4.4_PCR

May 26, 2025

[1]:
```python
import numpy as np
import pandas as pd
import math
import sklearn
import sklearn.preprocessing
import datetime
import os
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.decomposition import PCA
from sklearn.metrics import mean_squared_error


import warnings
warnings.simplefilter(action='ignore', category=Warning)
import seaborn as sns
sns.set()
pd.options.mode.chained_assignment = None  # default='warn'

#Program that executes the rolling window train-val-test split
%run TimeBasedCV.ipynb
```

[2]:
```python
#Read in the cleansed and winsorised data
df = pd.read_csv(r"C:\Users\krist\Documents\Data\ger_factor_data_from2003.csv",␣
 ↪dtype ={"comp_tpci": str}, parse_dates =["eom"])
#Convert to float 32 (format needed for the most ML models)
df[df.columns[2:]] = df[df.columns[2:]].astype('float32')
#Sort observations by date and stock id
df = df.sort_values(by = ['eom', 'id'], ascending = True)
df.head()
```

[2]:
```
                 id        eom        prc           me       ret   ret_exc  \
0  comp_001166_02W 2003-01-31  11.486148   567.074646 -0.018948 -0.019948
1  comp_001661_01W 2003-01-31  35.853958  5221.931641  0.005815  0.004815
2  comp_004367_02W 2003-01-31  36.068653  4139.599121 -0.103801 -0.104801
3  comp_004925_02W 2003-01-31  29.735168 15302.482422 -0.070425 -0.071425
4  comp_005959_01W 2003-01-31  39.181721  6355.691406 -0.085813 -0.086813
```

```
   ret_exc_lead1m   ret_6_1  ret_12_1  tax_gr1a  …  cowc_gr1a    pi_nix  \
0       -0.089504 -0.229560 -0.353251 -0.020556  …   0.041844  3.815513
1        0.108428  0.129149 -0.035109 -0.033306  …  -0.019596  1.284930
2        0.127227 -0.020286  0.087151 -0.037240  …   0.026114  1.725004
3        0.064832  0.046064  0.023265 -0.007344  …  -0.000724  1.961724
4        0.001832  0.123795  0.012811 -0.012241  …  -0.014214  1.069862

    ret_6_0   ret_1_0    noa_at  cop_atl1  prc_highprc_252d    ocf_at  \
0 -0.244158 -0.018948  0.692706  0.093015          0.398130 -0.007700
1  0.135715  0.005815  0.751569  0.164124          0.918059  0.096164
2 -0.121981 -0.103801  0.961141  0.240563          0.675468  0.070724
3 -0.027605 -0.070425  0.466852  0.221983          0.861333  0.084234
4  0.027359 -0.085813  0.635742  0.108581          0.721256  0.069331

   dbnetis_at  netdebt_me
0    0.085202    0.135368
1    0.063714    0.200036
2   -0.000607    0.410184
3   -0.008142   -0.075232
4   -0.038594    0.500641

[5 rows x 55 columns]
```

[3]:
```python
#Copy date variable and stock id to use them as multindex
df["id2"] = df["id"].copy()
df["eom2"] = df["eom"].copy()
df = df.set_index(['eom2','id2'])

#Make a copy of  the "me" variable (market equity) before rank standartization␣
↪to use afterwards for value weighting
df["me2"] = df["me"].copy()
```

To investigate the potential heterogeneity in model predictability, a subgroup analysis for small (the bottom 30% stocks by market equity each month) and large (the top 30% stocks each month) stocks is reported.

[4]:
```python
#Create two new dataframes containing only large and only small firms␣
↪respectively.
p=0.3
df_top = df.groupby('eom').apply(lambda x: x.nlargest(int(len(x)*p),"me")).
↪reset_index(drop=True)
df_bottom = df.groupby('eom').apply(lambda x: x.nsmallest(int(len(x)*p),"me")).
↪reset_index(drop=True)
```

0.0.1 Rank standardization in interval [-1,1]

A rank standardization procedure following Kelly, Pruitt, and Su (2019) and Freyberger, Neuhierl, and Weber (2020) is employed. The stock characteristics are ranked month-by-month crosssectionally and the ranks are mapped into the [-1,1] interval, thereby transforming features into a uniform distribution and increasing the insensitivity to outliers

[5]:
```
#Standardize all independent variables
features = df.columns[~df.columns.
 ↪isin(["eom","eom2","me2",'id',"id2","ret","ret_exc","ret_exc_lead1m"])].
 ↪tolist()

#Ranks in [0,1]interval
df[features]=df.groupby("eom")[features].rank(pct=True)

#Multiply by 2 and substract 1 to get ranks in interval [-1,1]
df[features] = 2*df[features] - 1
```

[6]:
```
#Standardize the big firms dataset
features = df_top.columns[~df_top.columns.
 ↪isin(["eom","eom2","me2",'id',"id2","ret","ret_exc","ret_exc_lead1m"])].
 ↪tolist()
df_top[features]=df_top.groupby("eom")[features].rank(pct=True)
df_top[features] = 2*df_top[features] - 1
```

[7]:
```
#standardize the small firms dataset
features = df_bottom.columns[~df_bottom.columns.
 ↪isin(["eom","eom2","me2",'id',"id2","ret","ret_exc","ret_exc_lead1m"])].
 ↪tolist()
df_bottom[features]=df_bottom.groupby("eom")[features].rank(pct=True)
df_bottom[features] = 2*df_bottom[features] - 1
```

1 Principal component regression

1.1 All firms

[8]:
```
# Define the splitting scheme:
# Rolling window  train-val-test split
# The rolling window is set to 96 months (8 years)
# 5 years for training, 2 years for validation, and 1 year for out-of-samlpe␣
 ↪testing
tscv = TimeBasedCV(train_period=60,
                   val_period=24,
                   test_period=12,
                   freq='months')

#Define the idependent variables (X) and the dependent variable (y)
features = df.columns[~df.columns.
 ↪isin(['id',"id2","me2","prc","eom2","ret","ret_exc","ret_exc_lead1m"])].
 ↪tolist()
X = df[features]
```

```
y = df["ret_exc_lead1m"]


#Empty containers to save results from each window
predictions = []
y_test_list =[]
dates = []
dic_r2_all = {}

# Model's complexity: dictionary to save the number of components over time
numpc_time = {}

# List of prespecified values to use to determine the optimal number of␣
 ↪components

numpc = [1,2,3,5,7,9,11,15,17,22,25,29,33,40,45,49]
# Empty container to save the objective loss function (mean squared errors) for␣
 ↪each number of components
mse = np.full((len(numpc),1),np.nan, dtype = np.float32)


for train_index, val_index, test_index in tscv.split(X, first_split_date=␣
 ↪datetime.date(2008,1,31), second_split_date= datetime.date(2010,1,31)):

    X_train   = X.loc[train_index].drop('eom', axis=1)
    y_train = y.loc[train_index]

    X_val   = X.loc[val_index].drop('eom', axis=1)
    y_val = y.loc[val_index]

    X_test    = X.loc[test_index].drop('eom', axis=1)
    y_test  = y.loc[test_index]


    # In Sklearn there is no PCR class, so one has to first perform the␣
 ↪dimention reduction using Principal
    # component analysis and than proceed with prediction using linear␣
 ↪regression

    #Loop over the list containing potential number of components, fit on the␣
 ↪training sample and use
    #validation set to generate predictions
    for i in range(len(numpc)):
        pca_val = PCA(n_components = numpc[i])
        # Run PCA producing the reduced variable X_reduced_val containing i␣
 ↪components
```

```python
        X_reduced_train = pca_val.fit_transform(X_train)
        X_reduced_val = pca_val.transform(X_val)
        # Create linear regression object and fit
        line_fitter_val = LinearRegression()
        line_fitter_val.fit(X_reduced_train, y_train)
        # Predict using the reduced variable
        Yval_predict=line_fitter_val.predict(X_reduced_val)
        #calculate mean squared error for each potential value of the numpc hyperparameter
        mse[i,0] = np.sqrt(mean_squared_error(y_val, Yval_predict))


    #The optimal value of the numpc hyperparameter is the value that causes the lowest loss
    optim_numpc = numpc[np.argmin(mse)]

    #Fit again using the train and validation set and the optimal numpc parameter
    pca = PCA(n_components = optim_numpc)
    principalComponents = pca.fit_transform(np.concatenate((X_train, X_val)))
    X_reduced_test = pca.transform(X_test)
    line_fitter = LinearRegression()
    line_fitter.fit(principalComponents, (np.concatenate((y_train, y_val))))
    #Use test set to generate final predictions using the redused variable
    preds=line_fitter.predict(X_reduced_test)


    #Save predictions, dates and the true values of the dependent variable to list
    predictions.append(preds)
    dates.append(y_test.index)
    y_test_list.append(y_test)

    #Calculate OOS model performance the for current window
    r2 = 1-sum(pow(y_test-preds,2))/sum(pow(y_test,2))
    #Save OOS model performance and the respective month to dictionary
    dic_r2_all["r2." + str(y_test.index)] = r2
    # Save the number of components to inspect  model's complexity over time
    numpc_time["numpc." + str(y_test.index)] = optim_numpc



#Concatenate to get results over the whole OOS test period (Jan 2010-Dec 2019)
predictions_all= np.concatenate(predictions, axis=0)
y_test_list_all= np.concatenate(y_test_list, axis=0)
dates_all= np.concatenate(dates, axis=0)
```

```
#Calculate OOS model performance over the entire test period in line with Gu et␣
↪al (2020)
R2OOS_PCR = 1-sum(pow(y_test_list_all-predictions_all,2))/
↪sum(pow(y_test_list_all,2))
print("R2OOS principal component regression: ", R2OOS_PCR)
```

```
Train period: 2003-01-31 - 2008-01-31 ,val period: 2008-01-31 - 2010-01-31 ,
Test period 2010-01-31 - 2011-01-31 # train records 37757 ,# val records 17356 ,
# test records 8974
Train period: 2004-01-31 - 2009-01-31 ,val period: 2009-01-31 - 2011-01-31 ,
Test period 2011-01-31 - 2012-01-31 # train records 40925 ,# val records 17143 ,
# test records 9537
Train period: 2005-01-31 - 2010-01-31 ,val period: 2010-01-31 - 2012-01-31 ,
Test period 2012-01-31 - 2013-01-31 # train records 42278 ,# val records 18511 ,
# test records 9107
Train period: 2006-01-31 - 2011-01-31 ,val period: 2011-01-31 - 2013-01-31 ,
Test period 2013-01-31 - 2014-01-31 # train records 43971 ,# val records 18644 ,
# test records 9636
Train period: 2007-01-31 - 2012-01-31 ,val period: 2012-01-31 - 2014-01-31 ,
Test period 2014-01-31 - 2015-01-31 # train records 45267 ,# val records 18743 ,
# test records 9919
Train period: 2008-01-31 - 2013-01-31 ,val period: 2013-01-31 - 2015-01-31 ,
Test period 2015-01-31 - 2016-01-31 # train records 44974 ,# val records 19555 ,
# test records 9260
Train period: 2009-01-31 - 2014-01-31 ,val period: 2014-01-31 - 2016-01-31 ,
Test period 2016-01-31 - 2017-01-31 # train records 45423 ,# val records 19179 ,
# test records 9109
Train period: 2010-01-31 - 2015-01-31 ,val period: 2015-01-31 - 2017-01-31 ,
Test period 2017-01-31 - 2018-01-31 # train records 47173 ,# val records 18369 ,
# test records 9667
Train period: 2011-01-31 - 2016-01-31 ,val period: 2016-01-31 - 2018-01-31 ,
Test period 2018-01-31 - 2019-01-31 # train records 47459 ,# val records 18776 ,
# test records 9569
Train period: 2012-01-31 - 2017-01-31 ,val period: 2017-01-31 - 2019-01-31 ,
Test period 2019-01-31 - 2020-01-31 # train records 47031 ,# val records 19236 ,
# test records 8639
R2OOS principal component regression:  0.008067757591002311
```

2 Big only

[14]:
```
tscv = TimeBasedCV(train_period=60,
                   val_period=24,
                   test_period=12,
                   freq='months')
```

```python
features = df_top.columns[~df_top.columns.
 ↪isin(['id',"id2","me2","prc","eom2","ret","ret_exc","ret_exc_lead1m"])].
 ↪tolist()
X = df_top[features]
y = df_top["ret_exc_lead1m"]


#Empty containers to save results from each window
predictions_top = []
y_test_list_top =[]
dates_top = []
dic_r2_all_top = {}

numpc = [1,2,3,5,7,9,11,15,17,22,25,29,33,40,45,49]
mse = np.full((len(numpc),1),np.nan, dtype = np.float32)


for train_index, val_index, test_index in tscv.split(X, first_split_date=␣
 ↪datetime.date(2008,1,31), second_split_date= datetime.date(2010,1,31)):

    X_train   = X.loc[train_index].drop('eom', axis=1)
    y_train = y.loc[train_index]

    X_val   = X.loc[val_index].drop('eom', axis=1)
    y_val = y.loc[val_index]

    X_test    = X.loc[test_index].drop('eom', axis=1)
    y_test   = y.loc[test_index]

    for i in range(len(numpc)):
        pca_val = PCA(n_components = numpc[i])
        X_reduced_train = pca_val.fit_transform(X_train)
        X_reduced_val = pca_val.transform(X_val)
        line_fitter_val = LinearRegression()
        line_fitter_val.fit(X_reduced_train, y_train)
        Yval_predict=line_fitter_val.predict(X_reduced_val)
        mse[i,0]  = np.sqrt(mean_squared_error(y_val, Yval_predict))


    optim_numpc = numpc[np.argmin(mse)]

    pca = PCA(n_components = optim_numpc)
    principalComponents = pca.fit_transform(np.concatenate((X_train, X_val)))
    X_reduced_test = pca.transform(X_test)
    line_fitter = LinearRegression()
    line_fitter.fit(principalComponents, (np.concatenate((y_train, y_val))))
    preds=line_fitter.predict(X_reduced_test)
```

```
    predictions_top.append(preds)
    dates_top.append(y_test.index)
    y_test_list_top.append(y_test)


    r2 = 1-sum(pow(y_test-preds,2))/sum(pow(y_test,2))
    dic_r2_all_top["r2." + str(y_test.index)] = r2



predictions_all_top_top= np.concatenate(predictions_top, axis=0)
y_test_list_all_top= np.concatenate(y_test_list_top, axis=0)
dates_all_top= np.concatenate(dates_top, axis=0)


R2OOS_PCR_top = 1-sum(pow(y_test_list_all_top-predictions_all_top_top,2))/
 ↪sum(pow(y_test_list_all_top,2))
print("R2OOS principal component regression Big only: ", R2OOS_PCR_top)
```

```
Train period: 2003-01-31 - 2008-01-31 ,val period: 2008-01-31 - 2010-01-31 ,
Test period 2010-01-31 - 2011-01-31 # train records 11301 ,# val records 5199 ,
# test records 2687
Train period: 2004-01-31 - 2009-01-31 ,val period: 2009-01-31 - 2011-01-31 ,
Test period 2011-01-31 - 2012-01-31 # train records 12252 ,# val records 5135 ,
# test records 2855
Train period: 2005-01-31 - 2010-01-31 ,val period: 2010-01-31 - 2012-01-31 ,
Test period 2012-01-31 - 2013-01-31 # train records 12661 ,# val records 5542 ,
# test records 2728
Train period: 2006-01-31 - 2011-01-31 ,val period: 2011-01-31 - 2013-01-31 ,
Test period 2013-01-31 - 2014-01-31 # train records 13170 ,# val records 5583 ,
# test records 2885
Train period: 2007-01-31 - 2012-01-31 ,val period: 2012-01-31 - 2014-01-31 ,
Test period 2014-01-31 - 2015-01-31 # train records 13558 ,# val records 5613 ,
# test records 2969
Train period: 2008-01-31 - 2013-01-31 ,val period: 2013-01-31 - 2015-01-31 ,
Test period 2015-01-31 - 2016-01-31 # train records 13469 ,# val records 5854 ,
# test records 2772
Train period: 2009-01-31 - 2014-01-31 ,val period: 2014-01-31 - 2016-01-31 ,
Test period 2016-01-31 - 2017-01-31 # train records 13603 ,# val records 5741 ,
# test records 2729
Train period: 2010-01-31 - 2015-01-31 ,val period: 2015-01-31 - 2017-01-31 ,
Test period 2017-01-31 - 2018-01-31 # train records 14124 ,# val records 5501 ,
# test records 2894
Train period: 2011-01-31 - 2016-01-31 ,val period: 2016-01-31 - 2018-01-31 ,
Test period 2018-01-31 - 2019-01-31 # train records 14209 ,# val records 5623 ,
# test records 2864
Train period: 2012-01-31 - 2017-01-31 ,val period: 2017-01-31 - 2019-01-31 ,
```

```
Test period 2019-01-31 - 2020-01-31 # train records 14083 ,# val records 5758 ,
# test records 2587
R2OOS principal component regression Big only:  0.006243024175388245
```

