Analyze Recommendations

MGMT 638: Data-Driven Investments: Equity

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Outline

- Read current data
- Interact features with market volatility
- Load saved model
- Make predictions

1. Preliminaries

Read data

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("whitegrid")
from joblib import load
from urllib.request import urlopen
```

Read the model

In [2]:

```
url = "https://www.dropbox.com/scl/fi/kssvcsgze16p36dwjyiaw/forest_ver2.joblil
file = urlopen(url)
forest = load(file)
```

Define features

In [3]:

```python
features = [
    "marketcap",
    "pb",
    "mom",
    "volume",
    "volatility",
    "roe",
    "accruals",
    "agr"
]
features.sort()
features_final = features + [x + "_vol" for x in features]
```

Read predictions and characteristics

In [4]:

```
df = pd.read_excel("https://www.dropbox.com/scl/fi/g8ymjrhppr9xhcoaxjsgg/pred
mktvol = df.loc[0, "mktvol"]
```

Calculate medians of characteristics

In [5]:
```
medians = df[features].median()
medians = pd.DataFrame(medians).T
medians
```

Out[5]:

	accruals	agr	marketcap	mom	pb	roe	volatility	volume
0	-0.085859	0.005876	782.7	-0.097035	1.4	0.062268	0.054299	220361.6

Function for varying one characteristic at a time

In [34]:

```
def predict1(char):
    data = medians.copy()
    grid = np.linspace(
        df[char].quantile(0.005),
        df[char].quantile(0.995),
        100
    )
    predictions = []
    for x in grid:
        data[char] = x
        for f in features:
            data[f+"_vol"] = data[f]*mktvol
        prediction = forest.predict(X=data)
        predictions.append(prediction)
    return grid, predictions
```

Function for varying two characteristics at a time

In [35]:

```python
def predict2(char1, char2):
    data = medians.copy()
    grid1 = np.linspace(
        df[char1].quantile(0.005),
        df[char1].quantile(0.995),
        20
    )
    grid2 = np.linspace(
        df[char2].quantile(0.01),
        df[char2].quantile(0.99),
        20
    )
    grid1, grid2 = np.meshgrid(grid1, grid2)
    predictions = np.empty(grid1.shape)
    for i in range(20):
        for j in range(20):
            data[char1] = grid1[i, j]
            data[char2] = grid2[i, j]
            for f in features:
                data[f+"_vol"] = data[f]*mktvol
            predictions[i, j] = forest.predict(data)
    return grid1, grid2, predictions
```

Function for varying one characteristic and market volatility

In [36]:

```python
def predict3(char):
    data = medians.copy()
    grid1 = np.linspace(
        df[char].quantile(0.005),
        df[char].quantile(0.995),
        20
    )
    grid2 = np.linspace(
        0.5*mktvol,
        1.5*mktvol,
        20
    )
    grid1, grid2 = np.meshgrid(grid1, grid2)
    predictions = np.empty(grid1.shape)
    for i in range(20):
        for j in range(20):
            data[char] = grid1[i, j]
            for f in features:
                data[f+"_vol"] = data[f]*grid2[i, j]
            predictions[i, j] = forest.predict(data)
    return grid1, grid2, predictions
```

2. Interpret model

2a. Feature importances

In [37]:
```python
importances = pd.Series(forest.feature_importances_, index=features_final)
importances.sort_values(ascending=False).round(3)
```

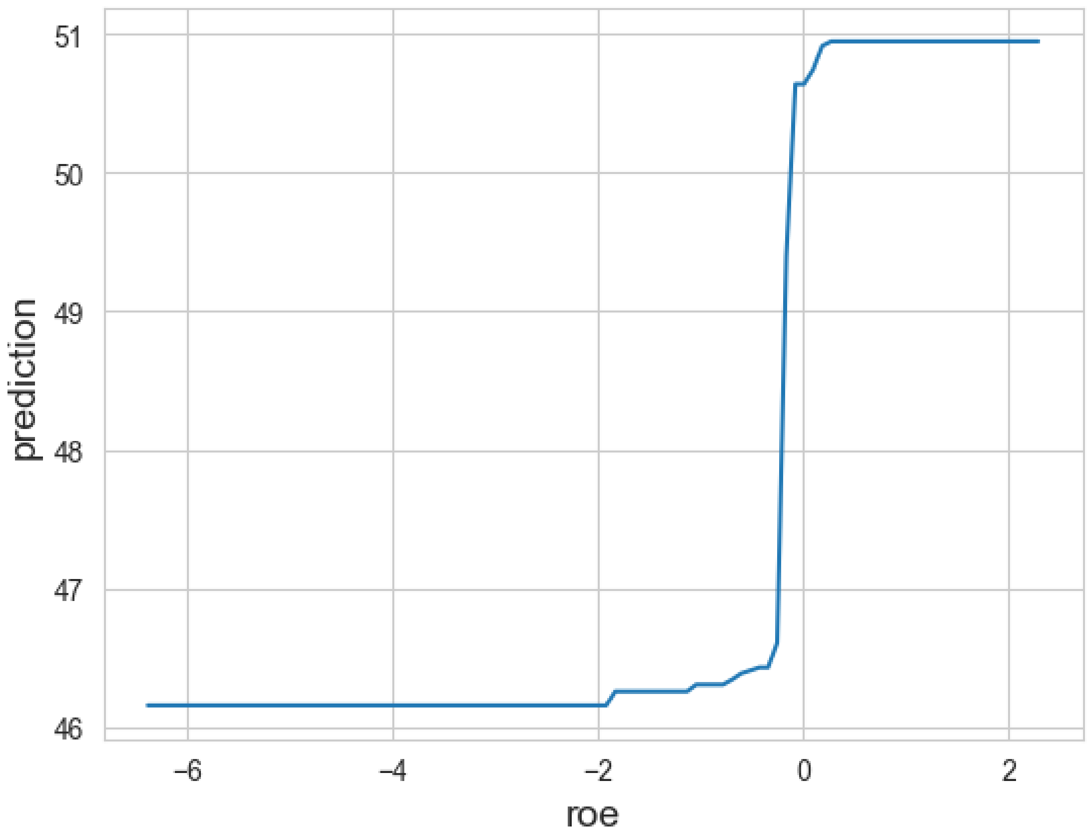
Out[37]:
```
roe               0.472
volatility        0.107
accruals_vol      0.069
volatility_vol    0.058
marketcap_vol     0.048
accruals          0.040
marketcap         0.031
volume            0.027
mom_vol           0.027
roe_vol           0.026
mom               0.025
agr               0.017
agr_vol           0.017
volume_vol        0.017
pb_vol            0.012
pb                0.009
dtype: float64
```

2b. Vary one characteristic at a time and plot

In [38]:

```
char = "roe"

grid, predictions = predict1(char)
plt.plot(grid, predictions)
plt.xlabel(char,  fontdict={"size": 14})
plt.ylabel("prediction",  fontdict={"size": 14})
plt.show()
```

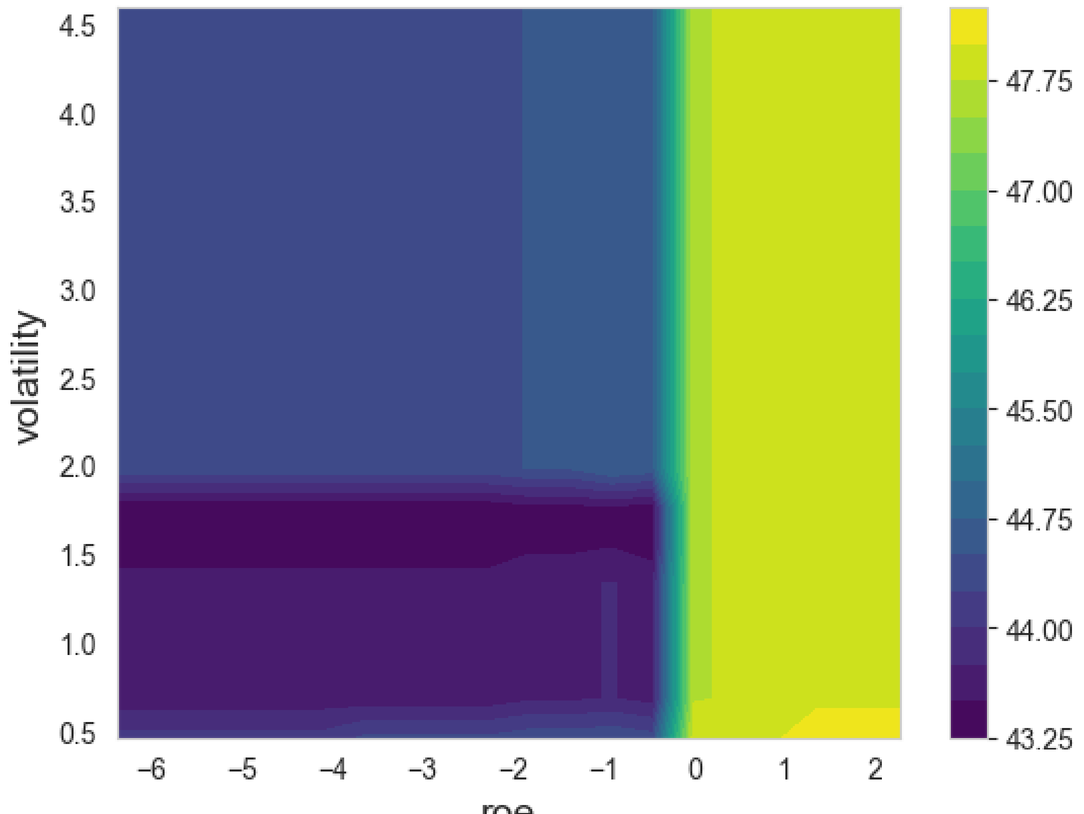


2c. Vary two characteristics at a time and plot

In [39]:

