hw4_notebook_v3

May 2, 2023

1 Data Analytics and Machine Learning - Lars Lochstoer

1.1 Problem Set 4

2 Question 1: Valiation with Machine Learning, version 1

2.1 Data work

[ ]:
```
# Packages
import os
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
import statsmodels.api as sm
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
from linearmodels.panel import PanelOLS, compare
from sklearn.linear_model import ElasticNetCV
from sklearn.linear_model import ElasticNet

# Set correct path to data directory
os.chdir("../data")

# Load data
data = pd.read_csv('StockRetAcct_DT.csv').iloc[:, 1:].dropna()
```

[ ]:
```
# Add lnBE and lnBE2
#data["lnMB"] = -data["lnBM"]
data["lnBE"] = data["lnBM"] + data["lnME"]
data["lnBE2"] = (data["lnBM"] + data["lnME"]) ** 2

# Square all other characteristics and interact them with lnBE
col = ["lnIssue", "lnProf", "lnInv", "lnLever", "lnMom", "lnROE", "rv"]
for c in col:
    data[f"{c}2"] = data[c] ** 2
    data[f"{c}inter"] = data[c] * data["lnBE"]
```

```
# De-mean by industry-year
for c in col:
    data[[c, f"{c}2", f"{c}inter"]] = data.groupby(['year', 'ff_ind'])[[c,␣
 ↪f"{c}2", f"{c}inter"]].transform(lambda x: x - x.mean())
data[['lnBM', 'lnBE', 'lnBE2']] = data.groupby(['year', 'ff_ind'])[['lnBM',␣
 ↪'lnBE', 'lnBE2']].transform(lambda x: x - x.mean())

# Data Overview
data.head()
```

[ ]:

```
   FirmID  year  lnAnnRet      lnRf      MEwt   lnIssue     lnMom       lnME  \
0       6  1980  0.363631  0.078944  0.000281 -0.031518 -0.043815  12.581472
1       6  1981 -0.290409  0.130199  0.000321 -0.016698  0.082219  12.907996
2       6  1982  0.186630  0.130703  0.000266 -0.119505  0.063051  12.557775
3       6  1983  0.489819  0.089830  0.000170 -0.134396 -0.432452  12.561954
4      10  1991 -0.508005  0.061216  0.000033 -0.121984  0.846865  11.565831

     lnProf      lnEP  …    lnInv2  lnInvinter  lnLever2  lnLeverinter  \
0 -0.065414  0.146411  … -0.045275   -0.877767 -0.135418      0.220836
1 -0.020724  0.102555  … -0.026850   -0.476887 -0.068848      0.693242
2 -0.040975  0.119548  … -0.017624    0.152454 -0.049602      1.087056
3  0.001125  0.115924  … -0.012699   -0.701114 -0.070404      0.772906
4  0.118796  0.023147  … -0.021621    0.541536 -0.291178     -2.780962

     lnMom2  lnMominter    lnROE2  lnROEinter       rv2   rvinter
0 -0.077018   -0.442526 -0.023986   -0.807718 -0.010919 -0.385629
1 -0.019577    1.503954 -0.019490   -0.677636 -0.012492 -0.657958
2 -0.131375    0.704359 -0.022464   -0.704323 -0.010319 -0.506714
3 -0.305134   -5.443163 -0.022040   -0.189306 -0.015790 -0.703336
4  1.383746    7.012217 -0.037233    0.290212  0.057670  0.689237

[5 rows x 32 columns]
```