3 Small only

[13]:
```
tscv = TimeBasedCV(train_period=60,
                   val_period=24,
                   test_period=12,
                   freq='months')

features = df_bottom.columns[~df_bottom.columns.
 ↪isin(['id',"id2","me2","prc","eom2","ret","ret_exc","ret_exc_lead1m"])].
 ↪tolist()
X = df_bottom[features]
y = df_bottom["ret_exc_lead1m"]


#Empty containers to save results from each window
predictions_bottom = []
y_test_list_bottom =[]
dates_bottom = []
dic_r2_all_bottom = {}

numpc = [1,2,3,5,7,9,11,15,17,22,25,29,33,40,45,49]
mse = np.full((len(numpc),1),np.nan, dtype = np.float32)


for train_index, val_index, test_index in tscv.split(X, first_split_date=␣
 ↪datetime.date(2008,1,31), second_split_date= datetime.date(2010,1,31)):

    X_train   = X.loc[train_index].drop('eom', axis=1)
    y_train = y.loc[train_index]

    X_val   = X.loc[val_index].drop('eom', axis=1)
    y_val = y.loc[val_index]

    X_test    = X.loc[test_index].drop('eom', axis=1)
    y_test  = y.loc[test_index]

    for i in range(len(numpc)):
        pca_val = PCA(n_components = numpc[i])
        X_reduced_train = pca_val.fit_transform(X_train)
        X_reduced_val = pca_val.transform(X_val)
        line_fitter_val = LinearRegression()
        line_fitter_val.fit(X_reduced_train, y_train)
```

```
        Yval_predict=line_fitter_val.predict(X_reduced_val)
        mse[i,0] = np.sqrt(mean_squared_error(y_val, Yval_predict))



    optim_numpc = numpc[np.argmin(mse)]

    pca = PCA(n_components = optim_numpc)
    principalComponents = pca.fit_transform(np.concatenate((X_train, X_val)))
    X_reduced_test = pca.transform(X_test)
    line_fitter = LinearRegression()
    line_fitter.fit(principalComponents, (np.concatenate((y_train, y_val))))
    preds=line_fitter.predict(X_reduced_test)

    predictions_bottom.append(preds)
    dates_bottom.append(y_test.index)
    y_test_list_bottom.append(y_test)


    r2 = 1-sum(pow(y_test-preds,2))/sum(pow(y_test,2))
    dic_r2_all_bottom["r2." + str(y_test.index)] = r2



predictions_all_bottom_bottom= np.concatenate(predictions_bottom, axis=0)
y_test_list_all_bottom= np.concatenate(y_test_list_bottom, axis=0)
dates_all_bottom= np.concatenate(dates_bottom, axis=0)


R2OOS_PCR_bottom =␣
 ↪1-sum(pow(y_test_list_all_bottom-predictions_all_bottom_bottom,2))/
 ↪sum(pow(y_test_list_all_bottom,2))
print("R2OOS principal component regression Small only: ", R2OOS_PCR_bottom)
```

```
Train period: 2003-01-31 - 2008-01-31 ,val period: 2008-01-31 - 2010-01-31 ,
Test period 2010-01-31 - 2011-01-31 # train records 11301 ,# val records 5199 ,
# test records 2687
Train period: 2004-01-31 - 2009-01-31 ,val period: 2009-01-31 - 2011-01-31 ,
Test period 2011-01-31 - 2012-01-31 # train records 12252 ,# val records 5135 ,
# test records 2855
Train period: 2005-01-31 - 2010-01-31 ,val period: 2010-01-31 - 2012-01-31 ,
Test period 2012-01-31 - 2013-01-31 # train records 12661 ,# val records 5542 ,
# test records 2728
Train period: 2006-01-31 - 2011-01-31 ,val period: 2011-01-31 - 2013-01-31 ,
Test period 2013-01-31 - 2014-01-31 # train records 13170 ,# val records 5583 ,
# test records 2885
Train period: 2007-01-31 - 2012-01-31 ,val period: 2012-01-31 - 2014-01-31 ,
Test period 2014-01-31 - 2015-01-31 # train records 13558 ,# val records 5613 ,
```

```
# test records 2969
Train period: 2008-01-31 - 2013-01-31 ,val period: 2013-01-31 - 2015-01-31 ,
Test period 2015-01-31 - 2016-01-31 # train records 13469 ,# val records 5854 ,
# test records 2772
Train period: 2009-01-31 - 2014-01-31 ,val period: 2014-01-31 - 2016-01-31 ,
Test period 2016-01-31 - 2017-01-31 # train records 13603 ,# val records 5741 ,
# test records 2729
Train period: 2010-01-31 - 2015-01-31 ,val period: 2015-01-31 - 2017-01-31 ,
Test period 2017-01-31 - 2018-01-31 # train records 14124 ,# val records 5501 ,
# test records 2894
Train period: 2011-01-31 - 2016-01-31 ,val period: 2016-01-31 - 2018-01-31 ,
Test period 2018-01-31 - 2019-01-31 # train records 14209 ,# val records 5623 ,
# test records 2864
Train period: 2012-01-31 - 2017-01-31 ,val period: 2017-01-31 - 2019-01-31 ,
Test period 2019-01-31 - 2020-01-31 # train records 14083 ,# val records 5758 ,
# test records 2587
R2OOS principal component regression Small only:  0.010347082445304134
```

[12]:
```
#Generate table containing the R2oos measures for all three datasets
chart = np.array([[R2OOS_PCR],
                  [R2OOS_PCR_top],
                  [R2OOS_PCR_bottom]])


r2oos_pcr = pd.DataFrame(chart, columns=['PCR'],
                         index=["Full sample", "Large firms", "Small␣
 ↪firms"])
r2oos_pcr
```

[12]:

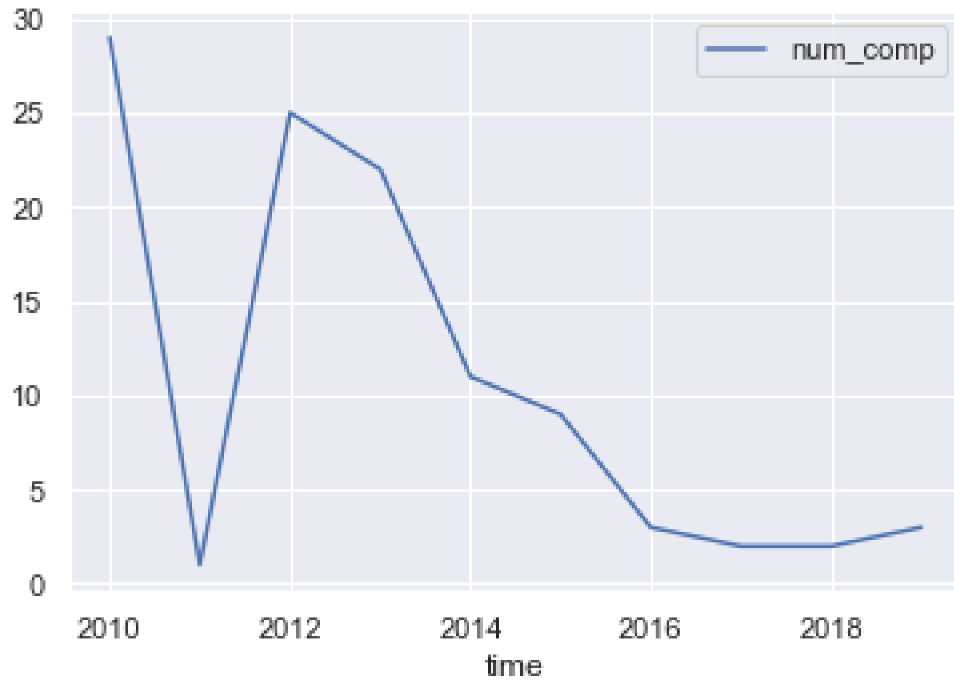
	PCR
Full sample	0.008066
Large firms	0.006243
Small firms	0.010347

[13]:
```
#Save the model's performance measures to compare with other models later.
r2oos_pcr.to_csv(r'C:\Users\krist\Documents\Data\r2oos results\r2oos_pcr.csv')
```

3.0.1 Time-varying model complexity

[24]:
```
# Convert dictionary containing the number of components over time in dataframe
pd.DataFrame(numpc_time.items())
numpc_table =pd.DataFrame(numpc_time.items(), columns=['Identifier',␣
 ↪'num_comp'])
numpc_table['Identifier'] = numpc_table['Identifier'].astype(str)
numpc_table["time"] = numpc_table["Identifier"].str[20:30]
numpc_table["time"] = pd.to_datetime(numpc_table["time"], utc = False)
numpc_table["time"] = numpc_table["time"].dt.year
```

```
numpc_table.drop(["Identifier"], axis = 1, inplace = True)

#Plot time-varying model complexity
numpc_table.set_index('time').plot();
#plt.xticks(rotation=45);
```



[25]:
```
#Save the model's complexity  to compare with other models later.
numpc_table.to_csv(r'C:\Users\krist\Documents\Data\model_complexity\comp_pcr.
↪csv')
```

3.0.2 Variable Importance

Variable importance is defined following Gu et al. (2020), i.e., for each model, all values of a given predictor are set to zero and the reduction in predictive R2OOS is calculated. Then, the absolute reductions in predictive R2OOS are normalized to sum to 1, indicating the relative contribution of each variable to a model. In contrast to Gu et al. (2020), variable importance is calculated based on the last rolling window observation sample and does not represent an average over the whole sample.

[39]:
```
# R2OOS based on the last rolling window when all variables are included
features = df.columns[~df.columns.
↪isin(['id',"id2","eom","eom2","me2","prc","ret","ret_exc","ret_exc_lead1m","year"])].
↪tolist()
df["year"] = df["eom"].dt.year
```

```
X_train = df[features].loc[(df["year"]>=2012) & (df["year"]<=2016)]
y_train = df["ret_exc_lead1m"].loc[(df["year"]>=2012) & (df["year"]<=2016)]

X_val = df[features].loc[(df["year"]>=2017) & (df["year"]<=2018)]
y_val = df["ret_exc_lead1m"].loc[(df["year"]>=2017) & (df["year"]<=2018)]

numpc = [1,2,3,5,7,9,11,15,17,22,25,29,33,40,45,49]
mse = np.full((len(numpc),1),np.nan, dtype = np.float32)

for i in range(len(numpc)):
    pca_val = PCA(n_components = numpc[i])
    X_reduced_train = pca_val.fit_transform(X_train)
    X_reduced_val = pca_val.transform(X_val)
    line_fitter_val = LinearRegression()
    line_fitter_val.fit(X_reduced_train, y_train)
    Yval_predict=line_fitter_val.predict(X_reduced_val)
    mse[i,0] = np.sqrt(mean_squared_error(y_val, Yval_predict))


optim_numpc = numpc[np.argmin(mse)]
pca = PCA(n_components = optim_numpc)
principalComponents = pca.fit_transform(np.concatenate((X_train, X_val)))
line_fitter = LinearRegression()
line_fitter.fit(principalComponents, (np.concatenate((y_train, y_val))))
preds=line_fitter.predict(principalComponents)
R2OOS_all = 1-sum(pow(np.concatenate((y_train, y_val))-preds,2))/sum(pow(np.
 ↪concatenate((y_train, y_val)),2))
print(R2OOS_all)
```

```
0.008041589337524191
```

[40]:
```
# Generate a separate dataframe for each independent variable, where all values␣
 ↪of that variable are set to zero

for j in features:
    globals()['df_' + str(j)] =  df.copy()
    globals()['df_' + str(j)][str(j)] = 0
```

[41]:
```
#e.g., df_ret_12_1 is a dataframe where all values of the ret_12_1 variable are␣
 ↪set to zero
df_ret_12_1
```

[41]:
```
                                           id         eom       prc        me  \
eom2       id2
2003-01-31 comp_001166_02W  comp_001166_02W 2003-01-31 -0.376652  0.162996
           comp_001661_01W  comp_001661_01W 2003-01-31  0.427313  0.718062
```

```
           comp_004367_02W  comp_004367_02W 2003-01-31  0.433921  0.674009
           comp_004925_02W  comp_004925_02W 2003-01-31  0.295154  0.881057
           comp_005959_01W  comp_005959_01W 2003-01-31  0.477974  0.762115
…                                         …          …         …         …
2020-12-31 comp_333885_01W  comp_333885_01W 2020-12-31  0.367156  0.484646
           comp_334302_02W  comp_334302_02W 2020-12-31 -0.842457 -0.487316
           comp_335706_02W  comp_335706_02W 2020-12-31 -0.722296 -0.618158
           comp_340115_01W  comp_340115_01W 2020-12-31 -0.392523 -0.025367
           comp_340153_01W  comp_340153_01W 2020-12-31  0.138852  0.711615

                                 ret   ret_exc  ret_exc_lead1m   ret_6_1  \
eom2       id2
2003-01-31 comp_001166_02W -0.018948 -0.019948       -0.089504 -0.665198
           comp_001661_01W  0.005815  0.004815        0.108428  0.669604
           comp_004367_02W -0.103801 -0.104801        0.127227  0.114537
           comp_004925_02W -0.070425 -0.071425        0.064832  0.392070
           comp_005959_01W -0.085813 -0.086813        0.001832  0.643172
…                                …         …               …         …
2020-12-31 comp_333885_01W  0.128645  0.128545       -0.037398 -0.957276
           comp_334302_02W  0.097961  0.097861       -0.033670 -0.420561
           comp_335706_02W  0.114381  0.114281        0.089684  0.097463
           comp_340115_01W  0.155813  0.155713        0.009796  0.001335
           comp_340153_01W  0.238817  0.238717        0.006943  0.001335

                            ret_12_1  tax_gr1a  …   ret_6_0   ret_1_0  \
eom2       id2                                  …
2003-01-31 comp_001166_02W         0 -0.726872  … -0.669604 -0.312775
           comp_001661_01W         0 -0.845815  …  0.577093 -0.110132
           comp_004367_02W         0 -0.894273  … -0.356828 -0.766520
           comp_004925_02W         0 -0.453744  …  0.096916 -0.612335
           comp_005959_01W         0 -0.599119  …  0.259912 -0.691630
…                                …         …  …       …         …
2020-12-31 comp_333885_01W         0 -0.951936  … -0.853138  0.591455
           comp_334302_02W         0  0.540721  … -0.268358  0.417891
           comp_335706_02W         0  0.311081  …  0.236315  0.511348
           comp_340115_01W         0  0.871829  …  0.001335  0.687583
           comp_340153_01W         0  0.847797  …  0.001335  0.879840

                              noa_at  cop_atl1  prc_highprc_252d    ocf_at  \
eom2       id2
2003-01-31 comp_001166_02W  0.585903 -0.735683         -0.859031 -0.797357
           comp_001661_01W  0.696035 -0.392070          0.607930  0.286344
           comp_004367_02W  0.881057  0.458150         -0.365639 -0.110132
           comp_004925_02W -0.264317  0.330396          0.422907  0.149780
           comp_005959_01W  0.458150 -0.669604         -0.255507 -0.118943
…                                …         …                 …         …
2020-12-31 comp_333885_01W  0.457944  0.815754         -0.319092  0.877170
```

```
            comp_334302_02W  0.791722  0.345794          0.754339  0.054740
            comp_335706_02W -0.241656 -0.935915         -0.313752 -0.917223
            comp_340115_01W -0.415220 -0.436582          0.001335  0.025367
            comp_340153_01W -0.815754 -0.636849          0.001335 -0.129506

                            dbnetis_at  netdebt_me           me2  year
eom2       id2
2003-01-31 comp_001166_02W    0.735683   -0.149780    567.074646  2003
           comp_001661_01W    0.647577    0.145374   5221.931641  2003
           comp_004367_02W   -0.207048    0.339207   4139.599121  2003
           comp_004925_02W   -0.370044   -0.709251  15302.482422  2003
           comp_005959_01W   -0.656388    0.436123   6355.691406  2003
…                                  …           …             …   …
2020-12-31 comp_333885_01W   -0.930574   -0.316422  10829.783203  2020
           comp_334302_02W    0.692924   -0.252336    297.482697  2020
           comp_335706_02W    0.164219   -0.730307    196.243454  2020
           comp_340115_01W    0.642190    0.562083   1799.958496  2020
           comp_340153_01W   -0.110814   -0.578104  26788.144531  2020

[156948 rows x 57 columns]
```

