

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

EF5058 HW1

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Full File found here: <https://github.com/Toby3220/EF-5058>

Q1) For Equity Market Neutral (EqMktNtr), run the following regression: a multivariate regression on the market (MktRf), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors

#Importing Data

```
data = pd.read_csv("Performance.csv")
```

#format Date to Datetime

```
data["Date"] = pd.to_datetime(data["Date"], format="%Y-%m-%d")
data.set_index("Date", inplace=True)
```

```
data.columns
```

```
Index(['LnShEq', 'EqMktNtr', 'DedShBs', 'GlobalMac ', 'MngdFut ',
      'EmgMkts',
      'EvntDrvn ', ' CnvrArb ', 'FxIncArb ', 'HFIndex', 'LRF',
      'MktRF',
      'SMB', 'HML', 'RMW', 'CMA', 'UMD', 'BondMkt', 'CreditS',
      'PTFSBD',
      'PTFSFX', 'PTFSCOM', 'LiqPS', 'LiqSadka', 'AlphaQuest',
      'Transtrend',
      'VFINX', 'VEXMX', 'NAESX', 'VVIAX', 'VBINX', 'VIMSX', 'VISGX',
      'VISVX',
      'MTUM', 'TSMOM', 'TSMOMCM', 'TSMOMEQ', 'TSMOMFI', 'TSMOMFX'],
      dtype='object')
```

working data group

```
wdata = data.loc[:, ["EqMktNtr", "MktRF", "SMB", "HML", "RMW", "CMA"]]
wdata.dropna(0, inplace=True)
```

creating X,y Datasets, inserting intercept

```
y = wdata.pop("EqMktNtr")
```

```
X = wdata
```

```
X["Intercept"] = 1
```

Running OLS Regression

```
mod = sm.OLS(y,X)
```

```
res = mod.fit()
print(res.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          EqMktNtr    R-squared:
0.111
Model:                  OLS        Adj. R-squared:
0.098
Method:                 Least Squares    F-statistic:
8.466
Date:                   Mon, 24 Feb 2025    Prob (F-statistic):
1.45e-07
Time:                   00:45:24    Log-Likelihood:
805.10
No. Observations:      346    AIC:
-1598.
Df Residuals:          340    BIC:
-1575.
Df Model:               5
```

```
Covariance Type:      nonrobust
```

```
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
MktRF          0.1159      0.033      3.557      0.000      0.052
0.180
SMB           -0.0026      0.048     -0.055      0.957     -0.096
0.091
HML            0.2060      0.055      3.757      0.000      0.098
0.314
RMW           -0.0928      0.061     -1.527      0.128     -0.212
0.027
CMA           -0.1831      0.081     -2.249      0.025     -0.343
-0.023
Intercept      0.0031      0.001      2.305      0.022      0.000
0.006
=====
=====
```

```
Omnibus:          655.665    Durbin-Watson:
1.995
Prob(Omnibus):    0.000    Jarque-Bera (JB):
494805.454
Skew:             -11.688    Prob(JB):
```

0.00

Kurtosis: 186.781 Cond. No.
72.5

=====

Notes:

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

1.1 & 1.2) Interpret the significance of alphas and betas in the regression. Based on the sign of estimated betas, can we say something about the general characteristics of the underlying portfolios?

Firstly, R^2 score of the regression is low, this suggest that a large part of the variance is not explained by current factors

α (the intercept) is significant with a p value of 0.02% although the size of the alpha is modest but positive, at 0.31% per month (3.8% annual). However this might be unreliable as with the low R^2 score suggest missing factors, and regression intercept could change when they are included

$\beta_{MktRF} \wedge \beta_{HML}$ are the most significant, with relatively low but positive exposures in both at 0.11 and 0.21 respectively. This means that there portfolio do have a slight preference towards "Value" stocks and do have very limited market risk exposure. (exposure of 0.11 and 0.21 means that portfolio returns are expected to increase by 0.11% and 0.21% per 1% point increase in the Market Risk Premium and Value factor respectively)

The portfolio is slightly negatively exposed to the investment factor β_{CMA} (-0.18, P value at 2.5%) this suggests slight preference to capital intensive companies

Lastly portfolio exposure to β_{RWM} is only significant at 10+% level and slightly negative (an occational tendency to favor low "profitability" companies), and has no exposure to β_{SMB} (both statistically insignificant and small magnitude of exposure)

Note factor exposure analysis only shows statistical exposure/ preference, and does not necessarily represent actual portfolio exposure/ preference.

1.3) What is EqMktNtr's monthly information ratio if we use the above five factors to calculate the benchmark?

```
def visualise_rets(port_ret, bench_ret, type:int = 0, name:str = None):  
    diff_ret = port_ret - bench_ret  
  
    port = port_ret + 1  
    bench = bench_ret + 1  
    diff = diff_ret + 1  
  
    port_cumret = port.cumprod(0)  
    bench_cumret = bench.cumprod(0)
```

```

    if type == 0:
        plt.plot(port_cumret)
        plt.plot(bench_cumret)
        plt.title("Cumulative Portfolio Returns: {} Entire
Period".format(name))
        plt.legend(["Portfolio", "Factor Portfolio"])
        print("Information Ratio for the Entire Period:
{}".format(round(diff_ret.mean()/diff_ret.std(),4)))

    if type == 1:
        plt.plot(port_cumret.loc[:"2008-06-
01"])/port_cumret.loc[:"2008-06-01"][0])
        plt.plot(bench_cumret.loc[:"2008-06-
01"])/bench_cumret.loc[:"2008-06-01"][0])
        plt.title("Cumulative Portfolio Returns: {} Pre Financial
Crisis".format(name))
        plt.legend(["Portfolio", "Factor Portfolio"])
        print("Information Ratio Pre Financial Crisis:
{}".format(round(diff_ret[:"2008-06-01"].mean()/diff_ret[:"2008-06-
01"].std(),4)))

    if type ==2:
        plt.plot(port_cumret.loc["2009-01-01":]/port_cumret.loc["2009-
01-01":][0])
        plt.plot(bench_cumret.loc["2009-01-
01":]/bench_cumret.loc["2009-01-01":][0])
        plt.title("Cumulative Portfolio Returns: {} Post
2009".format(name))
        plt.legend(["Portfolio", "Factor Portfolio"])
        print("Information Ratio Post 2009:
{}".format(round(diff_ret["2009-01-01":].mean()/diff_ret["2009-01-
01":].std(),4)))

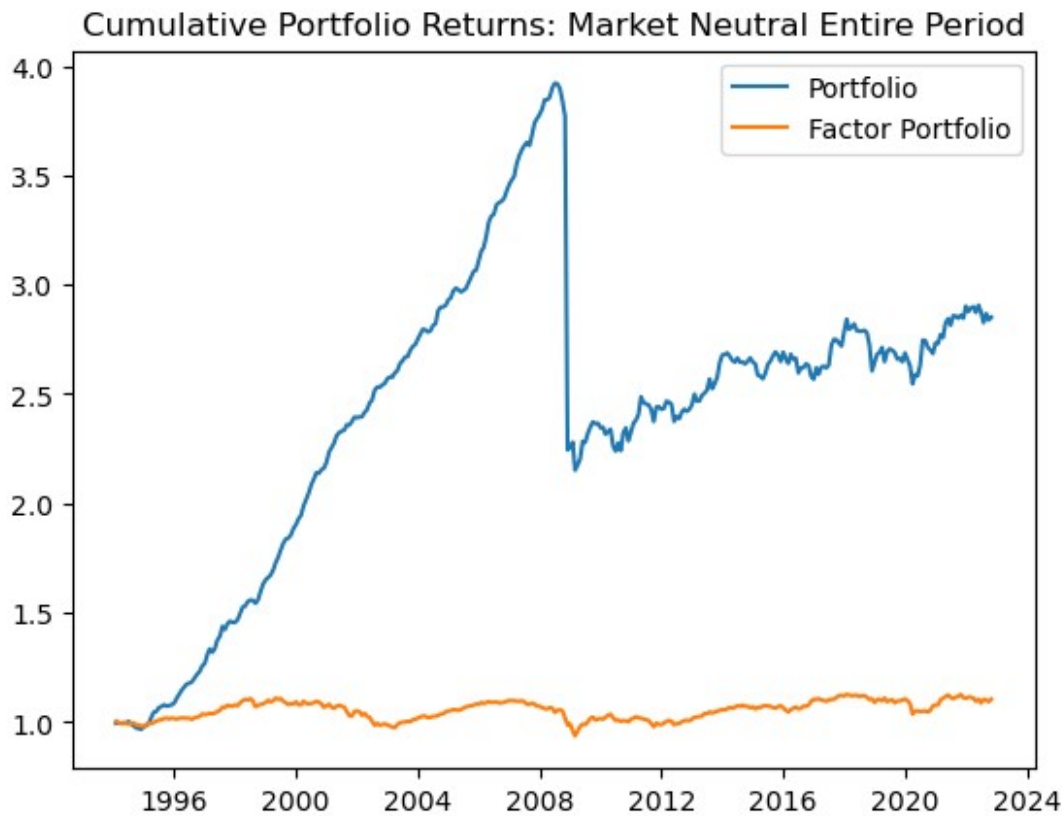
factor_params = res.params.copy()
factor_params["Intercept"] = 0
factor_params

bench_ret = pd.Series(mod.predict(factor_params,X),index=y.index)
port_ret = y

visualise_rets(port_ret,bench_ret,0,"Market Neutral")

Information Ratio for the Entire Period: 0.1317

```

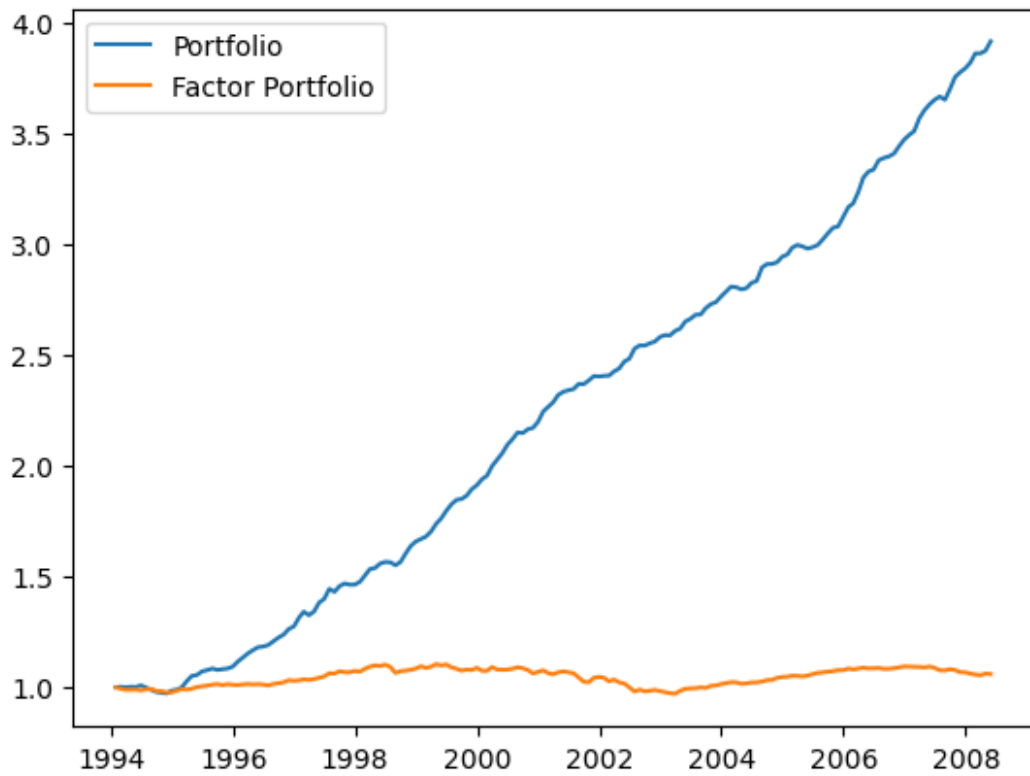


Visualising the data shows that there is a fundamental difference between pre and post financial crisis portfolio performances, this suggest a need for separate analysis for each period

```
visualise_rets(port_ret, bench_ret, 1, "Market Neutral")
```