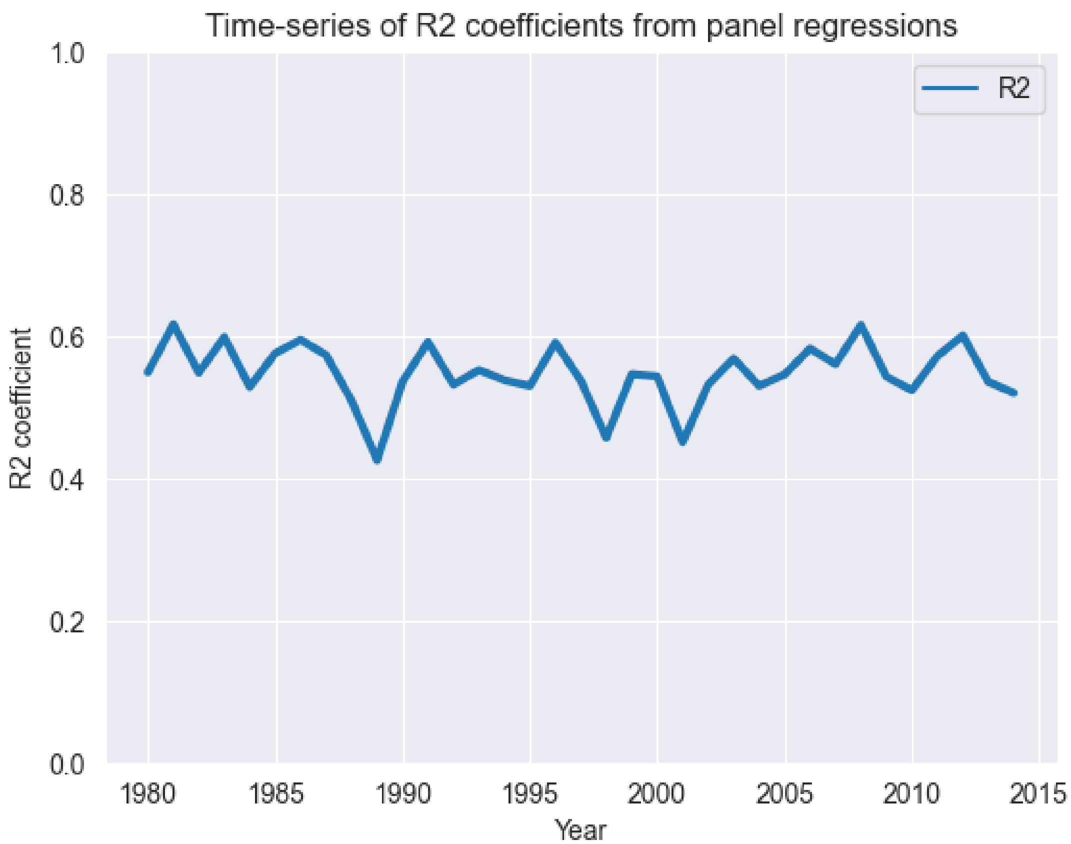
2.2 Cross-sectional valuation regressions

[ ]:

```
# Initiate iterator and output variables for cross-sectional regression
years = sorted(data['year'].unique())
R2 = np.zeros(len(years))
lnBM_hat_OLS = np.zeros(len(data))
coef_table = pd.DataFrame()

# Each year, regress lnME on all characteristics and industries
for i, t in enumerate(years):
    indx = data['year'] == t
    data_tmp = data.loc[indx].reset_index(drop=True)
```

```
    regtmp = smf.ols("lnBM ~ lnBE + lnBE2 + lnIssue + lnIssue2 + lnIssueinter +␣
↪\
                     lnProf + lnProf2 + lnProfinter + lnInv + lnInv2 + lnInvinter␣
↪+ \
                     lnLever + lnLever2 + lnLeverinter + lnMom + lnMom2 +␣
↪lnMominter +\
                     lnROE + lnROE2 + lnROEinter + rv + rv2 + rvinter",
                        data=data_tmp).fit()
    R2[i] = regtmp.rsquared  # extracts the R2 coefficient
    tmp = regtmp.params.to_dict()
    tmp['year'] = t
    coef_table = coef_table.append(tmp, ignore_index=True)
    lnBM_hat_OLS[indx] = regtmp.predict(data_tmp)  # extraces the fitted values

data["lnBM_hat_OLS"] = lnBM_hat_OLS

# Plot the R2 coefficients across time - these are R2 coefficients WITHIN␣
↪industries
summary = pd.DataFrame()
summary['year'] = years
summary['R2'] = R2
summary = summary.set_index('year')

sns.set_style('darkgrid')
plt.figure()
ax = sns.lineplot(data=summary, dashes=False, linewidth=3)
ax.set(xlabel='Year',
       ylabel='R2 coefficient',
       title="Time-series of R2 coefficients from panel regressions")
ax.set_ylim(bottom=0, top=1)
```