[42]:
```python
# calculate R2OOS based on the last rolling window for each dataframe and save
↪to dictionary

dic = {}
numpc =np.arange(2, 20, 1).tolist()
mse = np.full((len(numpc),1),np.nan, dtype = np.float32)

for j in features:
    df_var = globals()['df_' + str(j)]

    X_train = df_var[features].loc[(df_var["year"]>=2012) &
↪(df_var["year"]<=2016)]
    y_train = df_var["ret_exc_lead1m"].loc[(df_var["year"]>=2012) &
↪(df_var["year"]<=2016)]

    X_val = df_var[features].loc[(df_var["year"]>=2017) &
↪(df_var["year"]<=2018)]
    y_val = df_var["ret_exc_lead1m"].loc[(df_var["year"]>=2017) &
↪(df_var["year"]<=2018)]


    for i in range(len(numpc)):
        pca_val = PCA(n_components = numpc[i])
        X_reduced_train = pca_val.fit_transform(X_train)
        X_reduced_val = pca_val.transform(X_val)
        line_fitter_val = LinearRegression()
```

```
        line_fitter_val.fit(X_reduced_train, y_train)
        Yval_predict=line_fitter_val.predict(X_reduced_val)
        mse[i,0] = np.sqrt(mean_squared_error(y_val, Yval_predict))


    optim_numpc = numpc[np.argmin(mse)]
    pca = PCA(n_components = optim_numpc)
    principalComponents = pca.fit_transform(np.concatenate((X_train, X_val)))
    line_fitter = LinearRegression()
    line_fitter.fit(principalComponents, (np.concatenate((y_train, y_val))))
    preds=line_fitter.predict(principalComponents)
    R2OOS_var = 1-sum(pow(np.concatenate((y_train, y_val))-preds,2))/sum(pow(np.
 ↪concatenate((y_train, y_val)),2))
    dic['R2OOS_' + str(j)] = R2OOS_var
```

[43]:
```
# dictionary, containing OOS predictive R2, when the all values of a given␣
 ↪predictor are set to zero
dic
```

[43]:
```
{'R2OOS_me': 0.007882220039139964,
 'R2OOS_ret_6_1': 0.008586615999087055,
 'R2OOS_ret_12_1': 0.010370354590459319,
 'R2OOS_tax_gr1a': 0.007978826799963645,
 'R2OOS_be_me': 0.008288464095017045,
 'R2OOS_debt_me': 0.008631007521485379,
 'R2OOS_ni_me': 0.007984778018852445,
 'R2OOS_sale_gr3': 0.007874781125965735,
 'R2OOS_sale_gr1': 0.00784479918724379,
 'R2OOS_sale_me': 0.008299388634497529,
 'R2OOS_lnoa_gr1a': 0.0078019205425843285,
 'R2OOS_inv_gr1a': 0.007898867883029737,
 'R2OOS_oaccruals_at': 0.008941151477232179,
 'R2OOS_taccruals_at': 0.007747618429569503,
 'R2OOS_be_gr1a': 0.007906715343042992,
 'R2OOS_taccruals_ni': 0.00910221401604916,
 'R2OOS_ebit_sale': 0.007962942569583187,
 'R2OOS_sale_bev': 0.007977620633951465,
 'R2OOS_age': 0.007941142206918772,
 'R2OOS_beta_60m': 0.00804514105843046,
 'R2OOS_rmax1_21d': 0.007815170517090797,
 'R2OOS_bidaskhl_21d': 0.007816242034879517,
 'R2OOS_ret_9_1': 0.008364546881691193,
 'R2OOS_ret_12_7': 0.00883128264109212,
 'R2OOS_ni_be': 0.009038454681636221,
 'R2OOS_ocf_debt': 0.007985318772707695,
 'R2OOS_cash_gr1a': 0.00780605712852267,
 'R2OOS_at_gr1': 0.008163130085626302,
```

```
 'R2OOS_chcsho_12m': 0.008045981914818978,
 'R2OOS_ca_cl': 0.00847370291000693,
 'R2OOS_ivol_capm_252d': 0.007807258237678361,
 'R2OOS_debt_gr1': 0.007652747313190433,
 'R2OOS_debtlt_gr1a': 0.0077522462576546936,
 'R2OOS_ope_be': 0.009064548721107624,
 'R2OOS_caliq_cl': 0.008412886534385211,
 'R2OOS_dsale_drec': 0.008101990268522652,
 'R2OOS_f_score': 0.007948187101653792,
 'R2OOS_rvol_21d': 0.007790027924323817,
 'R2OOS_gp_bev': 0.007979135066951026,
 'R2OOS_cowc_gr1a': 0.008304409487430053,
 'R2OOS_pi_nix': 0.008129826232805115,
 'R2OOS_ret_6_0': 0.008641354157683634,
 'R2OOS_ret_1_0': 0.008078274095004057,
 'R2OOS_noa_at': 0.00798900050450091,
 'R2OOS_cop_atl1': 0.007862696111906153,
 'R2OOS_prc_highprc_252d': 0.008398339916934505,
 'R2OOS_ocf_at': 0.00784796720004255,
 'R2OOS_dbnetis_at': 0.007704580123266247,
 'R2OOS_netdebt_me': 0.008513387574519138}
```

[44]:

```
# Convert dictionary to dataframe
pd.DataFrame(dic.items())
imp=pd.DataFrame(dic.items(), columns=['Feature', 'R2OOS'])
# Feature: name of the variable whose values are set to zero
imp["Feature"] = imp["Feature"].str[6:]

# Calculate reduction in predictive R2OOS
imp["red_R2OOS"] = R2OOS_all -imp["R2OOS"]
imp["var_imp"] = imp["red_R2OOS"]/sum(imp["red_R2OOS"])
imp=imp.sort_values(by = ['var_imp'], ascending = False)
imp
```

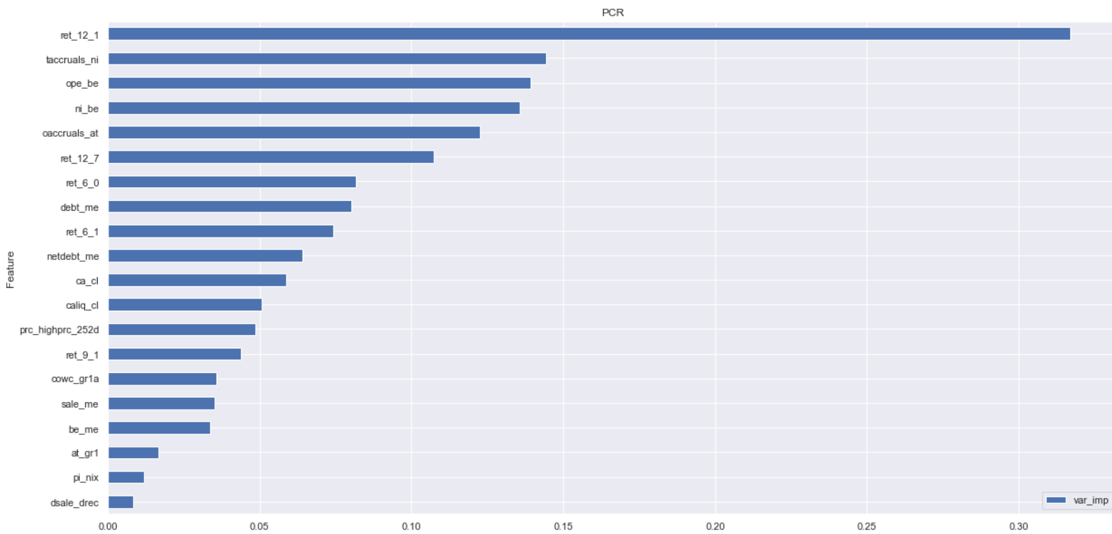
[44]:

	Feature	R2OOS	red_R2OOS	var_imp
2	ret_12_1	0.010370	-0.002329	0.316949
15	taccruals_ni	0.009102	-0.001061	0.144353
33	ope_be	0.009065	-0.001023	0.139227
24	ni_be	0.009038	-0.000997	0.135675
12	oaccruals_at	0.008941	-0.000900	0.122432
23	ret_12_7	0.008831	-0.000790	0.107479
41	ret_6_0	0.008641	-0.000600	0.081629
5	debt_me	0.008631	-0.000589	0.080221
1	ret_6_1	0.008587	-0.000545	0.074179
48	netdebt_me	0.008513	-0.000472	0.064213
29	ca_cl	0.008474	-0.000432	0.058811
34	caliq_cl	0.008413	-0.000371	0.050534

```
45  prc_highprc_252d  0.008398  -0.000357   0.048554
22           ret_9_1  0.008365  -0.000323   0.043955
39         cowc_gr1a  0.008304  -0.000263   0.035770
9            sale_me  0.008299  -0.000258   0.035087
4              be_me  0.008288  -0.000247   0.033600
27            at_gr1  0.008163  -0.000122   0.016542
40            pi_nix  0.008130  -0.000088   0.012009
35        dsale_drec  0.008102  -0.000060   0.008221
42           ret_1_0  0.008078  -0.000037   0.004993
28        chcsho_12m  0.008046  -0.000004   0.000598
19          beta_60m  0.008045  -0.000004   0.000483
43            noa_at  0.007989   0.000053  -0.007157
25          ocf_debt  0.007985   0.000056  -0.007659
6              ni_me  0.007985   0.000057  -0.007732
38            gp_bev  0.007979   0.000062  -0.008500
3           tax_gr1a  0.007979   0.000063  -0.008542
17          sale_bev  0.007978   0.000064  -0.008706
16         ebit_sale  0.007963   0.000079  -0.010704
36           f_score  0.007948   0.000093  -0.012712
18               age  0.007941   0.000100  -0.013671
14           be_gr1a  0.007907   0.000135  -0.018357
11          inv_gr1a  0.007899   0.000143  -0.019425
0                 me  0.007882   0.000159  -0.021690
7           sale_gr3  0.007875   0.000167  -0.022703
44          cop_atl1  0.007863   0.000179  -0.024348
46            ocf_at  0.007848   0.000194  -0.026352
8           sale_gr1  0.007845   0.000197  -0.026783
21      bidaskhl_21d  0.007816   0.000225  -0.030670
20        rmax1_21d   0.007815   0.000226  -0.030816
30    ivol_capm_252d  0.007807   0.000234  -0.031893
26         cash_gr1a  0.007806   0.000236  -0.032056
10         lnoa_gr1a  0.007802   0.000240  -0.032619
37          rvol_21d  0.007790   0.000252  -0.034238
32       debtlt_gr1a  0.007752   0.000289  -0.039380
13      taccruals_at  0.007748   0.000294  -0.040010
47        dbnetis_at  0.007705   0.000337  -0.045868
31          debt_gr1  0.007653   0.000389  -0.052922
```

[45]:

```python
# Plot variable importance measures for the top-20 most influential variables

fea_imp_graph = imp.sort_values(['var_imp', 'Feature'], ascending=[True,␣
 ↪False]).iloc[-20:]
_ = fea_imp_graph.plot(kind='barh', x='Feature', y='var_imp', figsize=(20, 10))
plt.title('PCR')
plt.show()
```



[46]:
```
var_imp_pcr=imp[["Feature", "var_imp"]]
var_imp_pcr.to_csv(r'C:\Users\krist\Documents\Data\variable importance\var_imp_pcr.csv', index = False)
```

4 Machine learning portfolios

Explore whether predictability translates into portfolio gains

[9]:
```
#Generate a results dataframe containing the model predictions (yhat) and the true values (y_true)
#of the dependent variable for each stock in each month

yhat = predictions_all.tolist()
y_true = y_test_list_all.tolist()
i = dates_all.tolist()

results = pd.DataFrame(
    {'identifier': i,
     'yhat': yhat,
     'y_true': y_true
    })

results["identifier"]= results["identifier"].astype("str")
results["date"] = results["identifier"].str[12:22]
results["id"] = results["identifier"].str[36:51]
results.drop(["identifier"],axis = 1, inplace=True)
results['date'] = pd.to_datetime(results['date'], format='%Y-%m-%d')
results['MonthYear'] = results['date'].dt.to_period('M')
results = results.sort_values(by = ['date', 'id'], ascending = True)
```

```
results = results.set_index(['MonthYear','id'])
results
```

[9]:

```
                                yhat    y_true       date
MonthYear id
2010-01   comp_001166_02W  0.015672  0.035512 2010-01-31
          comp_001661_01W  0.013568 -0.041371 2010-01-31
          comp_002410_04W  0.011608 -0.053836 2010-01-31
          comp_002597_02W  0.010799  0.001862 2010-01-31
          comp_003820_01W  0.004853  0.078967 2010-01-31
…                               …        …          …
2019-12   comp_330716_01W -0.000303 -0.012904 2019-12-31
          comp_331115_01W  0.001667  0.005400 2019-12-31
          comp_332311_01W  0.004555 -0.051340 2019-12-31
          comp_333885_01W  0.011020  0.003528 2019-12-31
          comp_334036_02W -0.000860 -0.100876 2019-12-31

[93417 rows x 3 columns]
```

[10]:

```
# Save results to use for Diebold-Mariano test
pcr= results.reset_index()
pcr.to_csv(r'C:\Users\krist\Documents\Data\Predictions\pcr.csv', index = False)
```

[5]:

```
## Import the original "me" avriable (before rank standartization) to use for␣
↪the value weighting scheme

unscaled_data = df[["id", 'eom', "me2","ret" ,"ret_exc"]].copy()
unscaled_data['MonthYear'] = unscaled_data['eom'].dt.to_period('M')
unscaled_data.drop('eom', axis=1, inplace=True)
unscaled_data = unscaled_data.set_index(['MonthYear','id'])
unscaled_data
```

[5]:

```
                                     me2       ret   ret_exc
MonthYear id
2003-01   comp_001166_02W    567.074646 -0.018948 -0.019948
          comp_001661_01W   5221.931641  0.005815  0.004815
          comp_004367_02W   4139.599121 -0.103801 -0.104801
          comp_004925_02W  15302.482422 -0.070425 -0.071425
          comp_005959_01W   6355.691406 -0.085813 -0.086813
…                                    …         …         …
2020-12   comp_333885_01W  10829.783203  0.128645  0.128545
          comp_334302_02W    297.482697  0.097961  0.097861
          comp_335706_02W    196.243454  0.114381  0.114281
          comp_340115_01W   1799.958496  0.155813  0.155713
          comp_340153_01W  26788.144531  0.238817  0.238717

[156948 rows x 3 columns]
```

