

Empirical Asset Pricing

Assignment 01

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Question 1

(a) Let's define the variables that we need to use in the estimation.

$$f(v_t, \theta) = \begin{bmatrix} R_{t1} - \mu_1 \\ R_{t2} - \mu_2 \\ (R_{t1} - \mu_1)^2 - \sigma_1^2 \\ (R_{t2} - \mu_2)^2 - \sigma_2^2 \end{bmatrix}, \quad \theta = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \sigma_1^2 \\ \sigma_2^2 \end{bmatrix}$$

$$g_T(\theta) = \frac{1}{T} \sum_{t=1}^T f(v_t, \theta)$$

We know from the lecture that we need to calculate the $\frac{\partial f}{\partial \theta'}$ to get the \hat{D}_T :

$$\frac{\partial f(v_t, \theta)}{\partial \theta'} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ -2(R_{t1} - \mu_1) & 0 & -1 & 0 \\ 0 & -2(R_{t2} - \mu_2) & 0 & -1 \end{bmatrix}$$

$$\Rightarrow \hat{D}_T = \frac{1}{T} \sum_{t=1}^T \frac{\partial f(v_t, \theta)}{\partial \theta'} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix} = -I$$

We also know that $A_T = I$ and $A_T g_T(\theta) = 0$. Therefore, we can calculate the $\hat{\theta}$:

$$A_T g_T(\theta) = 0 \Rightarrow g_T(\theta) = 0$$

$$g_T(\theta) = \begin{bmatrix} \frac{\sum_{t=1}^T R_{t1}}{T} - \mu_1 \\ \frac{\sum_{t=1}^T R_{t2}}{T} - \mu_2 \\ \frac{\sum_{t=1}^T (R_{t1} - \mu_1)^2}{T} - \sigma_1^2 \\ \frac{\sum_{t=1}^T (R_{t2} - \mu_2)^2}{T} - \sigma_2^2 \end{bmatrix} = 0 \Rightarrow \begin{bmatrix} \frac{\sum_{t=1}^T R_{t1}}{T} \\ \frac{\sum_{t=1}^T R_{t2}}{T} \\ \frac{\sum_{t=1}^T (R_{t1} - \hat{\mu}_1)^2}{T} \\ \frac{\sum_{t=1}^T (R_{t2} - \hat{\mu}_2)^2}{T} \end{bmatrix} = \begin{bmatrix} \hat{\mu}_1 \\ \hat{\mu}_2 \\ \hat{\sigma}_1^2 \\ \hat{\sigma}_2^2 \end{bmatrix} = \hat{\theta}$$

Our calculated $\hat{\theta}$ based on the given data is:

$$\hat{\theta} = \begin{bmatrix} 0.0162 \\ 0.0045 \\ 0.0212 \\ 0.0167 \end{bmatrix}$$