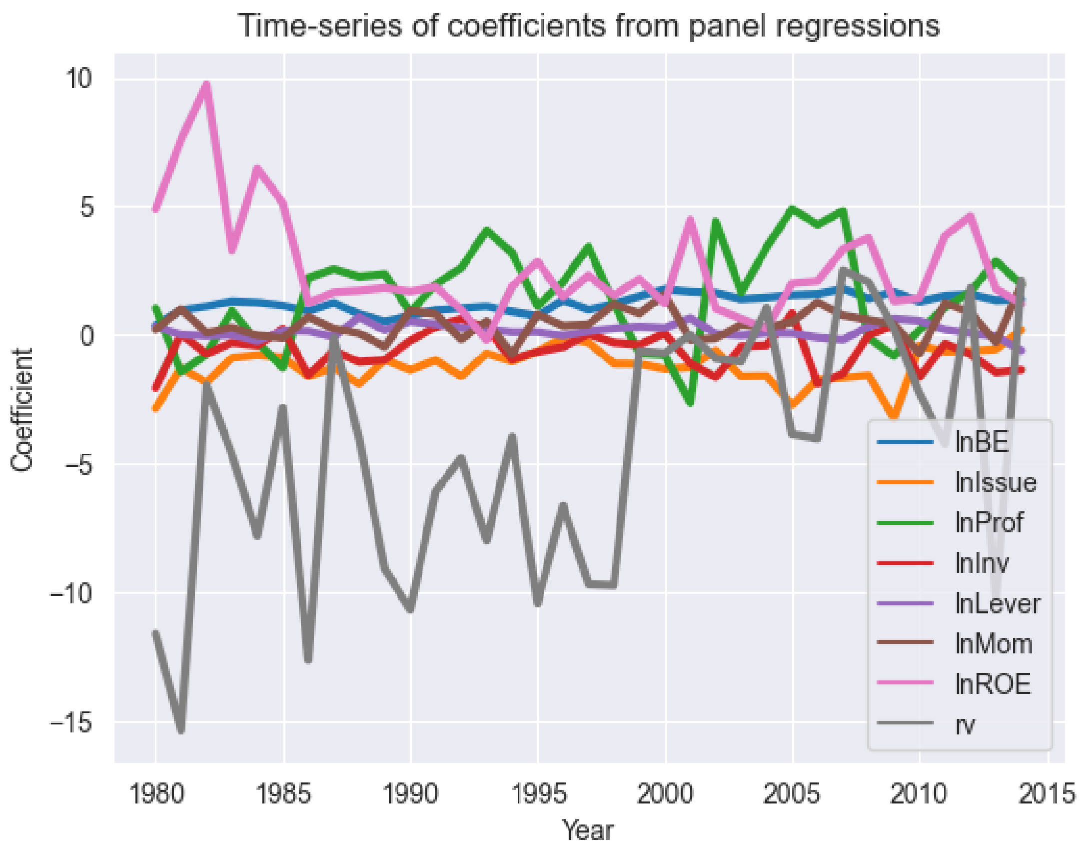
[ ]: (0.0, 1.0)



The cross-sectional regressions are able to explain just above 50% of within-industry variation in log market-to-book ratios.

[ ]:
```python
coef_table = coef_table.set_index('year')

sns.set_style('darkgrid')
plt.figure()
ax = sns.lineplot(data=coef_table[['lnBE'] + col], dashes=False, linewidth=3)
ax.set(xlabel='Year',
       ylabel='Coefficient',
       title="Time-series of coefficients from panel regressions")
#ax.set_ylim(bottom=0, top=1)
```

[ ]:
```
[Text(0.5, 0, 'Year'),
 Text(0, 0.5, 'Coefficient'),
 Text(0.5, 1.0, 'Time-series of coefficients from panel regressions')]
```



2.3 Excess returns based on mispricing

The idea here is to take the valuation-model implied predicted market equity as fundamental values, and define the deviation of the actual market equity from the fundamental value as mispricing. If mispricing reverts over time, then overvalued (undervalued) stocks should predict negative (positive) excess returns going forward.