[6]:
```
# Import price data in t+1 and ret t+1 --> Import from the original dataframe
# (otherwise there are missing values because shares with a price < $5 have␣
↪been excluded)

price_data= pd.read_csv(r"C:\Users\krist\Documents\Data\ger_factor_data.csv",␣
↪dtype ={"comp_tpci": str}, parse_dates =["eom"])
price_data["eom"] = pd.to_datetime(price_data["eom"], utc = False)

# Only the data between 2003 and 2020 is needed
price_data["year"] = price_data["eom"].dt.year
price_data = price_data.loc[(price_data["year"]>=2003) &␣
↪(price_data["year"]<=2020)]
price_data = price_data[["id", 'eom', 'prc', "ret"]]

#Generate a MonthYear variable (monthly observations are given, the day is not␣
↪needed)
price_data['MonthYear'] = price_data['eom'].dt.to_period('M')
price_data.drop('eom', axis=1, inplace=True)

#The original dataframe is not winsorized --> winsorize  at the 1% and 99%␣
↪level
price = ["prc"]
ret = ["ret"]
price_data["prc"] = price_data[price].apply(lambda x: x.clip(*x.quantile([0.01,␣
↪0.99])))
price_data["ret"] = price_data[ret].apply(lambda x: x.clip(*x.quantile([0.01, 0.
↪99])))

#Shift to get the price of each stock in month t+1
price_data['prc_t+1'] = price_data.groupby(['id'])['prc'].shift(-1)
# Shift to get return for each stock in month t+1
price_data["ret_t+1"]=price_data.groupby(['id'])['ret'].shift(-1)
price_data.drop('ret', axis=1, inplace=True)
price_data = price_data.set_index(['MonthYear','id'])
price_data
```

[6]:

MonthYear	id	prc	prc_t+1	ret_t+1
2003-01	comp_001166_02W	11.486148	10.468435	-0.088604
2003-02	comp_001166_02W	10.468435	10.107208	-0.034506
2003-03	comp_001166_02W	10.107208	13.610050	0.346569
2003-04	comp_001166_02W	13.610050	14.518828	0.066773
2003-05	comp_001166_02W	14.518828	15.212792	0.047798
…		…	…	…
2020-11	comp_340115_01W	14.831518	17.142462	0.155813
2020-12	comp_340115_01W	17.142462	NaN	NaN
2020-10	comp_340153_01W	21.909940	29.758645	0.358226

```
2020-11   comp_340153_01W  29.758645  36.865510  0.238817
2020-12   comp_340153_01W  36.865510        NaN       NaN

[274031 rows x 3 columns]
```

[7]:
```
#Merge with the results dataframe
bigdata = pd.merge(results, unscaled_data,left_index=True, right_index=True)
bigdata = pd.merge(bigdata, price_data,left_index=True, right_index=True)
bigdata = bigdata.reset_index()

# Original "me" (before rank normalization) to use for the value weighting␣
 ↪scheme
bigdata.rename(columns={'me2': 'me'}, inplace=True)

#Final df containing all information needed for the portfolio creation
bigdata
```

[7]:
```
      MonthYear               id      yhat    y_true       date  \
0       2010-01  comp_001166_02W  0.015672  0.035512 2010-01-31
1       2010-01  comp_001661_01W  0.013568 -0.041371 2010-01-31
2       2010-01  comp_002410_04W  0.011608 -0.053836 2010-01-31
3       2010-01  comp_002597_02W  0.010799  0.001862 2010-01-31
4       2010-01  comp_003820_01W  0.004853  0.078967 2010-01-31
…           …                …         …         …          …
93412   2019-12  comp_330716_01W -0.000303 -0.012904 2019-12-31
93413   2019-12  comp_331115_01W  0.001667  0.005400 2019-12-31
93414   2019-12  comp_332311_01W  0.004555 -0.051340 2019-12-31
93415   2019-12  comp_333885_01W  0.011020  0.003528 2019-12-31
93416   2019-12  comp_334036_02W -0.000860 -0.100876 2019-12-31

                  me       ret   ret_exc        prc    prc_t+1   ret_t+1
0        1233.673950 -0.099572 -0.099572  22.730003  23.537181  0.035512
1        6796.776367  0.036020  0.036020  22.730003  21.789641 -0.041371
2      132047.843750 -0.014941 -0.014941   9.453457   8.812790 -0.053836
3       18138.388672  0.035186  0.035186  13.191743  13.057401  0.001862
4         225.897369 -0.125756 -0.125756   6.339377   6.839981  0.078967
…                  …         …         …          …          …         …
93412      33.930836  0.066508  0.065108   6.169243   6.097655 -0.011604
93413      36.342445  0.005615  0.004215  18.171224  18.292966  0.006700
93414   13412.494141 -0.020668 -0.022068  26.824988  25.482656 -0.050040
93415    7151.834473  0.251631  0.250231  35.759173  35.931819  0.004828
93416     189.330505  0.377943  0.377359  21.424097  19.290764 -0.099576

[93417 rows x 11 columns]
```

[8]:

```
#Check for missing values (the original df has not yet been cleaned of missing␣
 ↪values)
bigdata.isna().sum()
```

[8]:
```
MonthYear     0
id            0
yhat          0
y_true        0
date          0
me            0
ret           0
ret_exc       0
prc           0
prc_t+1      12
ret_t+1      12
dtype: int64
```

[9]:
```
# Drop the twelve observations where prc_t+1 and ret_t+1 are still missing
bigdata = bigdata.dropna()
len(bigdata)
```

[9]:
```
93405
```

[10]:
```
# Calculate the 1-month risk-free rate as the average monthly difference␣
 ↪between returns and excess returns
bigdata["risk_free_rate"]=bigdata["ret_t+1"]-bigdata["y_true"]
bigdata["risk_free_rate"] =bigdata.groupby('MonthYear')["risk_free_rate"].
 ↪transform('mean')
```

[11]:
```
# Create a variable "NumMonth", indicating the number of the respectie month:
# January 2010 = 1,....,December 2019 = 120

bigdata["MonthYear1"]= bigdata["MonthYear"].copy()
bigdata["MonthYear"]= bigdata["MonthYear"].astype("int")
bigdata["NumMonth"]= bigdata["MonthYear"]-479
bigdata["NumMonth"].unique()
```

[11]:
```
array([  1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  12,  13,
        14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  25,  26,
        27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  38,  39,
        40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  51,  52,
        53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  64,  65,
        66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  76,  77,  78,
        79,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,  91,
        92,  93,  94,  95,  96,  97,  98,  99, 100, 101, 102, 103, 104,
       105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117,
       118, 119, 120], dtype=int64)
```

[12]:
```
# Create a separate dataframe for each month,e.g.:
# df_1=January 2010, df_2 = February 2010,....,df_120 = December 2019

for i in bigdata["NumMonth"].unique():
    globals()['df_' + str(i)] =  bigdata[bigdata["NumMonth"]==i]
```

[13]:
```
# Assign decile ranks to the stocks within each month based on the predicted␣
↪excess returns:

# 1)Generate ranks starting from the lowest predicted excess return to the␣
↪highest
for i in bigdata["NumMonth"].unique():
    globals()['df_' + str(i)]["rank"]= globals()['df_' + str(i)]['yhat'].
↪rank(method='first')

# 2)Split ranks into 10 deciles to get decile rank
# DecileRank = 0: stoks with lowest predicted excess returns
# DecileRank =9: stoks with highest predicted excess returns
for i in bigdata["NumMonth"].unique():
    globals()['df_' + str(i)]["DecileRank"]=pd.qcut(globals()['df_' +␣
↪str(i)]['rank'].values, 10, labels = False)

#Drop normal rank, retain only decile ranks
for i in bigdata["NumMonth"].unique():
     globals()['df_' + str(i)].drop('rank', axis=1, inplace=True)
```

[14]:
```
# Create a separate dataframe for each decile rank and each month,e.g.:
# df_1_0: the bottom decile in January 2010,
# d_1_9: the top decile in January 2010,....,
# df_120_0: the bottom decile in December 2019,
# df_120_9: the top decile in December 2019

for i in bigdata["NumMonth"].unique():
    for j,g in globals()['df_' + str(i)].groupby('DecileRank'):
        globals()['df_' + str(i)+ "_" + str(j)] =  g
```

[15]:
```
# All stocks are sorted into deciles based on their predicted returns for the␣
↪next month.
# Create 10 dataframes showing the portfolio composition of each decile␣
↪portfolio over time

for j in np.arange(0,10,1):
    globals()['rank_' + str(j)] = pd.concat([globals()['df_1_'+ str(j)],␣
↪globals()['df_2_'+ str(j)]], axis=0)

# Generate 10 Dataframes for the 10 Decile portfolios 0-9: rank_9: top␣
↪portfolio, rank_0: bottom portfolio
```

```python
for i in np.arange(2,120,1):
    for j in np.arange(0,10,1):
        globals()['rank_' + str(j)] = pd.concat([globals()['rank_' + str(j)],␣
 ↪globals()['df_' + str(i+1)+ "_" + str(j)]], axis = 0)
```

[16]:
```python
# We get 10 separate dataframes (rank_0, rank_1,...., rank_9), showing the␣
 ↪portfolio
# composition of each decile portfolio over time
#e.g.: compostion of the top decile portfolio over the entire OOS period (Jan␣
 ↪2010-Dec 2019):
rank_9
```

[16]:
```
       MonthYear              id      yhat    y_true       date  \
11           480  comp_007152_01W  0.025378  0.006088 2010-01-31
15           480  comp_010846_09W  0.023357 -0.014764 2010-01-31
21           480  comp_014269_01W  0.022640 -0.034796 2010-01-31
26           480  comp_015321_02W  0.021178 -0.053604 2010-01-31
27           480  comp_015334_02W  0.020462 -0.155894 2010-01-31
…            …               …       …       …          …
93335        599  comp_316581_90W  0.013199 -0.069927 2019-12-31
93337        599  comp_317329_02W  0.013119  0.008100 2019-12-31
93345        599  comp_318659_01W  0.013972 -0.148323 2019-12-31
93350        599  comp_319865_01W  0.015502  0.074787 2019-12-31
93390        599  comp_326765_01W  0.014321 -0.020752 2019-12-31

                 me       ret   ret_exc         prc     prc_t+1   ret_t+1  \
11      5164.601074 -0.065609 -0.065609   22.438058   22.574668  0.006088
15     52754.355469 -0.052386 -0.052386   30.765442   30.035846 -0.014764
21      2671.458984  0.006921  0.006921   40.510844   39.101210 -0.034796
26     32227.082031 -0.079324 -0.079324   30.438742   28.807106 -0.053604
27     13871.247070 -0.090486 -0.090486   59.876529   50.542136 -0.155894
…               …         …         …           …           …         …
93335   3372.102051  0.024598  0.023198    8.749108    8.148685 -0.068627
93337   2280.453613  0.099088  0.097688    8.973444    9.057790  0.009400
93345   6149.301758  0.025512  0.024112   55.343714   47.206938 -0.147023
93350   3019.115234  0.215243  0.213843  100.637172  108.294358  0.076087
93390  48030.359375 -0.009722 -0.011122   48.030358   47.096072 -0.019452

       risk_free_rate MonthYear1  NumMonth  DecileRank
11           0.000353    2010-01         1           9
15           0.000353    2010-01         1           9
21           0.000353    2010-01         1           9
26           0.000353    2010-01         1           9
27           0.000353    2010-01         1           9
…                 …          …        …          …
93335        0.001325    2019-12       120           9
93337        0.001325    2019-12       120           9
```

```
93345          0.001325    2019-12      120          9
93350          0.001325    2019-12      120          9
93390          0.001325    2019-12      120          9

[9386 rows x 15 columns]
```

5 Portfolio performance

Next, the performance of the prediction-sorted portfolios is calculated over the 10-year out-of-sample testing for both equal and value weighting schemes

[17]:
```
# Get equal und value weights per stock per month in each decile portfolio:
# ew = Equally weighted
# vw = Value weighted

for j in np.arange(0,10,1):
    globals()['rank_' + str(j)]["eq_weights"] = 1/globals()['rank_' + str(j)].
 ↪groupby('MonthYear')["id"].transform('size')
    globals()['rank_' + str(j)]["me_weights"] = globals()['rank_' +␣
 ↪str(j)]["me"]/globals()['rank_' + str(j)].groupby('MonthYear')["me"].
 ↪transform('sum')
```

The excess return of each decile portfolio in month t is modeled as the weighted sum of each stocks's excess return in month t:

$$R_{P,t} = \sum_{i=1}^{N} w_{i,t} * r_{i,t}$$

[18]:
```
# Weighted excess return per stock in t+1
for j in np.arange(0,10,1):
    globals()['rank_' + str(j)]['excess_return_stock_ew'] = globals()['rank_' +␣
 ↪str(j)]["y_true"]*globals()['rank_' + str(j)]["eq_weights"]
    globals()['rank_' + str(j)]['excess_return_stock_vw'] = globals()['rank_' +␣
 ↪str(j)]["y_true"]*globals()['rank_' + str(j)]["me_weights"]
```

[19]:
```
# weighted return per stock in t+1 (to use for the sharpe ratio)
for j in np.arange(0,10,1):
    globals()['rank_' + str(j)]['return_stock_ew'] = globals()['rank_' +␣
 ↪str(j)]["ret_t+1"]*globals()['rank_' + str(j)]["eq_weights"]
    globals()['rank_' + str(j)]['return_stock_vw'] = globals()['rank_' +␣
 ↪str(j)]["ret_t+1"]*globals()['rank_' + str(j)]["me_weights"]
```

[20]:
```
# Portfolio excess return in t+1
for j in np.arange(0,10,1):
```

```
    globals()['rank_' + str(j)]['excess_return_portfolio_ew'] =␣
↪globals()['rank_' + str(j)].groupby('MonthYear')["excess_return_stock_ew"].
↪transform('sum')
    globals()['rank_' + str(j)]['excess_return_portfolio_vw'] =␣
↪globals()['rank_' + str(j)].groupby('MonthYear')["excess_return_stock_vw"].
↪transform('sum')
```

[21]:
```
# Portfolio return in t+1 (to use for the sharpe ratio)
for j in np.arange(0,10,1):
    globals()['rank_' + str(j)]['return_portfolio_ew'] = globals()['rank_' +␣
↪str(j)].groupby('MonthYear')["return_stock_ew"].transform('sum')
    globals()['rank_' + str(j)]['return_portfolio_vw'] = globals()['rank_' +␣
↪str(j)].groupby('MonthYear')["return_stock_vw"].transform('sum')
```

[22]:
```
# Weighted predicted excess return per stock in t+1
for j in np.arange(0,10,1):
    globals()['rank_' + str(j)]['pred_excess_return_stock_ew'] =␣
↪globals()['rank_' + str(j)]["yhat"]*globals()['rank_' + str(j)]["eq_weights"]
    globals()['rank_' + str(j)]['pred_excess_return_stock_vw'] =␣
↪globals()['rank_' + str(j)]["yhat"]*globals()['rank_' + str(j)]["me_weights"]
```

[23]:
```
# Portfolio predicted excess return in t+1
for j in np.arange(0,10,1):
    globals()['rank_' + str(j)]['pred_excess_return_portfolio_ew'] =␣
↪globals()['rank_' + str(j)].
↪groupby('MonthYear')["pred_excess_return_stock_ew"].transform('sum')
    globals()['rank_' + str(j)]['pred_excess_return_portfolio_vw'] =␣
↪globals()['rank_' + str(j)].
↪groupby('MonthYear')["pred_excess_return_stock_vw"].transform('sum')
```

[24]:
```
# Generate dataframes, containing the portfolio returns on mohtly basis for␣
↪each decile portfolio
# e.g., montly_rank_0: dataframe, containing only the monthly portfolio excess␣
↪returns (predicted and real)
# for  the bottom rank

for j in np.arange(0,10,1):
    globals()['montly_rank_' + str(j)] = globals()['rank_' +␣
↪str(j)][["MonthYear1", "DecileRank",
                                                                        ␣
↪"excess_return_portfolio_ew",
                                                                        ␣
↪"excess_return_portfolio_vw",
                                                                        ␣
↪"pred_excess_return_portfolio_ew",
```

```
                                                                                    ␣
↪"pred_excess_return_portfolio_vw",
                                                                                    ␣
↪"return_portfolio_ew",
                                                                                    ␣
↪"return_portfolio_vw"]]

for j in np.arange(0,10,1):
    globals()['montly_rank_' + str(j)]=globals()['montly_rank_' + str(j)].
↪drop_duplicates()
    globals()['montly_rank_' + str(j)]=globals()['montly_rank_' + str(j)].
↪set_index("MonthYear1")
```

