EquallyWeighted

November 12, 2018

1 Portfolio Management Project

1.1 Objective:

In this project, we aim to build stylized long-short equity factor mimicking portfolios using different fundamental variables from Ken French's data library and explore empirically their univariate efficacy over time and across different size segments. We then go on to build multi-factor strategies using alternative weighting schemes and compare them to the static equally weighted multi-factor strategy. Two alternative top-down factor weighting schemes will be considered: 1) Equal risk contribution across factors 2) Weighting based on factor persistence

1.2 Data:

Attached with the project description are 6 csv files containing the monthly time series of value- and equal-weighted returns for portfolios formed on size and different fundamental variables consisting of book-to-price, cashflow-to-price, dividend yield, investment, profitability, prior 1-month return and 12-1 price momentum. In addition, there is a csv file named "F-F_Research_Data_Factors" which houses the Fama-French 3 factor model returns.

1.3 Project description:

1.For each of the six fundamental variables, construct long-short factor mimicking portfolios and plot their historical performance across different size segments. Taking the market return from Fama-French's 3-factor model, calculate and plot the rolling 3-year market beta for these stylized portfolios. Considering both size segments, construct a beta-neutral factor mimicking portfolio for each fundamental variable. Comment on your results.

2.Calculate the full sample correlation matrix of unadjusted factor returns (i.e. not the beta-neutral version) derived from 1. Comment on your findings. Using a lookback period of 5 years, employ an equal risk contribution factor weighting strategy with monthly rebalancing. The monthly resultant portfolios should be dollar neutral with a long leg exposure of 100%. Plot the monthly factor weights over time and evaluate the strategy performance against the static equally weighted factor portfolio. Comment on your results.

3.Using different lookback periods of 1,12 and 36 months to determine factor persistence, build adaptive multi-factor models that appropriately reflect your view on each factor. For example, you may want to consider a factor weighting approach such that the factor allocation is proportional to the historical Sharpe ratio for a given lookback period. Comment on your results.

1.3.1 Data Source:

Fama-Frence Libary

1.3.2 Factors:

BP: book value / stock price
CFP: cash flow / stock price
DP: dividend / stock price
INV: investment value
MOMENTUM_PRIOR_1: short-term reversal, return for prior 1 month
MOMENTUM_PRIOR_12_2: short-term momentum, return for prior 12 month to prior 2 month

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

from scipy.optimize import linprog
from scipy.optimize import minimize
import pymprog
from statsmodels import regression
import statsmodels.api as sm
import statsmodels.formula.api as smf


def long_short(filename,buy_high=True):
    data = pd.read_csv(filename)
    data['Month'] = pd.to_datetime(data['Month'],format ='%Y%m')
    data = data.set_index('Month')

    if buy_high:
        data['SMALL'] = (data.iloc[:,2] - data.iloc[:,0])
        data['BIG'] = (data.iloc[:,5] - data.iloc[:,3])

    else:
        data['SMALL'] = (-data.iloc[:,2] + data.iloc[:,0])
        data['BIG'] = (-data.iloc[:,5] + data.iloc[:,3])

    return data


def beta(data,market_data):
    data['MARKET'] = market_data['MARKET']
    column_beta = [data.columns[i] for i in [0,2,3,5,6,7]]
    a=[]
    for i in column_beta:
        a.append(i+'_BETA')
```

```
            data[i+'_BETA'] = pd.rolling_cov(data[i],data['MARKET'],window=36)/pd.rolling_v

        for i in column_beta[:4]:
            data[i+'_ALPHA'] = data[i] -data[i+'_BETA']* data['MARKET']

        return data.dropna(),a[:4]

    def beta_neutral_2(data,a,buy_high=True):

        b = [j[:-5]+'_ALPHA' for j in a]
        c = [j[:-5] for j in a]
        performance=[]
        for i in range(len(data)-1):
            beta1,beta2,beta3,beta4= data.iloc[i][a]
            alpha1,alpha2,alpha3,alpha4 = data.iloc[i][b]
            r1,r2,r3,r4 = data.iloc[i+1][c]

            target = np.array([alpha1,alpha2,alpha3,alpha4])

            if buy_high:

                results = linprog(-target,
                                  A_eq=[[beta1,beta2,beta3,beta4],[1,0,1,0],[0,1,0,1]],
                                  b_eq=[0,-1,1],
                                  bounds=((-1,0),(0,1),(-1,0),(0,1)))

                if not 'successfully' in results.message:
                    cons = ({'type': 'eq', 'fun': lambda p:beta1*p[0]+beta2*p[1]+beta3*p[2
                            {'type': 'eq', 'fun': lambda p:p[1]+p[3]-1},
                            {'type': 'eq', 'fun': lambda p:p[0]+p[2]+1},
                            {'type': 'ineq', 'fun': lambda p:p[0]+1},
                            {'type': 'ineq', 'fun': lambda p:p[2]+1},
                            {'type': 'ineq', 'fun': lambda p:1-p[1]},
                            {'type': 'ineq', 'fun': lambda p:1-p[3]})

                    results = minimize(fun=alpha_sum,
                                       x0=[0,0,0,0],
                                       method='SLSQP',
                                       constraints=cons,
                                       args=(alpha1,alpha2,alpha3,alpha4))



            else:
                results = linprog(-target,
                                  A_eq=[[beta1,beta2,beta3,beta4],[1,0,1,0],[0,1,0,1]],
                                  b_eq=[0,1,-1],
                                  bounds=((0,1),(-1,0),(0,1),(-1,0)))
```

```
            if not 'successfully' in results.message:
                cons = ({'type': 'eq', 'fun': lambda p:beta1*p[0]+beta2*p[1]+beta3*p[2
                        {'type': 'eq', 'fun': lambda p:p[0]+p[2]-1},
                        {'type': 'eq', 'fun': lambda p:p[1]+p[3]+1},
                        {'type': 'ineq', 'fun': lambda p:p[1]+1},
                        {'type': 'ineq', 'fun': lambda p:p[3]+1},
                        {'type': 'ineq', 'fun': lambda p:1-p[0]},
                        {'type': 'ineq', 'fun': lambda p:1-p[2]})


                results = minimize(fun=alpha_sum,
                                   x0=[0,0,0,0],
                                   method='SLSQP',
                                   constraints=cons,
                                   args=(alpha1,alpha2,alpha3,alpha4))



        rho1,rho2,rho3,rho4 = list(results.x)

        performance.append(r1*rho1+r2*rho2+r3*rho3+r4*rho4)

    output=pd.DataFrame()
    output['Beta_Neutral_Performance'] = pd.Series(performance)
    output.index = data.index[1:]

    return output


def alpha_sum(p,alpha1,alpha2,alpha3,alpha4):
    return -(alpha1*p[0]+alpha2*p[1]+alpha3*p[2]+alpha4*p[3])


def erc(df,look_back):
    origin_columns = list(df.columns)

    cov_name = []
    data=pd.DataFrame()
    data[origin_columns] = df[origin_columns]
    for a in origin_columns:
        for b in origin_columns:
            data[a+'_'+b+'_cov'] = df[a].rolling(window=look_back).cov(df[b])
            cov_name.append(a+'_'+b+'_cov')

    data = data.dropna()
    erc_df = data[origin_columns]

    x1=[]
```

```
x2=[]
x3=[]
x4=[]
x5=[]
x6=[]
x7=[]