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```

mu_1 = sum(df['Stock1'])/len(df['Stock1'])
mu_2 = sum(df['Stock2'])/len(df['Stock2'])
sigma_1 = sum((df.Stock1 - mu_1)**2)/(len(df.Stock1))
sigma_2 = sum((df.Stock2 - mu_2)**2)/(len(df.Stock2))

```

Listing 1: Python code for calculating $\hat{\theta}$

- (b) Still we assume that there is no serial correlation in the moments. Therefore, we can calculate the \hat{S}_T as follows:

$$\begin{aligned}
\hat{S}_T &= \frac{1}{T} \sum_{t=1}^T f(v_t, \theta) f(v_t, \theta)' \\
&= \frac{1}{T} \sum_{t=1}^T \begin{bmatrix} \frac{(R_{t1} - \mu_1)^2}{(R_{t1} - \mu_1)(R_{t2} - \mu_2)^2 - \sigma_2^2(R_{t1} - \mu_1)} & \frac{(R_{t1} - \mu_1)(R_{t2} - \mu_2)}{(R_{t2} - \mu_2)^2} & \frac{(R_{t1} - \mu_1)^3 - \sigma_1^2(R_{t1} - \mu_1)}{(R_{t1} - \mu_1)^2(R_{t2} - \mu_2) - \sigma_1^2(R_{t2} - \mu_2)} & \frac{(R_{t1} - \mu_1)(R_{t2} - \mu_2)^2 - \sigma_2^2(R_{t1} - \mu_1)}{(R_{t2} - \mu_2)^3 - \sigma_2^2(R_{t2} - \mu_2)} \\ \frac{(R_{t1} - \mu_1)^3 - \sigma_1^2(R_{t1} - \mu_1)}{(R_{t1} - \mu_1)(R_{t2} - \mu_2)^2 - \sigma_2^2(R_{t1} - \mu_1)} & \frac{(R_{t1} - \mu_1)^2(R_{t2} - \mu_2) - \sigma_1^2(R_{t2} - \mu_2)}{(R_{t2} - \mu_2)^3 - \sigma_2^2(R_{t2} - \mu_2)} & \frac{(R_{t1} - \mu_1)^4 - 2\sigma_1^2(R_{t1} - \mu_1)^2 + \sigma_1^4}{(R_{t1} - \mu_1)^2(R_{t2} - \mu_2)^2 - \sigma_1^2(R_{t1} - \mu_1)\sigma_2^2(R_{t2} - \mu_2)} & \frac{(R_{t2} - \mu_2)^3 - \sigma_2^2(R_{t2} - \mu_2)}{(R_{t1} - \mu_1)^2(R_{t2} - \mu_2)^2 - \sigma_1^2(R_{t1} - \mu_1)\sigma_2^2(R_{t2} - \mu_2)} \end{bmatrix} \\
&= \begin{bmatrix} \hat{\sigma}_1^2 & Cov(\hat{R}_1, \hat{R}_2) & \hat{m}_1^{(3)} & \hat{k}_{12}^{(2)} \\ Cov(\hat{R}_1, \hat{R}_2) & \hat{\sigma}_2^2 & \hat{k}_{21}^{(2)} & \hat{m}_2^{(3)} \\ \hat{m}_1^{(3)} & \hat{k}_{12}^{(2)} & \hat{m}_1^{(4)} - \hat{\sigma}_1^4 & \hat{k}_{12}^{(3)} \\ \hat{k}_{21}^{(2)} & \hat{m}_2^{(3)} & \hat{k}_{12}^{(3)} & \hat{m}_2^{(4)} - \hat{\sigma}_2^4 \end{bmatrix}
\end{aligned}$$

Here the definition of $\hat{m}_1^{(j)}$ is the one in the lecture notes. For the $\hat{k}_{mn}^{(j)}$, I do not have a good way to write it in the matrix form. Therefore, I just write it as a way to sum up the terms in the matrix.

As we know that two process are independent, and normally distributed, we can calculate the \hat{S}_T as follows:

$$\hat{S}_T = \begin{bmatrix} \hat{\sigma}_1^2 & 0 & 0 & 0 \\ 0 & \hat{\sigma}_2^2 & 0 & 0 \\ 0 & 0 & 2\hat{\sigma}_1^4 & 0 \\ 0 & 0 & 0 & 2\hat{\sigma}_2^4 \end{bmatrix}$$

Our calculated \hat{S}_T based on the given data is:

$$\hat{S}_T = \begin{bmatrix} 0.0212 & 0 & 0 & 0 \\ 0 & 0.0167 & 0 & 0 \\ 0 & 0 & 0.0347 & 0 \\ 0 & 0 & 0 & 0.0011 \end{bmatrix}$$

