Preprocessing and Analysis

BUSI 722: Data-Driven Finance II

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Outline

1. Build dataset of features, returns, and targets as before
2. Add industry features
3. Preprocessing: standardize features relative to other stocks at the same date
4. Train, predict, and form portfolios in loop as before
5. Interpret model

- Feature importances
- Shapley values
- Features of best and worst portfolios

6. Evaluate portfolio returns: mean-variance frontiers
7. Train and save

- Build dataset of features, returns, and targets as before
- Add preprocessing of features
    - Features standardized relative to other stocks at the same date
    - Add interactions of features
- Interpret model
    - Feature importances
    - Shapley values
    - Features of best and worst portfolios
- Evaluate portfolio returns
    -

1. Create dataset as before

In [19]:

```
import numpy as np
import pandas as pd
from sqlalchemy import create_engine
from sklearn.ensemble import RandomForestRegressor
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("whitegrid")
```

In [20]:

```
server = 'fs.rice.edu'
database = 'stocks'
username = 'stocks'
password = '6LAZH1'
driver = 'SQL+Server'
string = f"mssql+pyodbc://{username}:{password}@{server}/{database}"
try:
    conn = create_engine(string + "?driver='SQL+Server'").connect()
except:
    try:
        conn = create_engine(string + "?driver='ODBC+Driver+18+for+SQL+Server
    except:
        import pymssql
        string = f"mssql+pymssql://{username}:{password}@{server}/{database}"
        conn = create_engine(string).connect()
```

In [21]:

```
sep_weekly = pd.read_sql(
    """
    select date, ticker, closeadj, closeunadj, volume, lastupdated from sep_we
    where date >= '2010-01-01'
    order by ticker, date, lastupdated
    """,
    conn,
)
sep_weekly = sep_weekly.groupby(["ticker", "date"]).last()
sep_weekly = sep_weekly.drop(columns=["lastupdated"])

ret = sep_weekly.groupby("ticker", group_keys=False).closeadj.pct_change()
ret.name = "ret"

price = sep_weekly.closeunadj
price.name = "price"

volume = sep_weekly.volume
volume.name = "volume"
```

In [22]:

```
ret_annual = sep_weekly.groupby("ticker", group_keys=False).closeadj.pct_chan
ret_monthly = sep_weekly.groupby("ticker", group_keys=False).closeadj.pct_cha
mom = (1 + ret_annual) / (1 + ret_monthly) - 1
mom.name = "mom"
```

In [23]:

```python
weekly = pd.read_sql(
    """
    select date, ticker, pb, marketcap, lastupdated from weekly
    where date>='2010-01-01'
    order by ticker, date, lastupdated
    """,
    conn,
)
weekly = weekly.groupby(["ticker", "date"]).last()
weekly = weekly.drop(columns=["lastupdated"])

pb = weekly.pb
pb.name = "pb"
marketcap = weekly.marketcap
marketcap.name = "marketcap"
```

In [24]:

```python
sf1 = pd.read_sql(
    """
    select datekey as date, ticker, assets, netinc, equity, lastupdated from
    where datekey>='2010-01-01' and dimension='ARY' and assets>0 and equity>0
    order by ticker, datekey, lastupdated
    """,
    conn,
)
sf1 = sf1.groupby(["ticker", "date"]).last()
sf1 = sf1.drop(columns=["lastupdated"])

# change dates to Fridays
from datetime import timedelta
sf1 = sf1.reset_index()
sf1.date =sf1.date.map(
    lambda x: x + timedelta(4 - x.weekday())
)
sf1 = sf1.set_index(["ticker", "date"])
sf1 = sf1[~sf1.index.duplicated()]

assets = sf1.assets
assets.name = "assets"
netinc = sf1.netinc
netinc.name = "netinc"
equity = sf1.equity
equity.name = "equity"

equity = equity.groupby("ticker", group_keys=False).shift()
roe = netinc / equity
```

In [25]:

```
df = pd.concat(
    (
        ret,
        mom,
        volume,
        price,
        pb,
        marketcap,
        roe,
        assetgr
        ),
        axis=1
    )
df["ret"] = df.groupby("ticker", group_keys=False).ret.shift(-1)
df["roe"] = df.groupby("ticker", group_keys=False).roe.ffill()
df["assetgr"] = df.groupby("ticker", group_keys=False).assetgr.ffill()
df = df[df.price >= 5]
df = df.dropna()

df = df.reset_index()
df.date = df.date.astype(str)
df = df[df.date >= "2012-01-01"]

df["target1"] = df.groupby("date", group_keys=False).ret.apply(
    lambda x: x - x.median()
)
df["target2"] = df.groupby("date", group_keys=False).ret.apply(
    lambda x: 100*x.rank(pct=True)
)
```

