Backtesting Sector Strategy

MGMT 638: Data-Driven Investments: Equity

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Open in Colab

Read data

- Penny stocks have been eliminated
- Data includes both large caps and small caps. You can filter to small caps if you want.
- Filter to your sector.

In [1]:

```
import pandas as pd

url = "https://www.dropbox.com/s/lm4v48d51g64l0f/data-2023-11-29.csv?dl=1"
df = pd.read_csv(url)
```

In [2]:

```python
# uncomment and execute the following to filter to small caps

"""
df["rnk"] = df.groupby("date", group_keys=False).marketcap.rank(
    ascending=False,
    method="first"
)
df = df[(df.rnk>1000) & (df.rnk<=3000)]
df = df.drop(columns=["rnk"])
"""
```

Out[2]:

```
'    \ndf["rnk"] = df.groupby("date", group_keys=False).marketcap.ran
k(\n    ascending=False, \n    method="first"\n)\ndf = df[(df.rnk>100
0) & (df.rnk<=3000)]\ndf = df.drop(columns=["rnk"])\n'
```

Select a sector

In [3]:

```
sector = "Healthcare"
df = df[df.sector==sector]
```

Define model and target

- Current code uses max_depth=4 and n_estimators=200
- Two possible targets: return in excess of the median or rank of the return.
- Comment one of them out.

In [4]:

```
from sklearn.ensemble import RandomForestRegressor
forest = RandomForestRegressor(max_depth=4, n_estimators=200)


df["target"] = df.groupby("date", group_keys=False).ret.apply(
    lambda x: 100 * (x-x.median())
)

"""
# could use this instead

df["target"] = df.groupby("date", group_keys=False).ret.apply(
    lambda x: 100 * x.rank(pct=True)
)
"""
```

Out[4]:

```
' \n# could use this instead\n\ndf["target"] = df.groupby("date", gro
up_keys=False).ret.apply(\n    lambda x: 100 * x.rank(pct=True)\n)\n'
```

Define predictors (features)

- Leaving out interactions with market volatility, because they didn't seem to make much difference.

In [5]:

```python
features = [
    "marketcap",
    "pb",
    "mom",
    "volume",
    "volatility",
    "roe",
    "accruals",
    "agr"
]
features.sort()
```

Define training dates and training windows

- Start training once we have three years of data.
- Specify num_years_for_training ≥ 3 as the number of years of past data to train on in each iteration of the backtesting loop.

In [6]:

```
num_years_for_training = 5
```

In [7]:

```
dates = list(df.date.unique())
dates.sort()
train_dates = dates[156::52]  # once per year starting after three years

past_dates = {}               # dates on which to train for each training dat
future_dates = {}             # dates for which to predict for each training 
for date in train_dates:
    start_index = dates.index(date) - 52*num_years_for_training
    start_index = start_index if start_index >= 0 else 0
    past_dates[date] = dates[start_index:dates.index(date)]
    if date < train_dates[-1]:
        future_dates[date] = dates[dates.index(date):(dates.index(date)+52)]
    else:
        future_dates[date] = dates[dates.index(date):]
```

Run the loop

In [8]:

```
new_data = None
for date in train_dates:
    past = past_dates[date]
    past = df[df.date.isin(past)]
    future = future_dates[date]
    future = df[df.date.isin(future)]
    forest.fit(X=past[features], y=past.target)
    predictions = forest.predict(X=future[features])
    predictions = pd.DataFrame(predictions)
    predictions.columns = ["predict"]
    for col in ["ticker", "date"]:
        predictions[col] = future[col].to_list()
    new_data = pd.concat((new_data, predictions))

df = df.merge(new_data, on=["ticker", "date"], how="inner")
```

Calculate portfolio returns

- Specify how many stocks you want to hold in each (long or short) portfolio

In [10]:

```
numstocks = 50
```

In [11]:

```
df["rnk_long"] = df.groupby("date", group_keys=False).predict.rank(
    ascending=False,
    method="first"
)
df["rnk_short"] = df.groupby("date", group_keys=False).predict.rank(
    ascending=True,
    method="first"
)


longs = df[df.rnk_long<=numstocks]
shorts = df[df.rnk_short<=numstocks]
```

In [12]:

```
long_ret = longs.groupby("date").ret.mean()
short_ret = shorts.groupby("date").ret.mean()
print(f"mean annualized long return is {52*long_ret.mean():.2%}")
print(f"mean annualized short return is {52*short_ret.mean():.2%}")
```

```
mean annualized long return is 24.74%
mean annualized short return is -25.62%
```

Evaluate long returns

Get weekly factors and risk-free rate

- There is some weekly data on French's website, but not everything we want is available weekly.
- So, we will get daily data and compound to weekly.