for i in range(len(data)):
    cov_array = np.array(data.iloc[i][cov_name])
    cons = ({'type': 'eq', 'fun': lambda x:x[0]+x[1]+x[2]+x[3]+x[4]+x[5]+x[6]-1})
    results = minimize(fun=erc_target, x0=[0,0,0,0,0,0,0],  method='SLSQP',
                        constraints=cons,args=cov_array,bounds = ((0,1),(0,1),(0,1

    x1.append(list(results.x)[0])
    x2.append(list(results.x)[1])
    x3.append(list(results.x)[2])
    x4.append(list(results.x)[3])
    x5.append(list(results.x)[4])
    x6.append(list(results.x)[5])
    x7.append(list(results.x)[6])


weights_columns = [f+'_weight' for f in origin_columns]
x_all = [x1,x2,x3,x4,x5,x6,x7]
for num in range(7):
    weights_columns = [f+'_weight' for f in origin_columns]

    erc_df[weights_columns[num]] = pd.Series(x_all[num],index=erc_df.index)

simple_list = []
erc_list=[]

for i in range(len(erc_df)-1):
    simple_list.append(sum(erc_df.iloc[i+1][origin_columns])/7)

    w1 = x1[i]
    w2 = x2[i]
    w3 = x3[i]
    w4 = x4[i]
    w5 = x5[i]
    w6 = x6[i]
    w7 = x7[i]

    r1,r2,r3,r4,r5,r6,r7 = erc_df.iloc[i+1][origin_columns]

    erc_list.append(w1*r1+w2*r2+w3*r3+w4*r4+w5*r5+w6*r6+w7*r7)
```

```python
    return erc_df,simple_list,erc_list


def erc_target(x,cov_array):
    x_array = x.reshape(7,1)
    #cov_array = cov_array*(10**14)
    cov_matrix = cov_array.reshape(7,7)

    total_risk = np.dot(cov_matrix,x_array)

    x2=[]
    for i in range(7):
        x2.append((total_risk[i][0])*x_array[i][0])

    '''
    diff_sum=0
    for i in range(7):
        for j in range(7):
            diff_sum += (x[i]-x[j])**2


    return diff_sum'''

    var_sum = np.var(np.array(x2))
    return var_sum*(10**14)

def total_risk(x,cov_array):
    x_array = x.reshape(7,1)
    #cov_array = cov_array*(10**14)
    cov_matrix = cov_array.reshape(7,7)

    total_risk = np.dot(cov_matrix,x_array)

    x2=[]
    for i in range(7):
        x2.append((total_risk[i][0])*x_array[i][0])

    '''
    diff_sum=0
    for i in range(7):
        for j in range(7):
            diff_sum += (x[i]-x[j])**2


    return diff_sum'''

    return x2
```

```python
In [2]: def sharpe_ratio_equal(df,market_data,look_back,long_only=False):
            origin_columns = list(df.columns)
            simple_list=[]

            data=pd.DataFrame()
            data[origin_columns] = df[origin_columns]

            data['RF'] =  market_data['RF']
            sr_columns = [factor+'_SR' for factor in origin_columns]
            for factor in origin_columns:
                data[factor+'_RF'] = data[factor]-data['RF']
                data[factor+'_SR'] = data[factor+'_RF'].rolling(window=look_back).mean()\
                /data[factor].rolling(window=look_back).std()

            data=data.dropna()

            performance = []
            for i in range(len(data)-1):
                if not long_only:
                    sr_list = list(data.iloc[i][sr_columns])
                else:
                    sr_list = [i if i>0  else 0  for i in data.iloc[i][sr_columns]]

                sr_sum = np.array(sr_list).sum()

                simple_list.append(sum(data.iloc[i+1][origin_columns])/7)
                if sr_sum == 0:
                    performance.append(0)

                else:
                    w1,w2,w3,w4,w5,w6,w7= np.array(sr_list)/sr_sum
                    r1,r2,r3,r4,r5,r6,r7 = data.iloc[i+1][origin_columns]

                    performance.append(w1*r1+w2*r2+w3*r3+w4*r4+w5*r5+w6*r6+w7*r7)



            return data,performance,simple_list


        def average_mean_equal(df,market_data,look_back,long_only=False):
            origin_columns = list(df.columns)
            simple_list=[]

            data=pd.DataFrame()
            data[origin_columns] = df[origin_columns]

            data['RF'] =  market_data['RF']
```

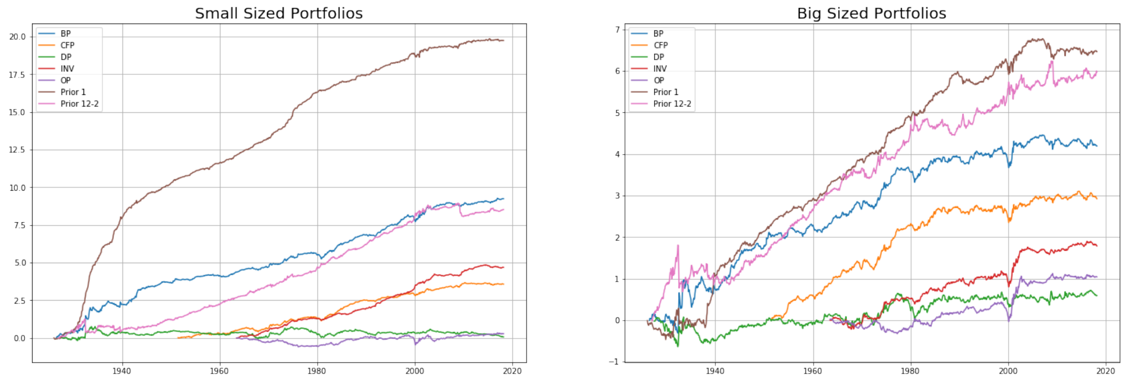
```python
    sr_columns = [factor+'_MEAN' for factor in origin_columns]

    for factor in origin_columns:
        data[factor+'_RF'] = data[factor]-data['RF']
        data[factor+'_MEAN'] = data[factor].rolling(window=look_back).mean()

    data=data.dropna()

    performance = []
    for i in range(len(data)-1):
        if not long_only:
            sr_list = list(data.iloc[i][sr_columns])
        else:
            sr_list = [i if i>0  else 0  for i in data.iloc[i][sr_columns]]

        sr_sum = np.array(sr_list).sum()

        if sr_sum == 0 :
            performance.append(0)
        else:
            w1,w2,w3,w4,w5,w6,w7= np.array(sr_list)/sr_sum
            r1,r2,r3,r4,r5,r6,r7 = data.iloc[i+1][origin_columns]

            performance.append(w1*r1+w2*r2+w3*r3+w4*r4+w5*r5+w6*r6+w7*r7)

    return performance


def information_ratio_equal(df,market_data,look_back,long_only=False):
    origin_columns = list(df.columns)
    simple_list=[]

    data=pd.DataFrame()
    data[origin_columns] = df[origin_columns]

    data['MARKET'] =  market_data['MARKET']
    sr_columns = [factor+'_IR' for factor in origin_columns]
    for factor in origin_columns:
        data[factor+'_M'] = data[factor]-data['MARKET']
        data[factor+'_IR'] = data[factor+'_M'].rolling(window=look_back).mean()\
        /data[factor+'_M'].rolling(window=look_back).std()

    data=data.dropna()

    performance = []
    for i in range(len(data)-1):
        if not long_only:
            sr_list = list(data.iloc[i][sr_columns])
```