2. Add industry features

- Deviations from industry medians: is a stock's ROE high relative to its industry, etc.
- Database includes "famaindustry" which is a classification into 48 industries (including other=almost nothing)

In [27]:

```
industries = pd.read_sql(
    """
    select ticker, famaindustry as industry from tickers
    """,
    conn,
)
df = df.merge(industries, on="ticker", how="left")
df = df.dropna()
```

In [28]:

```python
for x in features:
    df[f"{x}_industry"] = df.groupby(
        ["date", "industry"],
        group_keys=False
    )[x].apply(
        lambda x: x - x.median()
    )

features += [f"{x}_industry" for x in features]
```

3. Preprocessing: standardize at each date

We are predicting relative performance. It makes sense to use relative features: how does a stock compare to other stocks at the same date? There are multiple options:

- standard scaler (subtract mean and divide by std dev)
- quantile transformer (map to normal or uniform distribution)
- rank with pct=True (quantile transformer to uniform distribution)

Here we will rank.

```
In [29]: for f in features:
             df[f] = df.groupby("date", group_keys=False)[f].apply(
                 lambda x: x.rank(pct=True)
             )
```

4. Train, predict and form portfolios as before

- If we set train_freq to a large number, the loop will only train once. Use trained model to predict at all subsequent dates. Do this only for demonstration.
- Should validate but will use max_depth=4 and max_features=6 in the random forest.

In [30]:

```python
train_years = 4 # num years of past data to use for training
train_freq = 100  # num years between training
target = "target2"
model = RandomForestRegressor(max_depth=4, max_features=6)

years = range(2012+train_years, 2024, train_freq)
df2 = None
for i, year in enumerate(years):
    print(year)
    start_train = f"{year-train_years}-01-01"
    start_predict = f"{year}-01-01"
    if year == years[-1]:
        stop_predict = "2100-01-01"
    else:
        stop_predict = f"{years[i+1]}-01-01"
    past = df[(df.date >= start_train) & (df.date < start_predict)]
    future = df[(df.date>=start_predict) & (df.date<stop_predict)].copy()
    model.fit(X=past[features], y=past[target])
    future["predict"] = model.predict(X=future[features])
    df2 = pd.concat((df2, future))

df2.head()
```

```
2016
```

Out[30]:

	ticker	date	ret	mom	volume	price	pb	marketcap	
208	A	2016-	-0.023424	0.527660	0.861866	41.78	0.712111	0.895254	0.

In [31]:

```
num_stocks = 50

grouped = df2.groupby("date", group_keys=False).predict
starting_from_best = grouped.rank(ascending=False, method="first")
best = df2[starting_from_best <= num_stocks]
best_rets = best.groupby("date", group_keys=True).ret.mean()
best_rets.index = pd.to_datetime(best_rets.index)

starting_from_worst = grouped.rank(ascending=True, method="first")
worst = df2[starting_from_worst <= num_stocks]
worst_rets = worst.groupby("date", group_keys=True).ret.mean()
worst_rets.index = pd.to_datetime(worst_rets.index)

all_rets = df2.groupby("date", group_keys=True).ret.mean()
all_rets.index = pd.to_datetime(all_rets.index)
```

4. Interpret

Find feature importances for last trained model

In [32]:

```python
importances = pd.Series(
    model.feature_importances_,
    index=features
)
importances = importances.sort_values(ascending=False)
importances.round(2)
```

Out[32]:

```
mom                   0.26
volume_industry       0.26
volume                0.18
roe                   0.06
mom_industry          0.06
roe_industry          0.06
pb                    0.03
marketcap             0.03
pb_industry           0.02
marketcap_industry    0.02
assetgr_industry      0.01
assetgr               0.01
dtype: float64
```

Shapley values

- Shapley values are a way of calculating the contribution each feature makes to predictions.
- Values are calculated for each observation (each stock/date).
- Can use any part of the data, but look here at last prediction date.
- First look at the distribution of predictions, then at the contributions.