- Calculate time-series averages of both predicted and realized excess returns for each decile portfolio
- Calculate the standard deviations and the annualized sharpe ratios based on the realized excess returns
- Get measures for both equal- and value-weighted portfolios

5.0.1 Sharpe Ratio $= \frac{\textbf{Portfolio return-Risk Free Rate}}{\textbf{Standard deviation of portfolio reurn}} = \frac{R_p - R_F}{\sigma_P} = \frac{\textbf{Portfolio excess return}}{\textbf{Std(portfolio return)}}$

[25]:
```
for j in np.arange(0,10,1):
    #Time-series average of realized excess returns
    globals()["ew_mean_return_rank_" +  str(j)]= globals()['montly_rank_' +␣
↪str(j)]["excess_return_portfolio_ew"].mean()
    globals()["vw_mean_return_rank_" +  str(j)]= globals()['montly_rank_' +␣
↪str(j)]["excess_return_portfolio_vw"].mean()
    #Time-series average of predicted excess returns
    globals()["ew_mean_pred_return_rank_" +  str(j)]= globals()['montly_rank_'␣
↪+ str(j)]["pred_excess_return_portfolio_ew"].mean()
    globals()["vw_mean_pred_return_rank_" +  str(j)]= globals()['montly_rank_'␣
↪+ str(j)]["pred_excess_return_portfolio_vw"].mean()
    #Standard deviation of realized excess returns
    globals()["std_ew_rank_" +  str(j)]= globals()['montly_rank_' +␣
↪str(j)]["excess_return_portfolio_ew"].std()
    globals()["std_vw_rank_" +  str(j)]= globals()['montly_rank_' +␣
↪str(j)]["excess_return_portfolio_vw"].std()
    #Annualized sharpe ratio of realized excess returns
    globals()["sharpe_ew_rank_" +  str(j)]= (globals()['montly_rank_' +␣
↪str(j)]["excess_return_portfolio_ew"].mean()/globals()['montly_rank_' +␣
↪str(j)]["return_portfolio_ew"].std())* np.sqrt(12)
    globals()["sharpe_vw_rank_" +  str(j)]= (globals()['montly_rank_' +␣
↪str(j)]["excess_return_portfolio_vw"].mean()/globals()['montly_rank_' +␣
↪str(j)]["return_portfolio_vw"].std())* np.sqrt(12)
```

5.0.2 Zero net investment long-short portfolio

A zero-investment portfolio is a portfolio that has a net value of zero when the portfolio is assembled, and therefore requires an investor to take no equity stake in the portfolio. - e.g. short sell **USD 1,000** worth of the bottom portfolio, and use the proceeds to purchase **USD 1,000** worth of the top portfolio - this results in a net value of zero

$\sum_{i=1}^{N} w_{i,\ \textbf{long}} \ = 1$

$\sum_{i=1}^{N} w_{i,\ \textbf{short}} \ = -1$

$\sum_{i=1}^{N} w_{i,\ \textbf{long}} \ * \ \textbf{prc} \ _{i,\ \textbf{long}} \ = \sum_{i=1}^{N} w_{i,\ \textbf{short}} \ * \ \textbf{prc} \ _{i,\ \textbf{short}}$

$\textbf{Value Zero Net Portfolio in } t = \sum_{i=1}^{N} w_{i,\ \textbf{long}} * \textbf{prc} \ _{i,\ \textbf{long}} - \sum_{i=1}^{N} w_{i,\ \textbf{short}} * \textbf{prc} \ _{i,\ \textbf{short}} \ = 0$

$\textbf{Return Zero Net Portfolio in } t = \sum_{i=1}^{N} w_{i,\ \textbf{long}} \ * \ \textbf{ret} \ _{i,\ \textbf{long}} \ - \sum_{i=1}^{N} w_{i,\ \textbf{short}} \ * \ \textbf{ret} \ _{i,\ \textbf{short}}$

[26]:
```python
# For the zero-net-investment long-short portfolio the top (long) and␣
 ↪bottom(short) decile portfolios are needed

long_monthly = rank_9[["NumMonth","MonthYear1", "DecileRank",␣
 ↪"excess_return_portfolio_ew",
                                                                        ␣
 ↪"excess_return_portfolio_vw","pred_excess_return_portfolio_ew",
                        "pred_excess_return_portfolio_vw","return_portfolio_ew",
                         "return_portfolio_vw"]].drop_duplicates()

short_monthly = rank_0[["NumMonth","MonthYear1", "DecileRank",␣
 ↪"excess_return_portfolio_ew",
                                                                        ␣
 ↪"excess_return_portfolio_vw","pred_excess_return_portfolio_ew",
                        "pred_excess_return_portfolio_vw","return_portfolio_ew",
                         "return_portfolio_vw"]].drop_duplicates()

# Create a column, indication the stategy
long_monthly["Strategy"]= "long"
short_monthly["Strategy"]= "short"

# Merge to get the zero net investment portfolio
zeronet_monthly= pd.concat([long_monthly, short_monthly])
zeronet_monthly = zeronet_monthly.sort_values(by = ['NumMonth',"Strategy"])
zeronet_monthly["return_portfolio_vw"] = zeronet_monthly["return_portfolio_vw"].
 ↪astype('float64')

#Create two new columns containing the exess return of the portfolio and␣
 ↪initially set the values to zero.
```

```
zeronet_monthly["excess_return_zeronet_ew"] =0
zeronet_monthly["excess_return_zeronet_vw"] =0

# excess return zeronet in t = (weigted excess return long in t) - (weigted␣
 ↪excess return short in t)
for i in range(0, len(zeronet_monthly)):
    if zeronet_monthly.iloc[i,9] == "long":
        zeronet_monthly.iloc[i, -2] = zeronet_monthly.iloc[i,␣
 ↪3]-zeronet_monthly.iloc[i+1, 3]
    else:
        zeronet_monthly.iloc[i, -2] = zeronet_monthly.iloc[i-1,␣
 ↪3]-zeronet_monthly.iloc[i, 3]

for i in range(0, len(zeronet_monthly)):
    if zeronet_monthly.iloc[i,9] == "long":
        zeronet_monthly.iloc[i, -1] = zeronet_monthly.iloc[i,␣
 ↪4]-zeronet_monthly.iloc[i+1, 4]
    else:
        zeronet_monthly.iloc[i, -1] = zeronet_monthly.iloc[i-1,␣
 ↪4]-zeronet_monthly.iloc[i, 4]

#Create two new columns containing predicted the exess return of the portfolio␣
 ↪and initially set the values to zero.
zeronet_monthly["pred_excess_return_zeronet_ew"] =0
zeronet_monthly["pred_excess_return_zeronet_vw"] =0

# predicted excess return zeronet in t = (weigted predicted excess return long␣
 ↪in t) - (weigted predicted excess return short in t)
for i in range(0, len(zeronet_monthly)):
    if zeronet_monthly.iloc[i,9] == "long":
        zeronet_monthly.iloc[i, -2] = zeronet_monthly.iloc[i,␣
 ↪5]-zeronet_monthly.iloc[i+1, 5]
    else:
        zeronet_monthly.iloc[i, -2] = zeronet_monthly.iloc[i-1,␣
 ↪5]-zeronet_monthly.iloc[i, 5]

for i in range(0, len(zeronet_monthly)):
    if zeronet_monthly.iloc[i,9] == "long":
        zeronet_monthly.iloc[i, -1] = zeronet_monthly.iloc[i,␣
 ↪6]-zeronet_monthly.iloc[i+1, 6]
    else:
        zeronet_monthly.iloc[i, -1] = zeronet_monthly.iloc[i-1,␣
 ↪6]-zeronet_monthly.iloc[i, 6]

#Create two new columns containing return of the portfolio and initially set␣
 ↪the values to zero.
```

```
zeronet_monthly["return_zeronet_ew"] =0
zeronet_monthly["return_zeronet_vw"] =0

# return zeronet in t = (weigted return long in t) - (weigted return short in t)
for i in range(0, len(zeronet_monthly)):
    if zeronet_monthly.iloc[i,9] == "long":
        zeronet_monthly.iloc[i, -2] = zeronet_monthly.iloc[i,␣
↪7]-zeronet_monthly.iloc[i+1, 7]
    else:
        zeronet_monthly.iloc[i, -2] = zeronet_monthly.iloc[i-1,␣
↪7]-zeronet_monthly.iloc[i, 7]

for i in range(0, len(zeronet_monthly)):
    if zeronet_monthly.iloc[i,9] == "long":
        zeronet_monthly.iloc[i, -1] = zeronet_monthly.iloc[i,␣
↪8]-zeronet_monthly.iloc[i+1, 8]
    else:
        zeronet_monthly.iloc[i, -1] = zeronet_monthly.iloc[i-1,␣
↪8]-zeronet_monthly.iloc[i, 8]
```

[27]:
```
#Only the measures at portfolio level are needed
zeronet_monthly = zeronet_monthly[['NumMonth', 'MonthYear1',␣
↪'excess_return_zeronet_ew',
                                   'excess_return_zeronet_vw',␣
↪'pred_excess_return_zeronet_ew',
                                  ␣
↪'pred_excess_return_zeronet_vw','return_zeronet_ew',
                                   'return_zeronet_vw']].drop_duplicates()

zeronet_monthly
```

[27]:
```
       NumMonth MonthYear1  excess_return_zeronet_ew  \
11            1    2010-01                  0.025036
735           2    2010-02                  0.073855
1458          3    2010-03                  0.024195
2227          4    2010-04                  0.005667
2992          5    2010-05                  0.006859
…           …        …                       …
89857       116    2019-08                 -0.002446
90561       117    2019-09                  0.029029
91269       118    2019-10                  0.021879
91981       119    2019-11                  0.006756
92694       120    2019-12                  0.015541

       excess_return_zeronet_vw  pred_excess_return_zeronet_ew  \
11                     0.013763                       0.030796
735                   -0.008665                       0.029260
```

```
1458                    0.001179                        0.028525
2227                    0.077138                        0.030340
2992                    0.032550                        0.029577
…                          …                               …
89857                  -0.003758                        0.016334
90561                  -0.018734                        0.016095
91269                   0.040320                        0.016195
91981                   0.042114                        0.016111
92694                   0.051998                        0.015917

       pred_excess_return_zeronet_vw  return_zeronet_ew  return_zeronet_vw
11                          0.027712           0.022192           0.013920
735                         0.026742           0.072079          -0.008560
1458                        0.025629           0.024195           0.001179
2227                        0.027746           0.011387           0.078579
2992                        0.025736           0.005963           0.032525
…                               …                 …                 …
89857                       0.016093          -0.004718          -0.004014
90561                       0.016314           0.029029          -0.018734
91269                       0.016032           0.018938           0.039263
91981                       0.015523           0.004733           0.042020
92694                       0.015503           0.012242           0.049725

[120 rows x 8 columns]
```

[28]:

```
#Calculate zero-net portfolio performance measures                             ␣
↪
#Time-series average of realized excess returns                                ␣
↪
ew_mean_return_zeronet= zeronet_monthly["excess_return_zeronet_ew"].mean()
vw_mean_return_zeronet= zeronet_monthly["excess_return_zeronet_vw"].mean()
#Time-series average of predicted excess returns
ew_mean_pred_return_zeronet = zeronet_monthly["pred_excess_return_zeronet_ew"].
↪mean()
vw_mean_pred_return_zeronet = zeronet_monthly["pred_excess_return_zeronet_vw"].
↪mean()
#Standard deviation of realized excess returns
std_ew_zeronet = zeronet_monthly["excess_return_zeronet_ew"].std()
std_vw_zeronet = zeronet_monthly["excess_return_zeronet_vw"].std()
#Annualized sharpe ratio of realized excess returns
sharpe_ew_zeronet = (zeronet_monthly["excess_return_zeronet_ew"].mean()/
↪zeronet_monthly["return_zeronet_ew"].std())* np.sqrt(12)
sharpe_vw_zeronet = (zeronet_monthly["excess_return_zeronet_vw"].mean()/
↪zeronet_monthly["return_zeronet_vw"].std())* np.sqrt(12)
```

5.0.3 Generate table containing the performance measures for each decile portfolio and for the long-short portfolio for each weignting sheme respectively

Equally weighted table:

[29]:
```
chart_np = np.array([[ew_mean_pred_return_rank_0, ew_mean_return_rank_0,␣
↪std_ew_rank_0, sharpe_ew_rank_0],
                     [ew_mean_pred_return_rank_1, ew_mean_return_rank_1,␣
↪std_ew_rank_1, sharpe_ew_rank_1],
                     [ew_mean_pred_return_rank_2, ew_mean_return_rank_2,␣
↪std_ew_rank_2, sharpe_ew_rank_2],
                     [ew_mean_pred_return_rank_3, ew_mean_return_rank_3,␣
↪std_ew_rank_3, sharpe_ew_rank_3],
                     [ew_mean_pred_return_rank_4, ew_mean_return_rank_4,␣
↪std_ew_rank_4, sharpe_ew_rank_4],
                     [ew_mean_pred_return_rank_5, ew_mean_return_rank_5,␣
↪std_ew_rank_5, sharpe_ew_rank_5],
                     [ew_mean_pred_return_rank_6, ew_mean_return_rank_6,␣
↪std_ew_rank_6, sharpe_ew_rank_6],
                     [ew_mean_pred_return_rank_7, ew_mean_return_rank_7,␣
↪std_ew_rank_7, sharpe_ew_rank_7],
                     [ew_mean_pred_return_rank_8, ew_mean_return_rank_8,␣
↪std_ew_rank_8, sharpe_ew_rank_8],
                     [ew_mean_pred_return_rank_9, ew_mean_return_rank_9,␣
↪std_ew_rank_9, sharpe_ew_rank_9],
                     [ew_mean_pred_return_zeronet, ew_mean_return_zeronet,␣
↪std_ew_zeronet, sharpe_ew_zeronet]])

ew_df = pd.DataFrame(chart_np, columns=['Pred', 'Real', 'Std', 'Sharpe'],
                         index=['Low (L)', '2', '3', '4',␣
↪'5','6','7','8',"9",'High (H)', "H-L"])

ew_df['Pred'] = pd.Series(["{0:.2f}%".format(val * 100) for val in␣
↪ew_df['Pred']], index = ew_df.index)
ew_df['Real'] = pd.Series(["{0:.2f}%".format(val * 100) for val in␣
↪ew_df['Real']], index = ew_df.index)
ew_df['Std'] = pd.Series(["{0:.2f}%".format(val * 100) for val in␣
↪ew_df['Std']], index = ew_df.index)
ew_df['Sharpe'] = pd.Series([("%.2f" % round(val, 2)) for val in␣
↪ew_df['Sharpe']], index = ew_df.index)
ew_df
```

[29]:

	Pred	Real	Std	Sharpe
Low (L)	-0.58%	-0.53%	4.76%	-0.37
2	-0.11%	0.16%	4.45%	0.12
3	0.14%	0.25%	4.50%	0.19
4	0.33%	0.49%	4.31%	0.39
5	0.51%	0.63%	4.36%	0.49

```
6          0.67%   0.72%  4.33%   0.57
7          0.84%   0.83%  4.49%   0.64
8          1.02%   1.00%  4.37%   0.79
9          1.23%   1.17%  4.32%   0.93
High (H)   1.62%   1.51%  4.53%   1.14
H-L        2.20%   2.04%  2.38%   2.87
```