```
        else:
            sr_list = [i if i>0  else 0  for i in data.iloc[i][sr_columns]]

        sr_sum = np.array(sr_list).sum()

        if sr_sum == 0:
            performance.append(0)

        else:

            w1,w2,w3,w4,w5,w6,w7= np.array(sr_list)/sr_sum
            r1,r2,r3,r4,r5,r6,r7 = data.iloc[i+1][origin_columns]

            performance.append(w1*r1+w2*r2+w3*r3+w4*r4+w5*r5+w6*r6+w7*r7)

    return  performance
```

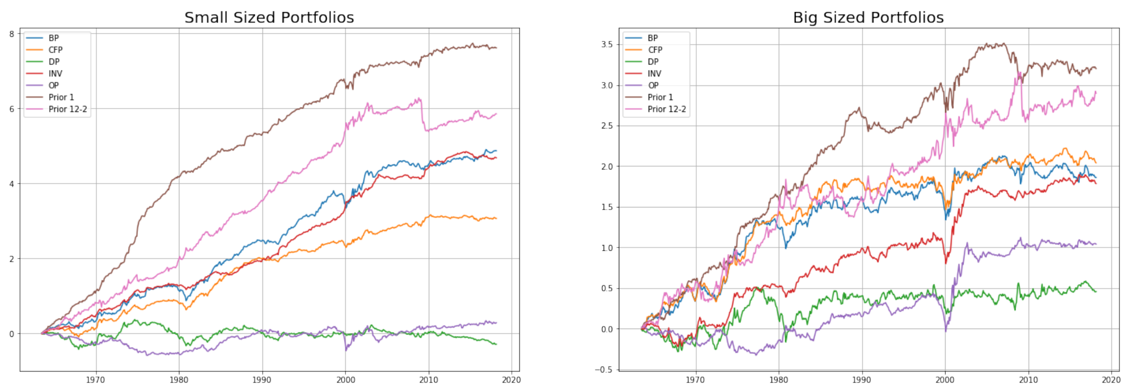
1.4 1. Performances for Small and Big Risk Premia Factors (Equally-Weighted Factors

```
In [3]: data1 = long_short('D:/PortfolioManagement/EW/BP_EW.csv')
        data2 = long_short('D:/PortfolioManagement/EW/CFP_EW.csv')
        data3 = long_short('D:/PortfolioManagement/EW/DP_EW.csv')
        data4 = long_short('D:/PortfolioManagement/EW/INV_EW.csv',False)
        data5 = long_short('D:/PortfolioManagement/EW/OP_EW.csv')
        data6 = long_short('D:/PortfolioManagement/EW/MOMENTUM_PRIOR_1_EW.csv',False)
        data7 = long_short('D:/PortfolioManagement/EW/MOMENTUM_PRIOR_12_2_EW.csv')



        data_list = [data1,data2,data3,data4,data5,data6,data7]
        factor_list = ['BP','CFP','DP','INV','OP','Prior 1','Prior 12-2']

        plt.figure(figsize=(20,12))

        for i in range(7):
            data = data_list[i]
            plt.subplot(3,3,i+1)
            plt.plot(data.index,data['SMALL'].cumsum()/100)
            plt.plot(data.index,data['BIG'].cumsum()/100)
            plt.legend(['SMALL)','BIG'])
            plt.title(factor_list[i],fontsize = 15)
            plt.grid(True)

        plt.show()
```


```
In [4]: plt.figure(figsize=(25,8))
        plt.subplot(1,2,1)
        for i in range(7):
            data = data_list[i]
            plt.plot(data.index,data['SMALL'].cumsum()/100)
        plt.legend(factor_list)
        plt.title('Small Sized Portfolios',fontsize=20)
        plt.grid(True)

        plt.subplot(1,2,2)
        for i in range(7):
            data = data_list[i]
            plt.plot(data.index,data['BIG'].cumsum()/100)
        plt.legend(factor_list)
        plt.title('Big Sized Portfolios',fontsize=20)
        plt.grid(True)

        plt.show()
```



In [5]:
```
index_min = data4.index
plt.figure(figsize=(25,8))
plt.subplot(1,2,1)
for i in range(7):
    data = data_list[i].loc[index_min,:]
    plt.plot(data.index,data['SMALL'].cumsum()/100)
plt.legend(factor_list)
plt.grid(True)
plt.title('Small Sized Portfolios',fontsize=20)

plt.subplot(1,2,2)
for i in range(7):
    data = data_list[i].loc[index_min,:]
    plt.plot(data.index,data['BIG'].cumsum()/100)
plt.legend(factor_list)
plt.grid(True)
plt.title('Big Sized Portfolios',fontsize=20)

plt.show()
```



1.5 2. Statistics for Small and Big Risk Premia Factors (Equally-Weighted Factors

In [6]:
```
big = pd.DataFrame()
small = pd.DataFrame()
market_data = pd.read_csv('D:/PortfolioManagement/F-F.csv')
market_data['MARKET'] = market_data['Mkt-RF'] + market_data['RF']
market_data['Month'] = pd.to_datetime(market_data['Month'],format ='%Y%m')
market_data = market_data.set_index('Month')

import numpy as np

index_min_1 = data4.index

for i in range(7):
    data=data_list[i].loc[index_min_1,:]
    data['RF'] =  market_data['RF']
    data['MARKET'] = market_data['MARKET']
    data['RM_RF'] = market_data['Mkt-RF']
    data['SMB'] = market_data['SMB']
    data['HML'] = market_data['HML']
    data['BIG_RF'] = data['BIG'] - data['RF']
    data['SMALL_RF'] = data['SMALL'] - data['RF']

    SMB = np.array(data['SMB'])
    HML = np.array(data['HML'])
    RM_RF = np.array(data['RM_RF'])

    X = np.column_stack((RM_RF,SMB,HML))

    Y_BIG = np.array(data['BIG_RF'] ).T
    Y_SMALL = np.array(data['SMALL_RF'] ).T

    X = sm.add_constant(X)
    MODEL_BIG = regression.linear_model.OLS(Y_BIG, X).fit()
    MODEL_SMALL = regression.linear_model.OLS(Y_SMALL, X).fit()

    data_big = data['BIG']
    data_small = data['SMALL']
    data_big_2 = data['BIG']-data['RF']
    data_small_2 = data['SMALL']-data['RF']
    data_big_3 = data['BIG']-data['MARKET']
    data_small_3 = data['SMALL']-data['MARKET']

    factor = factor_list[i]

    rm_rf_mean = RM_RF.mean()
    rf_mean = data['RF'].mean()
```

```
        big.loc['Average Returns',factor] = data_big.mean()
        big.loc['Std',factor] = np.std(data_big)
        big.loc['Sharpe Ratio',factor] = data_big_2.mean()/np.std(data_big)
        big.loc['Alpha',factor] = MODEL_BIG.params[0]
        big.loc['Beta',factor] = MODEL_BIG.params[1]
        big.loc['Treynor Ratio',factor] = data_big_2.mean()/MODEL_BIG.params[1]
        big.loc['Jensen Measure',factor] = data_big.mean()-rf_mean-MODEL_BIG.params[1]*rm_
        big.loc['Information Ratio',factor] = data_big_3.mean()/np.std(data_big_3)

        small.loc['Average Returns',factor] = data_small.mean()
        small.loc['Std',factor] = np.std(data_small)
        small.loc['Sharpe Ratio',factor] = data_small_2.mean()/np.std(data_small)
        small.loc['Alpha',factor] = MODEL_SMALL.params[0]
        small.loc['Beta',factor] = MODEL_SMALL.params[1]
        small.loc['Treynor Ratio',factor] = data_small_2.mean()/MODEL_SMALL.params[1]
        small.loc['Jensen Measure',factor] = data_small.mean()-rf_mean-MODEL_SMALL.params[
        small.loc['Information Ratio',factor] = data_small_3.mean()/np.std(data_small_3)
```

In [7]: small