```
char1 = "roe"
char2 = "volatility"

grid1, grid2, predictions = predict2(char1, char2)
contour = plt.contourf(grid1, grid2, predictions, 20, cmap="viridis")
cbar = plt.colorbar(contour)
plt.xlabel(char1, fontdict={"size": 14})
plt.ylabel(char2, fontdict={"size": 14})
plt.show()
```

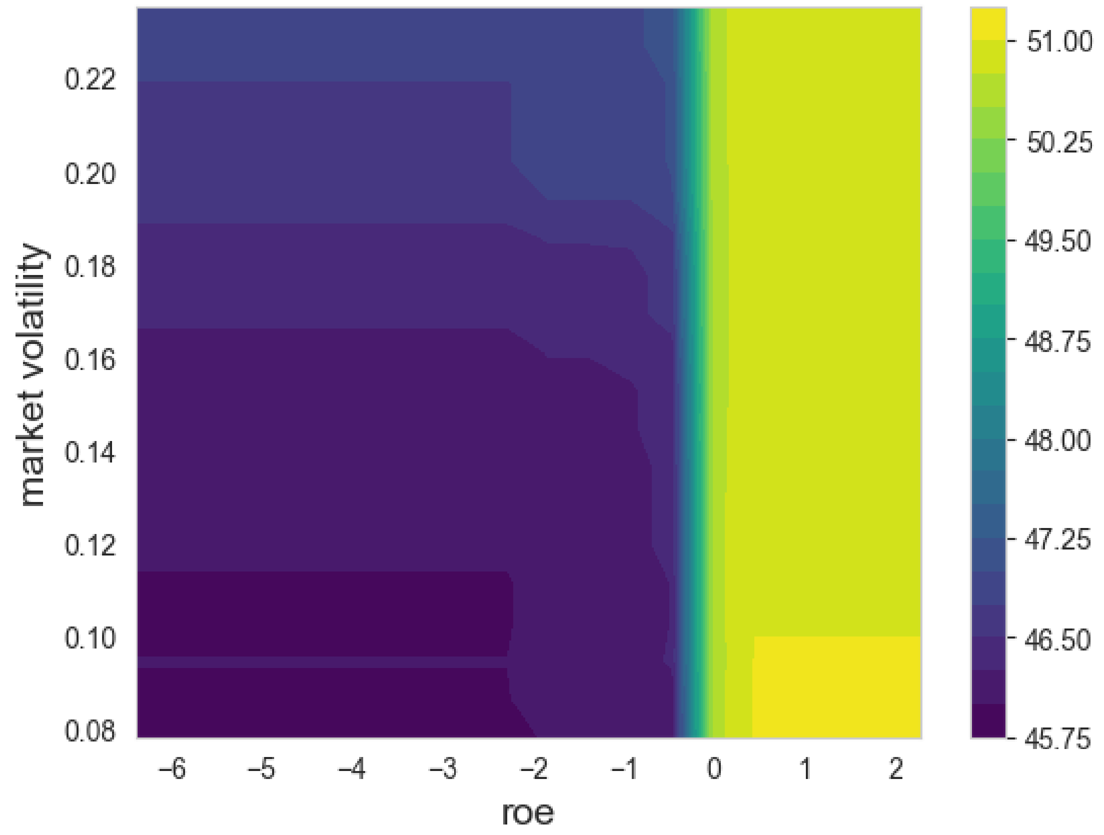


2d. Vary one characteristic and market volatility

In [40]:

```
char = "roe"

grid1, grid2, predictions = predict3(char)
contour = plt.contourf(grid1, grid2, predictions, 20, cmap="viridis")
cbar = plt.colorbar(contour)
plt.xlabel(char, fontdict={"size": 14})
plt.ylabel("market volatility", fontdict={"size": 14})
plt.show()
```



2e. Linear regression

In [41]:

```
import statsmodels.formula.api as smf

for f in features:
    df[f] = df[f] / df[f].std()

string = "predict ~ " + " + ".join(features)
model = smf.ols(string, data=df)
result = model.fit()
result.summary()
```

Out[41]:

OLS Regression Results

Dep. Variable:	predict	**R-squared:**	0.518
Model:	OLS	**Adj. R-squared:**	0.516
Method:	Least Squares	**F-statistic:**	234.5
Date:	Tue, 14 Nov 2023	**Prob (F-statistic):**	4.25e-270
Time:	15:25:57	**Log-Likelihood:**	-2687.7
No. Observations:	1753	**AIC:**	5393.
Df Residuals:	1744	**BIC:**	5443.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	50.8577	0.064	797.304	0.000	50.733	50.983