In [13]:

```
from pandas_datareader import DataReader as pdr

famafrench = pdr("F-F_Research_Data_5_Factors_2x3_daily", "famafrench", start
famafrench.index.name = "date"
famafrench = famafrench.reset_index()
famafrench["year"] = famafrench.date.apply(lambda x: x.isocalendar()[0])
famafrench["week"] = famafrench.date.apply(lambda x: x.isocalendar()[1])

ff = None
for col in ["Mkt-RF", "SMB", "HML", "CMA", "RMW", "RF"]:
    ser = famafrench.groupby(["year", "week"], group_keys=True)[col].apply(
        lambda x: (1+x).prod() - 1
    )
    ser.name = col
    ff = pd.concat((ff, ser), axis=1)
ff["date"] = famafrench.groupby(["year", "week"], group_keys=True).date.last(
ff = ff.reset_index(drop=True)
ff = ff.set_index("date")
```

In [20]:

```
mom = pdr("F-F_Momentum_Factor_daily", "famafrench", start=2010)[0]/100
mom.index.name = "date"
mom.columns = ["UMD"]
mom = mom.reset_index()
mom["year"] = mom.date.apply(lambda x: x.isocalendar()[0])
mom["week"] = mom.date.apply(lambda x: x.isocalendar()[1])

umd = mom.groupby(["year", "week"], group_keys=True).UMD.apply(
    lambda x: (1+x).prod() - 1
)
umd = pd.DataFrame(umd)
umd["date"] = mom.groupby(["year", "week"], group_keys=True).date.last()
umd = umd.reset_index(drop=True)
umd = umd.set_index("date")
```

Combine factors and long returns

In [28]:

```
long_ret.name = "ret"
long_ret.index = pd.to_datetime(long_ret.index)
data = pd.concat((ff, umd, long_ret), axis=1).dropna()
data.head(3)
```

Out[28]:

	Mkt-RF	SMB	HML	CMA	RMW	RF	UMD	
date								
2014-01-10	0.006690	0.003776	-0.014450	-0.009374	-0.016990	0.0	0.016774	0.016
2014-01-17	-0.001175	0.004805	-0.006908	-0.001320	-0.007482	0.0	-0.003429	0.101
2014-01-24	-0.025944	0.004589	-0.001517	-0.005691	0.000292	0.0	-0.012687	0.053

Sharpe ratio

In [30]:

```
import numpy as np

sharpe = np.sqrt(52) * (data.ret - data.RF).mean() / data.ret.std()
print(f"annualized Sharpe ratio is {sharpe:.2%}")
```

```
annualized Sharpe ratio is 71.08%
```

Market alpha and information ratio

In [31]:

```python
import statsmodels.formula.api as smf

data["ret_rf"] = data.ret - data.RF
data["mkt_rf"] = data["Mkt-RF"]
result = smf.ols("ret_rf ~ mkt_rf", data).fit()

alpha = 52*result.params["Intercept"]
resid_stdev = np.sqrt(52 * result.mse_resid)
info_ratio = alpha / resid_stdev

print(f"annualized alpha is {alpha:.2%}")
print(f"annualized information ratio is {info_ratio:.2%}")
```

```
annualized alpha is 18.65%
annualized information ratio is 56.31%
```

Attribution analysis

In [32]:

```
result = smf.ols("ret_rf ~ mkt_rf + SMB + HML + CMA + RMW + UMD", data).fit()
result.summary()
```

Out[32]:

OLS Regression Results

Dep. Variable:	ret_rf	**R-squared:**	0.152
Model:	OLS	**Adj. R-squared:**	0.141
Method:	Least Squares	**F-statistic:**	14.93
Date:	Wed, 29 Nov 2023	**Prob (F-statistic):**	9.78e-16
Time:	12:52:13	**Log-Likelihood:**	866.84
No. Observations:	508	**AIC:**	-1720.
Df Residuals:	501	**BIC:**	-1690.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0043	0.002	2.181	0.030	0.000	0.008
mkt_rf	0.4520	0.089	5.065	0.000	0.277	0.627
SMB	0.4939	0.166	2.974	0.003	0.168	0.820
HML	-0.5072	0.152	-3.330	0.001	-0.806	-0.208
CMA	0.6061	0.275	2.201	0.028	0.065	1.147
RMW	-0.5944	0.204	-2.911	0.004	-0.995	-0.193