```
Out[7]:                         BP       CFP        DP       INV        OP   Prior 1  \
        Average Returns    0.741755  0.467230 -0.043516  0.713096  0.043937  1.159361
        Std                3.263751  2.148074  2.396207  2.014588  2.641278  3.347462
        Sharpe Ratio       0.109273  0.038228 -0.178879  0.162804 -0.129171  0.231294
        Alpha              0.229776 -0.008737 -0.342152  0.255604 -0.357176  0.607128
        Beta              -0.175379 -0.063741 -0.237741 -0.083232  0.069509  0.180160
        Treynor Ratio     -2.033548 -1.288270  1.802929 -3.940581 -4.908415  4.297562
        Jensen Measure     0.449226  0.115766 -0.303123  0.371922 -0.377871  0.679138
        Information Ratio -0.026206 -0.081320 -0.156672 -0.038237 -0.168712  0.051934

                           Prior 12-2
        Average Returns      0.891446
        Std                  4.159649
        Sharpe Ratio         0.121725
        Alpha                0.713121
        Beta                -0.172492
        Treynor Ratio       -2.935389
        Jensen Measure       0.597393
        Information Ratio   -0.003369
```

In [8]: big

```
Out[8]:                          BP       CFP        DP       INV        OP  \
        Average Returns     0.283262  0.310654  0.069543  0.271853  0.158469
        Std                 3.031750  2.705481  3.012706  2.402203  2.560425
        Sharpe Ratio       -0.033595 -0.027522 -0.104747 -0.047149 -0.088519
        Alpha              -0.440822 -0.298866 -0.345655 -0.217600 -0.142743
        Beta                0.001529 -0.046102 -0.251593 -0.088198 -0.086196
        Treynor Ratio     -66.609758  1.615120  1.254293  1.284163  2.629420
```

```
Jensen Measure     -0.102660 -0.050122 -0.182751 -0.066700 -0.181141
Information Ratio  -0.107438 -0.104709 -0.129878 -0.112567 -0.137114

                    Prior 1  Prior 12-2
Average Returns    0.487108    0.440959
Std                3.381678    4.642842
Sharpe Ratio       0.030161    0.012028
Alpha             -0.065008    0.277264
Beta               0.237535   -0.191074
Treynor Ratio      0.429384   -0.292267
Jensen Measure    -0.023404    0.156716
Information Ratio -0.091660   -0.070061
```

1.6 3. Beta of SMALL and BIG for Market Model

In [4]:
```python
market_data = pd.read_csv('D:/PortfolioManagement/F-F.csv')
market_data['MARKET'] = market_data['Mkt-RF'] + market_data['RF']
market_data['Month'] = pd.to_datetime(market_data['Month'],format ='%Y%m')
market_data = market_data.set_index('Month')

data1,a1 = beta(data1,market_data)
data2,a2 = beta(data2,market_data)
data3,a3 = beta(data3,market_data)
data4,a4 = beta(data4,market_data)
data5,a5 = beta(data5,market_data)
data6,a6 = beta(data6,market_data)
data7,a7 = beta(data7,market_data)

a_list = [a1,a2,a3,a4,a5,a6,a7]
data_list=[data1,data2,data3,data4,data5,data6,data7]

plt.figure(figsize=(20,12))

for i in range(7):
    data = data_list[i]
    plt.subplot(3,3,i+1)
    plt.plot(data.index,data['SMALL_BETA'])
    plt.plot(data.index,data['BIG_BETA'])
    plt.legend(['SMALL-','BIG-'])
    plt.title(factor_list[i],fontsize = 15)
    plt.grid(True)

plt.show()
```

```
E:\Anaconda3\lib\site-packages\ipykernel_launcher.py:36: FutureWarning: pd.rolling_cov is depre
        Series.rolling(window=36).cov(other=<Series>)
E:\Anaconda3\lib\site-packages\ipykernel_launcher.py:36: FutureWarning: pd.rolling_var is depre
        Series.rolling(window=36,center=False).var()
```

1.7 4. Performances for Beta-Neutral Portfolios of 7 Risk Premia Factors

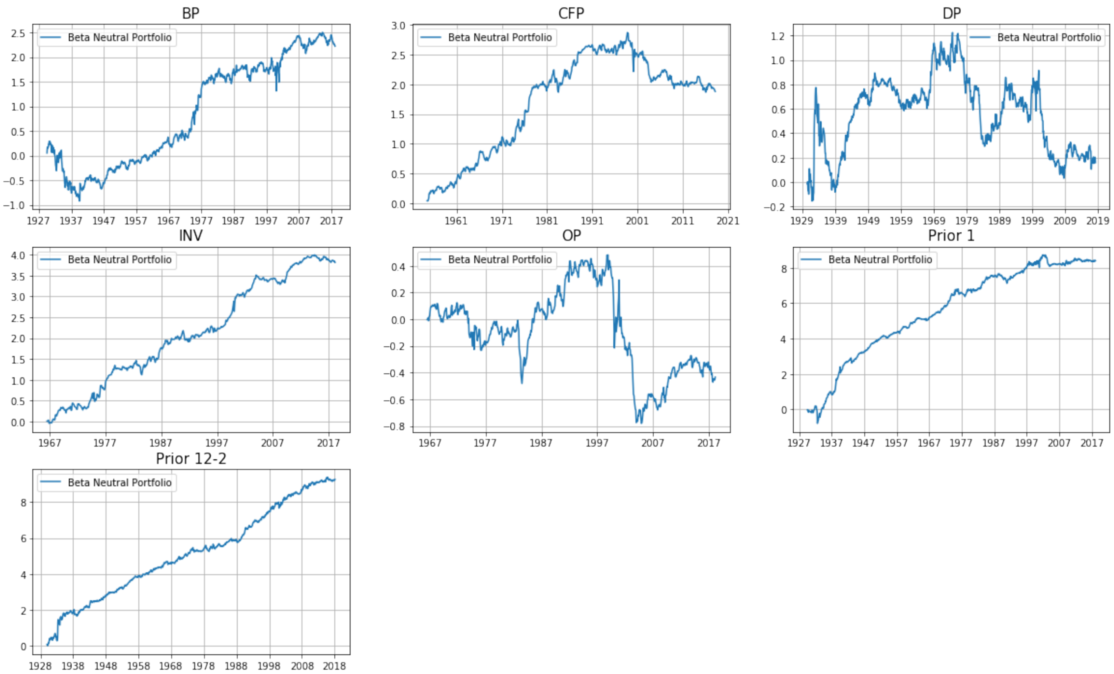
1.7.1 Beta-Neutral Portfolios are based on rolling dynamic Betas.

1.7.2 Holding a beta-neutral portfolio implies the investor can get an alpha without being exposed to any systematic risk.

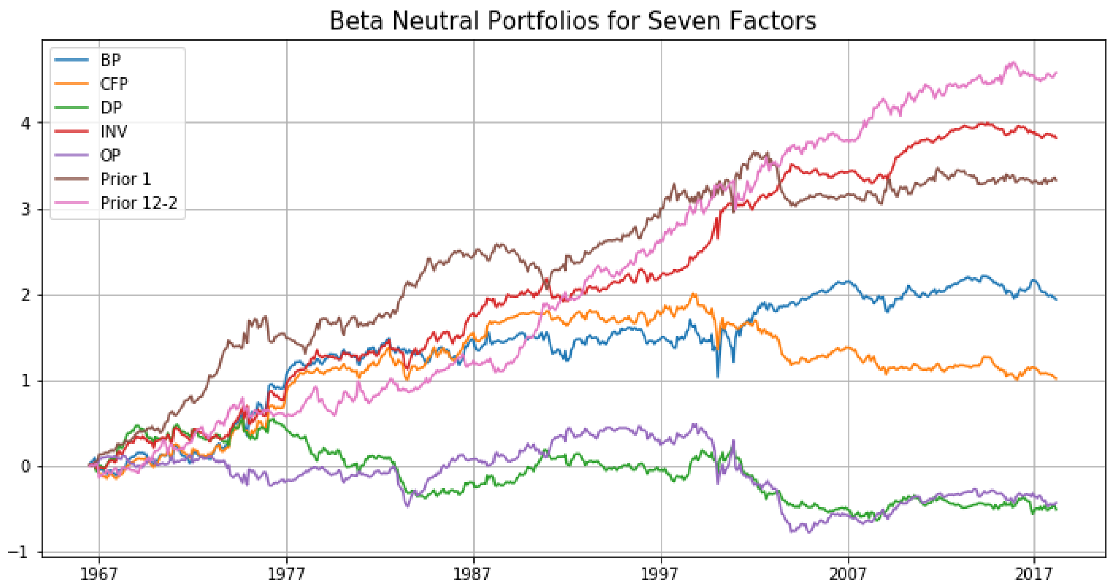
In [5]:
```
output1 = beta_neutral_2(data1,a1)
output2= beta_neutral_2(data2,a2)
output3 = beta_neutral_2(data3,a3)
output4 = beta_neutral_2(data4,a4,False)
output5 = beta_neutral_2(data5,a5)
output6 = beta_neutral_2(data6,a6,False)
output7 = beta_neutral_2(data7,a7)