[ ]:
```
# Define Fama-MacBeth regression
def ols_coef(x, formula):
    return smf.ols(formula, data=x).fit().params


# Define excess return
data['ExRet'] = np.exp(data.lnAnnRet) - np.exp(data.lnRf)

# Define the mispricing measure z_OLS
data['z_OLS'] = data.lnBM - data.lnBM_hat_OLS

# Run Fama-MacBeth regression
res = (data.groupby('year').apply(ols_coef, 'ExRet ~ z_OLS'))
```

```
# Print the result
print('Mean Return: ', str(res['z_OLS'].mean())+'\n',
      'Std Dev:      ', str(res['z_OLS'].std())+'\n',
      'Sharpe Ratio ', str(res['z_OLS'].mean() /
                           res['z_OLS'].std())+'\n',
      't-stat:      ', str(len(years)**.5*(res['z_OLS'].mean()) /
                           res['z_OLS'].std()), sep="\n")
```

```
Mean Return:
0.026386647363474142

Std Dev:
0.07801098640695324

Sharpe Ratio
0.33824270886443064

t-stat:
2.001070851693708
```

The mispricing variable appears useful for predicting excess returns in the expected direction.

[ ]:
```
# Run Fama-MacBeth regression controlling for lnBM, lnProf, lnInv, and lnMom
res = (data.groupby('year').apply(
    ols_coef, 'ExRet ~ z_OLS + lnBM_hat_OLS + lnProf + lnInv + lnMom'))

# Print the result
print('Mean Return: ', str(res['z_OLS'].mean())+'\n',
      'Std Dev:      ', str(res['z_OLS'].std())+'\n',
      'Sharpe Ratio ', str(res['z_OLS'].mean() /
                           res['z_OLS'].std())+'\n',
      't-stat:      ', str(len(years)**.5*(res['z_OLS'].mean()) /
                           res['z_OLS'].std()), sep="\n")
```

```
Mean Return:
0.026386647363474142

Std Dev:
0.0780109864069532

Sharpe Ratio
0.33824270886443086

t-stat:
2.001070851693709
```

[ ]:
```python
# Print the result
print('Mean Return: ', str(res['lnBM_hat_OLS'].mean())+'\n',
      'Std Dev:      ', str(res['lnBM_hat_OLS'].std())+'\n',
      'Sharpe Ratio ', str(res['lnBM_hat_OLS'].mean() /
                           res['lnBM_hat_OLS'].std())+'\n',
      't-stat:      ', str(len(years)**.5*(res['lnBM_hat_OLS'].mean()) /
                           res['lnBM_hat_OLS'].std()), sep="\n")
```

```
Mean Return:
0.02459360795277773

Std Dev:
0.09802425340392137

Sharpe Ratio
0.25089309123770265

t-stat:
1.4843035447907402
```