```

theta = np.array([mu_1, mu_2, sigma_1, sigma_2])
def f_v(theta, x):
    mu_1 = theta[0]
    mu_2 = theta[1]
    sigma_1 = theta[2]
    sigma_2 = theta[3]
    x_1 = x[0]
    x_2 = x[1]
    f = np.array([x_1 - mu_1, x_2 - mu_2, (x_1 - mu_1)**2 - sigma_1, (x_2 - mu_2)**2 - sigma_2]).reshape(len(theta), 1)
    return f
def s(theta, x):
    f = f_v(theta, x)
    return f @ f.T
x = np.array([df[['Stock1', 'Stock2']]] [0])
s_hat = sum([s(theta, i) for i in x])/len(x)
# set non-diagonal elements to zero

```

```
s_hat = s_hat * np.eye(4)
```

Listing 2: Python function for calculating standard error of estimation

- (c) Now we want to adjust the standard errors by Newey-West estimator. Therefore, we need to calculate the $\hat{\Gamma}_1$ by using the fact that two distributions are independent:

$$\hat{\Gamma}_1 = \begin{bmatrix} \frac{\sum_{t=2}^T (R_t^1 - \mu_1)(R_{t-1}^1 - \mu_1)}{T-1} & 0 & \frac{\sum_{t=2}^T (R_t^1 - \mu_1)(R_{t-1}^1 - \mu_1)^2}{T-1} & 0 \\ 0 & \frac{\sum_{t=2}^T (R_t^2 - \mu_2)(R_{t-1}^2 - \mu_2)}{T-1} & 0 & \frac{\sum_{t=2}^T (R_t^2 - \mu_2)(R_{t-1}^2 - \mu_2)^2}{T-1} \\ \frac{\sum_{t=2}^T (R_{t-1}^1 - \mu_1)(R_{t-1}^1 - \mu_1)^2}{T-1} & 0 & \frac{\sum_{t=2}^T (R_{t-1}^1 - \mu_1)^2 (R_{t-1}^1 - \mu_1)^2}{T-1} + \sigma_1^4 & 0 \\ 0 & \frac{\sum_{t=2}^T (R_{t-1}^2 - \mu_2)(R_{t-1}^2 - \mu_2)^2}{T-1} & 0 & \frac{\sum_{t=2}^T (R_{t-1}^2 - \mu_2)^2 (R_{t-1}^2 - \mu_2)^2}{T-1} + \sigma_2^4 \end{bmatrix}$$

and then we can calculate the \hat{S}_T as follows:

$$\hat{S}_T = \begin{bmatrix} \hat{\sigma}_1^2 & 0 & 0 & 0 \\ 0 & \hat{\sigma}_2^2 & 0 & 0 \\ 0 & 0 & 2\hat{\sigma}_1^4 & 0 \\ 0 & 0 & 0 & 2\hat{\sigma}_2^4 \end{bmatrix} + \frac{1}{2}(\hat{\Gamma}_1 + \hat{\Gamma}_1')$$

Our calculated \hat{S}_T based on the given data is:

$$\hat{S}_T = \begin{bmatrix} 0.0162 & 0 & 0 & 0 \\ 0 & 0.0160 & 0 & 0 \\ 0 & 0 & 0.04 & 0 \\ 0 & 0 & 0 & 0.0013 \end{bmatrix}$$

```
theta = np.array([mu_1, mu_2, sigma_1, sigma_2])
lag = 1
def gamma(theta, x, lag):
    gamma = {}
    for i in range(1, lag + 1):
        lag = np.array(df[['Stock1', 'Stock2']].shift(i).dropna())
        tempt = []
        for num, j in enumerate(x[i:]):
            tempt.append(f_v(theta, j) @ f_v(theta, lag[num]).T)
        gamma[i] = sum(tempt) / len(tempt)
    gamma = [gamma[i] for i in gamma]
    return sum(gamma)