data_list = [data1,data2,data3,data4,data5,data6,data7]
output_list = [output1,output2,output3,output4,output5,output6,output7]
```

In [27]:
```
plt.figure(figsize=(20,12))

for i in range(7):
    output=output_list[i]
    plt.subplot(3,3,i+1)
    plt.plot(output.index,output['Beta_Neutral_Performance'].cumsum()/100)
    plt.legend(['Beta Neutral Portfolio'])
```

```
        plt.title(factor_list[i],fontsize = 15)
        plt.grid(True)

    plt.show()
```




```
In [8]: plt.figure(figsize=(12,6))
        index_min_2 = data4.index[1:]
        for i in range(7):
            output = output_list[i].loc[index_min_2,:]
            plt.plot(output.index,output['Beta_Neutral_Performance'].cumsum()/100)
            plt.legend(factor_list)
            plt.title('Beta Neutral Portfolios for Seven Factors',fontsize = 15)
        plt.grid(True)
        plt.show()
```



In [10]:
```
output_2 = pd.DataFrame()


import numpy as np

for i in range(7):
    data = output_list[i].loc[index_min_2,:]
    data['RF'] =  market_data['RF']
    data['MARKET'] = market_data['MARKET']
    data['RM_RF'] = market_data['Mkt-RF']
    data['SMB'] = market_data['SMB']
    data['HML'] = market_data['HML']
    data['BIG_RF'] = data['Beta_Neutral_Performance'] - data['RF']

    SMB = np.array(data['SMB'])
    HML = np.array(data['HML'])
    RM_RF = np.array(data['RM_RF'])

    X = np.column_stack((RM_RF,SMB,HML))

    Y = np.array(data['Beta_Neutral_Performance'] ).T
    X = sm.add_constant(X)
    MODEL = regression.linear_model.OLS(Y, X).fit()

    data_p = data['Beta_Neutral_Performance']
    data_p_2 = data['Beta_Neutral_Performance']-data['RF']
    data_p_3 = data['Beta_Neutral_Performance']-data['MARKET']
```

```
        factor = factor_list[i]

        rm_rf_mean = RM_RF.mean()
        rf_mean = data['RF'].mean()

        output_2.loc['Average Returns',factor] = data_p.mean()
        output_2.loc['Std',factor] = np.std(data_p)
        output_2.loc['Sharpe Ratio',factor] = data_p_2.mean()/np.std(data_p)
        output_2.loc['Alpha',factor] = MODEL.params[0]
        output_2.loc['Beta',factor] = MODEL.params[1]
        output_2.loc['Treynor Ratio',factor] = data_p_2.mean()/MODEL.params[1]
        output_2.loc['Jensen Measure',factor] = data_p.mean()-rf_mean-MODEL.params[1]*rm_r
        output_2.loc['Information Ratio',factor] = data_p_3.mean()/np.std(data_p_3)
```

```
In [11]: output_2
```

```
Out[11]:                          BP        CFP         DP        INV         OP  \
         Average Returns    0.311722   0.163409  -0.082319   0.614781  -0.069899
         Std                4.357839   3.394123   3.345104   3.463404   3.575216
         Sharpe Ratio      -0.017826  -0.066584  -0.141019   0.065074  -0.128469
         Alpha              0.062331   0.047130  -0.091116   0.544450  -0.093230
         Beta               0.021329   0.017703  -0.011328  -0.032332   0.117748
         Treynor Ratio     -3.642067 -12.766084  41.640411  -6.970796  -3.900718
         Jensen Measure    -0.088897  -0.235303  -0.465767   0.242377  -0.521215
         Information Ratio -0.091896  -0.126021  -0.167658  -0.050009  -0.176502

                             Prior 1  Prior 12-2
         Average Returns    0.536486    0.737231
         Std                4.619919    4.124678
         Sharpe Ratio       0.031700    0.084328
         Alpha                   NaN    0.814947
         Beta                    NaN   -0.095644
         Treynor Ratio           NaN   -3.636660
         Jensen Measure          NaN    0.398116
         Information Ratio -0.063960   -0.027717
```

1.8 5. Performances for Equal-Risk Contribution Portfolios of 7 Risk Premia Factors

How to get a best portfolio is a popular and important question to answer.In the Efficient-Frontier problem, the tangency portfolio has a maximum Sharpe Ratio and is generally seen as the best portfolio, given expected returns and expected Correlation matrix. However, there is a large drawdown of the traditional tangency portfolio. The weights are highly dependent on inputed expected returns. Once there is a slight change in expected returns, it will lead to a very large change in outputed weights.

The reason why this happens is because the tangency portfolio is to minimize the total portfolio variance, and the stock which has large variance and large marginal covariance will always have a small weight.

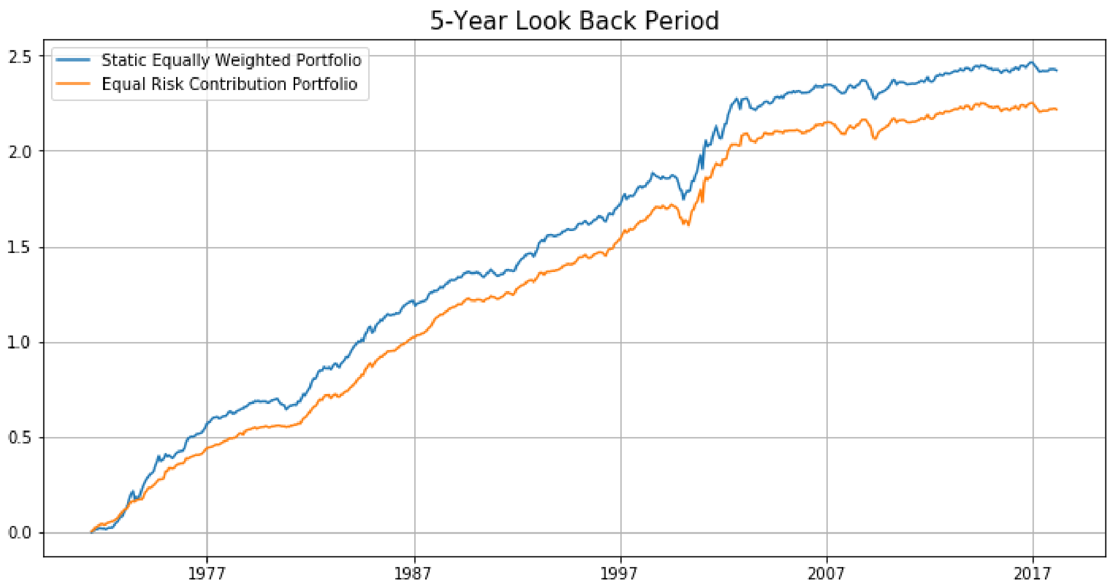
To solve this problem, the Equal-Risk Contribution portfolio is introduced. All stocks have not negative weights. Besides, all stocks have equl risk contribution to the portfolio.

To get the ERC portfolio, optimization technique is applied to minimize the sum of differences of stocks' marginal risk contributions.

In [15]:
```
df = pd.DataFrame()

