Introduction to Quantitative Equity Strategies

MGMT 767: Data-Driven Investments Lab

Kerry Back and Kevin Crotty, Rice University

Typess of characteristics

- Company financials
    - Financial ratios
    - Growth rates
- Past returns
    - Momentum and reversal
    - Moving averages
    - Pairs trading

- Trade data
    - Corporate insiders
    - Short sellers
    - Retail orders
- Corporate events
    - Dividends, earnings, other
- Nontraditional data
    - Social media
    - NLP of corporate announcements
    - Image data
    - Cellphone location data

Basic strategy

- Combine characteristics to form a return predictor
- Buy good stocks and maybe short sell bad stocks

Plan for the course

- Backtest strategies and choose one
- Use daily updated database to update return predictions at least weekly
- Implement paper trades at Alpaca brokerage
- Reassess and revise strategy regularly

Example for today

Momentum and value characteristics of small-cap stocks

Database

- SQL database on Rice server. Must be on campus or on Rice VPN.
- Data is downloaded from Nasdaq Data Link and updated on the server daily.
- Access the database
    - In python using pyodbc.
        - On a Mac, you will need to install Microsoft's ODBC Server
        - Everyone will need to pip install pyodbc
    - Or with Azure Data Studio

In [2]:

```
from sqlalchemy import create_engine

server = 'fs.rice.edu'
database = 'stocks'
username = 'stocks'
password = '6LAZH1'
driver1 = 'SQL+Server'
driver2 = 'ODBC+Driver+17+for+SQL+Server'
string1 = f"mssql+pyodbc://{username}:{password}@{server}/{database}?driver={
string2 = f"mssql+pyodbc://{username}:{password}@{server}/{database}?driver={
try:
    conn = create_engine(string1).connect()
except:
    conn = create_engine(string2).connect()
```

Database tables

- tickers has one row for each ticker, with general company information
- indicators has one row for each variable in the other tables with definitions
- sf1 has annual and quarterly reports for all NYSE/Nasdaq stocks back to 2000
- sep has daily open, high, low, close and adjusted close for same stocks
- daily has marketcap, pb, pe, ps, ev, evebit, evebitda for same stocks
- sep_weekly is a weekly version of sep
- weekly is a weekly version of daily

Basic SQL

- select [] from [] join [] on [] where [] order by []
- select * means select all columns
- select top 3 * means select all columns for top 3 rows
- join [] on [] where [] order by [] are all optional
- information_schema.tables lists the other tables.

In [3]:
```python
import pandas as pd
pd.read_sql("select * from information_schema.tables", conn)
```

Out[3]:

	TABLE_CATALOG	TABLE_SCHEMA	TABLE_NAME	TABLE_TYPE
0	stocks	dbo	today	BASE TABLE
1	stocks	dbo	ghz	BASE TABLE
2	stocks	dbo	indicators	BASE TABLE
3	stocks	dbo	tickers	BASE TABLE
4	stocks	dbo	prices_weekly	BASE TABLE
5	stocks	dbo	sep2	BASE TABLE
6	stocks	dbo	weekly	BASE TABLE
7	stocks	dbo	sep_weekly	BASE TABLE
8	stocks	dbo	sf1	BASE TABLE
9	stocks	dbo	daily	BASE TABLE
10	stocks	dbo	sep	BASE TABLE

In [4]:

```
pd.read_sql("select top 3 * from tickers", conn)
```

Out[4]:

	permaticker	siccode	lastupdated	firstadded	firstpricedate	lastpricedate	fi
0	196290	3826	2023-12-20	2014-09-26	1999-11-18	2024-01-05	1
1	124392	3334	2023-10-26	2016-11-01	2016-11-01	2024-01-05	2
2	122827	6022	2019-07-29	2017-09-09	1998-09-25	2003-01-28	1

3 rows × 26 columns

In [5]:
```
pd.read_sql("select top 3 * from indicators", conn)
```

Out[5]:

	tbl	indicator	isfilter	isprimarykey	title	description	unittype
0	SF1	revenue	N	N	Revenues	[Income Statement] The amount of Revenue recog...	currency
1	SF1	cor	N	N	Cost of Revenue	[Income Statement] The aggregate cost of goods...	currency
2	SF1	sgna	N	N	Selling General and Administrative Expense	[Income Statement] A component of [OpEx] repre...	currency

In [6]:

```
pd.read_sql("select top 3 * from sep", conn)
```

Out[6]:

	ticker	date	lastupdated	opn	high	low	cls	volume	cl
0	PTMN	2018-10-17	2023-11-17	31.900	32.200	31.800	31.900	4428.200	
1	RELI	2019-06-14	2023-02-23	192.855	192.855	177.105	177.105	91.267	1
2	REX	2019-06-14	2022-08-08	23.607	23.667	22.630	22.663	142662.000	