In [33]:

```
last_date = df2.date.max()
df3 = df2[df2.date==last_date]
df3.predict.describe().round(3)
```

Out[33]:

```
count    2962.000
mean       50.016
std         1.095
min        43.057
25%        49.451
50%        50.493
75%        50.846
max        51.508
Name: predict, dtype: float64
```

In [34]:

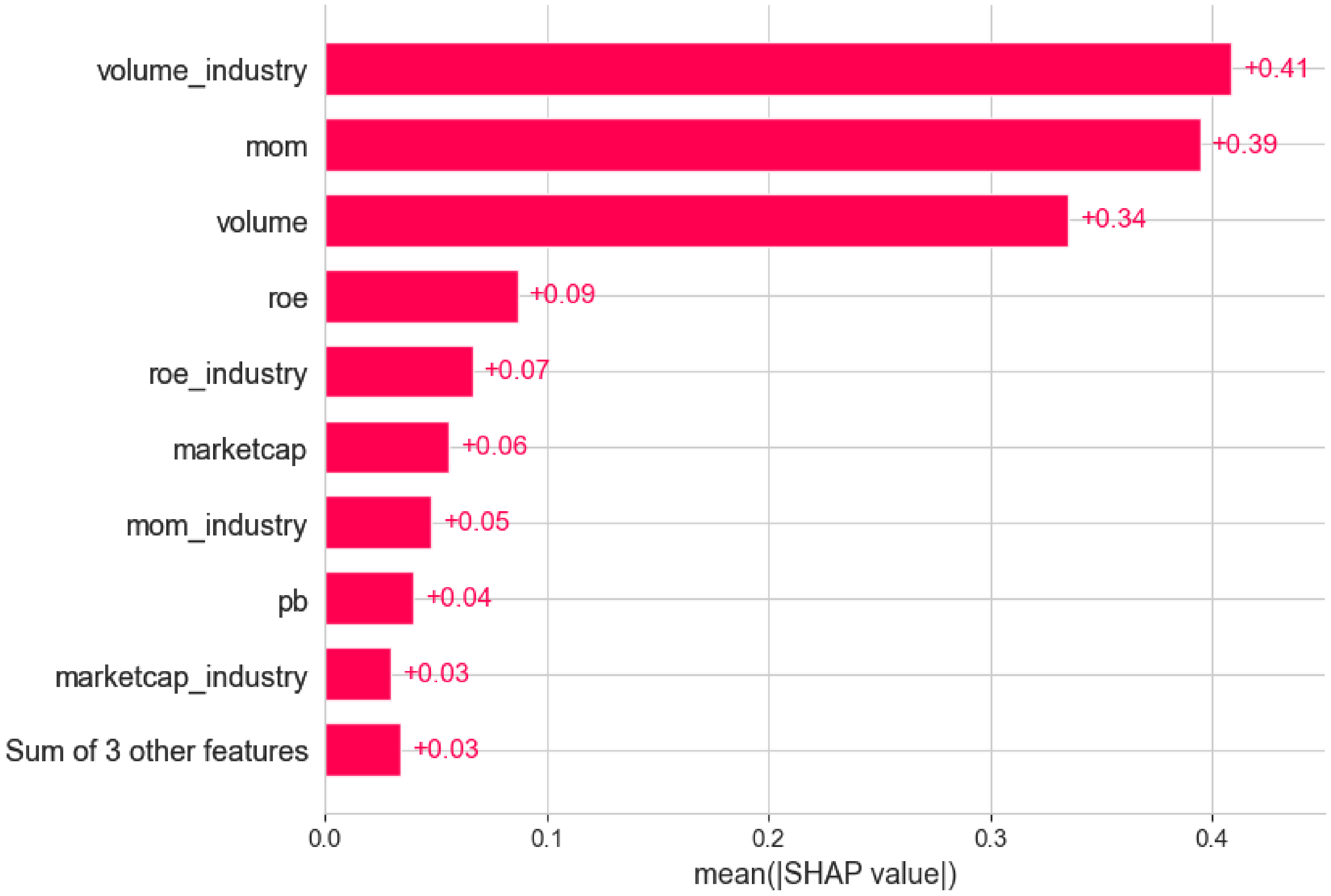
```
import shap

explainer = shap.Explainer(model)
shap_values = explainer(df3[features])
```

Mean absolute Shapley values

- Shapley values are positive or negative, depending on whether a feature is positively or negatively related to the prediction.
- Here we average the absolute Shapley values across observations to see which features are on average most important (like feature_importances).