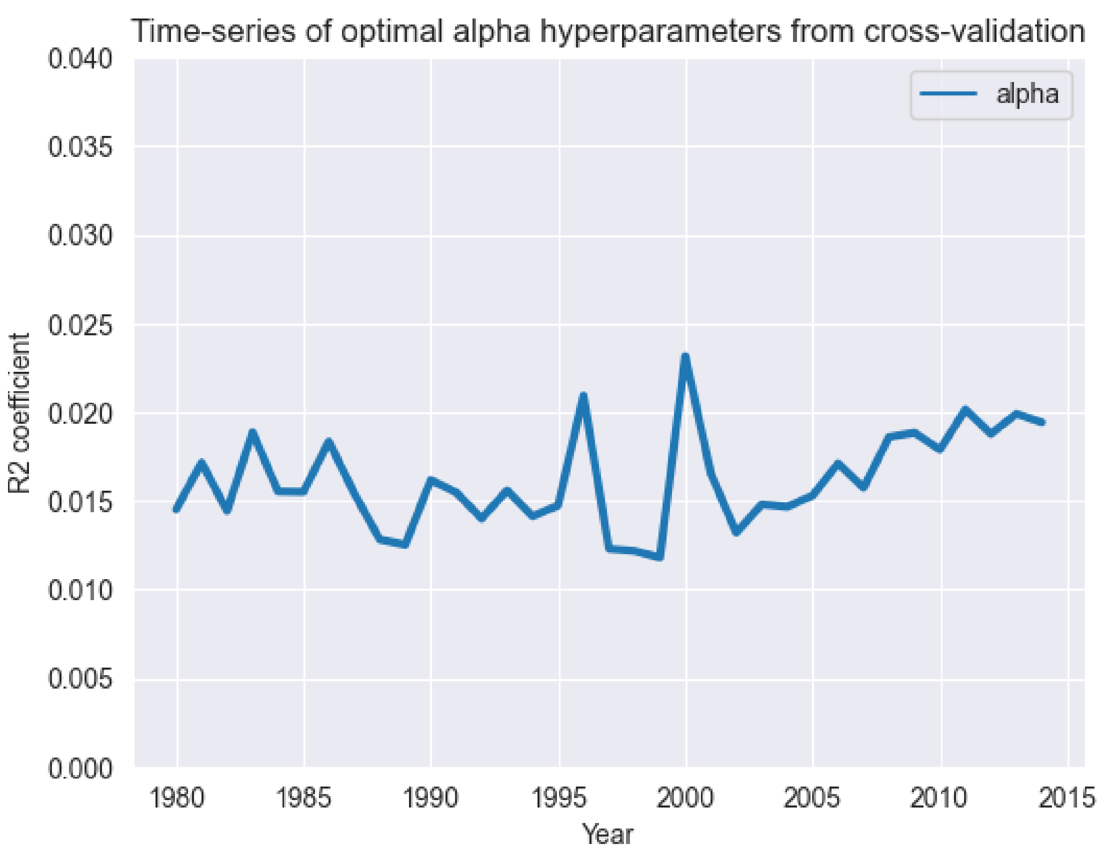
When controling for other stock characteristics the mispricing measure remains signficant. However, the OLS version of the valuation model appears to perform poorly in terms of separating the part of the book-to-market ratio that is related to mispricing and the part that is related to fundamentals; their point estimates are almost identical.

2.4 Cross-sectional valuation regressions with elastic nets

[ ]:
```python
# Initialize array to store optimal alpha for each year
optimal_alphas = np.zeros(len(years))
data["lnBM_hat_EN"] = np.nan

# Loop over years
for i in range(len(years)):
    year = years[i]
    data_year = data[data["year"] == year]

    # ElasticNet with cross-validation
    y_year = data_year["lnBM"]
    X_year = data_year.drop(["lnME", "FirmID", "lnAnnRet", "lnRf", "MEwt",␣
 ↪"lnEP", "year", "ff_ind", "lnBM_hat_OLS",
                             "z_OLS", "ExRet", "lnBM_hat_EN", "lnBM"], axis=1)
    model_year = ElasticNetCV(l1_ratio=0.5, cv=10)
    model_year.fit(X_year, y_year)
    alpha_optim = model_year.alpha_
    optimal_alphas[i] = alpha_optim

    # ElasticNet without cross-validation
    model = ElasticNet(alpha=alpha_optim, l1_ratio=0.5, max_iter=10000)
```