Value weighted table

[30]:

```python
chart_np = np.array([[vw_mean_pred_return_rank_0, vw_mean_return_rank_0,␣
 ↪std_vw_rank_0, sharpe_vw_rank_0],
                     [vw_mean_pred_return_rank_1, vw_mean_return_rank_1,␣
 ↪std_vw_rank_1, sharpe_vw_rank_1],
                     [vw_mean_pred_return_rank_2, vw_mean_return_rank_2,␣
 ↪std_vw_rank_2, sharpe_vw_rank_2],
                     [vw_mean_pred_return_rank_3, vw_mean_return_rank_3,␣
 ↪std_vw_rank_3, sharpe_vw_rank_3],
                     [vw_mean_pred_return_rank_4, vw_mean_return_rank_4,␣
 ↪std_vw_rank_4, sharpe_vw_rank_4],
                     [vw_mean_pred_return_rank_5, vw_mean_return_rank_5,␣
 ↪std_vw_rank_5, sharpe_vw_rank_5],
                     [vw_mean_pred_return_rank_6, vw_mean_return_rank_6,␣
 ↪std_vw_rank_6, sharpe_vw_rank_6],
                     [vw_mean_pred_return_rank_7, vw_mean_return_rank_7,␣
 ↪std_vw_rank_7, sharpe_vw_rank_7],
                     [vw_mean_pred_return_rank_8, vw_mean_return_rank_8,␣
 ↪std_vw_rank_8, sharpe_vw_rank_8],
                     [vw_mean_pred_return_rank_9, vw_mean_return_rank_9,␣
 ↪std_vw_rank_9, sharpe_vw_rank_9],
                     [vw_mean_pred_return_zeronet, vw_mean_return_zeronet,␣
 ↪std_vw_zeronet, sharpe_vw_zeronet]])

vw_df = pd.DataFrame(chart_np, columns=['Pred', 'Real', 'Std', 'Sharpe'],
                     index=['Low (L)', '2', '3', '4',␣
 ↪'5','6','7','8',"9",'High (H)', "H-L"])

vw_df['Pred'] = pd.Series(["{0:.2f}%".format(val * 100) for val in␣
 ↪vw_df['Pred']], index = vw_df.index)
vw_df['Real'] = pd.Series(["{0:.2f}%".format(val * 100) for val in␣
 ↪vw_df['Real']], index = vw_df.index)
vw_df['Std'] = pd.Series(["{0:.2f}%".format(val * 100) for val in␣
 ↪vw_df['Std']], index = vw_df.index)
vw_df['Sharpe'] = pd.Series([("%.2f" % round(val, 2)) for val in␣
 ↪vw_df['Sharpe']], index = vw_df.index)
vw_df
```

```
[30]:             Pred    Real    Std  Sharpe
       Low (L)   -0.48%  -0.35%  6.43%  -0.19
       2         -0.10%   0.24%  5.36%   0.16
       3          0.14%   0.21%  5.29%   0.13
       4          0.34%   0.48%  4.93%   0.34
       5          0.50%   0.48%  4.94%   0.34
       6          0.67%   0.56%  4.84%   0.40
       7          0.84%   0.55%  4.87%   0.39
       8          1.02%   0.86%  4.70%   0.63
       9          1.23%   0.88%  4.67%   0.65
       High (H)   1.59%   0.75%  4.31%   0.60
       H-L        2.07%   1.10%  4.44%   0.86
```

```
[31]: #Save to compare with the other ML models
ew_df.to_csv(r'C:\Users\krist\Documents\Data\decile_portfolios_results\pcr_ew.
 ↪csv')
vw_df.to_csv(r'C:\Users\krist\Documents\Data\decile_portfolios_results\pcr_vw.
 ↪csv')
```

6 Additional performance measures of zero net investment long-short portfolio with monthly restructuring, 2010:01-2019:12

6.0.1 Drawdown, turnover, and risk-adjusted performance of the long-short portfolio

6.1 Trunover

Portfolio turnover:

6.1.1

$$\textbf{Turnover} = \frac{1}{T}\sum_{t=1}^{T}\left(\sum_{i}|w_{i,t+1} - w_{i,t}|\right)$$

, where $w_{i,t}$ denotes the weight of stock i in the portfolio in month t.

```
[32]: # Only stock weights are needed for the calculation of the portfolio turnover
long = rank_9.copy()
long=long[["MonthYear1",'NumMonth','id', 'eq_weights', 'me_weights']]
short = rank_0.copy()
short=short[["MonthYear1",'NumMonth','id', 'eq_weights','me_weights']]
short["eq_weights"]=short["eq_weights"]*(-1)
short["me_weights"]=short["me_weights"]*(-1)
```

Create lead weight variables $w_{i,t+1}$ for the equal- uand value-weighting scheme (eq_weights_lead1 and me_weights_lead1)

- lead weight variable = 0, when the stock is not included in the portfolio in the subsequent month

[33]:
```python
# Equal weights in t+1 for the top decile portfolio
def create_lead_eq_weights(long):
    mn = long.NumMonth.min()
    mx = long.NumMonth.max() + 1
    d = long.set_index('NumMonth').reindex(pd.RangeIndex(mn, mx,␣
 ↪name='NumMonth'))
    return pd.concat([d, d['eq_weights'].shift(-1).rename('eq_weights_lead1')],␣
 ↪axis=1)

eq_weights_lead1_long=long.groupby('id')[['NumMonth', 'eq_weights']].
 ↪apply(create_lead_eq_weights) \
    .sort_index(level=[1, 0]).dropna(subset=['eq_weights']).reset_index()
```

[34]:
```python
#Value weights in t+1 for the top decile portfolio
def create_lead_me_weights(long):
    mn = long.NumMonth.min()
    mx = long.NumMonth.max() + 1
    d = long.set_index('NumMonth').reindex(pd.RangeIndex(mn, mx,␣
 ↪name='NumMonth'))
    return pd.concat([d, d['me_weights'].shift(-1).rename('me_weights_lead1')],␣
 ↪axis=1)

me_weights_lead1_long=long.groupby('id')[['NumMonth', 'me_weights']].
 ↪apply(create_lead_me_weights) \
    .sort_index(level=[1, 0]).dropna(subset=['me_weights']).reset_index()
```

[35]:
```python
# Equal weights in t+1 for the bottom decile portfolio
def create_lead_eq_weights(short):
    mn = short.NumMonth.min()
    mx = short.NumMonth.max() + 1
    d = short.set_index('NumMonth').reindex(pd.RangeIndex(mn, mx,␣
 ↪name='NumMonth'))
    return pd.concat([d, d['eq_weights'].shift(-1).rename('eq_weights_lead1')],␣
 ↪axis=1)

eq_weights_lead1_short=short.groupby('id')[['NumMonth', 'eq_weights']].
 ↪apply(create_lead_eq_weights) \
    .sort_index(level=[1, 0]).dropna(subset=['eq_weights']).reset_index()
```

[36]:
```python
# Value weights in t+1 for the bottom decile portfolio
def create_lead_me_weights(short):
    mn = short.NumMonth.min()
    mx = short.NumMonth.max() + 1
    d = short.set_index('NumMonth').reindex(pd.RangeIndex(mn, mx,␣
 ↪name='NumMonth'))
```

```
    return pd.concat([d, d['me_weights'].shift(-1).rename('me_weights_lead1')],␣
↪axis=1)

me_weights_lead1_short=short.groupby('id')[['NumMonth', 'me_weights']].
↪apply(create_lead_me_weights) \
    .sort_index(level=[1, 0]).dropna(subset=['me_weights']).reset_index()
```

[37]:
```
# Merge lead weight variables to the dataframe containing the top decile␣
↪portfolio
long=long.set_index(['NumMonth','id'])
eq_weights_lead1_long=eq_weights_lead1_long.set_index(['NumMonth','id'])
me_weights_lead1_long=me_weights_lead1_long.set_index(['NumMonth','id'])
long = pd.merge(long,␣
↪eq_weights_lead1_long[["eq_weights_lead1"]],left_index=True,␣
↪right_index=True)
long = pd.merge(long,␣
↪me_weights_lead1_long[["me_weights_lead1"]],left_index=True,␣
↪right_index=True)
long=long.reset_index()

# Merge lead weight variables to the dataframe containing the bottom decile␣
↪portfolio
short=short.set_index(['NumMonth','id'])
eq_weights_lead1_short=eq_weights_lead1_short.set_index(['NumMonth','id'])
me_weights_lead1_short=me_weights_lead1_short.set_index(['NumMonth','id'])
short = pd.merge(short,␣
↪eq_weights_lead1_short[["eq_weights_lead1"]],left_index=True,␣
↪right_index=True)
short = pd.merge(short,␣
↪me_weights_lead1_short[["me_weights_lead1"]],left_index=True,␣
↪right_index=True)
short=short.reset_index()

# Merge to get the zeronet portfolio
long["Strategy"]= "long"
short["Strategy"]= "short"
zeronet= pd.concat([long, short])
zeronet = zeronet.sort_values(by = ['NumMonth',"id","Strategy"])
```

- Absolute difference between the weight of the stocks in the two following months $|w_{i,t+1} - w_{i,t}|$

[38]:
```
zeronet["abs_ew"] = abs(zeronet["eq_weights_lead1"] -zeronet["eq_weights"])
zeronet["abs_vw"] = abs(zeronet["me_weights_lead1"] -zeronet["me_weights"])
```

- Sum of the absolute diffrernces over all stocks per month $\sum_i |w_{i,t+1} - w_{i,t}|$

[39]:
```
zeronet["sum_abs_ew"] = zeronet.groupby('NumMonth', sort=False)["abs_ew"].
 ↪transform('sum')
zeronet["sum_abs_vw"] = zeronet.groupby('NumMonth', sort=False)["abs_vw"].
 ↪transform('sum')
```

- Turnover $= \frac{1}{T}\sum_{t=1}^{T}\left(\sum_i \left|w_{i,t+1} - w_{i,t}\right|\right)$

[40]:
```
turnover_ew = (zeronet[["NumMonth","sum_abs_ew"]].drop_duplicates().sum_abs_ew.
 ↪sum())/zeronet["NumMonth"].nunique()
turnover_vw = (zeronet[["NumMonth","sum_abs_vw"]].drop_duplicates().sum_abs_vw.
 ↪sum())/zeronet["NumMonth"].nunique()
```

[41]:
```
# Multiply by 100 to get percent values
turnover_ew_pct = turnover_ew*100
turnover_vw_pct = turnover_vw*100
```

[42]:
```
print("Trunover equally weighted: ", turnover_ew_pct)
print("Trunover value weighted: ", turnover_vw_pct)
```

```
Trunover equally weighted:  2.045604785666251
Trunover value weighted:  31.126073201497395
```

7 Maximum Drawdown

$$\text{MaxDD} \max_{0\leq t_1\leq t_2\leq T}\left(Y_{t_1} - Y_{t_2}\right)$$

, where Y_t is the cumulative log excess return from date 0 through t

[43]:
```
def MDD(returns):

    cum_rets = (1 + np.log(returns+1)).cumprod() - 1
    nav = ((1 + cum_rets) * 100).fillna(100)
    hwm = nav.cummax()
    dd = nav / hwm - 1

    return min(dd)

maxDD_ew_pct = (MDD(zeronet_monthly["excess_return_zeronet_ew"])*-100)
maxDD_vw_pct = (MDD(zeronet_monthly["excess_return_zeronet_vw"])*-100)

print("MaxDD equally weighted: ", maxDD_ew_pct)
print("MaxDD value weighted: ", maxDD_vw_pct)
```

```
MaxDD equally weighted:  6.157246653417059
MaxDD value weighted:  20.64887737270781
```

7.1 Max 1M loss (%)

- the most extreme negative monthly return

[44]:
```
max_1m_loss_ew= (zeronet_monthly["excess_return_zeronet_ew"].min())*(-100)
max_1m_loss_vw= (zeronet_monthly["excess_return_zeronet_vw"].min())*(-100)

print("Max 1M loss equally weighted: ", max_1m_loss_ew)
print("Max 1M loss value weighted: ", max_1m_loss_vw)
```

```
Max 1M loss equally weighted:  3.4707079091004998
Max 1M loss value weighted:  14.179001083920111
```

8 Risk-adjusted performance

Mean active return and information ratio relative to DAX (benchmark)

[45]:
```
#get DAX price data
dax = pd.read_csv(r"C:\Users\krist\Documents\Data\Dax monthly.csv",parse_dates␣
↪=["Date"])
dax= dax[dax['Date'] <= '2020-02-01']

# Share prices are given on the first day of each month and in the data set at␣
↪the end of the month.
# Shift by one month to match the months in both datasets
dax['MonthYear_t+1'] = dax['Date'].dt.to_period('M')
dax['MonthYear'] = dax["MonthYear_t+1"].shift(1)
dax.drop(["MonthYear_t+1"], axis = 1, inplace = True)

# We only need the prices from January 2010
dax= dax[dax['MonthYear'] >= '2010-01']

# Set MonthYear as index to  merge with the portfolio dataframe afterwards
dax=dax.set_index(["MonthYear"])

# Get monthly returns
dax["monthly_return_dax"] = dax["Close"].pct_change()
```

[46]:
```
#Get Dax excess returns
risk_free = bigdata[["MonthYear1", "risk_free_rate"]].drop_duplicates()
risk_free=risk_free.set_index("MonthYear1")
dax = pd.merge(dax[["monthly_return_dax"]], risk_free ,left_index=True,␣
↪right_index=True)
dax["monthly_excess_return_dax"] = dax["monthly_return_dax"]-␣
↪dax["risk_free_rate"]
```

[47]:
```
#Merge zeronet and DAX dataframes
zeronet_monthly=zeronet_monthly.set_index("MonthYear1")
```

```
dax_zeronet = pd.merge(dax[["monthly_return_dax","monthly_excess_return_dax"]],
 ↪zeronet_monthly[["excess_return_zeronet_ew", "excess_return_zeronet_vw",
 ↪"return_zeronet_ew", "return_zeronet_vw"]],left_index=True, right_index=True)
```

[48]:
```
# Calculate portfolio performance measures

#Time-series average of portfolio excess_returns
mean_ret_ew = dax_zeronet["excess_return_zeronet_ew"].mean()
mean_ret_vw = dax_zeronet["excess_return_zeronet_vw"].mean()
mean_ret_dax = dax_zeronet["monthly_excess_return_dax"].mean()
#Multiply by 100 to get percent values
mean_ret_ew_pct = mean_ret_ew*100
mean_ret_vw_pct= mean_ret_vw*100
mean_ret_dax_pct = mean_ret_dax*100

#Standard deviation ofportfolio excess_returns
std_ew = dax_zeronet["excess_return_zeronet_ew"].std()
std_vw = dax_zeronet["excess_return_zeronet_vw"].std()
std_dax = dax_zeronet["monthly_excess_return_dax"].std()
#Multiply by 100 to get percent values
std_ew_pct = std_ew*100
std_vw_pct = std_vw*100
std_dax_pct = std_dax*100

#Annualized sharpe ratio of portfolio excess_returns
sr_ew = ((dax_zeronet["excess_return_zeronet_ew"]).mean() /
 ↪(dax_zeronet["return_zeronet_ew"]).std()) * np.sqrt(12)
sr_vw = ((dax_zeronet["excess_return_zeronet_vw"]).mean() /
 ↪(dax_zeronet["return_zeronet_vw"]).std()) * np.sqrt(12)
sr_dax = ((dax_zeronet["monthly_excess_return_dax"]).mean() /
 ↪(dax_zeronet["monthly_return_dax"]).std()) * np.sqrt(12)
#Multiply by 100 to get percent values
sr_ew_pct = sr_ew*100
sr_vw_pct = sr_vw*100
sr_dax_pcr= sr_dax*100
```

8.0.1 Mean active return: difference between the benchmark return and the portfolio return

[49]:
```
mean_act_ret_ew =
 ↪(dax_zeronet["excess_return_zeronet_ew"]-dax_zeronet["monthly_excess_return_dax"]).
 ↪mean()
mean_act_ret_vw =
 ↪(dax_zeronet["excess_return_zeronet_vw"]-dax_zeronet["monthly_excess_return_dax"]).
 ↪mean()
```