In [35]:

```
shap.plots.bar(shap_values)
```

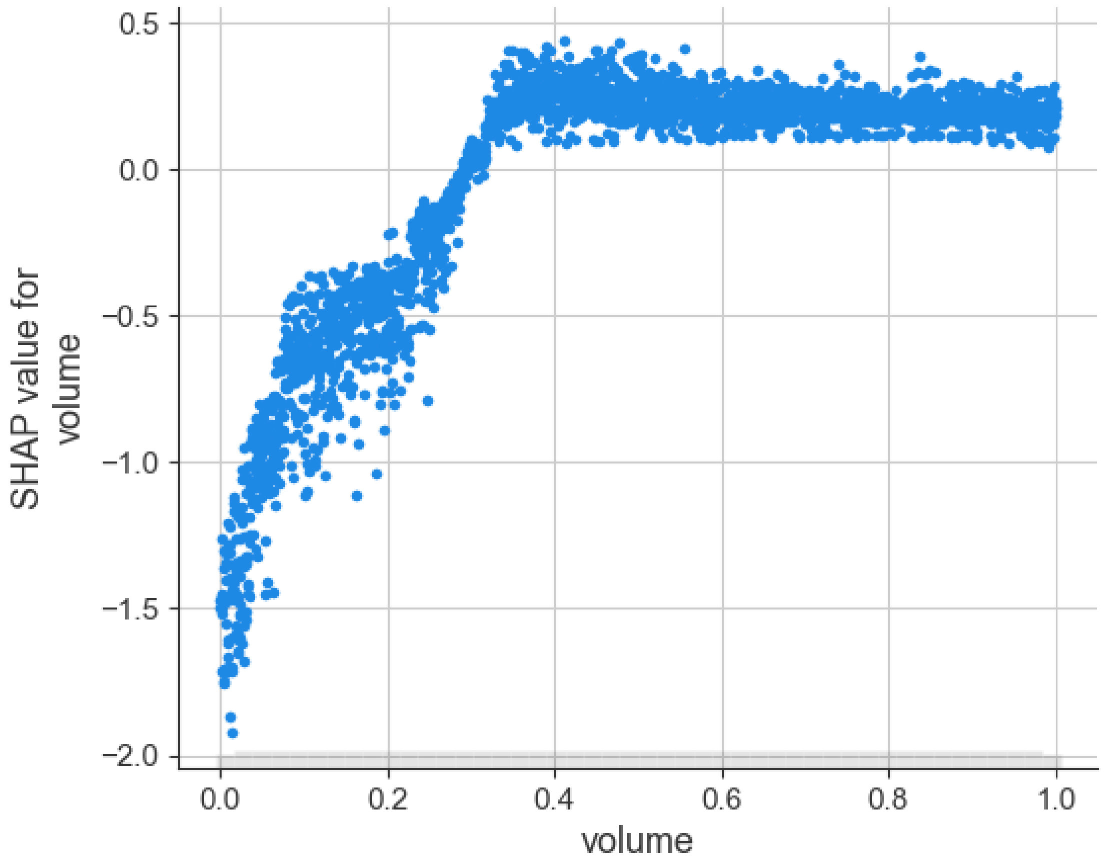


Look at Shapley values across observations

- Look at Shapley values one feature at a time
- Plot the Shapley value across observations as a function of the feature
- Shaded plot at bottom is histogram of the feature