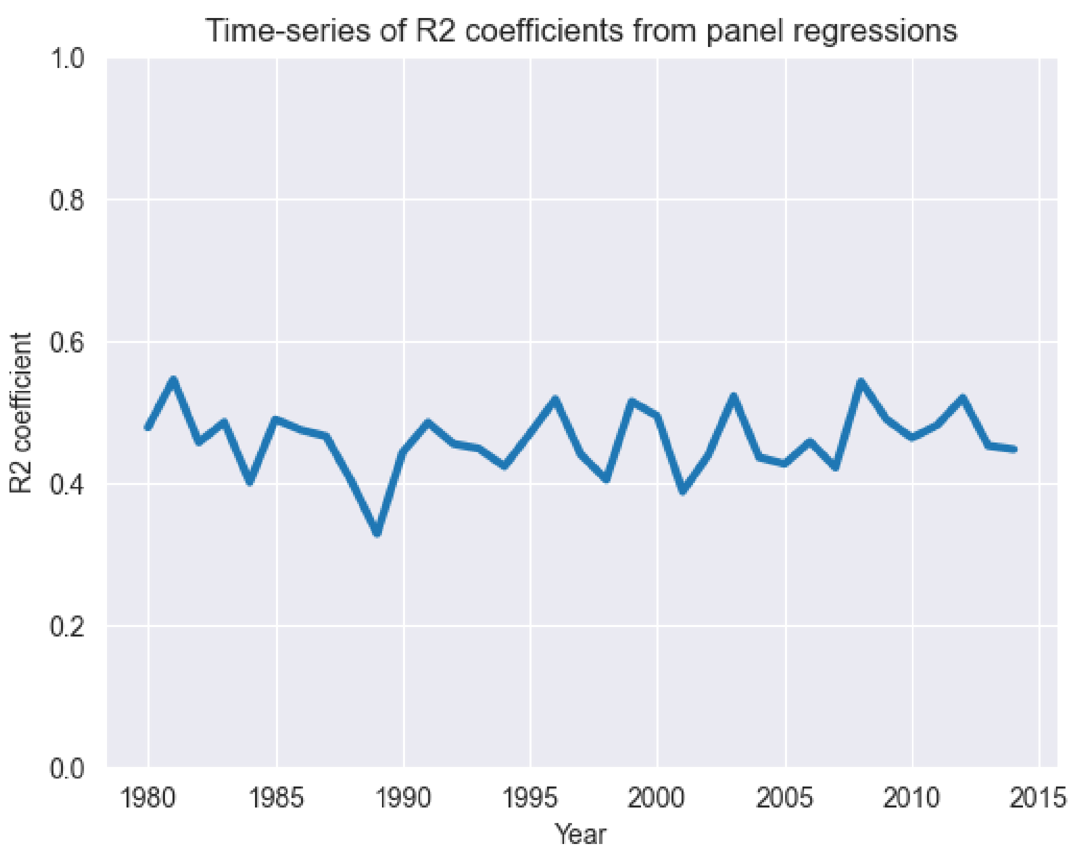
```
    model.fit(X_year, y_year)
    data.loc[data.year == year, "lnBM_hat_EN"] = model.predict(X_year)


# Plot the optimal alpha coefficients from cross-validation
summary = pd.DataFrame()
summary['year'] = years
summary['alpha'] = optimal_alphas
summary = summary.set_index('year')

sns.set_style('darkgrid')
plt.figure()
ax = sns.lineplot(data=summary, dashes=False, linewidth=3)
ax.set(xlabel='Year',
       ylabel='alpha',
       title="Time-series of optimal alpha hyperparameters from␣
 ↪cross-validation")
ax.set_ylim(bottom=0, top=0.04)
```

[ ]: (0.0, 0.04)



[ ]:
```python
def ols_r2(x, formula):
    return smf.ols(formula, data=x).fit().rsquared


# Plot the R2 coefficients across time
resr2 = (data.groupby('year').apply(ols_r2, 'lnBM ~ lnBM_hat_EN'))

sns.set_style('darkgrid')
plt.figure()
ax = sns.lineplot(data=resr2, dashes=False, linewidth=3)
ax.set(xlabel='Year',
       ylabel='R2 coefficient',
       title="Time-series of R2 coefficients from panel regressions")
ax.set_ylim(bottom=0, top=1)
```

[ ]: (0.0, 1.0)



Per definition, in-sample the model with shrinkage explains less variation in valuations. However, it still explains more than 40%.