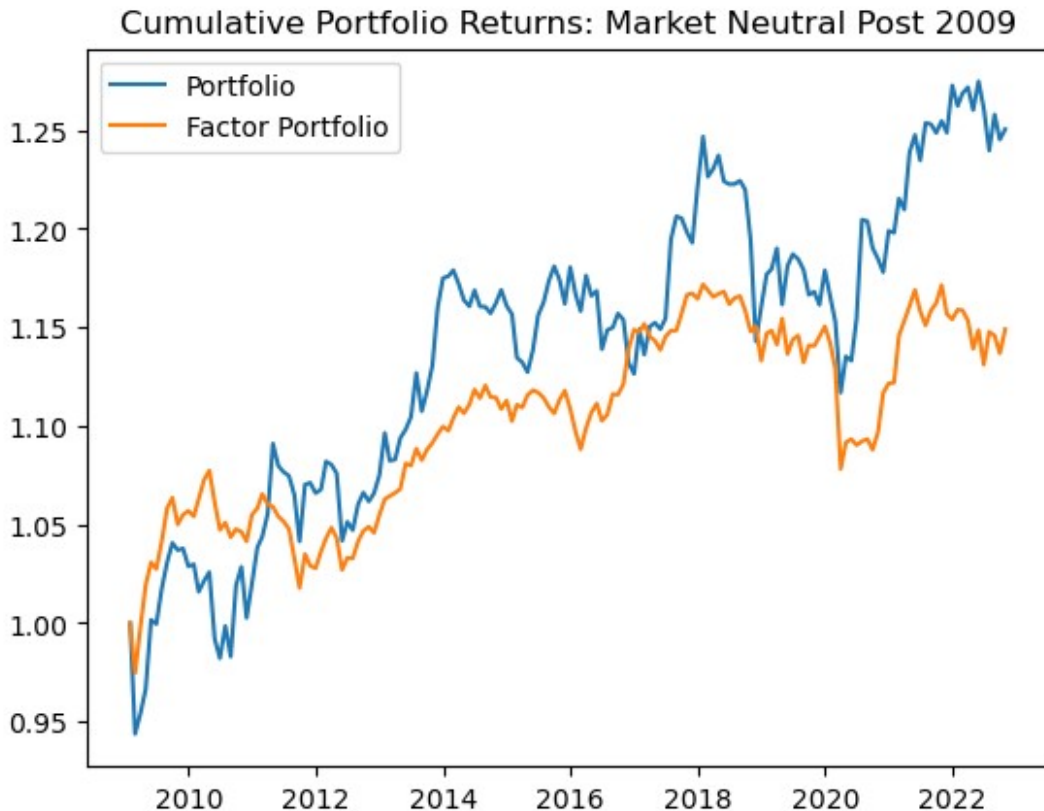
Information Ratio Pre Financial Crisis: 0.8411

Cumulative Portfolio Returns: Market Neutral Pre Financial Crisis



```
visualise_rets(port_ret,bench_ret,2,"Market Neutral")
```

Information Ratio Post 2009: 0.0593



Portfolio "alpha" has disappeared after financial crisis (assuming regressed factors over the entire period), and is reflected in the Information Ratio

2) For Equity Long/Short (LnShEq), run the following two regressions:
 (i) a univariate regression on the market factor; (ii) a multivariate regression on the market, size, value, and momentum (UMD) factor.

Single Factor Regression

```
wdata2 = data.loc[:, ["LnShEq", "MktRF", "SMB", "HML", "UMD"]]
wdata2.dropna(0, inplace=True)
```

```
y2 = wdata2.pop("LnShEq")
wdata2["Intercept"] = 1
X2 = wdata2.loc[:, ["MktRF", "Intercept"]]
```

```
mod = sm.OLS(y2, X2)
res = mod.fit()
print(res.summary())
```

OLS Regression Results

```
=====
=====
Dep. Variable:          LnShEq    R-squared:
```

```

0.563
Model: OLS Adj. R-squared:
0.561
Method: Least Squares F-statistic:
442.6
Date: Mon, 24 Feb 2025 Prob (F-statistic):
9.43e-64
Time: 00:45:24 Log-Likelihood:
920.26
No. Observations: 346 AIC:
-1837.
Df Residuals: 344 BIC:
-1829.
Df Model: 1

```

Covariance Type: nonrobust

```

=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
MktRF          0.4251      0.020     21.038      0.000      0.385
0.465
Intercept      0.0035      0.001      3.842      0.000      0.002
0.005
=====
=====

```

```

Omnibus: 91.243 Durbin-Watson:
1.692
Prob(Omnibus): 0.000 Jarque-Bera (JB):
581.470
Skew: 0.923 Prob(JB):
5.44e-127
Kurtosis: 9.077 Cond. No.
22.1
=====
=====

```

Notes:

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

Full Regression

```

X2=wdata2
mod = sm.OLS(y2,X2)
res = mod.fit()
print(res.summary())

```


OLS Regression Results

```

=====
Dep. Variable:          LnShEq    R-squared:
0.701
Model:                  OLS      Adj. R-squared:
0.697
Method:                 Least Squares    F-statistic:
199.8
Date:                   Mon, 24 Feb 2025    Prob (F-statistic):
4.94e-88
Time:                   00:45:24    Log-Likelihood:
986.01
No. Observations:       346    AIC:
-1962.
Df Residuals:           341    BIC:
-1943.
Df Model:                4
Covariance Type:        nonrobust

```

```

=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
MktRF          0.4408      0.018      23.996      0.000      0.405
0.477
SMB             0.1751      0.025       6.950      0.000      0.126
0.225
HML            -0.0673      0.024      -2.836      0.005     -0.114
-0.021
UMD             0.1469      0.017       8.628      0.000      0.113
0.180
Intercept       0.0027      0.001       3.502      0.001      0.001
0.004

```

```

=====
=====
Omnibus:           13.020    Durbin-Watson:
1.708
Prob(Omnibus):     0.001    Jarque-Bera (JB):
24.337
Skew:              0.175    Prob(JB):
5.19e-06
Kurtosis:          4.251    Cond. No.
34.9

```

Notes:

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

2.1) Interpret the significance of the multivariate alpha and the alpha from the univariate market regression. Discuss the difference between these two alphas. Based on your own research of the availability of equity momentum-style products, do you think the equity long/short strategy should be rewarded for its exposure to UMD?

Alpha is reduced from 0.35% to 0.27% (4.3% to 3.3% annual), but still significant for both. This is due to the introduction of other factors that explain a portion of the alpha, and is a common phenomenon.

There is also significant Momentum factor exposure (statistical, and in magnitude) at 0.14. As Long Short Strategies are typically Long Biased, it can have significant Momentum Factor Exposures. This is different to Market Neutral where exposure to (Long) Momentum cancels out (Short) momentum in terms of factor exposure (this is reflected in the regression of our Market Neutral dataset UMD = 0.018; p val = 0.52 for Market Neutral)

Momentum style products are widely available, so from a market efficient and risk exposure framework, it should not be rewarded. **However** whilst over the long term, markets are typically efficient, in the short term/ locally markets are necessarily inefficient. This can be due to a range of reasons (market psychology/ emergent behaviours, short & market limitations); Therefore participants can be rewarded due to market inefficiencies.

Furthermore, Managers should be additionally rewarded if there is skillful exploitation of momentum effects, i.e. market timing with skillful withdrawal of exposure or "riding the fool". Unfortunately, this is not measurable under momentum factor exposure and instead would be a part of the alpha; however under this process, exposure to momentum factor should be **necessary to attain the market timing alpha** (i.e. **Hypothesis**: a skillful market timing manager would have an alpha compared to a simple momentum portfolio with the same exposure, whilst the simple portfolio would not; However is it not possible for the manager to obtain the market timing alpha without momentum exposure)

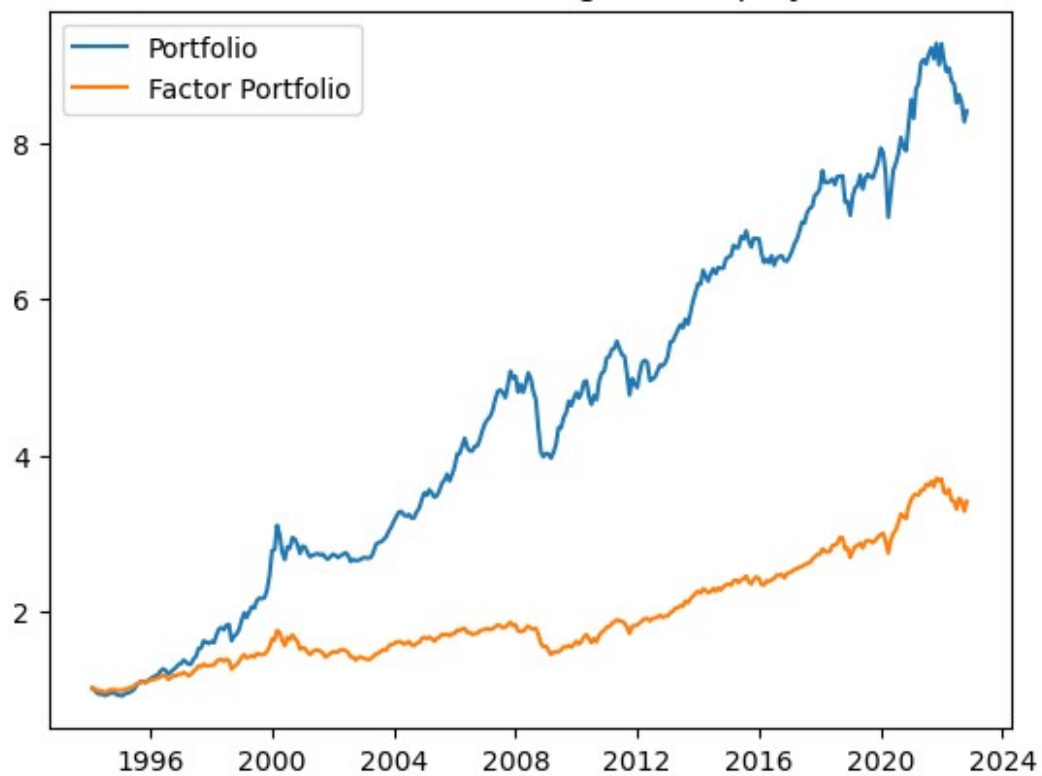
```
factor_params = res.params.copy()
factor_params["Intercept"] = 0
factor_params

bench_ret = pd.Series(mod.predict(factor_params,X2),index=y.index)
port_ret = y2

visualise_rets(port_ret,bench_ret,0,"Long Short Equity")

Information Ratio for the Entire Period: 0.1943
```

