Omnibus:	403.430	Durbin-Watson:	1.989
Prob(Omnibus):	0.000	Jarque-Bera (JB):	6244.410
Skew:	1.131	Prob(JB):	0.000
Kurtosis:	13.978	Condition No.:	83

Table 7: NFLX Beta obtained from OLS

Model:	OLS	Adj. R-squared:	0.238
Dependent Variable:	%ret_NFLX	AIC:	-5803.1402
Date:	2021-12-06 17:57	BIC:	-5792.9717
No. Observations:	1193	Log-Likelihood:	2903.6
Df Model:	1	F-statistic:	373.7
Df Residuals:	1191	Prob (F-statistic):	1.27e-72
R-squared:	0.239	Scale:	0.00045107

	Coef.	Std.Err.	t	P> |t|	[0.025	0.975]
const	0.0009	0.0006	1.4691	0.1421	-0.0003	0.0021
%ret_SPY	0.9886	0.0511	19.3302	0.0000	0.8883	1.0890

Omnibus:	222.599	Durbin-Watson:	2.011
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2179.164
Skew:	0.554	Prob(JB):	0.000
Kurtosis:	9.528	Condition No.:	83

Table 8: WMT Beta obtained from OLS

Model:	OLS	Adj. R-squared:	0.228
Dependent Variable:	%ret_WMT	AIC:	-7124.7892
Date:	2021-12-06 17:57	BIC:	-7114.6208
No. Observations:	1193	Log-Likelihood:	3564.4
Df Model:	1	F-statistic:	353.3
Df Residuals:	1191	Prob (F-statistic):	3.21e-69
R-squared:	0.229	Scale:	0.00014898

	Coef.	Std.Err.	t	P> |t|	[0.025	0.975]
const	0.0004	0.0004	1.0611	0.2889	-0.0003	0.0011
%ret_SPY	0.5524	0.0294	18.7950	0.0000	0.4948	0.6101

Omnibus:	416.290	Durbin-Watson:	2.041
Prob(Omnibus):	0.000	Jarque-Bera (JB):	12388.448
Skew:	0.983	Prob(JB):	0.000
Kurtosis:	18.664	Condition No.:	83

Table 9: MA Beta obtained from OLS

Model:	OLS	Adj. R-squared:	0.662
Dependent Variable:	%ret_MA	AIC:	-7360.6919
Date:	2021-12-06 18:13	BIC:	-7350.5235
No. Observations:	1193	Log-Likelihood:	3682.3
Df Model:	1	F-statistic:	2333.
Df Residuals:	1191	Prob (F-statistic):	8.19e-283
R-squared:	0.662	Scale:	0.00012225

	Coef.	Std.Err.	t	P> |t|	[0.025	0.975]
const	0.0003	0.0003	1.0446	0.2964	-0.0003	0.0010
%ret_SPY	1.2860	0.0266	48.2991	0.0000	1.2337	1.3382

Omnibus:	163.997	Durbin-Watson:	2.062
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1935.573
Skew:	0.066	Prob(JB):	0.000
Kurtosis:	9.239	Condition No.:	83

Table 10: portfolio_returns_percentage Beta obtained from OLS

Model:	OLS	Adj. R-squared:	0.787
Dependent Variable:	portfolio_returns_percentage	AIC:	-8895.2341
Date:	2021-12-06 17:57	BIC:	-8885.0657
No. Observations:	1193	Log-Likelihood:	4449.6
Df Model:	1	F-statistic:	4402.
Df Residuals:	1191	Prob (F-statistic):	0.00
R-squared:	0.787	Scale:	3.3777e-05

	Coef.	Std.Err.	t	P> |t|	[0.025	0.975]
const	0.0003	0.0002	1.8203	0.0690	-0.0000	0.0006
%ret_SPY	0.9285	0.0140	66.3474	0.0000	0.9011	0.9560

Omnibus:	69.193	Durbin-Watson:	2.028
Prob(Omnibus):	0.000	Jarque-Bera (JB):	247.699
Skew:	0.134	Prob(JB):	0.000
Kurtosis:	5.216	Condition No.:	83

From the above tables we have, $\beta_{portfolio} = 0.9285, \beta_{MA} = 1.286, \beta_{WMT} = 0.5524, \beta_{NFLX} = 0.9886, \beta_{JPM} = 1.2149, \beta_{DBE} = 0.6008$

This is roughly equivalent to the beta obtained using the covariance matrix.

We see from the standard error and p-value results above that the α is 0 for each of the stocks and the portfolio.

e

Idiosyncratic Risk is the risk associated with the individual stock or investment which cannot be modelled by CAPM. For eg the risk of a company going bankrupt.

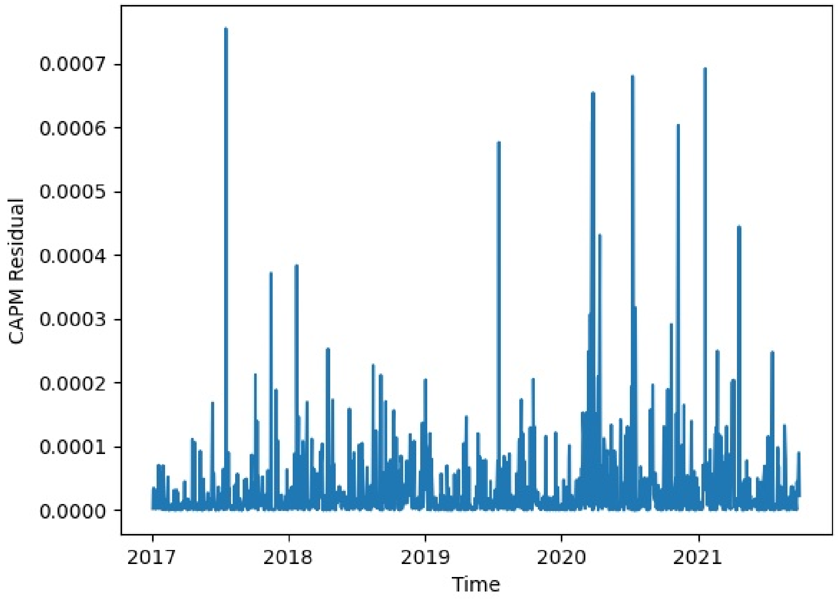
From the above regression, we get R-squared as 0.787 and hence the unsystemic risk of the portfolio is $1 - 0.787 = 0.213$.