8.1 Information Ratio $= \frac{R_p - R_b}{\sigma_{(R_p - R_b)}}$

- R_p – Return of Portfolio
- R_b – Return of Benchmark (Dax)
- $\sigma_{(R_p - R_b)}$ – Tracking Error

[50]:
```
ir_ew = ␣
↪((dax_zeronet["excess_return_zeronet_ew"]-dax_zeronet["monthly_excess_return_dax"]).
↪mean() /
        ␣
↪(dax_zeronet["excess_return_zeronet_ew"]-dax_zeronet["monthly_excess_return_dax"]).
↪std())

ir_vw = ␣
↪((dax_zeronet["excess_return_zeronet_vw"]-dax_zeronet["monthly_excess_return_dax"]).
↪mean() /
        ␣
↪(dax_zeronet["excess_return_zeronet_vw"]-dax_zeronet["monthly_excess_return_dax"]).
↪std())
```

[51]:
```
# This measures we only need to represent for the long-short portfolio
turnover_dax=0
ir_dax=0
mean_act_ret_dax=0
maxDD_dax=0
```

[52]:
```
# Generate table representing the portfolio performance measures for the equal␣
↪weighting scheme
ew_chart = np.array([[mean_ret_dax_pct, mean_ret_ew_pct],
                     [std_dax_pct,std_ew_pct],
                     [sr_dax, sr_ew],
                     [maxDD_dax, maxDD_ew_pct],
                     [turnover_dax, turnover_ew_pct],
                     [mean_act_ret_dax, mean_act_ret_ew],
                     [ir_dax, ir_ew]])


ew_chart = pd.DataFrame(ew_chart, columns=['DAX', 'PCR'],
                        index=["Mean return [%]",'Std [%]',
                               "Sharpe ratio", "Maximum drawdown [%]","Turnover␣
↪[%]",
                               "Mean active return","Information ratio"])
ew_chart
```

[52]:

	DAX	PCR
Mean return [%]	0.752467	2.039947
Std [%]	4.610969	2.380671

```
Sharpe ratio           0.561110  2.867392
Maximum drawdown [%]   0.000000  6.157247
Turnover [%]           0.000000  2.045605
Mean active return     0.000000  0.012836
Information ratio      0.000000  0.240930
```

[53]:
```python
# Generate table representing the portfolio performance measures for the value␣
 ↪weighting scheme
vw_chart = np.array([[mean_ret_dax_pct, mean_ret_vw_pct],
                     [std_dax_pct,std_vw_pct],
                     [sr_dax, sr_vw],
                     [maxDD_dax, maxDD_vw_pct],
                     [turnover_dax, turnover_vw_pct],
                     [mean_act_ret_dax, mean_act_ret_vw],
                     [ir_dax, ir_vw]])


vw_chart = pd.DataFrame(vw_chart, columns=['DAX', 'PCR'],
                        index=["Mean return [%]",'Std [%]',
                               "Sharpe ratio", "Maximum drawdown [%]","Turnover␣
 ↪[%]",
                               "Mean active return","Information ratio"])
vw_chart
```

[53]:

	DAX	PCR
Mean return [%]	0.752467	1.101198
Std [%]	4.610969	4.435544
Sharpe ratio	0.561110	0.856219
Maximum drawdown [%]	0.000000	20.648877
Turnover [%]	0.000000	31.126073
Mean active return	0.000000	0.003464
Information ratio	0.000000	0.045552

[54]:
```python
# Save results to compare with the other ML models
ew_chart.to_csv(r'C:
 ↪\Users\krist\Documents\Data\performance_zeronet\pcr_zeronet_ew.csv')
vw_chart.to_csv(r'C:
 ↪\Users\krist\Documents\Data\performance_zeronet\pcr_zeronet_vw.csv')
```

9 Cumulative performance of long-only investment portfolio with monthly restructuring, 2010:01-2019:12

The H-L returns, tend to be driven more by the long side (top decile) than the short side (bottom decile), so the long-only portfolio performace is also examined separately.

9.0.1 Turnover

[55]:
```
long["abs_ew"] = abs(long["eq_weights_lead1"] -long["eq_weights"])
long["abs_vw"] = abs(long["me_weights_lead1"] -long["me_weights"])
long["sum_abs_ew"] = long.groupby('NumMonth', sort=False)["abs_ew"].
    ↪transform('sum')
long["sum_abs_vw"] = long.groupby('NumMonth', sort=False)["abs_vw"].
    ↪transform('sum')
turnover_ew_long = (long[["NumMonth","sum_abs_ew"]].drop_duplicates().
    ↪sum_abs_ew.sum())/long["NumMonth"].nunique()
turnover_vw_long = (long[["NumMonth","sum_abs_vw"]].drop_duplicates().
    ↪sum_abs_vw.sum())/long["NumMonth"].nunique()
turnover_ew_pct_long = turnover_ew_long*100
turnover_vw_pct_long = turnover_vw_long*100
print("Trunover equally weighted: ", turnover_ew_pct_long)
print("Trunover value weighted: ", turnover_vw_pct_long)
```

```
Trunover equally weighted:  1.0205656330404196
Trunover value weighted:  13.710231781005861
```

9.0.2 Maximum Drawdown

[56]:
```
long_monthly = rank_9[['MonthYear1','NumMonth', 'return_portfolio_ew',␣
    ↪'return_portfolio_vw', "excess_return_portfolio_ew",␣
    ↪"excess_return_portfolio_vw"]].drop_duplicates()

maxDD_ew_pct_long = (MDD(long_monthly["excess_return_portfolio_ew"])*-100)
maxDD_vw_pct_long = (MDD(long_monthly["excess_return_portfolio_vw"])*-100)

print("MaxDD equally weighted: ", maxDD_ew_pct_long)
print("MaxDD value weighted: ", maxDD_vw_pct_long)
```

```
MaxDD equally weighted:  23.874493011710342
MaxDD value weighted:  26.975509464813076
```

9.0.3 Max 1M loss (%)

[57]:
```
max_1m_loss_ew_long= (long_monthly["excess_return_portfolio_ew"].min())*(-100)
max_1m_loss_vw_long= (long_monthly["excess_return_portfolio_vw"].min())*(-100)

print("Max 1M loss equally weighted: ", max_1m_loss_ew_long)
print("Max 1M loss value weighted: ", max_1m_loss_vw_long)
```

```
Max 1M loss equally weighted:  10.734665875819012
Max 1M loss value weighted:  10.72582048589566
```

[58]:
```
long_monthly=long_monthly.set_index("MonthYear1")
```

```
dax_long = pd.merge(dax[["monthly_return_dax","monthly_excess_return_dax"]],␣
 ↪long_monthly[["return_portfolio_ew", "return_portfolio_vw",␣
 ↪"excess_return_portfolio_ew",␣
 ↪"excess_return_portfolio_vw"]],left_index=True, right_index=True)
```

[59]:
```
#Time-series average of portfolio excess returns
mean_ret_ew_long = dax_long["excess_return_portfolio_ew"].mean()
mean_ret_vw_long = dax_long["excess_return_portfolio_vw"].mean()
mean_ret_dax = dax_long["monthly_excess_return_dax"].mean()
#Multiply by 100 to get percent values
mean_ret_ew_long_pct = mean_ret_ew_long*100
mean_ret_vw_long_pct= mean_ret_vw_long*100
mean_ret_dax_pct = mean_ret_dax*100

#Standard deviation ofportfolio excess returns
std_ew_long = dax_long["excess_return_portfolio_ew"].std()
std_vw_long = dax_long["excess_return_portfolio_vw"].std()
std_dax = dax_long["monthly_excess_return_dax"].std()
#Multiply by 100 to get percent values
std_ew_long_pct = std_ew_long*100
std_vw_long_pct = std_vw_long*100
std_dax_pct = std_dax*100

#Annualized sharpe ratio of portfolio excess returns
sr_ew_long = ((dax_long["excess_return_portfolio_ew"]).mean() /␣
 ↪(dax_long["return_portfolio_ew"]).std()) * np.sqrt(12)
sr_vw_long = ((dax_long["excess_return_portfolio_vw"]).mean() /␣
 ↪(dax_long["return_portfolio_vw"]).std()) * np.sqrt(12)
sr_dax = ((dax_long["monthly_excess_return_dax"]).mean() /␣
 ↪(dax_long["monthly_return_dax"]).std()) * np.sqrt(12)
#Multiply by 100 to get percent values
sr_ew_long_pct = sr_ew_long*100
sr_vw_long_pct = sr_vw_long*100
sr_dax_pcr= sr_dax*100

#Mean active excess_return:  difference between the benchmark excess return and␣
 ↪the portfolio excess return
mean_act_ret_ew_long =␣
 ↪(dax_long["excess_return_portfolio_ew"]-dax_long["monthly_excess_return_dax"]).
 ↪mean()
mean_act_ret_vw_long =␣
 ↪(dax_long["excess_return_portfolio_vw"]-dax_long["monthly_excess_return_dax"]).
 ↪mean()

# Calculate the information ratio
```

```
ir_ew_long =␣
 ↪((dax_long["excess_return_portfolio_ew"]-dax_long["monthly_excess_return_dax"]).
 ↪mean() /
        ␣
 ↪(dax_long["excess_return_portfolio_ew"]-dax_long["monthly_excess_return_dax"]).
 ↪std())

ir_vw_long =␣
 ↪((dax_long["excess_return_portfolio_vw"]-dax_long["monthly_excess_return_dax"]).
 ↪mean() /
        ␣
 ↪(dax_long["excess_return_portfolio_vw"]-dax_long["monthly_excess_return_dax"]).
 ↪std())
```

[60]:
```
# Generate table representing the portfolio performance measures for the equal␣
 ↪weighting scheme
ew_long_chart = np.array([[mean_ret_dax_pct, mean_ret_ew_long_pct],
                     [std_dax_pct,std_ew_long_pct],
                     [sr_dax, sr_ew_long],
                     [maxDD_dax, maxDD_ew_pct_long],
                     [turnover_dax, turnover_ew_pct_long],
                     [mean_act_ret_dax, mean_act_ret_ew_long],
                     [ir_dax, ir_ew_long]])


ew_long_chart = pd.DataFrame(ew_long_chart, columns=['DAX', 'PCR_long'],
                        index=["Mean return [%]",'Std [%]',
                               "Sharpe ratio", "Maximum drawdown [%]","Turnover␣
 ↪[%]",
                               "Mean active return","Information ratio"])

ew_long_chart
```

[60]:

	DAX	PCR_long
Mean return [%]	0.752467	1.510029
Std [%]	4.610969	4.528445
Sharpe ratio	0.561110	1.138538
Maximum drawdown [%]	0.000000	23.874493
Turnover [%]	0.000000	1.020566
Mean active return	0.000000	0.007637
Information ratio	0.000000	0.207883

[61]:
```
# Generate table representing the portfolio performance measures for the value␣
 ↪weighting scheme
vw_long_chart = np.array([[mean_ret_dax_pct, mean_ret_vw_long_pct],
                     [std_dax_pct,std_vw_long_pct],
                     [sr_dax, sr_vw_long],
```

```
                            [maxDD_dax, maxDD_vw_pct_long],
                            [turnover_dax, turnover_vw_pct_long],
                            [mean_act_ret_dax, mean_act_ret_vw_long],
                            [ir_dax, ir_vw_long]])


vw_long_chart = pd.DataFrame(vw_long_chart, columns=['DAX', 'PCR_long'],
                    index=["Mean return [%]",'Std [%]',
                           "Sharpe ratio", "Maximum drawdown [%]","Turnover␣
 ↪[%]",
                           "Mean active return","Information ratio"])

vw_long_chart
```

[61]:

	DAX	PCR_long
Mean return [%]	0.752467	0.748578
Std [%]	4.610969	4.314071
Sharpe ratio	0.561110	0.600264
Maximum drawdown [%]	0.000000	26.975509
Turnover [%]	0.000000	13.710232
Mean active return	0.000000	0.000380
Information ratio	0.000000	0.010639

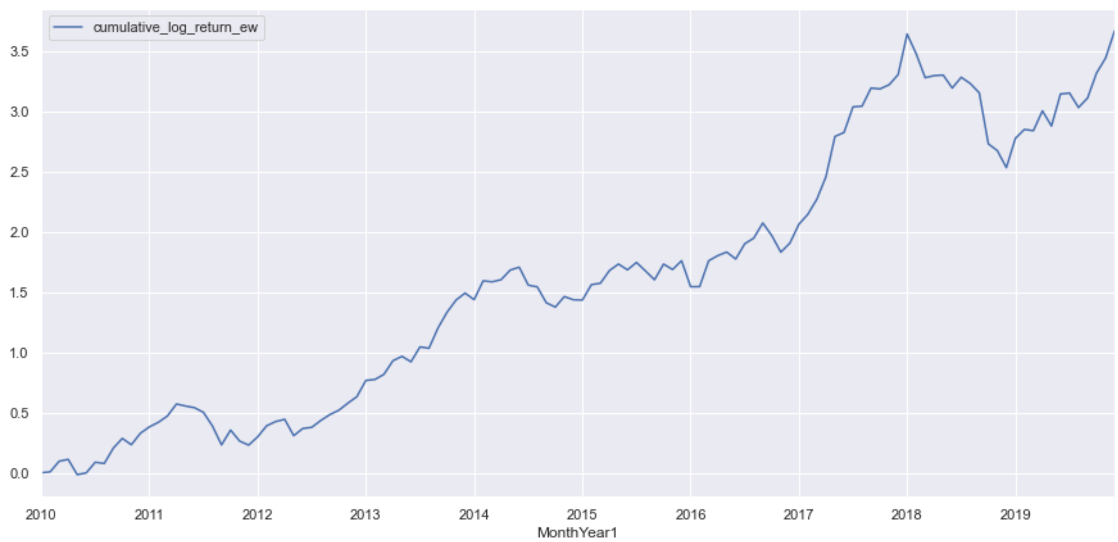
[62]:
```
# Save results to compare with the other ML models
ew_long_chart.to_csv(r'C:
 ↪\Users\krist\Documents\Data\performance_long_only\pcr_long_ew.csv')
vw_long_chart.to_csv(r'C:
 ↪\Users\krist\Documents\Data\performance_long_only\pcr_long_vw.csv')
```

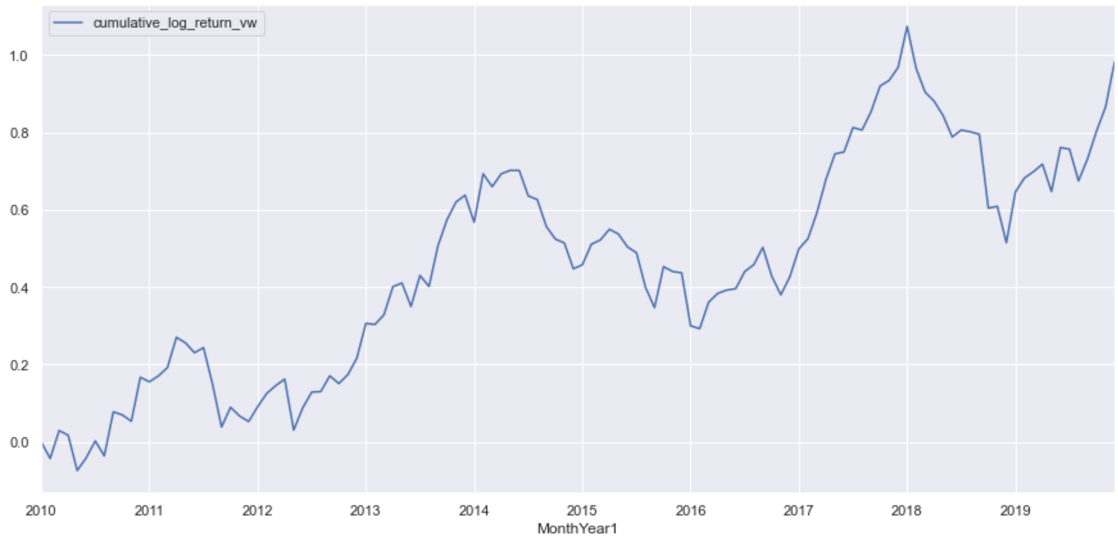
10 Cumulative performance graph of expected return-sorted portfolios with monthly restructuring, 2010:01-2019:12

Calculate the cumulative log returns of the long (top decile) and short (bottom decile) portfolios for both weighting schemes. Let's assume one invests 1 USD in January 2010 and buys a fraction of the top decile portfolio.