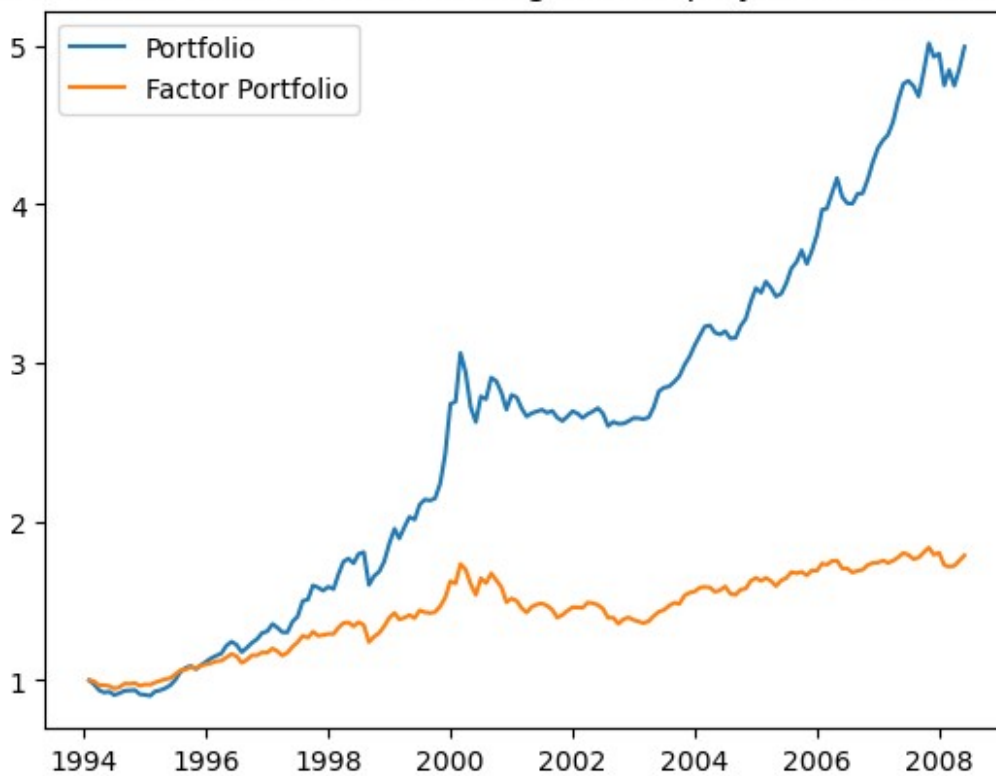
Cumulative Portfolio Returns: Long Short Equity Entire Period



```
visualise_rets(port_ret,bench_ret,1,"Long Short Equity")
```

Information Ratio Pre Financial Crisis: 0.446

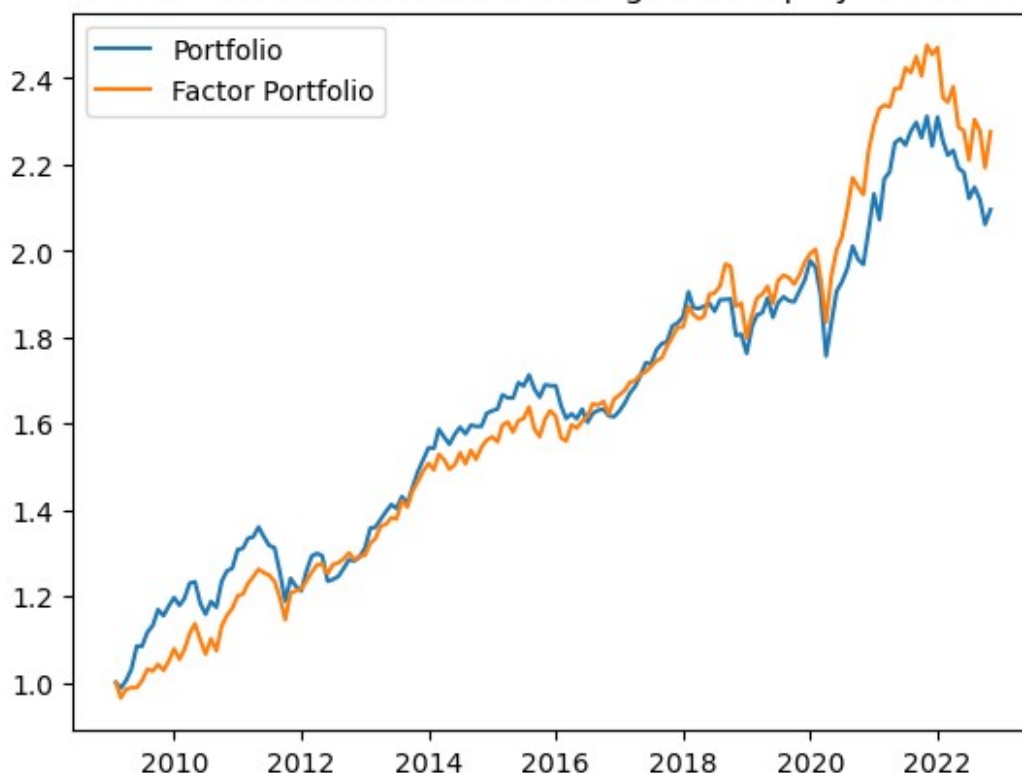
Cumulative Portfolio Returns: Long Short Equity Pre Financial Crisis



```
visualise_rets(port_ret,bench_ret,2,"Long Short Equity")
```

Information Ratio Post 2009: -0.0222

Cumulative Portfolio Returns: Long Short Equity Post 2009



Portfolio "alpha" has disappeared after financial crisis (assuming regressed factors over the entire period), and is reflected in the Information Ratio

3) For Equity Market Neutral (EqMktNtr) and Dedicated Short Bias (DedShBs), report the results of regressing their excess returns on the current, one-month-lagged, two-month-lagged, and three-month-lagged market factor:

```
wdata3 = data.loc[:, ["EqMktNtr", "DedShBs", "MktRF"]]
wdata3["Intercept"] = 1

wdata3["MktRF_L1"] = wdata3["MktRF"].shift(1)
wdata3["MktRF_L2"] = wdata3["MktRF"].shift(2)
wdata3["MktRF_L3"] = wdata3["MktRF"].shift(3)

wdata3.dropna(0, inplace=True)

X31=wdata3.loc[:,
["Intercept", "EqMktNtr", "MktRF", "MktRF_L1", "MktRF_L2", "MktRF_L3"]]
y31=X31.pop("EqMktNtr")

X32=wdata3.loc[:,
["Intercept", "DedShBs", "MktRF", "MktRF_L1", "MktRF_L2", "MktRF_L3"]]
```

```

y32=X32.pop("DedShBs")

mod31 = sm.OLS(y31,X31)
res31 = mod31.fit()
print(res31.summary())

```

OLS Regression Results

```

=====
=====
Dep. Variable:          EqMktNtr    R-squared:
0.138
Model:                  OLS         Adj. R-squared:
0.127
Method:                 Least Squares   F-statistic:
13.49
Date:                   Mon, 24 Feb 2025   Prob (F-statistic):
3.29e-10
Time:                   00:48:27    Log-Likelihood:
801.98
No. Observations:       343    AIC:
-1594.
Df Residuals:           338    BIC:
-1575.
Df Model:                4

Covariance Type:        nonrobust

=====
=====

```

	coef	std err	t	P> t	[0.025
Intercept	0.0013	0.001	0.957	0.339	-0.001
MktRF	0.1509	0.028	5.355	0.000	0.095
MktRF_L1	0.1223	0.028	4.338	0.000	0.067
MktRF_L2	0.0632	0.028	2.228	0.027	0.007
MktRF_L3	-0.0184	0.028	-0.648	0.517	-0.074

```

=====
=====
Omnibus:                639.152    Durbin-Watson:
2.031
Prob(Omnibus):          0.000    Jarque-Bera (JB):
442801.018

```

```
Skew: -11.279 Prob(JB):
0.00
Kurtosis: 177.569 Cond. No.
23.7
```

Notes:

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

```
mod32 = sm.OLS(y32,X32)
res32 = mod32.fit()
print(res32.summary())
```

OLS Regression Results

```
Dep. Variable: DedShBs R-squared:
0.633
Model: OLS Adj. R-squared:
0.629
Method: Least Squares F-statistic:
145.7
Date: Mon, 24 Feb 2025 Prob (F-statistic):
3.05e-72
Time: 00:48:49 Log-Likelihood:
690.74
No. Observations: 343 AIC:
-1371.
Df Residuals: 338 BIC:
-1352.
Df Model: 4
```

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025
Intercept	0.0004	0.002	0.202	0.840	-0.003
MktRF	-0.9333	0.039	-23.953	0.000	-1.010
MktRF_L1	-0.0581	0.039	-1.491	0.137	-0.135
MktRF_L2	0.0313	0.039	0.797	0.426	-0.046

```
0.108
MktRF_L3      0.0702    0.039    1.785    0.075    -0.007
0.148
```

```
=====
```

```
=====
Omnibus:                    53.041    Durbin-Watson:
1.765
Prob(Omnibus):              0.000    Jarque-Bera (JB):
344.073
Skew:                      -0.394    Prob(JB):
1.93e-75
Kurtosis:                  7.843    Cond. No.
23.7
```

```
=====
```

Notes:

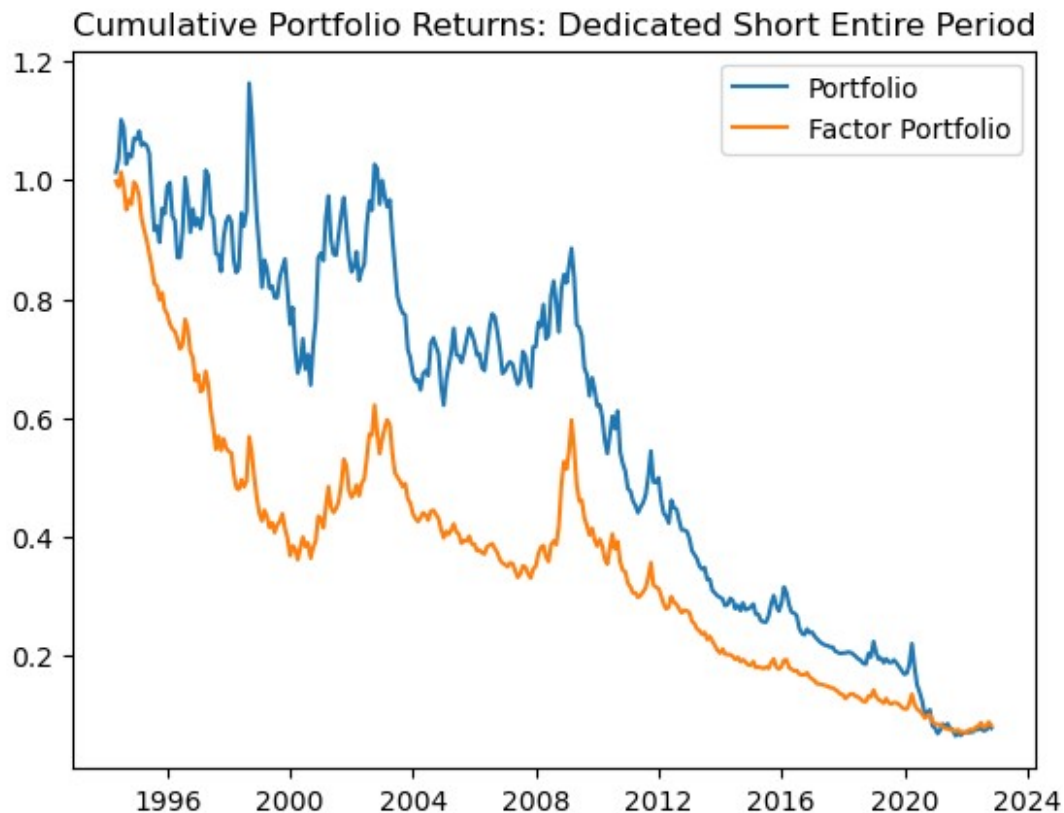
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
factor_params = res32.params.copy()
factor_params["Intercept"] = 0
factor_params
```