for i in range(7):
    df[factor_list[i]] =( data_list[i]['SMALL']+data_list[i]['BIG'])/2
df = df.dropna()
```

In [23]:
```
erc_df_1,simple_1,erc_list_1 = erc(df,60)
look_back = [1,2,3,4,5]
erc_df_all=[]
simple_all=[]
erc_all=[]

plt.figure(figsize=(12,6))
idx = erc_df_1.index[1:]
plt.plot(idx,pd.Series(simple_1).cumsum()/100)
plt.plot(idx,pd.Series(erc_list_1).cumsum()/100)
plt.legend(['Static Equally Weighted Portfolio','Equal Risk Contribution Portfolio'])
plt.title('5-Year Look Back Period',fontsize = 15)
plt.grid(True)
plt.show()
```

```
E:\Anaconda3\lib\site-packages\ipykernel_launcher.py:160: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

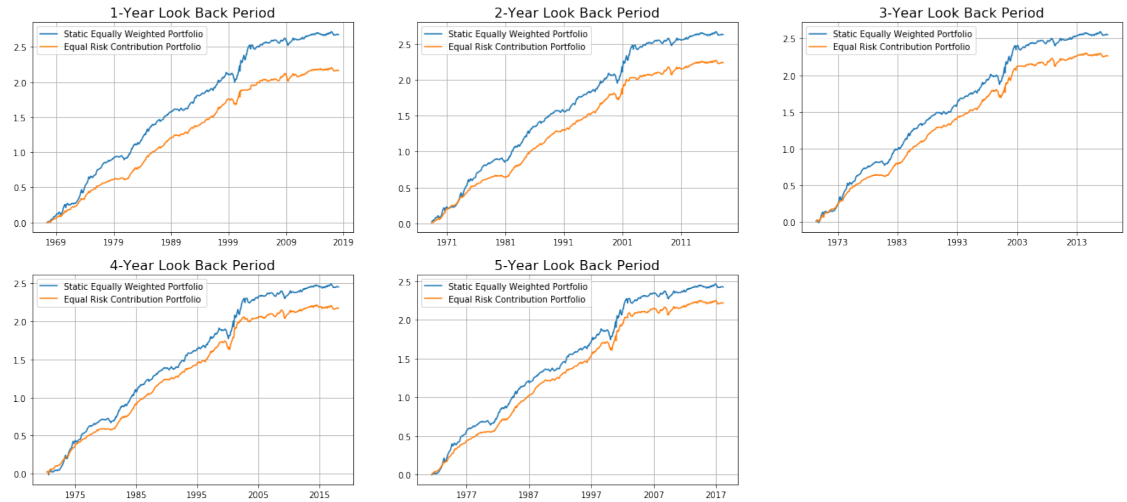


1.9 Performances for ERC Portfolios with Varies Look-Back Periods

```
In [28]: for i in range(5):
             year = look_back[i]
             erc_df,simple,erc_list = erc(df,12*year)
             erc_df_all.append(erc_df)
             simple_all.append(simple)
             erc_all.append(erc_list)


         plt.figure(figsize=(23,10))

         for i in range(5):
             year = look_back[i]
             erc_df = erc_df_all[i]
             simple = simple_all[i]
             erc_list = erc_all[i]
             plt.subplot(2,3,i+1)
             plt.plot(erc_df.index[1:],pd.Series(simple).cumsum()/100)
             plt.plot(erc_df.index[1:],pd.Series(erc_list).cumsum()/100)
             plt.legend(['Static Equally Weighted Portfolio','Equal Risk Contribution Portfolio
             plt.title(str(year)+'-Year Look Back Period',fontsize = 16)
             plt.grid(True)

         plt.show()
```

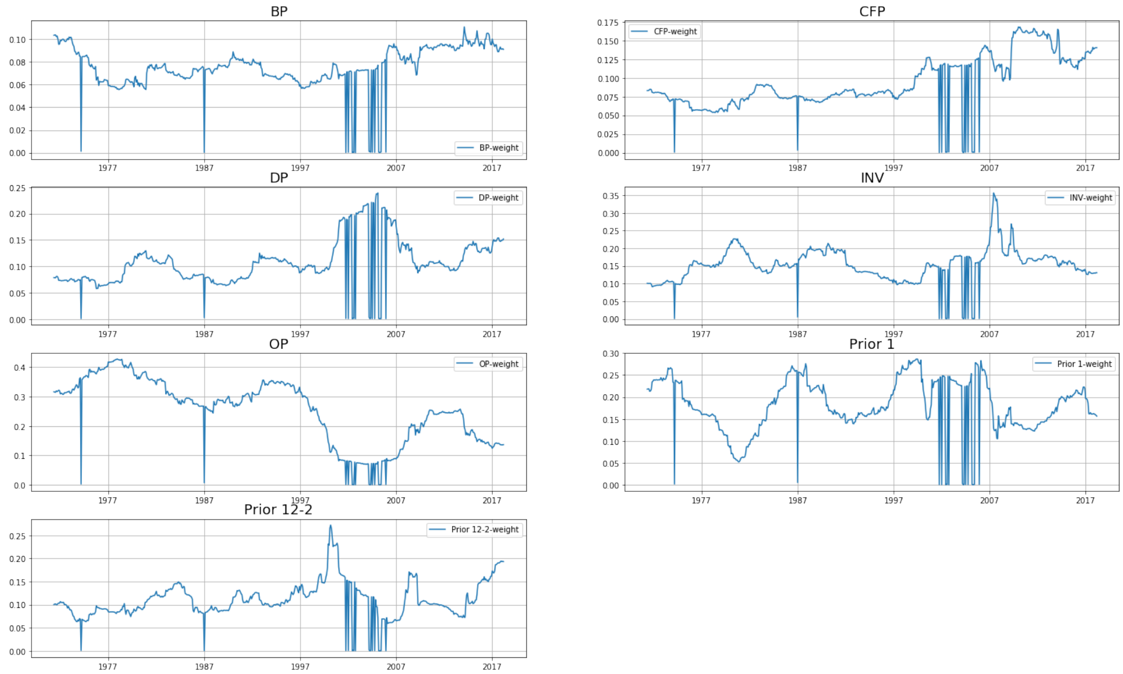
```
E:\Anaconda3\lib\site-packages\ipykernel_launcher.py:160: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```



1.10 6. Weights in ERC Portfolio

In [24]:
```
weights_columns = [i+'_weight' for i in factor_list]