def s_newywest(theta, x):
    gamma_hat = gamma(theta, x, lag)
    return sum([s(theta, i) for i in x]) / len(x) + 0.5 * (gamma_hat +
        gamma_hat.T)
s_hat_newywest = s_newywest(theta, x)
s_hat_newywest * np.eye(4)
```

Listing 3: Python function for calculating Newey-West standard error

- (d) Now we want to compare the Sharpe ratio of two stocks. Therefore, we need to test the hypothesis that:

$$\begin{cases} H_0 : \frac{\mu_1}{\sigma_1} = \frac{\mu_2}{\sigma_2} \\ H_1 : \frac{\mu_1}{\sigma_1} \neq \frac{\mu_2}{\sigma_2} \end{cases} \Rightarrow \begin{cases} H_0 : \mu_1\sigma_2 - \mu_2\sigma_1 = 0 \\ H_1 : \mu_1\sigma_2 - \mu_2\sigma_1 \neq 0 \end{cases}$$

now we can define the $R(\theta)$ as follows:

$$R(\theta) = \mu_1\sigma_2 - \mu_2\sigma_1$$

and then rewrite the hypothesis as follows:

$$H_0 : R(\theta) = 0$$

$$H_1 : R(\theta) \neq 0$$

Now we can use the Delta method to find the distribution of $R(\hat{\theta})$:

$$\begin{aligned}\sqrt{T}(R(\hat{\theta}) - R(\theta)) &\xrightarrow{d} N(0, \frac{\partial R(\theta)}{\partial \theta'} V_{\theta} \frac{\partial R(\theta)}{\partial \theta'}) \\ \sqrt{T}(R(\hat{\theta})) &\xrightarrow{d} N(0, \frac{\partial R(\theta)}{\partial \theta'} V_{\theta} \frac{\partial R(\theta)}{\partial \theta'})\end{aligned}$$

where V_{θ} is the variance of $\hat{\theta}$. Now we can calculate the $\frac{\partial R(\theta)}{\partial \theta'}$ as follows:

$$\frac{\partial R(\theta)}{\partial \theta'} = [\sigma_2 \quad -\sigma_1 \quad -\mu_2 \quad \mu_1]$$

and we know that $V_{\theta} = \hat{S}_T$. Therefore, we can find the distribution of $R(\hat{\theta})$ as follows:

$$\frac{\partial R(\theta)}{\partial \theta'} V_{\theta} \frac{\partial R(\theta)}{\partial \theta'} = [\sigma_2 \quad -\sigma_1 \quad -\mu_2 \quad \mu_1] \hat{S}_T \begin{bmatrix} \sigma_2 \\ -\sigma_1 \\ -\mu_2 \\ \mu_1 \end{bmatrix} = \hat{V}_T$$

Now we can calculate the test statistic as follows:

$$\begin{aligned}TR(\hat{\theta})' \hat{V}_T^{-1} R(\hat{\theta}) &\xrightarrow{d} \chi_1^2 \\ \frac{T(\mu_1\sigma_2 - \mu_2\sigma_1)^2}{\hat{S}_T} &\xrightarrow{d} \chi_1^2\end{aligned}$$

Let's calculate the test statistic:

$$\hat{V}_T = \begin{bmatrix} 0.0167 & -0.0212 & -0.0045 & 0.0162 \end{bmatrix} \begin{bmatrix} 0.0212 & 0 & 0 & 0 \\ 0 & 0.0167 & 0 & 0 \\ 0 & 0 & 0.0347 & 0 \\ 0 & 0 & 0 & 0.0011 \end{bmatrix} \begin{bmatrix} 0.0167 \\ -0.0212 \\ -0.0045 \\ 0.0162 \end{bmatrix} = 0.001449$$

therefore, the test statistic is 1.2602 and the p-value is 0.2612. Therefore, we cannot reject the null hypothesis under 5% significance level. Therefore, we can conclude that there is no significant difference between the Sharpe ratios of two stocks.