```
bench_ret =
pd.Series(mod32.predict(factor_params,X32),index=y32.index)
port_ret = y32
```

```
visualise_rets(port_ret,bench_ret,0,"Dedicated Short")
```

Information Ratio for the Entire Period: 0.0115

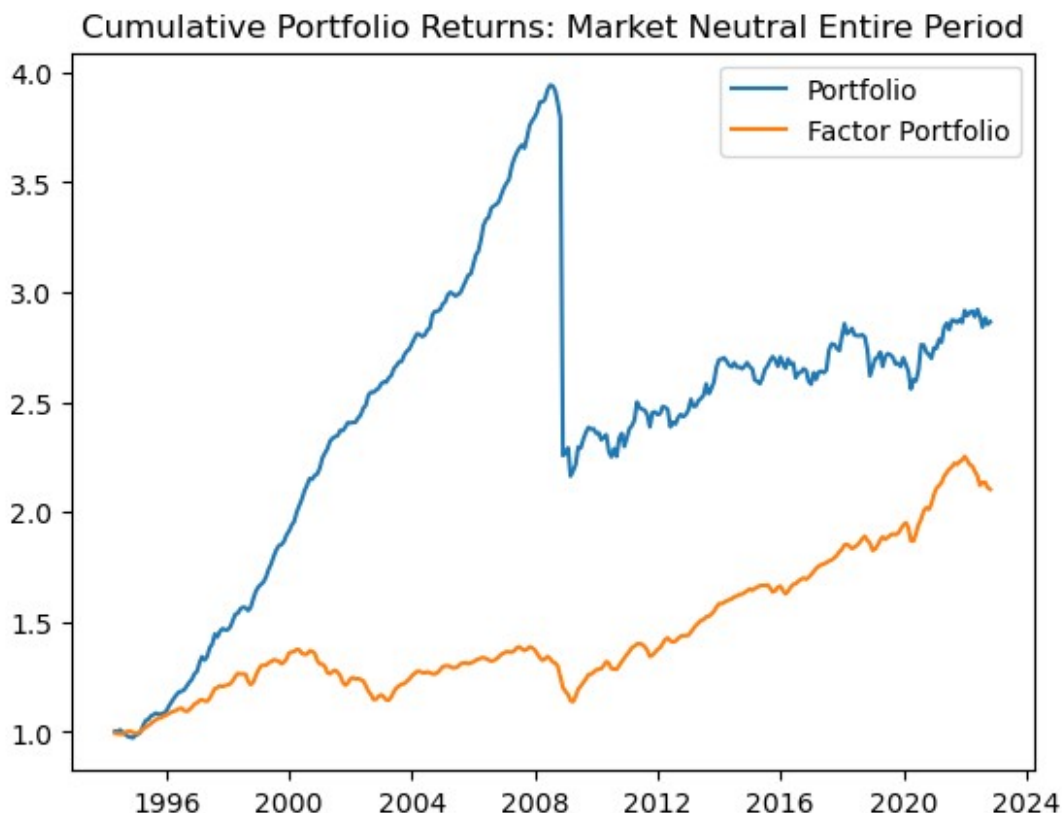


```
factor_params = res31.params.copy()
factor_params["Intercept"] = 0
factor_params

bench_ret =
pd.Series(mod31.predict(factor_params,X31),index=y31.index)
port_ret = y31

visualise_rets(port_ret,bench_ret,0,"Market Neutral")

Information Ratio for the Entire Period: 0.0543
```



3.1) Discuss the significance of the factor loadings. Can you say something about the liquidity of the underlying portfolios of these two strategies?

For Market Neutral; $\beta_{MktRF}, \beta_{MktRFL1} \wedge \beta_{MktRFL2}$ Factors are significant at the 5% level, whilst for the Dedicated Short Bias only β_{MktRF} is significant at the 5% level. This indicates that the Market Neutral Strategy are more illiquid as it demonstrate a delayed marking to market, smoothing the results to make results appear better when updating portfolio values

The risks and limitation of a dedicated short strategy means, that they can be more liquid, than a market neutral strategy. This is because there can be high barrier (borrowing availability, borrowing costs and transaction fees) and liquidity risks (trading induced price movement, short squeeze risks) for illiquid names; whilst market neutral strategy can take long positions in more illiquid names. Furthermore, it is also fundamentally harder to take long term short positions which should lead to quickly realised gains and losses/ & higher turn overs.

Appendix: Disappearing Alphas Post Financial Crisis

most alphas Disappeared post 2009... Why? talent drain/ culture shift in big banks? (not clear if this is data from credit suisse internal desks or industry wide) industry overcrowding? new wave quants eating everyone's lunch?

```
wdata = data.loc[:, ["MktRF", "SMB", "HML", "RMW", "CMA", "UMD"]]
wdata["MktRF_L1"] = wdata["MktRF"].shift(1)
wdata["MktRF_L2"] = wdata["MktRF"].shift(2)
```

```

wdata["MktRF_L3"] = wdata["MktRF"].shift(3)
wdata["Intercept"] = 1

X_EMN = wdata.copy()
X_EMN["EqMktNtr"] = data.loc[:, "EqMktNtr"]
X_EMN.dropna(inplace=True)
y_EMN = X_EMN.pop("EqMktNtr")

X_DSB = wdata.copy()
X_DSB["DedShBs"] = data.loc[:, "DedShBs"]
X_DSB.dropna(inplace=True)
y_DSB = X_DSB.pop("DedShBs")

X_ELS = wdata.copy()
X_ELS["LnShEq"] = data.loc[:, "LnShEq"]
X_ELS.dropna(inplace=True)
y_ELS = X_ELS.pop("LnShEq")

X_ELS = wdata.copy()
X_ELS["LnShEq"] = data.loc[:, "LnShEq"]
X_ELS.dropna(inplace=True)
y_ELS = X_ELS.pop("LnShEq")

X_GMC = wdata.copy()
X_GMC["GlobalMac "] = data.loc[:, "GlobalMac "]
X_GMC.dropna(inplace=True)
y_GMC = X_GMC.pop("GlobalMac ")

X_EME = wdata.copy()
X_EME["EmgMkts"] = data.loc[:, "EmgMkts"]
X_EME.dropna(inplace=True)
y_EME = X_EME.pop("EmgMkts")

def fit_period(y,X,type: int = 0, name: str=None):
    d1 = "2008-06-01"
    d2 = "2009-01-01"

    if type == 0:
        mod = sm.OLS(y,X)
        y_ret = y

    if type == 1:
        mod = sm.OLS(y[:d1],X.loc[:d1,:])
        y_ret = y[:d1]

    if type ==2:
        mod = sm.OLS(y[d2:],X.loc[d2:,:])
        y_ret = y[d2:]

```

```

res = mod.fit()
print(res.summary())

params = res.params.copy()
params["Intercept"] = 0
bench_ret = pd.Series(mod.predict(params,X),index=y.index)

params = res.params.copy()

params.loc[["MktRF_L1","MktRF_L2","MktRF_L3"]]=res.pvalues.loc[["MktRF
_L1","MktRF_L2","MktRF_L3"]]
return y_ret, bench_ret, params

```

Equity Market Neutral

```

# Pre FC
y_ret_d1, EMN_bench_ret_d1, EMN_params_d1 =
fit_period(y_EMN,X_EMN,1,"Equity Market Neutral")

visualise_rets(y_EMN,EMN_bench_ret_d1,1,"Equity Market Neutral")

```

OLS Regression Results

```

=====
=====
Dep. Variable:                  EqMktNtr    R-squared:
0.131
Model:                          OLS        Adj. R-squared:
0.082
Method:                        Least Squares    F-statistic:
2.670
Date:                          Mon, 24 Feb 2025    Prob (F-statistic):
0.00650
Time:                          00:45:26    Log-Likelihood:
591.56
No. Observations:              170    AIC:
-1163.
Df Residuals:                  160    BIC:
-1132.
Df Model:                      9

Covariance Type:               nonrobust

=====
=====

```

	coef	std err	t	P> t	[0.025
	0.975]				

```

-----
-----

```

MktRF	0.0772	0.019	4.030	0.000	0.039
0.115					
SMB	0.0067	0.021	0.320	0.749	-0.035
0.048					
HML	-0.0109	0.034	-0.321	0.749	-0.078
0.056					
RMW	0.0420	0.030	1.385	0.168	-0.018
0.102					
CMA	0.0022	0.038	0.057	0.954	-0.073
0.077					
UMD	-0.0035	0.013	-0.264	0.792	-0.029
0.022					
MktRF_L1	0.0117	0.015	0.792	0.430	-0.018
0.041					
MktRF_L2	0.0023	0.015	0.155	0.877	-0.027
0.031					
MktRF_L3	0.0016	0.014	0.112	0.911	-0.027
0.030					
Intercept	0.0074	0.001	11.291	0.000	0.006
0.009					

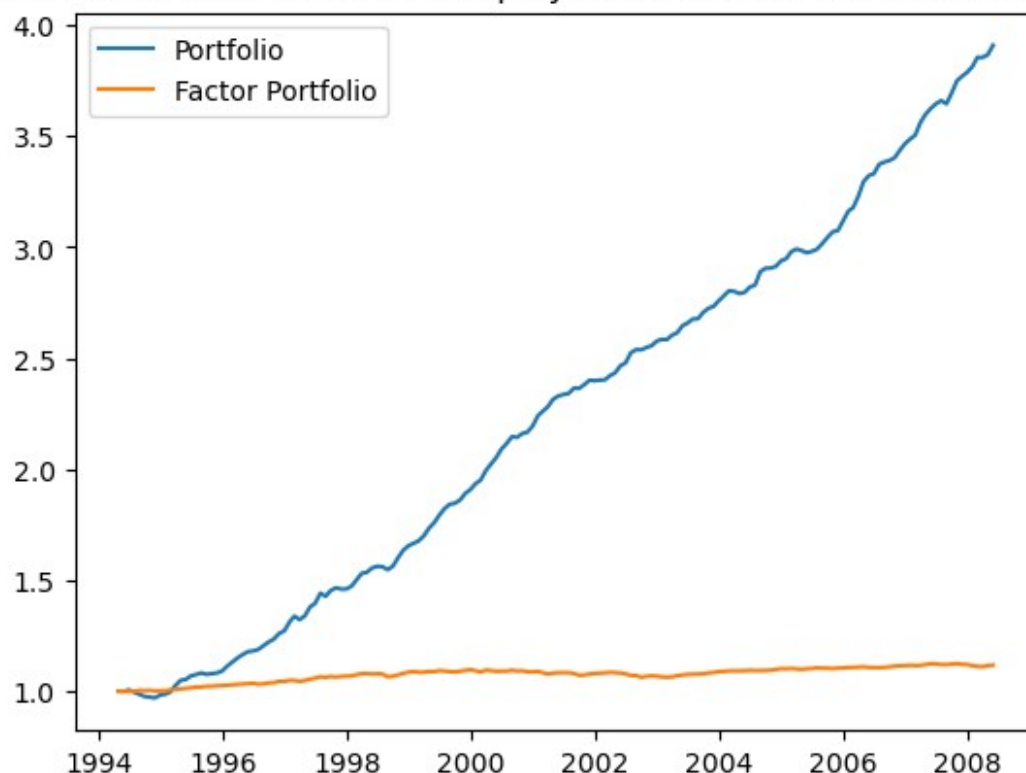
```
=====
=====
Omnibus:                0.863    Durbin-Watson:
1.371
Prob(Omnibus):          0.649    Jarque-Bera (JB):
0.526
Skew:                   0.088    Prob(JB):
0.769
Kurtosis:               3.208    Cond. No.
84.7
=====
=====
```

Notes:

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

Information Ratio Pre Financial Crisis: 0.9947

Cumulative Portfolio Returns: Equity Market Neutral Pre Financial Crisis