plt.figure(figsize=(25,15))
for i in range(7):
    w = weights_columns[i]
    plt.subplot(4,2,i+1)
    plt.plot(erc_df_1.index,erc_df_1[w])
    plt.legend([factor_list[i]+'-weight'])
    plt.title(factor_list[i],fontsize = 18)
    plt.grid(True)

plt.show()
```



1.11 7. SAMPLE CORRELATION

In [27]:
```
df.corr()
```

Out[27]:
```
                  BP       CFP        DP       INV        OP   Prior 1  \
BP          1.000000  0.849261  0.674611  0.693908  0.080970  0.002582
CFP         0.849261  1.000000  0.661933  0.608805  0.219449 -0.054607
DP          0.674611  0.661933  1.000000  0.611033  0.056343 -0.094664
INV         0.693908  0.608805  0.611033  1.000000 -0.036048 -0.125791
OP          0.080970  0.219449  0.056343 -0.036048  1.000000 -0.086440
Prior 1     0.002582 -0.054607 -0.094664 -0.125791 -0.086440  1.000000
Prior 12-2 -0.192215 -0.117848 -0.195671 -0.016750  0.114908 -0.283565

            Prior 12-2
BP           -0.192215
CFP          -0.117848
DP           -0.195671
INV          -0.016750
OP            0.114908
Prior 1      -0.283565
Prior 12-2    1.000000
```

1.12 8. Performances of Risk Premia Factor Based Portfolios

In [4]:
```
market_data = pd.read_csv('D:/PortfolioManagement/F-F.csv')
market_data['MARKET'] = market_data['Mkt-RF'] + market_data['RF']
```

```
market_data['Month'] = pd.to_datetime(market_data['Month'],format ='%Y%m')
market_data = market_data.set_index('Month')
```

In [5]:
```
df = pd.DataFrame()

for i in range(7):
    df[factor_list[i]] =( data_list[i]['SMALL']+data_list[i]['BIG'])/2
df = df.dropna()
```

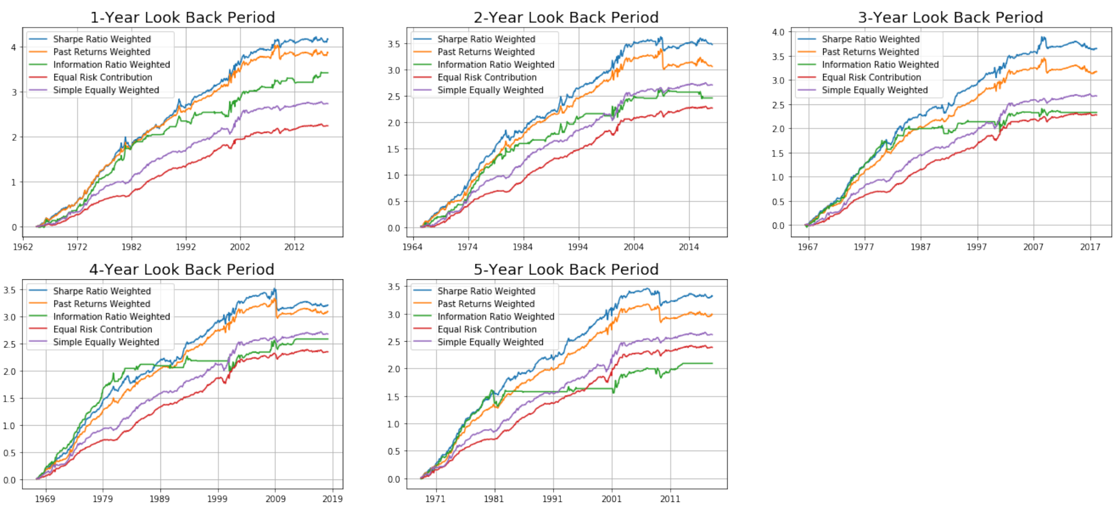
In [6]:
```
look_back_periods = [1,2,3,4,5]

sharpe_ratio_long_short = []
sharpe_ratio_long_only = []

average_mean_long_short = []
average_mean_long_only = []

information_ratio_long_short = []
information_ratio_long_only = []

simple_all = []
df_all=[]
erc_all_data=[]

for year in look_back_periods:
    look_back =year*12
    erc_df,simple,erc_list = erc(df,12*year)
    erc_all_data.append(erc_list)


    data,x11,x12 = sharpe_ratio_equal(df,market_data,look_back,long_only=False)
    sharpe_ratio_long_short.append(x11)
    simple_all.append(x12)
    df_all.append(data)

    data,x21,x22 = sharpe_ratio_equal(df,market_data,look_back,long_only=True)

    sharpe_ratio_long_only.append(x21)

    average_mean_long_short.append(average_mean_equal(df,market_data,look_back,long_onl
    average_mean_long_only.append(average_mean_equal(df,market_data,look_back,long_only

    information_ratio_long_short.append(information_ratio_equal(df,market_data,look_bac
    information_ratio_long_only.append(information_ratio_equal(df,market_data,look_back
```