In [7]:
```
pd.read_sql("select top 3 * from daily", conn)
```

Out[7]:

	ticker	date	lastupdated	ev	evebit	evebitda	marketcap	pb	pe
0	APCC	2000-05-19	2019-03-28	6145.0	21.0	19.0	6601.2	7.3	32.0
1	MYGN	2006-12-29	2018-10-18	1158.0	-28.0	-33.7	1246.6	5.2	-30.1
2	GNI	2006-07-21	2018-10-18	177.3	11.9	11.7	178.1	12.1	11.9

In [8]:
```
pd.read_sql("select top 3 * from sf1", conn)
```

Out[8]:

	ticker	dimension	calendardate	datekey	reportperiod	lastupdated	acco
0	DWAC	ARQ	2021-06-30	2021-09-01	2021-06-30	2023-11-13	0
1	WEX	ARQ	2009-12-31	2010-02-26	2009-12-31	2023-10-28	-287000
2	WEX	ARQ	2010-03-31	2010-04-30	2010-03-31	2023-10-28	-568000

3 rows × 111 columns

Weekly tables

- Weekly versions of sep and daily (sep_weekly $\sim$ sep, weekly $\sim$ daily)
- Convenient for looking at strategies that trade weekly
- Calculate weekly returns from weekly adjusted closing prices
    - Prices are dividend and split adjusted
    - So % changes are total returns including dividends
- Can use end-of-prior-week pb (price-to-book) from weekly table to pick stocks (for example).

Momentum

- What people have found in equities and other markets (see "Value and Momentum Everywhere" by Asness and other AQR people) is
  - long-term reversals (5 year returns reverse somewhat)
  - medium-term momentum (1 year or 6 month returns continue)
  - short-term reversals (1 month or 1 week returns reverse)
- The conventional definition of momentum in academic work (including the Asness paper) is last year's return excluding the most recent month
  - In other words, the return over the first 11 of the previous 12 months.

Calculating momentum

- Each week, we want to look back one year and compound the returns, excluding the most recent month.
- Count the weeks in the prior year as 1, 2, ..., 52.
- We want to calculate $(1+r_1)\cdots(1+r_{48})$.
- We can do this as

$$\frac{(1+r_1)\cdots(1+r_{52})}{(1+r_{49})\cdots(1+r_{52})}$$

- In other words,

$$\frac{1+\text{last year's return}}{1+\text{last month's return}}$$

Get data

- Start in 2010 just to make the example quicker to run (data starts in 2000).
- Get closeadj to compute returns.
- Get closeunadj to filter out penny stocks (will impose price ≥ 5).
- In case there are two rows for the same stock/date, keep the one with the latest "lastupdated."

In [9]:

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

In [10]:

```
rets = prices.groupby(
    "ticker",
    group_keys=False
).closeadj.pct_change()

rets_annual = prices.groupby(
    "ticker",
    group_keys=False
).closeadj.pct_change(52)

rets_monthly = prices.groupby(
    "ticker",
    group_keys=False
).closeadj.pct_change(4)

mom = (1 + rets_annual) / (1 + rets_monthly) - 1
```

Value investing

- Value means cheap relative to quality. Value investing has a very long tradition.
- Conventional measures are price-to-earnings (PE) and price-to-book (PB).
- Low PE or low PB stocks are value stocks. High PE or PB stocks are "growth stocks" or "glamour stocks."
- We'll use PB in this example, but PE is also worth exploring (also price-to-sales, price-to-clicks, ...)

Get data

- Follow same recipe as when getting prices but use the weekly table.
- Get pb and marketcap (so we can filter to small caps)

In [11]:

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

Merge and lag

- The return shown at a given date is the return over the week ending on that date.
- To pick stocks, we need to use characteristics known at the beginning of the week.
    - This is the same as the end of the prior week.
- We will line up marketcap, closeunadj, mom, and pb from the prior week with the return of the current week.

In [12]:

```
df["close"] = prices.closeunadj
df["ret"] = rets
df["mom"] = mom
for col in ["marketcap", "close", "mom", "pb"]:
    df[col] = df.groupby("ticker", group_keys=False)[col].shift()
df = df.dropna()
```

Filter to small caps and exclude penny stocks

- Rank on marketcap each week, with 1=largest, etc. Drop largest 1,000.
- Drop all stocks with price < 5.