In [36]:

```
feature = "volume"
shap.plots.scatter(shap_values[:, feature])
```



Extract best, worst, and all stocks in last portfolios

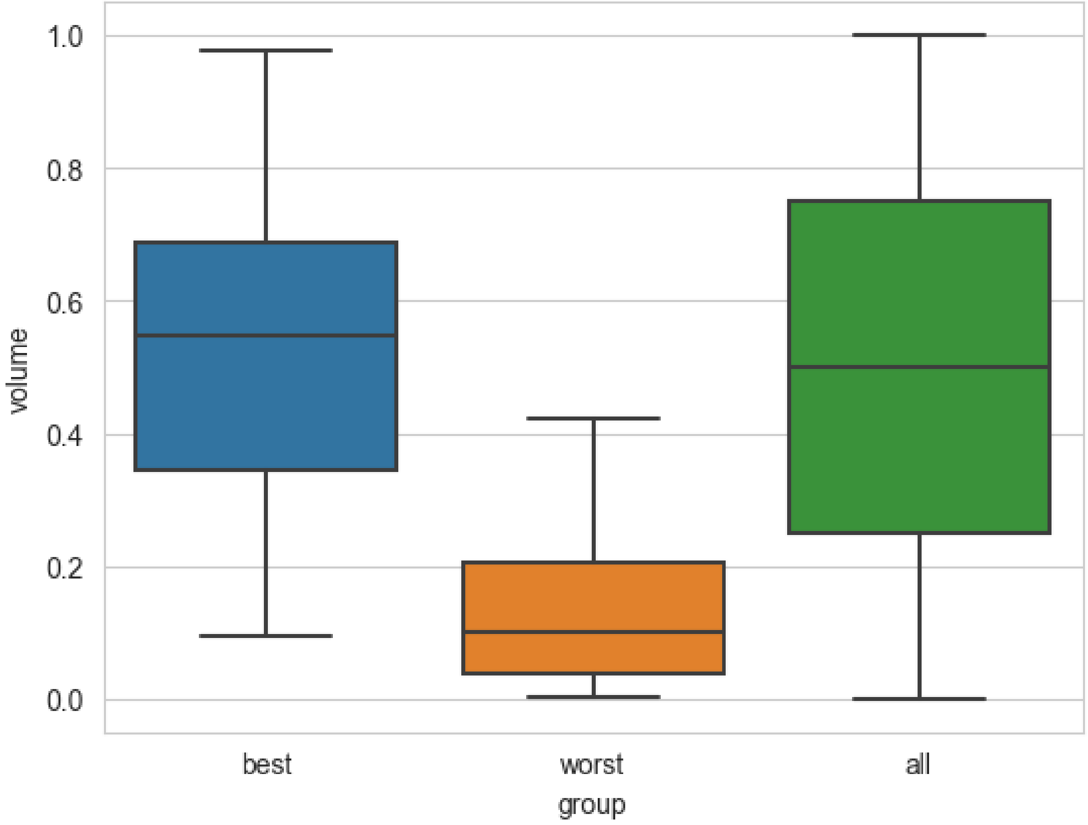
In [37]:

```
best_last = best[best.date==last_date].copy()
worst_last = worst[worst.date==last_date].copy()
all_last = df2[df2.date==last_date].copy()

best_last["group"] = "best"
worst_last["group"] = "worst"
all_last["group"] = "all"

last = pd.concat((best_last, worst_last, all_last))
```

Compare features of best, worst, and all portfolios

In [38]:

```
feature = "volume"
sns.boxplot(last, x="group", y=feature)
plt.show()
```



6. Evaluate

Add SPY returns

In [53]:

```python
import yfinance as yf

spy = yf.download("SPY", start=2017)["Adj Close"]
spy = pd.DataFrame(spy)
spy["date"] = spy.index.map(
    lambda x: x + timedelta(4 - x.weekday())
)
spy = spy.groupby(["date"])["Adj Close"].last()
spy = spy.pct_change()

rets = pd.concat((spy, best_rets, worst_rets), axis=1).dropna()
rets.columns = ["spy", "best", "worst"]
```

```
[*********************100%%**********************]  1 of 1 completed
```

Return statistics

In [54]:

```
means = 52 * rets.mean()
stdevs = np.sqrt(52) * rets.std()
rf = 0.05
sharpes = (means - rf) / stdevs
stats = pd.concat((means, stdevs, sharpes), axis=1)
stats.columns = ["mean", "std", "sharpe"]
stats.round(2)
```

Out[54]:

	mean	std	sharpe
spy	0.14	0.18	0.52
best	0.35	0.28	1.04
worst	-0.25	0.32	-0.93

In [55]:

```python
rets.corr().round(2)
```

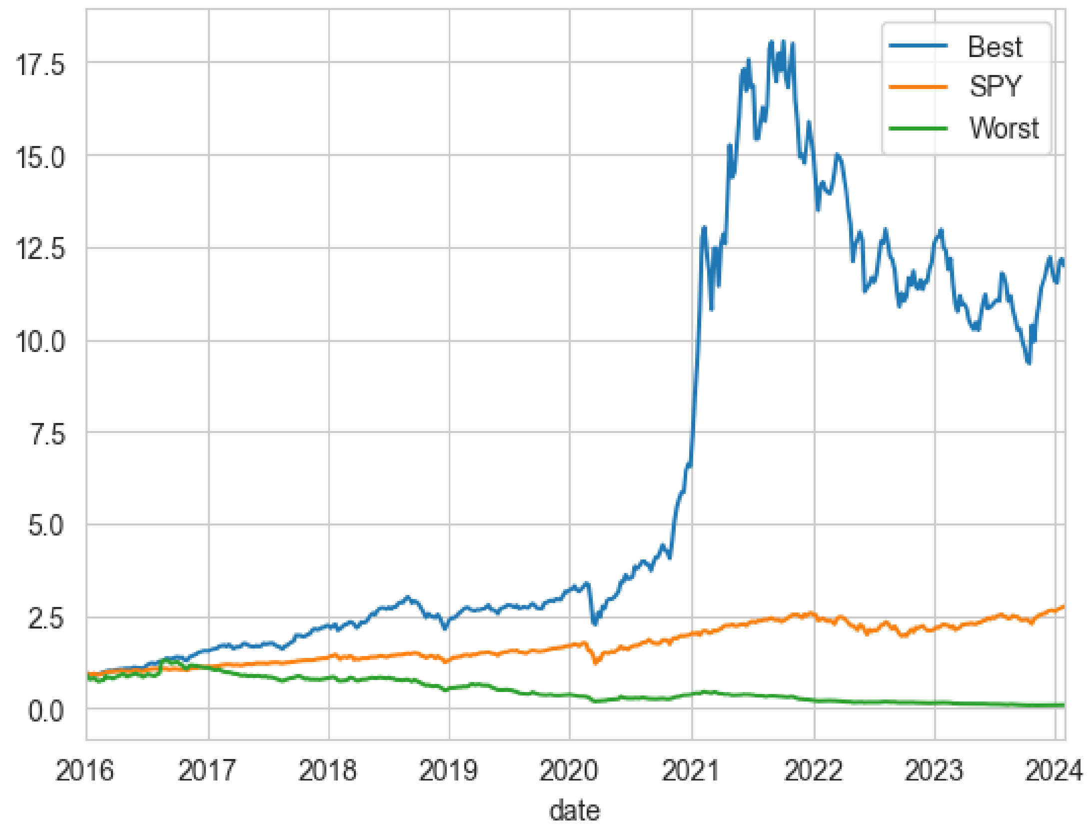
Out[55]:

	spy	best	worst
spy	1.00	0.40	0.36
best	0.40	1.00	0.59
worst	0.36	0.59	1.00

Plot performance

In [56]:

```
logy = False

(1+rets.best).cumprod().plot(label="Best", logy=logy)
(1+rets.spy).cumprod().plot(label="SPY", logy=logy)
(1+rets.worst).cumprod().plot(label="Worst", logy=logy)
plt.legend()
plt.show()
```