```
E:\Anaconda3\lib\site-packages\ipykernel_launcher.py:160: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

```
In [7]: plt.figure(figsize=(23,10))

        output_combine = []

        for i in range(5):
            year = look_back_periods[i]
            sr = sharpe_ratio_long_only[i]
            am = average_mean_long_only[i]
            ir = information_ratio_long_only[i]
            si = simple_all[i]
            new_df = df_all[i]
            idx = new_df.index[1:]
            erc_list = erc_all_data[i]

            plt.subplot(2,3,i+1)
            plt.plot(idx,pd.Series(sr).cumsum()/100)
            plt.plot(idx,pd.Series(am).cumsum()/100)
            plt.plot(idx,pd.Series(ir).cumsum()/100)
            plt.plot(idx,pd.Series(erc_list).cumsum()/100)
            plt.plot(idx,pd.Series(si).cumsum()/100)
            plt.title(str(year)+'-Year Look Back Period',fontsize = 18)

            plt.legend(['Sharpe Ratio Weighted','Past Returns Weighted',\
                        'Information Ratio Weighted','Equal Risk Contribution','Simple Equally

            plt.grid(True)

            data = pd.DataFrame()
            data['sr'] = pd.Series(sr,index=idx)
            data['am'] = pd.Series(am,index=idx)
            data['ir'] = pd.Series(ir,index=idx)
            data['erc'] = pd.Series(erc_list,index=idx)
            data['si'] = pd.Series(si,index=idx)



            data['RF'] =  market_data['RF']
            data['MARKET'] = market_data['MARKET']
            data['RM_RF'] = market_data['Mkt-RF']
            data['SMB'] = market_data['SMB']
            data['HML'] = market_data['HML']

            SMB = np.array(data['SMB'])
```

```
HML = np.array(data['HML'])
RM_RF = np.array(data['RM_RF'])

X = np.column_stack((RM_RF,SMB,HML))
X = sm.add_constant(X)

factor_list_2 = ['sr','am','ir','erc','si']
factor_full_name = ['Sharpe Ratio Weighted','Past Returns Weighted',\
                    'Information Ratio Weighted','Equal Risk Contribution','Simple

output_3 = pd.DataFrame()
for j in range(5):
    factor = factor_list_2[j]
    factor_full = factor_full_name[j]
    Y = np.array(data[factor] ).T

    MODEL = regression.linear_model.OLS(Y, X).fit()

    data_p = data[factor]
    data_p_2 = data[factor]-data['RF']
    data_p_3 = data[factor]-data['MARKET']

    rm_rf_mean = RM_RF.mean()
    rf_mean = data['RF'].mean()

    output_3.loc['Average Returns',factor_full] = data_p.mean()
    output_3.loc['Std',factor_full] = np.std(data_p)
    output_3.loc['Sharpe Ratio',factor_full] = data_p_2.mean()/np.std(data_p)
    output_3.loc['Alpha',factor_full] = MODEL.params[0]
    output_3.loc['Beta',factor_full] = MODEL.params[1]
    output_3.loc['Treynor Ratio',factor_full] = data_p_2.mean()/MODEL.params[1]
    output_3.loc['Jensen Measure',factor_full] = data_p.mean()-rf_mean-MODEL.params
    output_3.loc['Information Ratio',factor_full] = data_p_3.mean()/np.std(data_p_3

output_combine.append(output_3)
```




```
In [8]: output_combine[0]
```

```
Out[8]:                     Sharpe Ratio Weighted  Past Returns Weighted  \
        Average Returns                  0.646187               0.600075
        Std                              2.377167               2.403688
        Sharpe Ratio                     0.109003               0.088616
        Alpha                            0.614601               0.596197
        Beta                            -0.069530              -0.091566
        Treynor Ratio                   -3.726680              -2.326245
        Jensen Measure                   0.294933               0.260172
        Information Ratio               -0.048855              -0.056718

                            Information Ratio Weighted  Equal Risk Contribution  \
        Average Returns                       0.530572                 0.348039
        Std                                   2.432164                 0.955118
        Sharpe Ratio                          0.059002                -0.040865
        Alpha                                 0.499280                 0.316954
        Beta                                 -0.048778                -0.021275
        Treynor Ratio                        -2.941923                 1.834554
        Jensen Measure                        0.168628                -0.028072
        Information Ratio                    -0.072862                -0.117562

                            Simple Equally Weighted
        Average Returns                    0.424207
        Std                                1.314044
        Sharpe Ratio                       0.028262
        Alpha                              0.375700
        Beta                              -0.068762
        Treynor Ratio                     -0.540091
        Jensen Measure                     0.072557
        Information Ratio                 -0.093602
```

```
In [9]: output_combine[1]
```

```
Out[9]:                       Sharpe Ratio Weighted  Past Returns Weighted  \
        Average Returns                    0.549117               0.483091
        Std                                2.270413               2.279075
        Sharpe Ratio                       0.070688               0.041449
        Alpha                              0.553792               0.509856
        Beta                              -0.080813              -0.110529
        Treynor Ratio                     -1.985965              -0.854666
        Jensen Measure                     0.202514               0.151941
        Information Ratio                 -0.068471              -0.079006

                              Information Ratio Weighted  Equal Risk Contribution  \
        Average Returns                         0.388495                 0.358242
        Std                                     2.353345                 1.002930
        Sharpe Ratio                           -0.000056                -0.030295
        Alpha                                   0.372187                 0.326206
        Beta                                   -0.051938                -0.020390
        Treynor Ratio                           0.002520                 1.490116
        Jensen Measure                          0.026877                -0.019781
        Information Ratio                      -0.101935                -0.115363

                              Simple Equally Weighted
        Average Returns                      0.427546
        Std                                  1.325066
        Sharpe Ratio                         0.029372
        Alpha                                0.377934
        Beta                                -0.069194
        Treynor Ratio                       -0.562474
        Jensen Measure                       0.074901
        Information Ratio                   -0.093514
```

```
In [10]: output_combine[2]
```

```
Out[10]:                       Sharpe Ratio Weighted  Past Returns Weighted  \
         Average Returns                    0.587510               0.510590
         Std                                2.221848               1.991933
         Sharpe Ratio                       0.089163               0.060838
         Alpha                              0.581100               0.527117
         Beta                              -0.073211              -0.093892
         Treynor Ratio                     -2.705938              -1.290698
         Jensen Measure                     0.236600               0.170554
         Information Ratio                 -0.062588              -0.076905

                               Information Ratio Weighted  Equal Risk Contribution  \
         Average Returns                         0.374552                 0.366135
         Std                                     2.121046                 0.988253
         Sharpe Ratio                           -0.007002                -0.023546
```

```
Alpha                             0.329933                  0.342721
Beta                             -0.027284                 -0.029509
Treynor Ratio                     0.544375                  0.788544
Jensen Measure                   -0.000507                 -0.007753
Information Ratio                -0.106655                 -0.113910

                   Simple Equally Weighted
Average Returns                   0.429333
Std                               1.335885
Sharpe Ratio                      0.029889
Alpha                             0.379167
Beta                             -0.069390
Treynor Ratio                    -0.575421
Jensen Measure                    0.076414
Information Ratio                -0.093744
```

In [44]: output_combine[3]

```
Out[44]:           Sharpe Ratio Weighted  Past Returns Weighted  \
Average Returns                 0.417721               0.354440
Std                             2.838203               2.260521
Sharpe Ratio                    0.011529              -0.013519
Alpha                           0.482189               0.406925
Beta                           -0.109343              -0.117801
Treynor Ratio                  -0.299253               0.259423
Jensen Measure                  0.097416               0.039139
Information Ratio              -0.100091              -0.114877

                   Information Ratio Weighted  \
Average Returns                      0.353950
Std                                  2.337596
Sharpe Ratio                        -0.013283
Alpha                                0.362989
Beta                                -0.057616
Treynor Ratio                        0.538911
Jensen Measure                       0.003040
Information Ratio                   -0.117559

                   Equal Risk Contribution Portfolio  Simple Equally Weighted
Average Returns                             0.351544                 0.338191
Std                                         1.429670                 1.424255
Sharpe Ratio                               -0.023401                -0.032865
Alpha                                       0.291301                 0.273511
Beta                                       -0.066918                -0.068169
Treynor Ratio                               0.499953                 0.686657
Jensen Measure                              0.006138                -0.006475
Information Ratio                          -0.119809                -0.122171
```

In [11]: output_combine[4]

Out[11]:

	Sharpe Ratio Weighted	Past Returns Weighted	Information Ratio Weighted	Equal Risk Contribution	Simple Equally Weighted
Average Returns	0.556491	0.500314	0.350775	0.399665	0.438524
Std	2.019738	1.800122	1.719645	1.074829	1.352189
Sharpe Ratio	0.082449	0.061300	-0.022791	0.009023	0.035910
Alpha	0.535468	0.487006	0.338639	0.358182	0.380003
Beta	-0.061503	-0.081192	-0.044961	-0.024501	-0.069100
Treynor Ratio	-2.707585	-1.359095	0.871676	-0.395819	-0.702709
Jensen Measure	0.197977	0.151869	-0.016199	0.022228	0.083895
Information Ratio	-0.067171	-0.076921	-0.110132	-0.103095	-0.088760