[63]:
```
long =rank_9.copy()
long = long.set_index("MonthYear1")
long=long[["excess_return_portfolio_ew", "excess_return_portfolio_vw"]].
 ↪drop_duplicates()

#Shift to get the returns in the current month
long["curr_ret_port_ew"]=long['excess_return_portfolio_ew'].shift(1)
long["curr_ret_port_vw"]=long['excess_return_portfolio_vw'].shift(1)
```

```python
#Calculate cumulative returns and cumulative log returns for the equal␣
↪weighting scheme
long["cumulative_return_ew"]= (1 + long["curr_ret_port_ew"]).cumprod()-1
long["cumulative_log_return_ew"]= (1 + np.log(long["curr_ret_port_ew"]+1)).
↪cumprod()-1
# return in January 2010 = 0 (one invests in the end of the month)
long.iloc[0, 2:] = 0
#Plot cumulative log returns for the equal weighting scheme
long[["cumulative_log_return_ew"]].plot(grid=True,figsize=(15, 7))

#Calculate cumulative returns and cumulative log returns for the value␣
↪weighting scheme
long["cumulative_return_vw"]= (1 + long["curr_ret_port_vw"]).cumprod()-1
long["cumulative_log_return_vw"]= (1 + np.log(long["curr_ret_port_vw"]+1)).
↪cumprod()-1
# Return in January 2010 = 0(one invests in the end of the month)
long.iloc[0, 2:] = 0
# Plot cumulative log returns for the  value weighting scheme
long[["cumulative_log_return_vw"]].plot(grid=True,figsize=(15, 7));
```

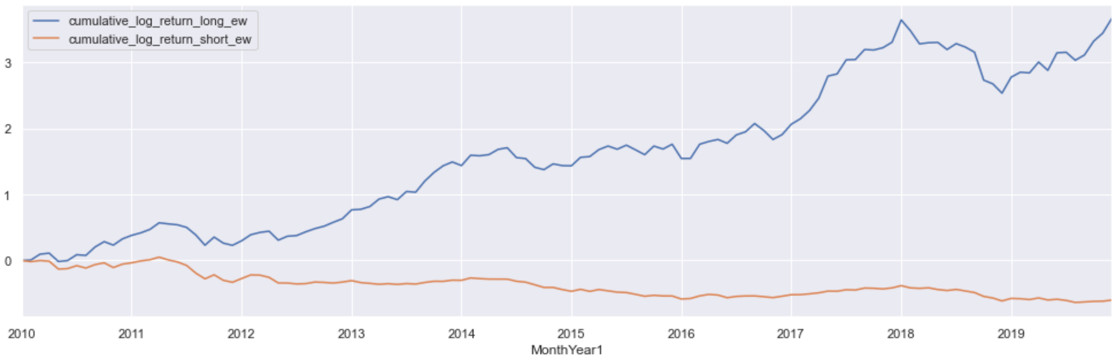




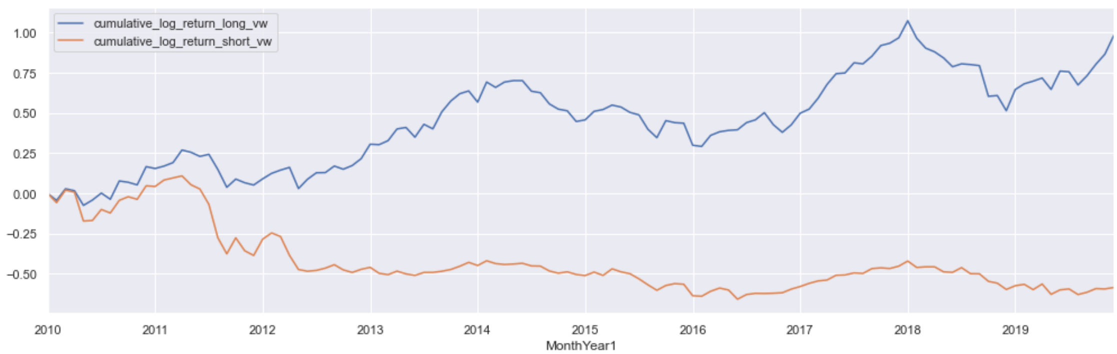
[64]:
```
short =rank_0.copy()
short = short.set_index("MonthYear1")
short=short[["excess_return_portfolio_ew", "excess_return_portfolio_vw"]].
 ↪drop_duplicates()

#Shift to get the returns in the current month
short["curr_ret_port_ew"]=short['excess_return_portfolio_ew'].shift(1)
short["curr_ret_port_vw"]=short['excess_return_portfolio_vw'].shift(1)

#Calculate cumulative returns and cumulative log returns for the equal␣
 ↪weighting scheme
short["cumulative_return_ew"]= (1 + short["curr_ret_port_ew"]).cumprod()-1
short["cumulative_log_return_ew"]= (1 + np.log(short["curr_ret_port_ew"]+1)).
 ↪cumprod()-1
# return in January 2010 = 0 (one invests in the end of the month)
short.iloc[0, 2:] = 0
#Plot cumulative log returns for the equal weighting scheme
short[["cumulative_log_return_ew"]].plot(grid=True,figsize=(15, 7))

#Calculate cumulative returns and cumulative log returns for the value␣
 ↪weighting scheme
short["cumulative_return_vw"]= (1 + short["curr_ret_port_vw"]).cumprod()-1
short["cumulative_log_return_vw"]= (1 + np.log(short["curr_ret_port_vw"]+1)).
 ↪cumprod()-1
# Return in January 2010 = 0(one invests in the end of the month)
short.iloc[0, 2:] = 0
# Plot cumulative log returns for the  value weighting scheme
short[["cumulative_log_return_vw"]].plot(grid=True,figsize=(15, 7));
```

[65]:
```
#Merge results to compare cumulative returns of both portfolios for the equal␣
↪weighting scheme
long = long.rename(columns={'cumulative_log_return_ew':␣
↪'cumulative_log_return_long_ew'})
short = short.rename(columns={'cumulative_log_return_ew':␣
↪'cumulative_log_return_short_ew'})
long_short_ew = pd.
↪merge(long[["cumulative_log_return_long_ew"]],short[["cumulative_log_return_short_ew"]],lef
↪right_index=True)
#Plot
```

```
long_short_ew[["cumulative_log_return_long_ew",␣
↪"cumulative_log_return_short_ew"]].plot(grid=True,figsize=(17, 5));
```



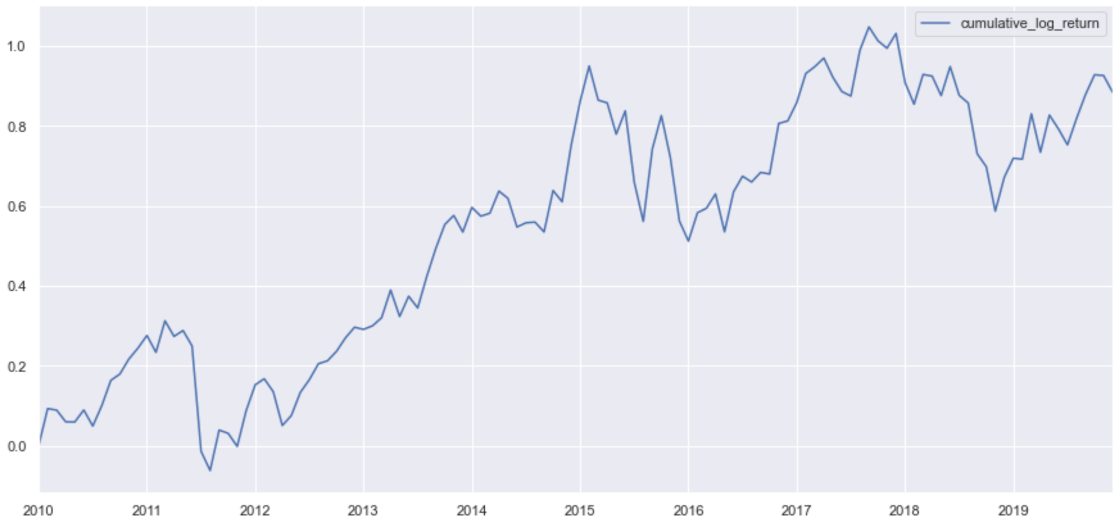
[66]:
```
#Merge results to compare cumulative returns of both portfolios for the value␣
↪weighting scheme
long = long.rename(columns={'cumulative_log_return_vw':␣
↪'cumulative_log_return_long_vw'})
short = short.rename(columns={'cumulative_log_return_vw':␣
↪'cumulative_log_return_short_vw'})
long_short_vw = pd.
↪merge(long[["cumulative_log_return_long_vw"]],short[["cumulative_log_return_short_vw"]],left
↪right_index=True)
#Plot
long_short_vw[["cumulative_log_return_long_vw",␣
↪"cumulative_log_return_short_vw"]].plot(grid=True,figsize=(17, 5));
```



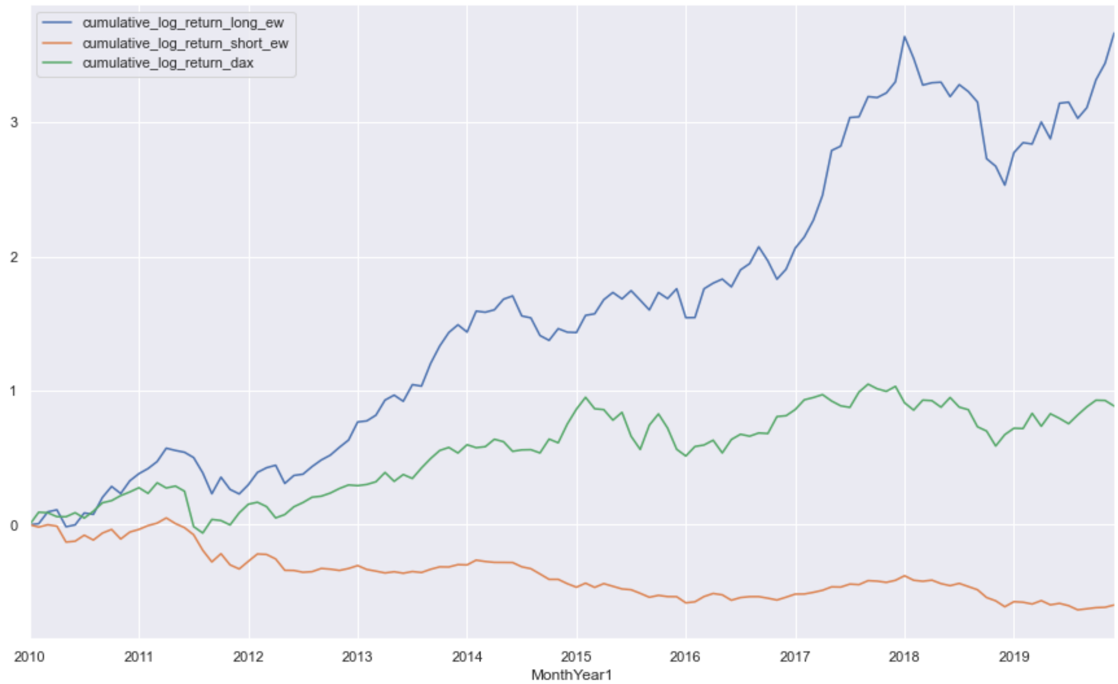
11 DAX Returns

Compare the cumulative returns of both portfolios with DAX cumulative returs over the same period

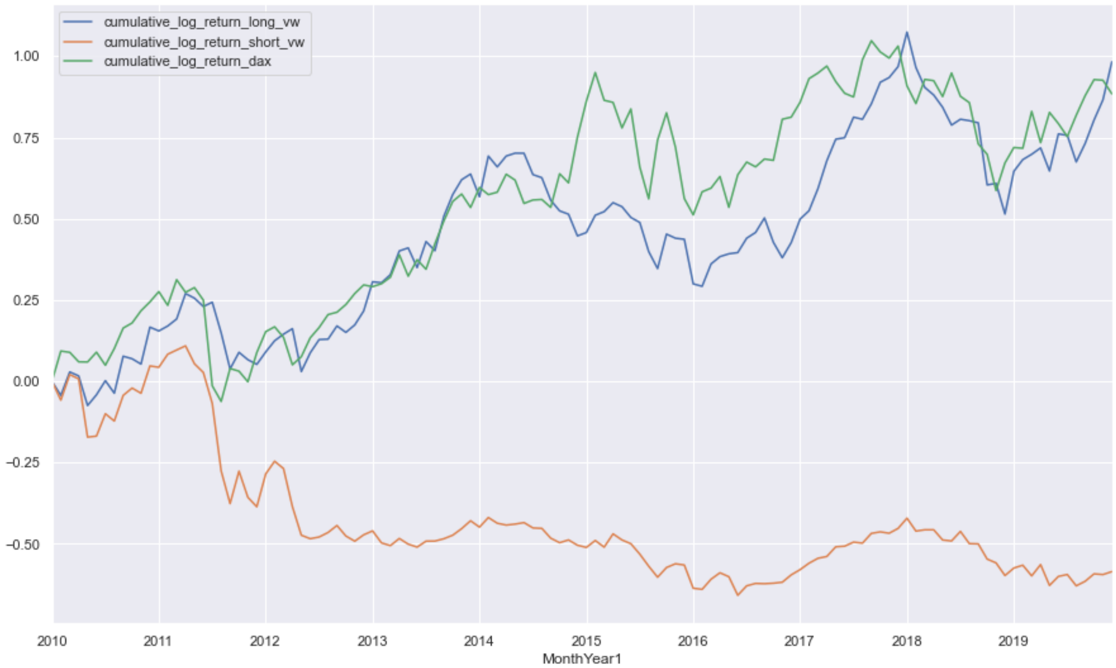
```
[67]: # calculate cumulative returns
dax["cumulative_return"]= (1 + dax["monthly_excess_return_dax"]).cumprod()-1
dax["cumulative_log_return"]= (1 + np.log(dax["monthly_excess_return_dax"]+1)).
 ↪cumprod()-1

#replace NaN with 0: return and cumulative return on Jan 2010=0
dax.iloc[0,4:]=0
#plot
dax[["cumulative_log_return"]].plot(grid=True,figsize=(15, 7));
```




```
[68]: # Merge DAX cumulative log returns with the cumulative log returns of the␣
 ↪equally weighted portfolios and plot
dax = dax.rename(columns={'cumulative_log_return': 'cumulative_log_return_dax'})
long_short_dax_ew = pd.
 ↪merge(long_short_ew,dax[["cumulative_log_return_dax"]],left_index=True,␣
 ↪right_index=True)
long_short_dax_ew[["cumulative_log_return_long_ew",␣
 ↪"cumulative_log_return_short_ew","cumulative_log_return_dax"]].
 ↪plot(grid=True,figsize=(15, 9));
```



[69]:
```
# Merge DAX cumulative log returns with the cumulative log returns of the value␣
↪weighted portfolios and plot
dax = dax.rename(columns={'cumulative_log_return': 'cumulative_log_return_dax'})
long_short_dax_vw = pd.
↪merge(long_short_vw,dax[["cumulative_log_return_dax"]],left_index=True,␣
↪right_index=True)
long_short_dax_vw[["cumulative_log_return_long_vw",␣
↪"cumulative_log_return_short_vw","cumulative_log_return_dax"]].
↪plot(grid=True,figsize=(15, 9));
```



[70]:
```
# Save results to compare with the other ML models
long_short_dax_ew.to_csv(r'C:
 ↪\Users\krist\Documents\Data\cumulative_log_returns\pcr_ew.csv')
long_short_dax_vw.to_csv(r'C:
 ↪\Users\krist\Documents\Data\cumulative_log_returns\pcr_vw.csv')
```