```
R_theta = mu_1*sigma_2 - mu_2*sigma_1
R_prime = np.array([sigma_2, -sigma_1, -mu_2, mu_1])
V_T = R_prime @ s_hat @ R_prime.T
test_stat = len(df) * (R_theta)**2 / V_T
```

Listing 4: Python code for calculating the test statistics

- (e) Now we need to recalculate the standard error with the results in part (c). Our \hat{V}_T is equal to 0.000005 and test statistics is 3.1692. The test statistics has been increased but it is still under the critical value of 3.841, which means that we cannot reject the null hypothesis.
- (f) Now we use the bootstrap method to find a distribution of the Sharpe ratios. As we conducted the sample, we realized that our 95% confidence interval contains zero, which means that still we cannot reject the null hypothesis and two stocks' Sharpe ratio are statistically indifferent.

```
# Function to calculate Sharpe ratio
def calculate_sharpe_ratio(returns):
    return np.mean(returns) / np.std(returns)

# Parameters
n_iterations = 10000
confidence_level = 0.95

# Calculate observed Sharpe ratio difference
```

```

sharpe_ratio_diff_observed = calculate_sharpe_ratio(R1) -
    calculate_sharpe_ratio(R2)

# Bootstrap procedure

sharpe_ratio_diff_bootstrap = []
np.random.seed(123)
for _ in range(n_iterations):
    # Generate bootstrapped samples
    bootstrap_sample_stock1 = np.random.choice(R1, size=len(R1), replace=
        True)
    bootstrap_sample_stock2 = np.random.choice(R2, size=len(R2), replace=
        True)

    # Calculate Sharpe ratios for bootstrapped samples
    sharpe_ratio_stock1 = calculate_sharpe_ratio(bootstrap_sample_stock1)
    sharpe_ratio_stock2 = calculate_sharpe_ratio(bootstrap_sample_stock2)

    # Store the Sharpe ratio difference
    sharpe_ratio_diff_bootstrap.append(sharpe_ratio_stock1 -
        sharpe_ratio_stock2)

# Calculate 95% confidence interval
lower_bound, upper_bound = np.percentile(sharpe_ratio_diff_bootstrap, [(1
    - confidence_level) * 100 / 2, confidence_level * 100 - (1 -
    confidence_level) * 100 / 2])