$\text{Residual}_t = ((R_t - R_f) - (\beta * (R_{mt} - R_f) + \alpha))^2$

where, in this case R_t is portfolio return at time t and R_{mt} is the market index return at time t.

and R_f is the risk free rate.

Figure 4: Idiosyncratic Risk of Portfolio over time



Appendix(Python Code)

All the neccesary imports

```
import pandas as pd
import os
import statsmodels.api as sm
import yfinance as yf
import numpy as np
import matplotlib.pyplot as plt
```

Downloading Data

```
# Downloading Data of certain stocks and S&P500 from Yahoo Finance
k = yf.download('SPY DBE JPM MA NFLX WMT',start='2016-12-31',end='2021-09-30')
# Remove all columns except adjusted Close
k=k[[i for i in k.columns if 'Adj Close' in i]]
k=k.set_axis(k.columns.map('_'.join), axis=1, inplace=False)
```

Calculating Returns and Saving Figure

~~~
    for i in k.columns:
        logcolname = f"ln_ret_{i[10:]}"
        ord_ret = f"%ret_{i[10:]}" # Column name for percentage returns
        k[logcolname] = np.log(k[i]/k[i].shift(1)) # Calculating log returns
        k[ord_ret] = np.exp(k[logcolname])-1 # calculating percentage returns from log retu
    print(k)
# Extracting Columns Names of only stocks
```python
    per_ret=[i for i in k.columns if "%ret" in i and 'SPY' not in i]
    log_ret=[i for i in k.columns if "ln_ret" in i and 'SPY' not in i]
    k['portfolio_returns_percentage'] = k[per_ret].mean(axis=1) #Calculating Portfolio Retu
    k['portfolio_log_returns'] = k[log_ret].mean(axis=1 # Calculating log portfolio returns
    plt.scatter(k.portfolio_returns_percentage,k['%ret_SPY']) #Plotting Scatter Plot
    plt.xlabel("SPY % Returns")
    plt.ylabel("Portfolio % Returns")
    plt.savefig("ScatterPlot.jpg")
~~~

Calculating Means

```
    return_info1 = pd.DataFrame() # For calculating Mean of all series
    for i in cov_mat_cols:
        return_info1[f"{i}_mean"] = [k[i].mean()]
```

Calculating Covariance and Beta

Extracting Columns for covariance matrix

```
    cov_mat_cols =[i for i in k.columns if 'ln_ret' in i or 'log_returns' in i]
    cov_mat = k[cov_mat_cols].cov() # covariance matrix of markets and portfolio
    info = pd.DataFrame()
    for i in cov_mat.columns[:-1]:
```

```
        info[f"{i[7:]}_beta"]=[cov_mat.loc['ln_ret_SPY',i]/cov_mat.loc[
        'ln_ret_SPY','ln_ret_SPY']]
```

Computing beta for portfolio returns

```
    info[f"portfolio_returns_beta"]=[
        cov_mat.loc[
        'ln_ret_SPY','portfolio_log_returns']/cov_mat.loc['ln_ret_SPY','ln_ret_SPY']]
    print(info)
```

Calculating Annualized Mean and Standard Deviation

```
    return_info = pd.dataFrame()
    return_info['portfolio_annual_mean_returns'] = [k.portfolio_log_returns.mean()*250]
    return_info['portfolio_std_returns'] = [k.portfolio_log_returns.std()*250**.5]
```

Calculating Beta using OLS

```
    per_ret=[i for i in k.columns if "%ret" in i and 'SPY' not in i]
    per_ret1 = per_ret + ['portfolio_returns_percentage']
    latexdict = dict()

    for i in per_ret1:
        y = k[i].dropna()
        x = k['%ret_SPY'].dropna()
        x = x-0.01/250 # Subtract risk free rate
        x = sm.add_constant(x) # Add constant for intercept
        model = sm.OLS(y-0.01/250,x)
        res = model.fit()
        print(res.summary())
        if i!='portfolio_returns_percentage':
         # Converting to Latex table
         lat = res.summary2(title=f"{i[5:]} Beta obtained from OLS").as_latex()
        else:
         lat = res.summary2(title=f"{i} Beta obtained from OLS").as_latex()
        latexdict[i] = lat
    lkey = list(latexdict.keys())
```

Calculating and Plotting Idiosyncratic Risk

```
    k['residual'] = ((k.portfolio_returns_percentage-0.01/250) -
    0.9285*(k['%ret_SPY']-0.01/250))**2
    # Only beta is considered above as alpha is 0
    plt.clf()
```

```
plt.plot(k.residual)
plt.xlabel("Time")
plt.ylabel("CAPM Residual")
plt.savefig("residualplot.jpg")

plt.show()
```