2.5 Excess returns based on mispricing

[ ]:
```
# Define the mispricing measure z_EN
data['z_EN'] = data.lnBM - data.lnBM_hat_EN

# Run Fama MacBeth regression
res = (data.groupby('year').apply(ols_coef, 'ExRet ~ z_EN'))

# Print the result
print('Mean Return: ', str(res['z_EN'].mean())+'\n',
      'Std Dev:      ', str(res['z_EN'].std())+'\n',
      'Sharpe Ratio ', str(res['z_EN'].mean() /
                           res['z_EN'].std())+'\n',
      't-stat:      ', str(len(years)**.5*(res['z_EN'].mean()) /
                           res['z_EN'].std()), sep="\n")
```

```
Mean Return:
0.03318679060072934

Std Dev:
0.0819857416867269

Sharpe Ratio
0.40478734372542885

t-stat:
2.394754220668605
```

[ ]:
```
# Run Fama-MacBeth regression controlling for lnBM, lnProf, lnInv, and lnMom
res = (data.groupby('year').apply(
    ols_coef, 'ExRet ~ z_EN + lnBM_hat_EN + lnProf + lnInv + lnMom'))

# Print the result
print('Mean Return: ', str(res['z_EN'].mean())+'\n',
      'Std Dev:      ', str(res['z_EN'].std())+'\n',
      'Sharpe Ratio ', str(res['z_EN'].mean() /
                           res['z_EN'].std())+'\n',
      't-stat:      ', str(len(years)**.5*(res['z_EN'].mean()) /
                           res['z_EN'].std()), sep="\n")
```

```
Mean Return:
0.03165453586084274

Std Dev:
0.07938444035774021

Sharpe Ratio
0.39874987740914813
```

```
t-stat:
2.3590360882537116
```

```
[ ]: # Print the result
print('Mean Return: ', str(res['lnBM_hat_EN'].mean())+'\n',
      'Std Dev:      ', str(res['lnBM_hat_EN'].std())+'\n',
      'Sharpe Ratio ', str(res['lnBM_hat_EN'].mean() /
                          res['lnBM_hat_EN'].std())+'\n',
      't-stat:      ', str(len(years)**.5*(res['lnBM_hat_EN'].mean()) /
                          res['lnBM_hat_EN'].std()), sep="\n")
```

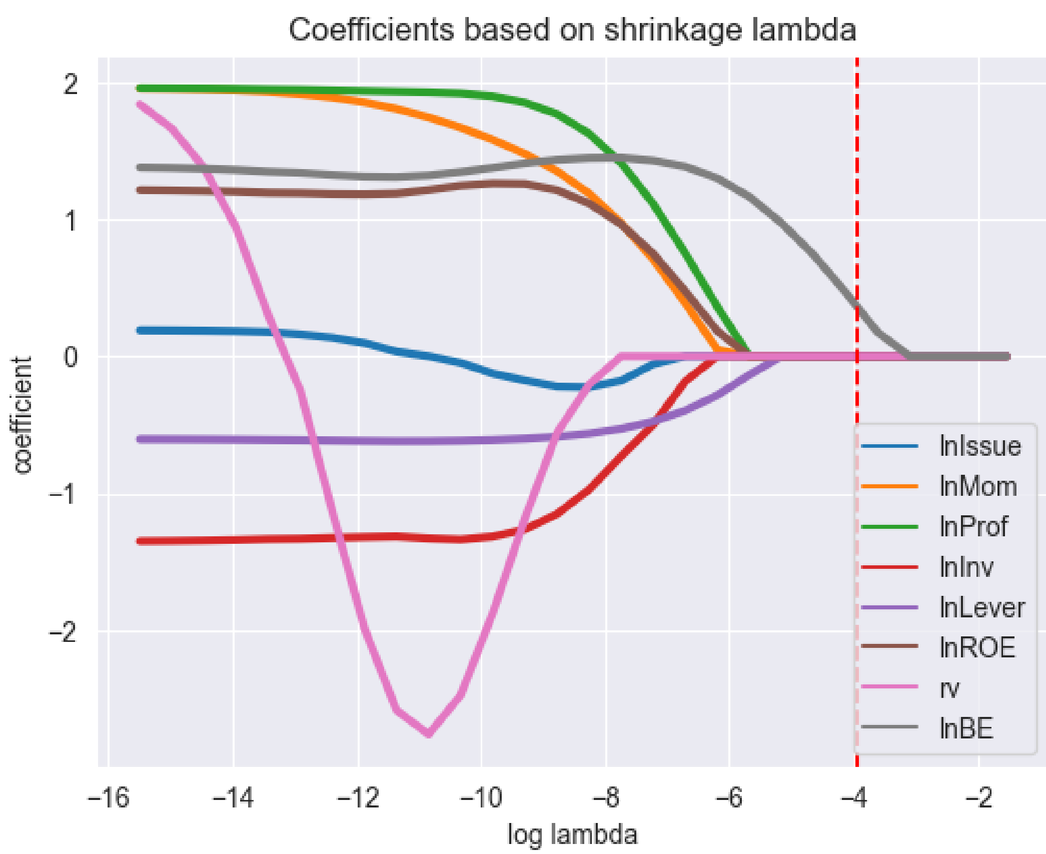
```
Mean Return:
0.011991094387608306

Std Dev:
0.13166909759263964

Sharpe Ratio
0.09106992154458733

t-stat:
0.5387769216984013
```