print(f'Observed Sharpe Ratio Difference: {sharpe_ratio_diff_observed:.4 f
    }')
print(f'95% Confidence Interval: [{lower_bound:.4 f}, {upper_bound:.4 f}]')
# The sharp ratio difference is not significant at 5% level.

```

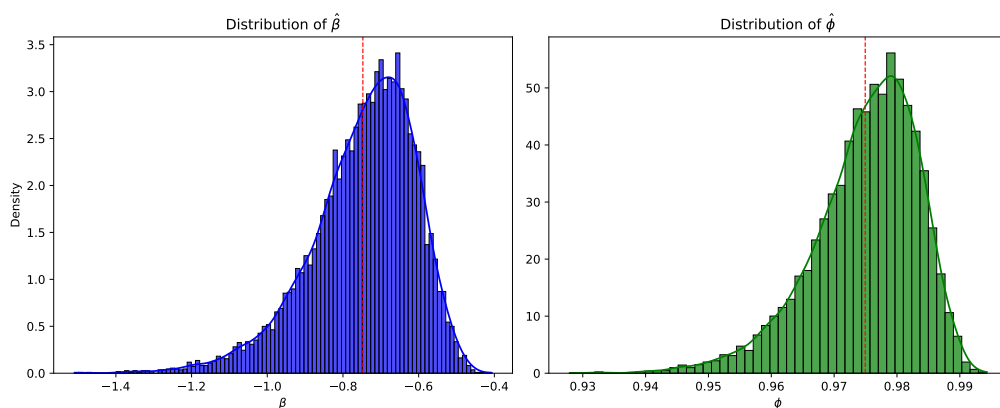
Listing 5: Python code for Bootstrapping

Question 2

(a) Optional

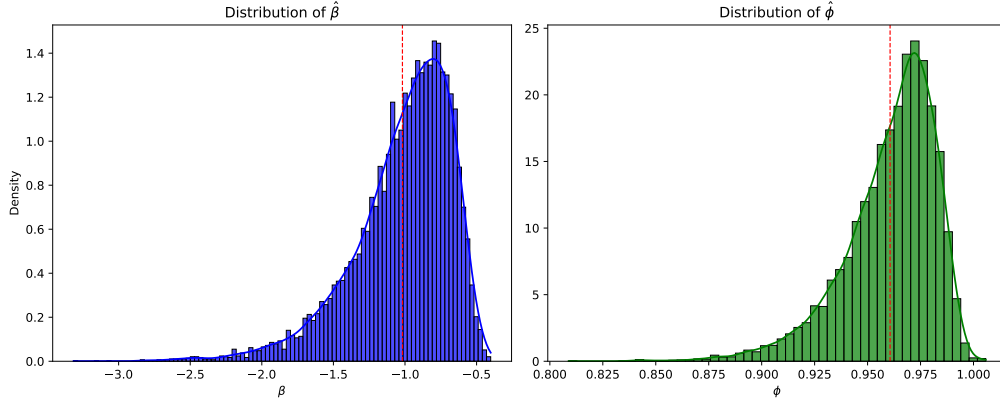
Question 3

(a) N=840



(b) N=240

Looks more skewed to the right side for $\hat{\phi}$



- (c) A rejection rate of 475 out of 10,000 replications corresponds to a 4.75% rejection rate. In hypothesis testing, this would be close to the commonly chosen significance level of 5%. The reason for this difference might be that the number of replications is not big enough and we need to conduct more simulations to see a more precise result; however, 4.75% is quite close to the ideal 5% level.
- (d) The null hypothesis (H_0) is rejected 512 times out of 10,000 when using Newey-West standard errors, suggesting that there might be autocorrelation present in the errors, and the standard errors are adjusted to account for this.

Comparing this result to the rejection rate from problem 3b (475 out of 10,000) when standard errors assuming IID errors were used, the increased number of rejections and being closer to the 5% ideal level with Newey-West standard errors indicate that autocorrelation might be influencing the precision of the coefficient estimates.

Question 4

(a) We predict the out-of-sample returns based on three different models:

i. Using dividend-price ratio:

$$\hat{R}_{t,DP}^e = \hat{\alpha} + \hat{\beta}_{t-1} dp_{t-1}$$

ii. Using all the variables from Dong et al. (2022):

$$\hat{R}_{t,OLS}^e = \hat{\alpha} + \sum_{i=1}^K \hat{\beta}_{i,t-1} X_{i,t-1}$$

iii. Using combination-mean forecast:

$$\hat{R}_{t,CM}^e = \frac{1}{K} \sum_{i=1}^K \hat{R}_{t,i}^e$$

where, for each i ,

$$\hat{R}_{t,i}^e = \hat{\alpha}_i + \hat{\beta}_{i,t-1} dp_{t-1}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are estimated using OLS regression for the in-sample data which is an expanding window from 1970/01 until the previous month of the out-of-sample period. The out-of-sample

period is from 1985/01 until 2017/12. We compare each model using the out-of-sample R^2 which is defined as:

$$R_{oc}^2 = 1 - \frac{\sum_{t=1}^T (R_t^e - \hat{R}_t^e)^2}{\sum_{t=1}^T (R_t^e - \bar{R}_t^e)^2}$$

where R_t^e is the realized excess return and \hat{R}_t^e is the predicted excess return. The out-of-sample R^2 for each model :

Model	R_{oc}^2
DP	-0.0237
OLS	-0.6856
CM	0.0128

Table 1: Out-of-sample R^2 for each model

As we can see, the out-of-sample R^2 for the DP and OLS model is negative which means that the DP model is not able to predict better than the benchmark which is the historical mean and the OLS model is worse than the DP model. However, the CM model has a positive out-of-sample R^2 which means that it is able to predict better than the benchmark.