```
# Post 2009
y_ret_d1, EMN_bench_ret_d2, EMN_params_d2 =
fit_period(y_EMN,X_EMN,2,"Equity Market Neutral")

visualise_rets(y_EMN,EMN_bench_ret_d2,2,"Equity Market Neutral")
```

OLS Regression Results

```
=====
=====
Dep. Variable:                  EqMktNtr    R-squared:
0.260
Model:                          OLS        Adj. R-squared:
0.218
Method:                        Least Squares    F-statistic:
6.097
Date:                          Mon, 24 Feb 2025    Prob (F-statistic):
2.51e-07
Time:                          00:45:26    Log-Likelihood:
493.42
No. Observations:              166    AIC:
-966.8
Df Residuals:                  156    BIC:
-935.7
```

Df Model: 9

Covariance Type: nonrobust

=====					
	coef	std err	t	P> t	[0.025
0.975]					

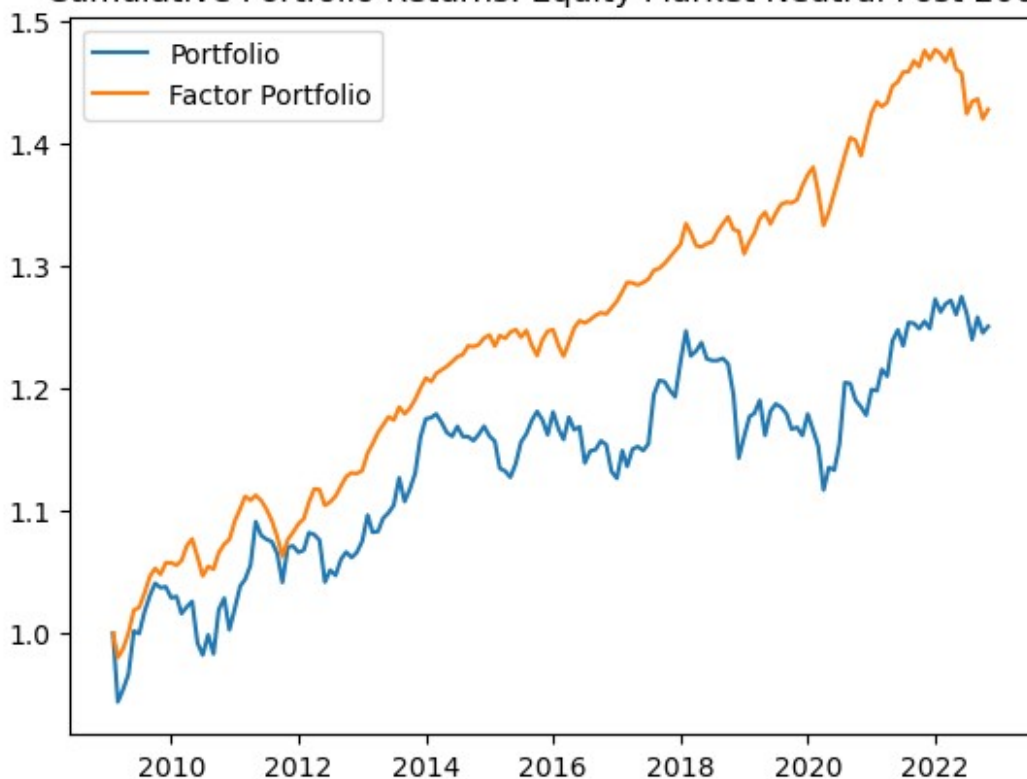
MktRF	0.1661	0.025	6.540	0.000	0.116
0.216					
SMB	-0.0849	0.046	-1.847	0.067	-0.176
0.006					
HML	0.0171	0.045	0.383	0.702	-0.071
0.105					
RMW	-0.0930	0.057	-1.631	0.105	-0.206
0.020					
CMA	0.0531	0.069	0.775	0.440	-0.082
0.188					
UMD	0.0097	0.026	0.369	0.712	-0.042
0.062					
MktRF_L1	0.0535	0.022	2.420	0.017	0.010
0.097					
MktRF_L2	0.0177	0.023	0.780	0.437	-0.027
0.062					
MktRF_L3	-0.0281	0.022	-1.257	0.211	-0.072
0.016					
Intercept	-0.0006	0.001	-0.516	0.607	-0.003
0.002					
=====					
=====					
Omnibus:		3.480	Durbin-Watson:		
2.350					
Prob(Omnibus):		0.175	Jarque-Bera (JB):		
3.653					
Skew:		-0.135	Prob(JB):		
0.161					
Kurtosis:		3.675	Cond. No.		
77.3					
=====					
=====					

Notes:

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

Information Ratio Post 2009: -0.0477

Cumulative Portfolio Returns: Equity Market Neutral Post 2009



```
#MktRF_L1, L2, L3 shows p values instead
EMN_Params = EMN_params_d1.to_frame("PFC")
EMN_Params["Post09"] = EMN_params_d2
EMN_Params.round(4)
```

	PFC	Post09
MktRF	0.0772	0.1661
SMB	0.0067	-0.0849
HML	-0.0109	0.0171
RMW	0.0420	-0.0930
CMA	0.0022	0.0531
UMD	-0.0035	0.0097
MktRF_L1	0.4298	0.0167
MktRF_L2	0.8773	0.4366
MktRF_L3	0.9111	0.2107
Intercept	0.0074	-0.0006

There's a different style and reduced liquidity Post 2009; No alpha

Equity Long Short

```
# Pre FC
y_ret_d1, ELS_bench_ret_d1, ELS_params_d1 =
fit_period(y_ELS, X_ELS, 1, "Equity Long Short")
```



```
visualise_rets(y_ELS,ELS_bench_ret_d1,1,"Equity Long Short")
```

OLS Regression Results

```
=====
Dep. Variable:          LnShEq    R-squared:
0.812
Model:                  OLS      Adj. R-squared:
0.801
Method:                 Least Squares    F-statistic:
76.55
Date:                   Mon, 24 Feb 2025    Prob (F-statistic):
2.20e-53
Time:                   00:45:26    Log-Likelihood:
507.78
No. Observations:       170    AIC:
-995.6
Df Residuals:           160    BIC:
-964.2
Df Model:                9
```

```
Covariance Type:        nonrobust
```

```
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
MktRF          0.4384      0.031     13.990      0.000      0.377
0.500
SMB             0.2027      0.035      5.870      0.000      0.135
0.271
HML            -0.0087      0.056     -0.157      0.876     -0.118
0.101
RMW            -0.0617      0.050     -1.242      0.216     -0.160
0.036
CMA            -0.1322      0.062     -2.118      0.036     -0.255
-0.009
UMD             0.2160      0.021     10.073      0.000      0.174
0.258
MktRF_L1        0.0775      0.024      3.199      0.002      0.030
0.125
MktRF_L2        0.0377      0.024      1.556      0.122     -0.010
0.085
MktRF_L3        0.0089      0.024      0.380      0.704     -0.038
0.055
Intercept       0.0056      0.001      5.239      0.000      0.004
```

0.008

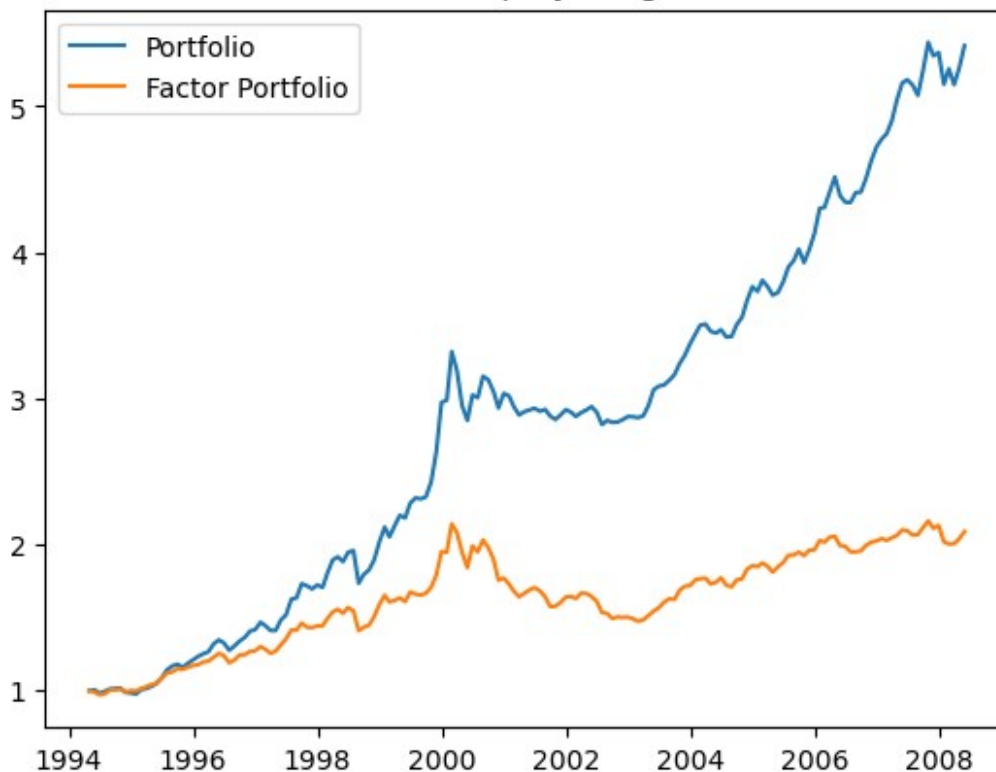
```
=====
=====
Omnibus:                                0.320    Durbin-Watson:
1.840
Prob(Omnibus):                          0.852    Jarque-Bera (JB):
0.435
Skew:                                   0.093    Prob(JB):
0.805
Kurtosis:                              2.836    Cond. No.
84.7
=====
=====
```

Notes:

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

Information Ratio Pre Financial Crisis: 0.4615

Cumulative Portfolio Returns: Equity Long Short Pre Financial Crisis



```
# Pre FC
y_ret_d1, ELS_bench_ret_d2, ELS_params_d2 =
fit_period(y_ELS,X_ELS,2,"Equity Long Short")

visualise_rets(y_ELS,ELS_bench_ret_d2,2,"Equity Long Short")
```

OLS Regression Results

```

=====
Dep. Variable:          LnShEq    R-squared:
0.756
Model:                  OLS      Adj. R-squared:
0.742
Method:                 Least Squares    F-statistic:
53.80
Date:                   Mon, 24 Feb 2025    Prob (F-statistic):
2.25e-43
Time:                   00:45:26    Log-Likelihood:
526.81
No. Observations:      166    AIC:
-1034.
Df Residuals:          156    BIC:
-1002.
Df Model:               9
Covariance Type:       nonrobust

```