Unlike before with the OLS estimates, the elastic net framework appears to be better at separating mispricing and fundamental value. The mispricing component is still strongly significant with an estimate similar to the univariate Fama MacBeth regression, while for the fundamental component the coefficient is insignificant and close to zero.

```
[ ]: # Initialize array to store optimal alpha for each year
alphas = 10**np.linspace(10, -1, 50)*0.02
lambdas = 1/alphas[7:35]

data_year = data.loc[data['year'] == 2014]
y_year = data_year["lnBM"]
X_year = data_year.drop(["lnME", "FirmID", "lnAnnRet", "lnRf", "MEwt", "lnEP",␣
 ↪"year", "ff_ind", "lnBM_hat_OLS",
                             "z_OLS", "ExRet", "lnBM_hat_EN", "lnBM", "z_EN"],␣
 ↪axis=1)
coef_names = list(X_year.columns)[0:8]
summary = pd.DataFrame(columns=coef_names)

# Loop over lambdas
for i in range(len(lambdas)):
    lambdai = lambdas[i]

    # ElasticNet without cross-validation
    model = ElasticNet(alpha=lambdai, l1_ratio=0.5, max_iter=10000)
```

```python
    model.fit(X_year, y_year)
    summary.loc[i] = model.coef_[0:8]

summary['lnLambda'] = np.log(lambdas)
summary = summary.set_index('lnLambda')

sns.set_style('darkgrid')
plt.figure()
ax = sns.lineplot(data=summary, dashes=False, linewidth=3)
ax.set(xlabel='log lambda',
       ylabel='coefficient',
       title="Coefficients based on shrinkage lambda")
plt.axvline(x=np.log(optimal_alphas[len(years)-1]), color='r', linestyle='--')
```

[ ]: <matplotlib.lines.Line2D at 0x23992bf9c10>



We can see from the figure that almost all linear characteristics are shrunk to zero. The only exception is log book equity. Below, we see that instead, the model mostly chooses non-linear variables: four quadratic terms (book equity, profitability, leverage and ROE), and all interaction terms with book equity other than realized volatility.

[ ]:

```
# For comparison, the optimal parameters:
model = ElasticNet(alpha=optimal_alphas[len(optimal_alphas)-1], l1_ratio=0.5,␣
 ↪max_iter=10000)
model.fit(X_year, y_year)
summary = pd.DataFrame()
summary['variable'] = list(X_year.columns)
summary['coefficient'] = model.coef_

print(summary.loc[summary['coefficient'] != 0.0])
```

```
       variable  coefficient
7          lnBE     0.361705
8         lnBE2    -0.006750
10  lnIssueinter     0.001211
11       lnProf2    -0.914941
12   lnProfinter    -0.038586
14    lnInvinter    -0.035197
15      lnLever2    -0.029956
16  lnLeverinter     0.002173
18    lnMominter    -0.025145
19        lnROE2    -0.289742
20    lnROEinter    -0.028754
```