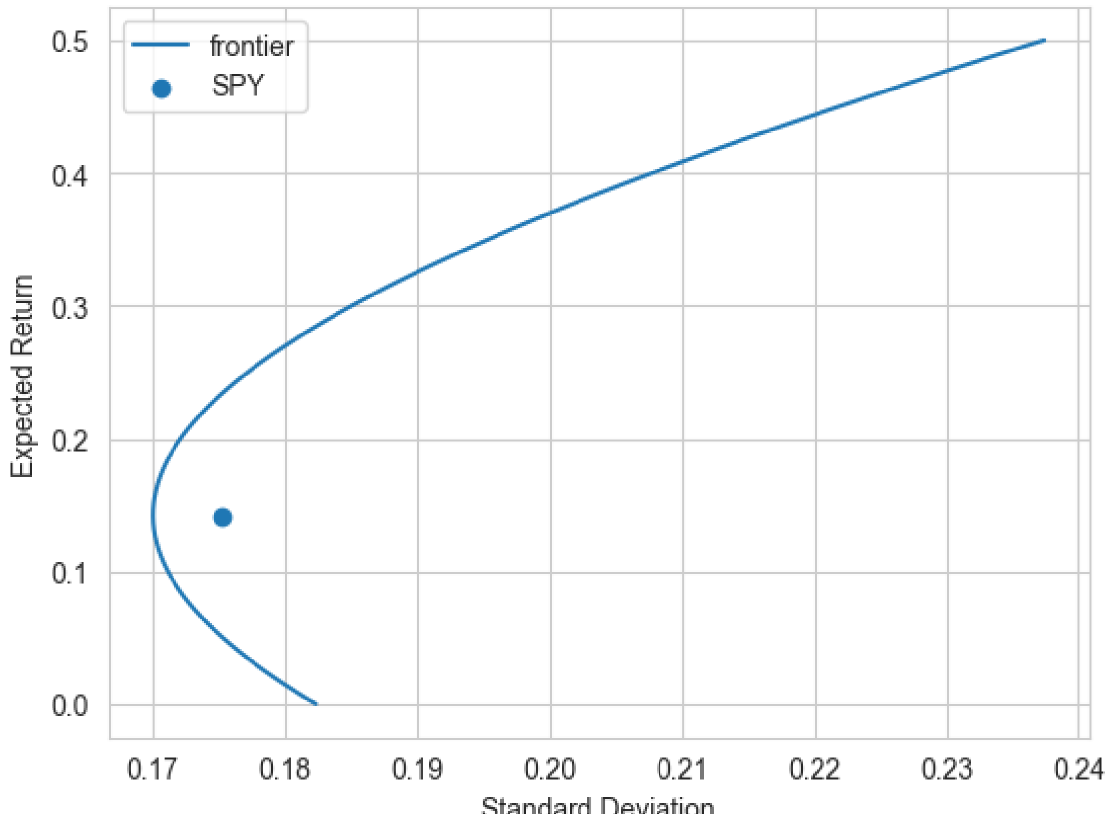
Find frontier of SPY, best, and worst

In [57]:

```
from cvxopt import matrix
from cvxopt.solvers import qp

cov = rets.cov()
means = rets.mean()

P = cov
A = np.array(
    [
        means.to_numpy(),
        [1., 1., 1.]
    ]
)
P = matrix(P.to_numpy())
q = matrix(np.zeros((3, 1)))
A = matrix(A)

mns = []
vars = []
ports = []
for targ in np.linspace(0, 0.5/52, 100):
    b = matrix(
        np.array([targ, 1]).reshape(2, 1)
    )
    sol = qp(
        P=P,
        q=q,
        A=A,
        b=b
```

In [58]:

```
mns = 52 * np.array(mns)
sds = np.sqrt(52*np.array(vars))

plt.plot(sds, mns, label="frontier")
plt.scatter(x=[np.sqrt(52)*rets.spy.std()], y=[52*rets.spy.mean()], label="SP
plt.xlabel("Standard Deviation")
plt.ylabel("Expected Return")
plt.legend()
plt.show()
```



Find best portfolio with same risk as SPY

In [59]:

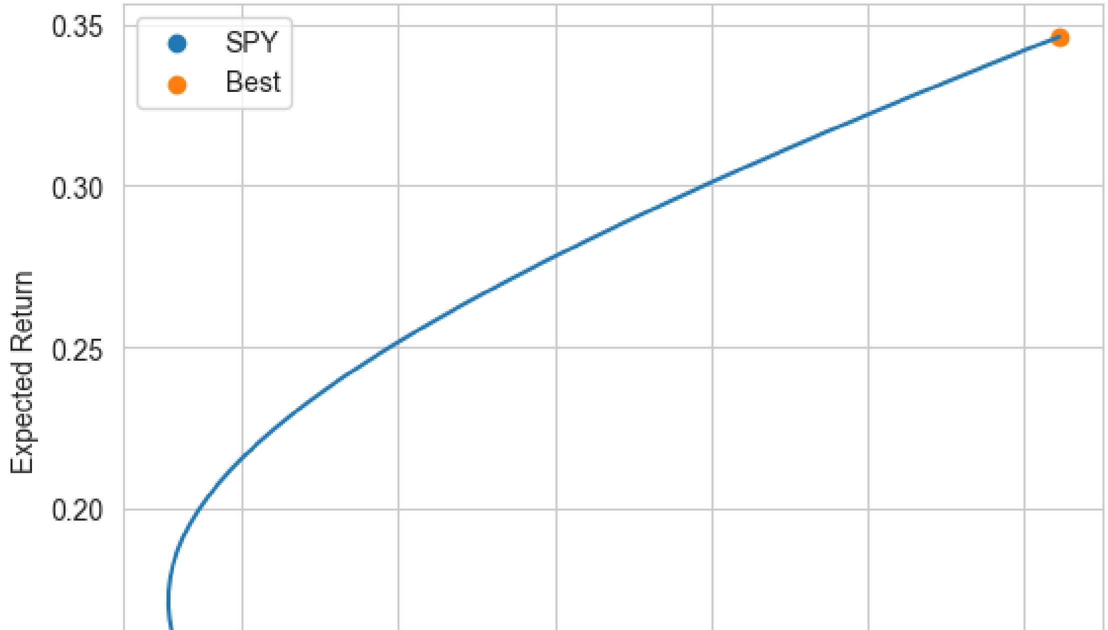
```
stdev = np.max(
    [
        s for s, m in zip(sds, mns)
        if s <= np.sqrt(52)*rets.spy.std()
        and m >= 52*rets.spy.mean()
    ]
)
indx = np.where(sds==stdev)[0].item()
mean = mns[indx]
port = ports[indx]
print(port.round(2))
print(f"portfolio expected return is {mean:.1%}")
```

```
spy       0.83
best      0.26
worst    -0.10
dtype: float64
portfolio expected return is 23.2%
```