```

=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
MktRF          0.3843      0.021     18.502      0.000      0.343
0.425
SMB            -0.0360      0.038     -0.958      0.340     -0.110
0.038
HML             0.0560      0.037      1.533      0.127     -0.016
0.128
RMW            -0.0546      0.047     -1.171      0.243     -0.147
0.037
CMA            -0.1633      0.056     -2.915      0.004     -0.274
-0.053
UMD             0.0144      0.022      0.669      0.505     -0.028
0.057
MktRF_L1        0.0501      0.018      2.771      0.006      0.014
0.086
MktRF_L2         0.0169      0.019      0.914      0.362     -0.020
0.053
MktRF_L3        -0.0142      0.018     -0.776      0.439     -0.050
0.022
Intercept       0.0002      0.001      0.218      0.828     -0.002
0.002

```

Omnibus:	7.016	Durbin-Watson:
2.049		
Prob(Omnibus):	0.030	Jarque-Bera (JB):
8.642		
Skew:	0.284	Prob(JB):
0.0133		
Kurtosis:	3.963	Cond. No.
77.3		

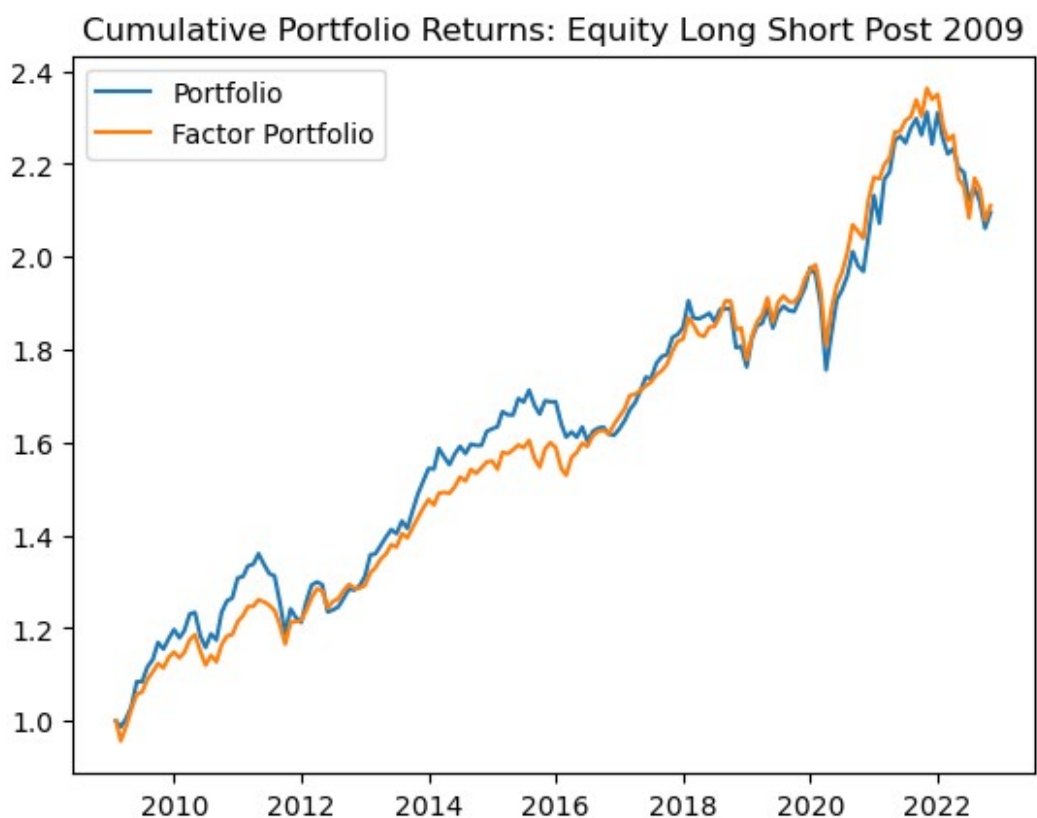
=====

=====

Notes:

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

Information Ratio Post 2009: 0.0201



```
# MktRF_L1, L2, L3 shows pvalues instead
ELS_Params = ELS_params_d1.to_frame("PFC")
ELS_Params["Post09"] = ELS_params_d2
ELS_Params.round(4)
```

	PFC	Post09
MktRF	0.4384	0.3843
SMB	0.2027	-0.0360

HML	-0.0087	0.0560
RMW	-0.0617	-0.0546
CMA	-0.1322	-0.1633
UMD	0.2160	0.0144
MktRF_L1	0.0017	0.0063
MktRF_L2	0.1217	0.3623
MktRF_L3	0.7044	0.4387
Intercept	0.0056	0.0002

There's a change in style; again next to No alpha

Short Bias

```
# Pre FC
y_ret_d1, DSB_bench_ret_d1, DSB_params_d1 =
fit_period(y_DSB,X_DSB,1,"Dedicated Short Bias")

visualise_rets(y_DSB,DSB_bench_ret_d1,1,"Dedicated Short Bias")
```

OLS Regression Results

```
=====
=====
Dep. Variable:                DedShBs    R-squared:
0.767
Model:                        OLS        Adj. R-squared:
0.754
Method:                       Least Squares    F-statistic:
58.65
Date:                          Mon, 24 Feb 2025    Prob (F-statistic):
3.72e-46
Time:                          00:45:27    Log-Likelihood:
397.60
No. Observations:              170    AIC:
-775.2
Df Residuals:                  160    BIC:
-743.9
Df Model:                       9

Covariance Type:              nonrobust

=====
=====
               coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
MktRF          -0.9155      0.060     -15.280      0.000     -1.034
-0.797
SMB            -0.3809      0.066      -5.770      0.000     -0.511
```

-0.251					
HML	0.1643	0.106	1.548	0.124	-0.045
0.374					
RMW	-0.2014	0.095	-2.122	0.035	-0.389
-0.014					
CMA	0.1425	0.119	1.195	0.234	-0.093
0.378					
UMD	-0.0275	0.041	-0.671	0.503	-0.108
0.053					
MktRF_L1	-0.0512	0.046	-1.107	0.270	-0.143
0.040					
MktRF_L2	0.0639	0.046	1.380	0.169	-0.028
0.155					
MktRF_L3	-0.0230	0.045	-0.510	0.611	-0.112
0.066					
Intercept	0.0054	0.002	2.609	0.010	0.001
0.009					

```

=====
=====
Omnibus:                4.130    Durbin-Watson:
1.810
Prob(Omnibus):          0.127    Jarque-Bera (JB):
3.940
Skew:                   -0.246    Prob(JB):
0.139
Kurtosis:               3.561    Cond. No.
84.7
=====
=====

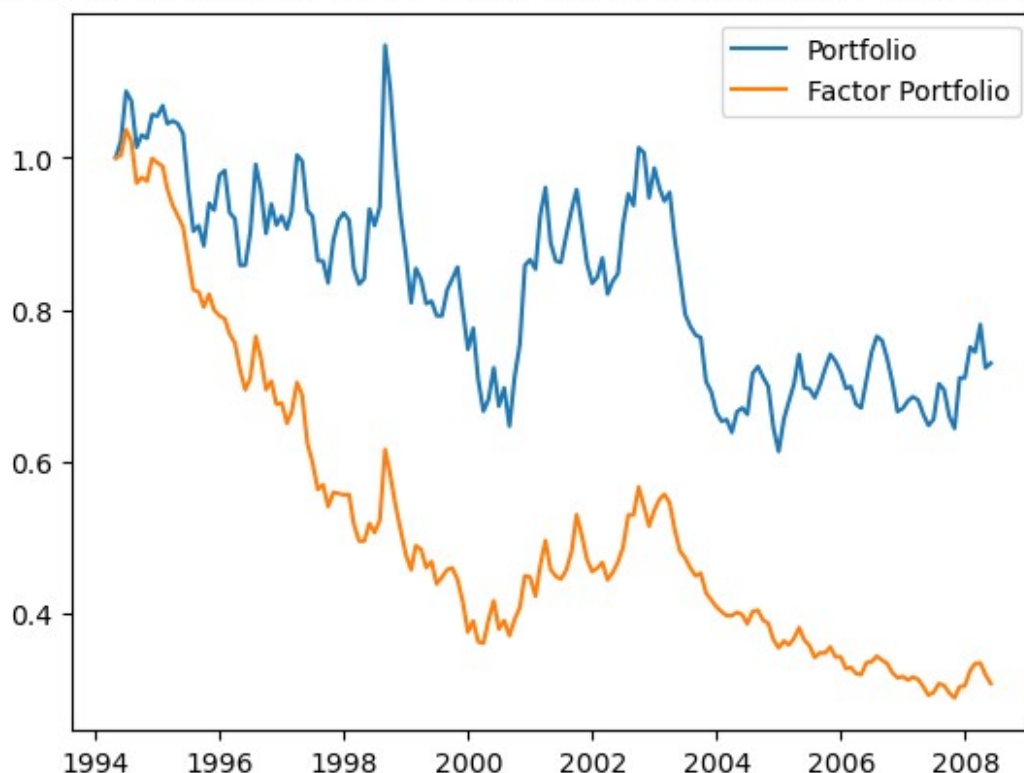
```

Notes:

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

Information Ratio Pre Financial Crisis: 0.2299

Cumulative Portfolio Returns: Dedicated Short Bias Pre Financial Crisis



```
# Pre FC
y_ret_d2, DSB_bench_ret_d2, DSB_params_d2 =
fit_period(y_DSB,X_DSB,2,"Dedicated Short Bias")

visualise_rets(y_DSB,DSB_bench_ret_d2,2,"Dedicated Short Bias")
```

OLS Regression Results