```
data = pd.read_excel("Assignment1Data_G1.xlsx", sheet_name="
    Predictability")
data = data.dropna()
years = range(1970,2018)
periods = [int(str(i) + "0" + str(j)) for i in years for j in
    range(1,10) if len(str(j)) == 1]
periods.extend([int(str(i) + str(j)) for i in years for j in
    range(10,13) if len(str(j)) == 2 ])
periods.sort()
# %% Estimation
def prediction(X,y):
    beta = sm.OLS(y,X).fit().params.to_numpy()
    return X.iloc[-1].to_numpy() @ beta
BM_results = {}
DP_results = {}
OLS_results = {}
CM_results = {}
for prediction_period in tqdm([j for j in periods if j >=
    198501]):
    in_sample_period = [i for i in periods if i <
        prediction_period]
    in_sample_data = data[data["Month"].isin(in_sample_period)]
    X = sm.add_constant(in_sample_data["dp"])
    y = in_sample_data["ExcessRet"]
    BM_results[prediction_period] = y.mean()
    DP_results[prediction_period] = prediction(X,y)
    columns = list(data)
    columns.remove('Month')
    columns.remove('ExcessRet')
    columns.remove('Rfree')
    columns.remove('dp')
    X = sm.add_constant(in_sample_data[columns])
    OLS_results[prediction_period] = prediction(X,y)
    CM_list= []
    for i in columns:
        X = sm.add_constant(in_sample_data[i])
        CM_list.append(prediction(X,y))
    CM_results[prediction_period] = np.mean(CM_list)
```

Listing 6: Python code for prediction

- (b) We need to perform the Diebold-Mariano test to test for the statistical significance of the difference between the out-of-sample R^2 of the models. The null hypothesis is that the difference between the out-of-sample R^2 is zero. The test statistic is defined as:

$$DM = \frac{\bar{d}}{\sqrt{\frac{1}{T} \sum_{t=1}^T (d_t - \bar{d}_t)^2}}$$

where $d_t = \hat{\varepsilon}_t^2 - \tilde{\varepsilon}_t^2$ and $\bar{d}_t = \frac{1}{T_{os}} \sum d_t$. Also, we use the Clark-West test which has a different definition for the d_t :

$$d_t = \hat{\varepsilon}_t^2 - [\tilde{\varepsilon}_t^2 - (\tilde{R}_t - \hat{R}_t)^2]$$

The calculated test statistics for each model are:

Model	DM	CW
DP	-1.418	-0.0606
OLS	-5.3738	1.321
CM	0.5262	2.0521

Table 2: Out-of-sample R^2 for each model

The critical values for the Diebold-Mariano test are -1.96 and 1.96 for the two-tailed test. Since the test statistics for the DP and CM models are not statistically significant, we cannot reject the null hypothesis that the difference between the out-of-sample R^2 is zero. On the other hand, the test statistic for the OLS model is statistically significant which means that the out-of-sample R^2 of the OLS model is statistically predict less than benchmark model due to the negative sign of the test statistic.

In addition, we can see that the test statistics for the Clark-West test are different from the Diebold-Mariano test. The critical values for the Clark-West test are the same as before. The test statistic for the DP and OLS model are not statistically significant which means that the null hypothesis cannot be rejected. However, the test statistic for the CM model is positive and statistically significant which means that the model is statistically predicts better than benchmark model.