Long-only portfolios of SPY and best

In [60]:

```
means = rets[["spy", "best"]].mean()
cov = rets[["spy", "best"]].cov()
ports = [np.array([w, 1-w]) for w in np.linspace(0, 1, 50)]
mns = [52 * means @ w for w in ports]
sds = [np.sqrt(52 * w @ cov @ w) for w in ports]

plt.plot(sds, mns, label=None)
plt.scatter(x=[np.sqrt(52)*rets.spy.std()], y=[52*rets.spy.mean()], label="SP
plt.scatter(x=[np.sqrt(52)*rets.best.std()], y=[52*rets.best.mean()], label="
plt.xlabel("Standard Deviation")
plt.ylabel("Expected Return")
plt.legend()
plt.show()
```



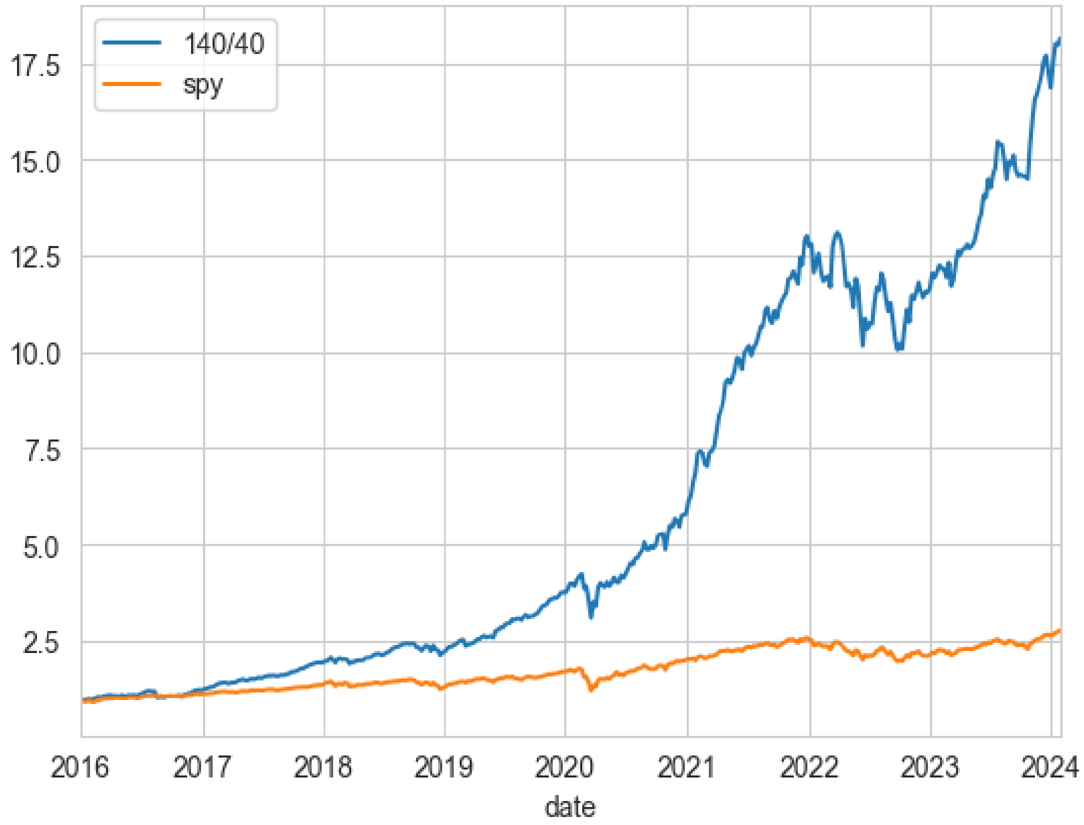
140/40 portfolio

In [61]:

```
rets["140/40"] = rets.spy + 0.4*rets.best - 0.4*rets.worst
```

In [62]:

```
(1+rets[["140/40", "spy"]]).cumprod().plot()
plt.show()
```



7. Train and save

- Train on the most recent train_years of data
- Save with joblib

In [63]:

```
from joblib import dump

dates = df.date.unique()
dates.sort()
date = dates[-52*train_years]
df3 = df[df.date>=date]
model.fit(df3[features], df3["target2"])
dump(model, "mymodel.joblib")
```

Out[63]:

```
['mymodel.joblib']
```