```
=====
=====
Dep. Variable:                DedShBs    R-squared:
0.699
Model:                        OLS        Adj. R-squared:
0.682
Method:                       Least Squares    F-statistic:
40.30
Date:                          Mon, 24 Feb 2025    Prob (F-statistic):
2.30e-36
Time:                          00:45:27    Log-Likelihood:
339.95
No. Observations:              166    AIC:
-659.9
Df Residuals:                  156    BIC:
-628.8
```

Df Model: 9

Covariance Type: nonrobust

=====					
	coef	std err	t	P> t	[0.025
0.975]					

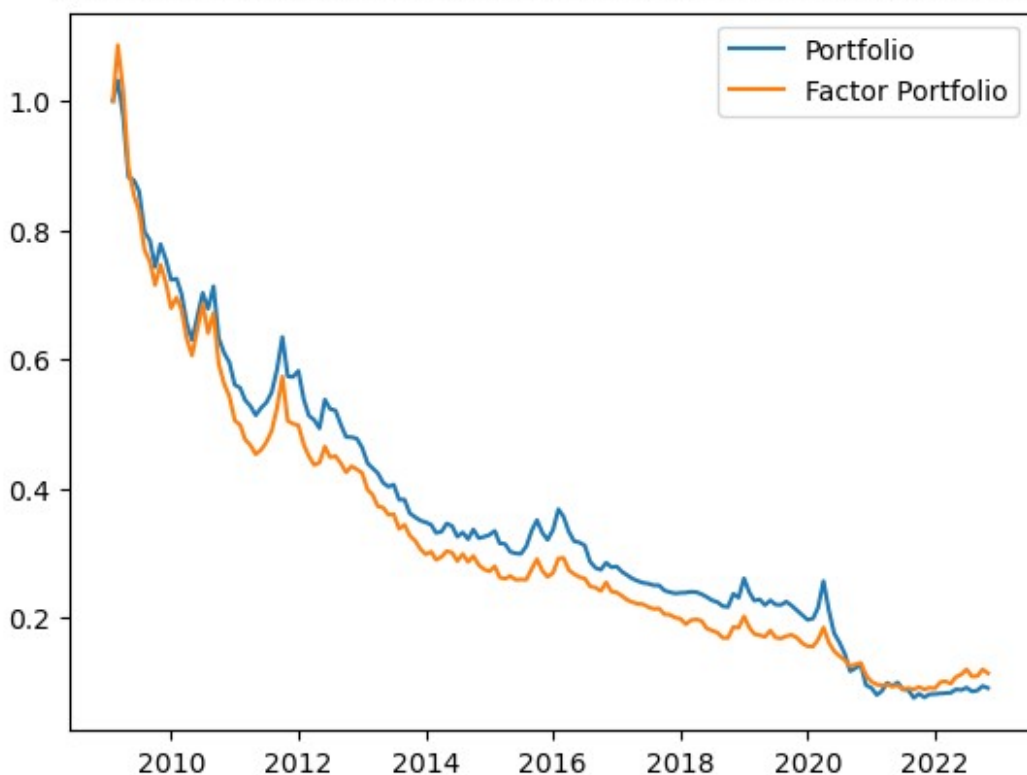
MktRF	-0.9468	0.064	-14.789	0.000	-1.073
-0.820					
SMB	-0.4497	0.116	-3.882	0.000	-0.679
-0.221					
HML	0.3658	0.113	3.247	0.001	0.143
0.588					
RMW	0.2498	0.144	1.738	0.084	-0.034
0.534					
CMA	-0.2403	0.173	-1.391	0.166	-0.581
0.101					
UMD	-0.0004	0.066	-0.006	0.995	-0.131
0.131					
MktRF_L1	-0.0896	0.056	-1.608	0.110	-0.200
0.020					
MktRF_L2	-0.0029	0.057	-0.050	0.960	-0.116
0.110					
MktRF_L3	0.0307	0.056	0.545	0.587	-0.081
0.142					
Intercept	-0.0008	0.003	-0.284	0.777	-0.007
0.005					
=====					
=====					
Omnibus:	30.780		Durbin-Watson:		
2.035					
Prob(Omnibus):	0.000		Jarque-Bera (JB):		
152.633					
Skew:	-0.484		Prob(JB):		
7.18e-34					
Kurtosis:	7.597		Cond. No.		
77.3					
=====					
=====					

Notes:

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

Information Ratio Post 2009: -0.0263

Cumulative Portfolio Returns: Dedicated Short Bias Post 2009



```
# MktRF_L1, L2, L3 shows pvalues instead
DSB_Params = DSB_params_d1.to_frame("PFC")
DSB_Params["Post09"] = DSB_params_d2
DSB_Params.round(4)
```

	PFC	Post09
MktRF	-0.9155	-0.9468
SMB	-0.3809	-0.4497
HML	0.1643	0.3658
RMW	-0.2014	0.2498
CMA	0.1425	-0.2403
UMD	-0.0275	-0.0004
MktRF_L1	0.2701	0.1099
MktRF_L2	0.1694	0.9599
MktRF_L3	0.6105	0.5866
Intercept	0.0054	-0.0008

style mostly the same, Momentum just disappeared, Again there's no alpha

Global Macro

```
# Pre FC
y_ret_d1, GMC_bench_ret_d1, GMC_params_d1 =
fit_period(y_GMC, X_GMC, 1, "Global Macro")
```

visualise_rets(y_GMC,GMC_bench_ret_d1,1,"Global Macro")

OLS Regression Results

```
=====
=====
Dep. Variable:          GlobalMac      R-squared:
0.140
Model:                  OLS           Adj. R-squared:
0.092
Method:                 Least Squares   F-statistic:
2.891
Date:                   Mon, 24 Feb 2025   Prob (F-statistic):
0.00341
Time:                   00:45:27         Log-Likelihood:
371.14
No. Observations:       170             AIC:
-722.3
Df Residuals:           160             BIC:
-690.9
Df Model:                9
Covariance Type:        nonrobust
=====
=====
```

	coef	std err	t	P> t	[0.025
0.975]					

MktRF	0.2332	0.070	3.331	0.001	0.095
0.371					
SMB	0.0664	0.077	0.860	0.391	-0.086
0.219					
HML	0.1509	0.124	1.217	0.225	-0.094
0.396					
RMW	-0.0069	0.111	-0.062	0.950	-0.226
0.212					
CMA	0.0177	0.139	0.127	0.899	-0.258
0.293					
UMD	0.1147	0.048	2.394	0.018	0.020
0.209					
MktRF_L1	-0.0132	0.054	-0.244	0.808	-0.120
0.094					
MktRF_L2	0.1122	0.054	2.075	0.040	0.005
0.219					
MktRF_L3	-0.0144	0.053	-0.273	0.785	-0.118
0.089					
Intercept	0.0087	0.002	3.605	0.000	0.004

0.013

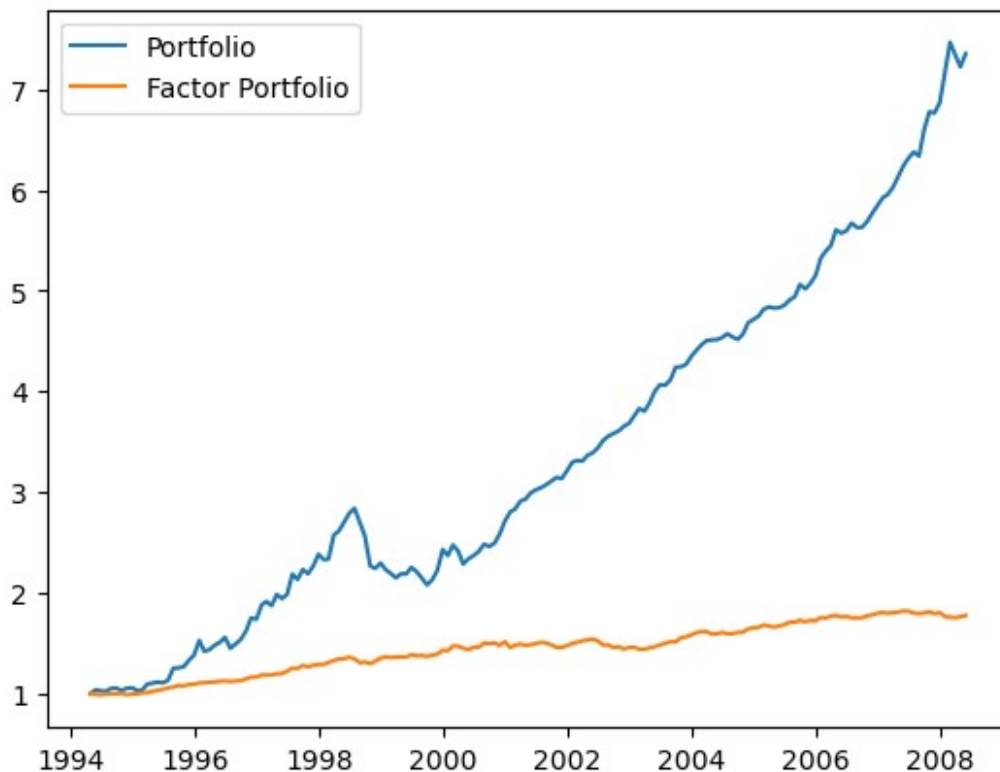
```
=====
=====
Omnibus:                15.121    Durbin-Watson:
1.952
Prob(Omnibus):          0.001    Jarque-Bera (JB):
48.230
Skew:                   0.086    Prob(JB):
3.36e-11
Kurtosis:               5.604    Cond. No.
84.7
=====
=====
```

Notes:

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

Information Ratio Pre Financial Crisis: 0.3175

Cumulative Portfolio Returns: Global Macro Pre Financial Crisis



```
# Pre FC
y_ret_d2, GMC_bench_ret_d2, GMC_params_d2 =
fit_period(y_GMC,X_GMC,2,"Global Macro")

visualise_rets(y_GMC,GMC_bench_ret_d2,2,"Global Macro")
```

OLS Regression Results

```

=====
Dep. Variable:          GlobalMac      R-squared:
0.216
Model:                  OLS           Adj. R-squared:
0.170
Method:                 Least Squares   F-statistic:
4.764
Date:                   Mon, 24 Feb 2025   Prob (F-statistic):
1.30e-05
Time:                   00:45:28         Log-Likelihood:
466.12
No. Observations:      166             AIC:
-912.2
Df Residuals:          156             BIC:
-881.1
Df Model:               9
Covariance Type:       nonrobust

```

```

=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
MktRF          0.1589      0.030        5.306      0.000        0.100
0.218
SMB           -0.1115      0.054       -2.057      0.041       -0.218
-0.004
HML            0.0949      0.053        1.800      0.074       -0.009
0.199
RMW           -0.0304      0.067       -0.452      0.652       -0.163
0.102
CMA            0.1102      0.081        1.365      0.174       -0.049
0.270
UMD            0.0481      0.031        1.551      0.123       -0.013
0.109
MktRF_L1        0.0186      0.026        0.715      0.476       -0.033
0.070
MktRF_L2       -0.0282      0.027       -1.056      0.293       -0.081
0.025
MktRF_L3       -0.0612      0.026       -2.322      0.022       -0.113
-0.009
Intercept       0.0049      0.001        3.583      0.000        0.002
0.008

```

Omnibus:	32.222	Durbin-Watson:
1.743		
Prob(Omnibus):	0.000	Jarque-Bera (JB):
89.386		
Skew:	0.758	Prob(JB):
3.89e-20		
Kurtosis:	6.260	Cond. No.
77.3		

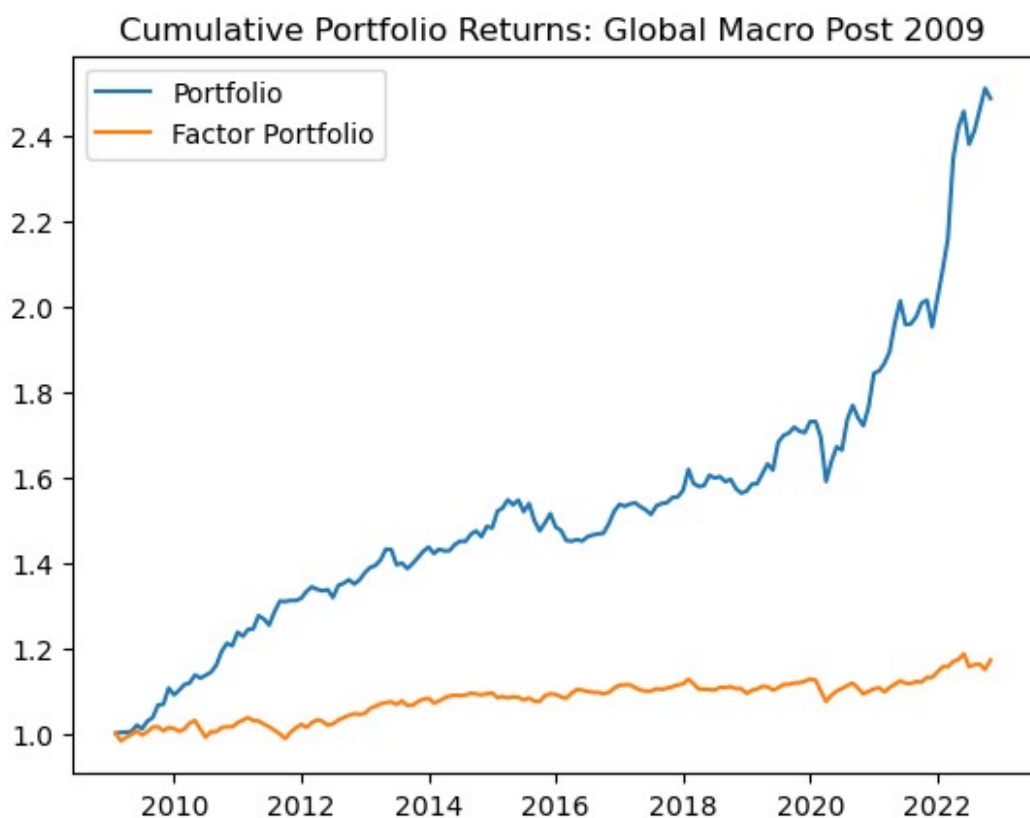
=====

=====

Notes:

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

Information Ratio Post 2009: 0.3316