```
def DM_test(y_tilde, y_hat):
    T = len(y_hat)
    d = y_tilde**2 - y_hat**2
    delta_hat = np.mean(d)
    # sigma_hat = np.sqrt(np.sum((d - delta_hat)**2)/(T-1))
    # Newey-West correction with on lag
    sigma_hat = np.sqrt(np.sum((d - delta_hat)**2)/(T-1) + 2*np.sum([d[i]
        ]*d[i-1] for i in range(1,T)])/(T-1))

    DM = delta_hat/sigma_hat * np.sqrt(T)
    return DM

def Clark_West_test(y_tilde, y_hat, R_tilde, R_hat):
    T = len(y_hat)
    d = y_tilde**2 - (y_hat**2 - (R_tilde - R_hat)**2)
    delta_hat = np.mean(d)
    # sigma_hat = np.sqrt(np.sum((d - delta_hat)**2)/(T-1))
    sigma_hat = np.sqrt(np.sum((d - delta_hat)**2)/(T-1) + 2*np.sum([d[i]
        ]*d[i-1] for i in range(1,T)])/(T-1))
    CW = delta_hat/sigma_hat * np.sqrt(T)
    return CW
```

Listing 7: Python code for Diebold-Mariano test

- (c) Now we want to compare the cumulative returns of the portfolios constructed based on the predicted excess returns of each model. The cumulative returns are calculated as:

$$R_{t+1} = R_t + \hat{\omega}_{t,j}^* R_t^e$$

where $\hat{\omega}_{t,j}^*$ is the optimal weight of the portfolio at time t and j is the model. The optimal weights are calculated as:

$$\hat{\omega}_{t,j}^* = \begin{cases} 2 & \text{if } \hat{\omega}_{t,j} \geq 2 \\ \hat{\omega}_{t,j} & \text{if } -1 < \hat{\omega}_{t,j} < 2 \\ -2 & \text{if } \hat{\omega}_{t,j} \leq -1 \end{cases} \quad \text{where} \quad \hat{\omega}_{t,j} = \frac{1}{\gamma} \frac{\hat{R}_{t,j}^e}{\hat{\sigma}_{R^e,t}^2}$$

where γ is the risk aversion parameter and $\hat{\sigma}_{R^e,t}^2$ is the variance of the predicted excess returns over the last 60 months. The cumulative returns of the portfolios are shown in Figure 1. We can see that the cumulative returns of the portfolios based on the DP and OLS models could not beat the benchmark which is the historical mean. However, the cumulative returns of the portfolio based on the CM model is able to beat the benchmark.

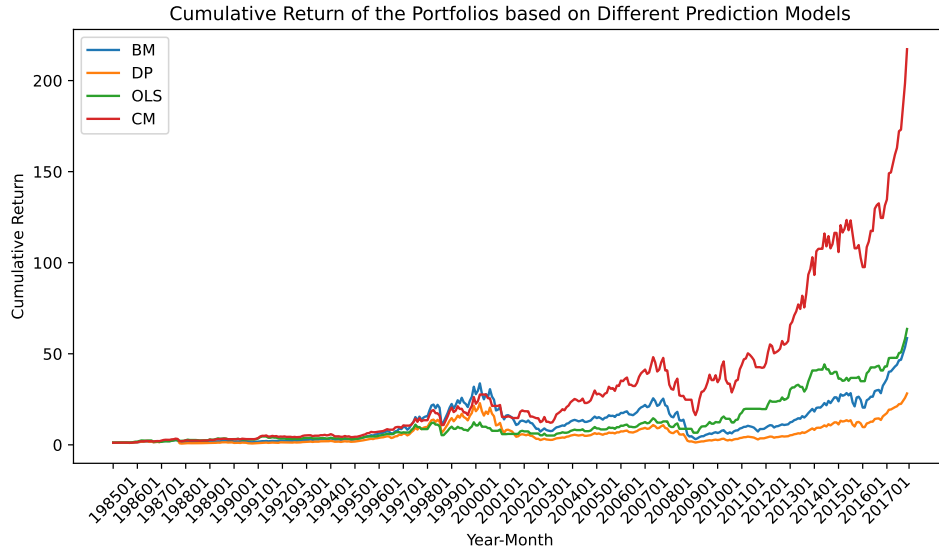


Figure 1: Cumulative returns of the portfolios