Analyze fitted model on most recent data

Get most recent data from backtest data

In [39]:

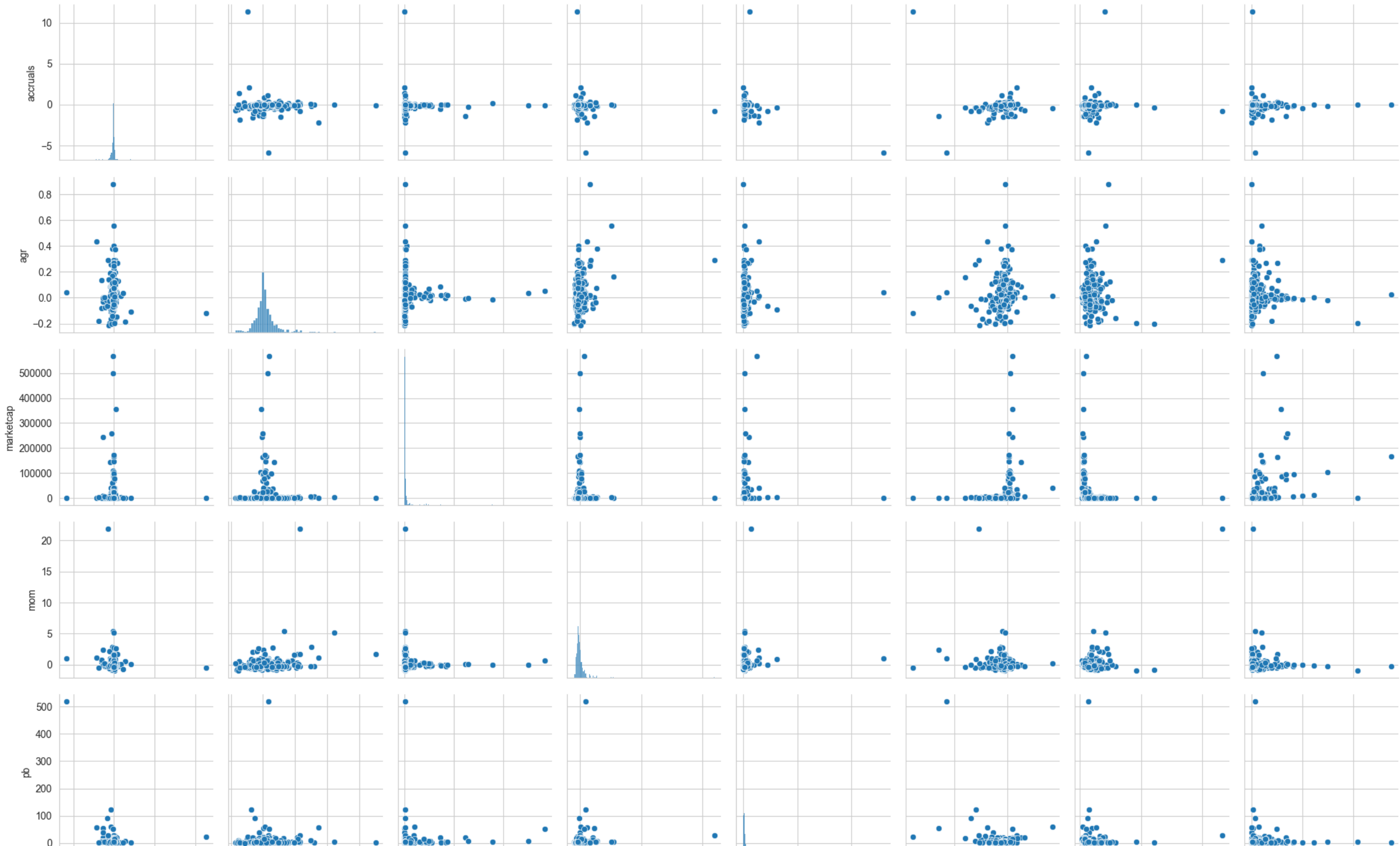
```
present = future[future.date==future.date.max()]
```

Visualize distributions of characteristics

In [41]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("whitegrid")

sns.pairplot(present[features])
```

Out[41]: <seaborn.axisgrid.PairGrid at 0x208d2a27c70>



Calculate medians to use as base values for characteristics

In [33]:

```
present = future[future.date==future.date.max()]
medians = present[features].median()
medians = pd.DataFrame(medians).T
```

Define plotting functions

In [51]:

```
def predict1(char):
    data = medians.copy()
    grid = np.linspace(
        present[char].quantile(0.01),
        present[char].quantile(0.99),
        100
    )
    predictions = []
    for x in grid:
        data[char] = x
        prediction = forest.predict(X=data).item()
        predictions.append(prediction)
    return grid, predictions
```

In [52]:

```
def predict2(char1, char2):
    data = medians.copy()
    grid1 = np.linspace(
        present[char1].quantile(0.01),
        present[char1].quantile(0.99),
        20
    )
    grid2 = np.linspace(
        present[char2].quantile(0.01),
        present[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]
            predictions[i, j] = forest.predict(data)
    return grid1, grid2, predictions
```

Feature importances

In [44]:
```python
importances = pd.Series(forest.feature_importances_, index=features)
importances.sort_values(ascending=False).round(3)
```

Out[44]:
```
pb            0.464
volume        0.134
marketcap     0.115
agr           0.082
volatility    0.068
mom           0.064
accruals      0.047
roe           0.027
dtype: float64
```

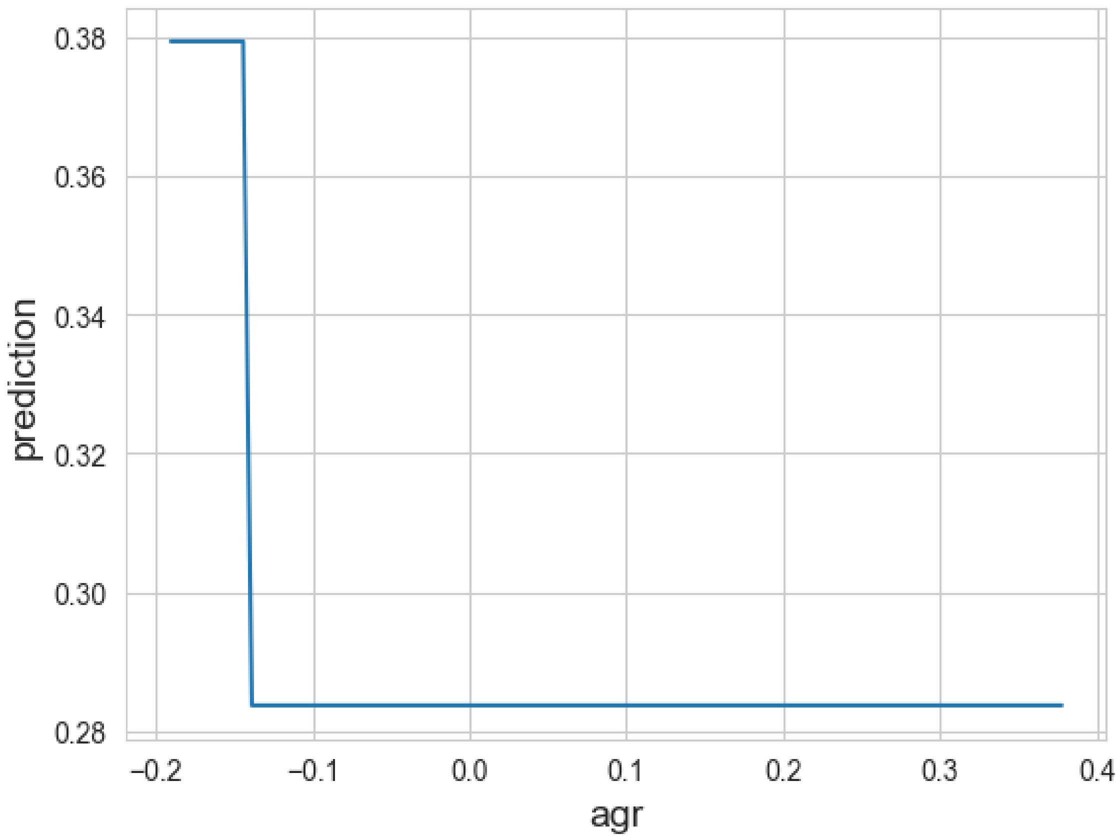
Vary one characteristic at a time and plot

- Specify which characteristic

In [53]:

```
char = "agr"

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



Vary two characteristics at a time and plot

- Specify which characteristics

In [54]:

```
char1 = "pb"
char2 = "marketcap"

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()
```