```
# MktRF_L1, L2, L3 shows pvalues instead
GMC_Params = GMC_params_d1.to_frame("PFC")
GMC_Params["Post09"] = GMC_params_d2
GMC_Params.round(4)
```

	PFC	Post09
MktRF	0.2332	0.1589
SMB	0.0664	-0.1115

HML	0.1509	0.0949
RMW	-0.0069	-0.0304
CMA	0.0177	0.1102
UMD	0.1147	0.0481
MktRF_L1	0.8078	0.4758
MktRF_L2	0.0395	0.2925
MktRF_L3	0.7849	0.0215
Intercept	0.0087	0.0049

Emerging markets

```
# Pre FC
```

```
y_ret_d1, EME_bench_ret_d1, EME_params_d1 =  
fit_period(y_EME,X_EME,1,"Emerging Markets")
```

```
visualise_rets(y_EME,EME_bench_ret_d1,1,"Emerging Markets")
```

OLS Regression Results

```
=====
=====
Dep. Variable:                  EmgMkts    R-squared:
0.365
Model:                          OLS      Adj. R-squared:
0.330
Method:                        Least Squares    F-statistic:
10.24
Date:                          Mon, 24 Feb 2025    Prob (F-statistic):
2.17e-12
Time:                          00:45:28    Log-Likelihood:
328.92
No. Observations:              170    AIC:
-637.8
Df Residuals:                  160    BIC:
-606.5
Df Model:                      9
```

```
Covariance Type:              nonrobust
```

```
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
MktRF              0.5815      0.090       6.479      0.000       0.404
0.759
SMB                0.2898      0.099       2.930      0.004       0.094
0.485
HML               -0.0229      0.159      -0.144      0.886      -0.337
```

0.291					
RMW	0.1252	0.142	0.881	0.380	-0.156
0.406					
CMA	-0.0382	0.179	-0.214	0.831	-0.391
0.315					
UMD	0.1041	0.061	1.695	0.092	-0.017
0.225					
MktRF_L1	0.1327	0.069	1.914	0.057	-0.004
0.270					
MktRF_L2	0.0171	0.069	0.247	0.805	-0.120
0.154					
MktRF_L3	-0.0507	0.067	-0.753	0.453	-0.184
0.082					
Intercept	0.0029	0.003	0.941	0.348	-0.003
0.009					

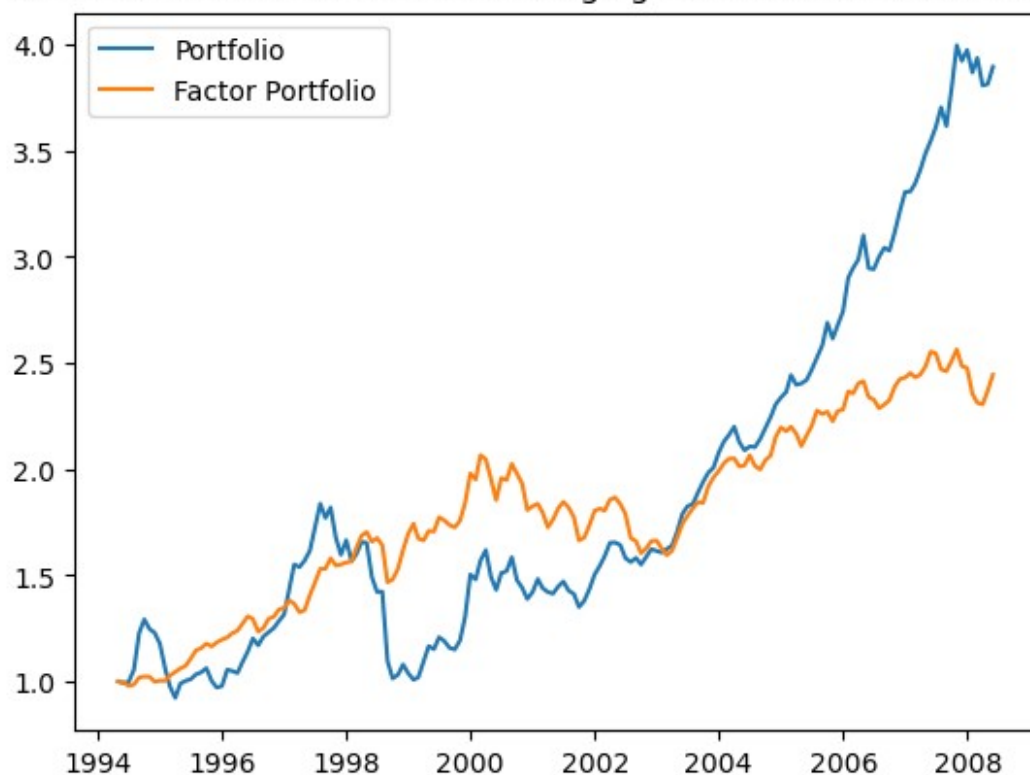
```
=====
=====
Omnibus:                17.500    Durbin-Watson:
1.279
Prob(Omnibus):          0.000    Jarque-Bera (JB):
37.915
Skew:                   -0.431    Prob(JB):
5.85e-09
Kurtosis:               5.147    Cond. No.
84.7
=====
=====
```

Notes:

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

Information Ratio Pre Financial Crisis: 0.0829

Cumulative Portfolio Returns: Emerging Markets Pre Financial Crisis



```
# Pre FC
y_ret_d1, EME_bench_ret_d2, EME_params_d2 =
fit_period(y_EME,X_EME,2,"Emerging Markets")

visualise_rets(y_EME,EME_bench_ret_d1,2,"Emerging Markets")
```

OLS Regression Results

```
=====
=====
Dep. Variable:                  EmgMkts    R-squared:
0.496
Model:                          OLS        Adj. R-squared:
0.467
Method:                        Least Squares    F-statistic:
17.09
Date:                          Mon, 24 Feb 2025    Prob (F-statistic):
2.06e-19
Time:                          00:45:28    Log-Likelihood:
442.12
No. Observations:                166    AIC:
-864.2
Df Residuals:                    156    BIC:
-833.1
```


Df Model: 9

Covariance Type: nonrobust

=====					
	coef	std err	t	P> t	[0.025
0.975]					

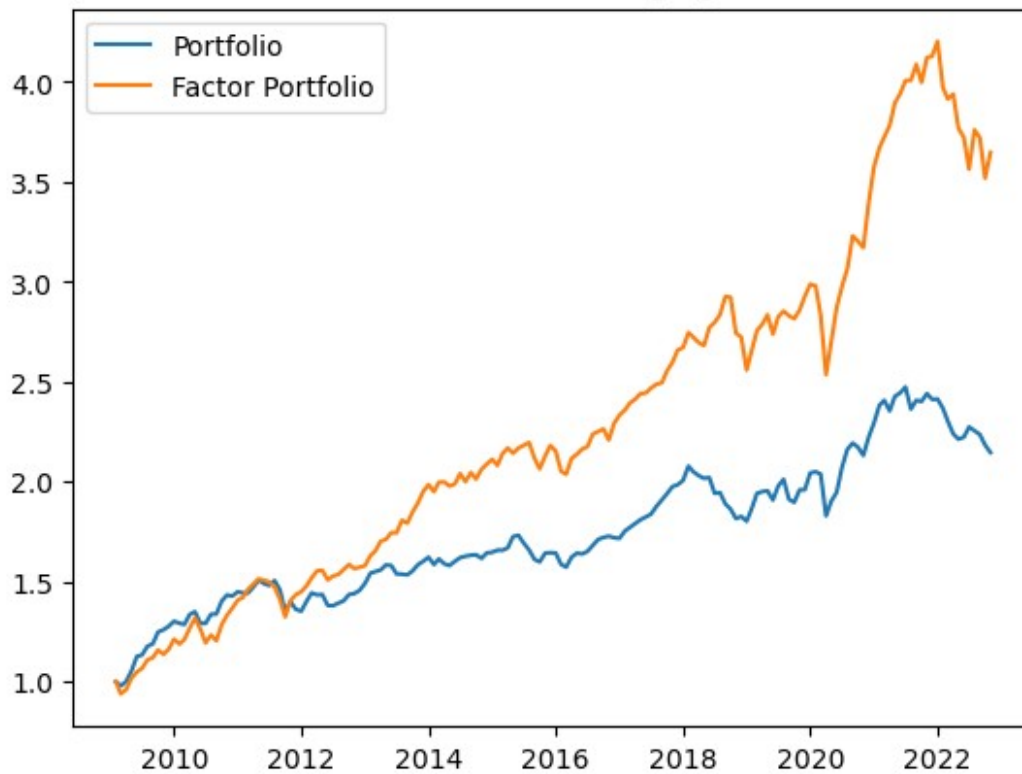
MktRF	0.3094	0.035	8.943	0.000	0.241
0.378					
SMB	0.0354	0.063	0.565	0.573	-0.088
0.159					
HML	0.0218	0.061	0.358	0.721	-0.098
0.142					
RMW	-0.0866	0.078	-1.115	0.267	-0.240
0.067					
CMA	-0.1327	0.093	-1.422	0.157	-0.317
0.052					
UMD	-0.0532	0.036	-1.483	0.140	-0.124
0.018					
MktRF_L1	0.1064	0.030	3.535	0.001	0.047
0.166					
MktRF_L2	0.0313	0.031	1.015	0.312	-0.030
0.092					
MktRF_L3	-0.0216	0.030	-0.711	0.478	-0.082
0.039					
Intercept	0.0005	0.002	0.295	0.768	-0.003
0.004					
=====					
=====					
Omnibus:		4.614	Durbin-Watson:		
1.974					
Prob(Omnibus):		0.100	Jarque-Bera (JB):		
4.324					
Skew:		-0.294	Prob(JB):		
0.115					
Kurtosis:		3.530	Cond. No.		
77.3					
=====					
=====					

Notes:

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

Information Ratio Post 2009: -0.1392

Cumulative Portfolio Returns: Emerging Markets Post 2009



```
# MktRF_L1, L2, L3 shows pvalues instead
EME_Params = EME_params_d1.to_frame("PFC")
EME_Params["Post09"] = EME_params_d2
EME_Params.round(4)
```

	PFC	Post09
MktRF	0.5815	0.3094
SMB	0.2898	0.0354
HML	-0.0229	0.0218
RMW	0.1252	-0.0866
CMA	-0.0382	-0.1327
UMD	0.1041	-0.0532
MktRF_L1	0.0575	0.0005
MktRF_L2	0.8052	0.3118
MktRF_L3	0.4526	0.4784
Intercept	0.0029	0.0005