In [13]:

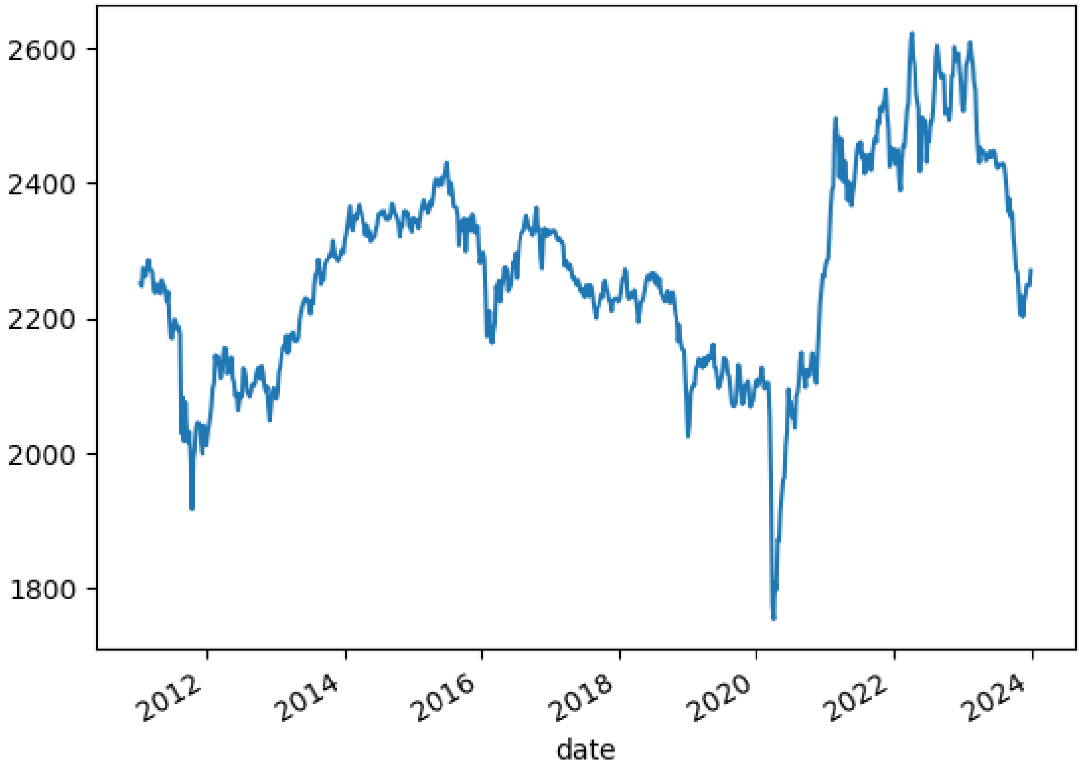
```
size_rank = df.groupby(
    "date",
    group_keys=False
).marketcap.rank(ascending=False)

df = df[size_rank>1000]
df = df[df.close > 5]
```

Number of stocks by week

In [14]:
```
num_stocks = df.groupby("date", group_keys=True).ret.count()
num_stocks.index = pd.to_datetime(num_stocks.index)
num_stocks.plot()
```

Out[14]: <AxesSubplot: xlabel='date'>



Preliminary analysis

- To understand how returns depend on momentum and value, we start by sorting into quintiles each week on each characteristic.
- We intersect the two sorts, forming 25 groups each week.
- We calculate average returns within each group. These are equally weighted portfolio returns.

In [15]:

```
df["pb_quintile"] = df.groupby("date", group_keys=False).pb.apply(
    lambda x: pd.qcut(x, 5, labels=range(1, 6))
)
df["mom_quintile"] = df.groupby("date", group_keys=False).mom.apply(
    lambda x: pd.qcut(x, 5, labels=range(1, 6))
)
sorted_rets = df.groupby(
    ["date", "pb_quintile", "mom_quintile"],
    observed=True,
    group_keys=True
).ret.mean()
sorted_rets = sorted_rets.unstack(["pb_quintile", "mom_quintile"])
```

In [16]:

```
sorted_rets.head()
```

Out[16]:

pb_quintile					1		
mom_quintile	1	2	3	4	5	1	
date							
2011-01-14	0.003848	-0.002287	0.006847	-0.000550	0.000852	-0.014294	-
2011-01-21	0.012342	0.008409	0.009834	0.015451	0.002926	0.016729	
2011-01-28	-0.019970	-0.003331	-0.005422	-0.011979	-0.021571	-0.018761	-
2011-02-04	-0.004283	0.006279	-0.005805	0.010473	0.014758	-0.005800	
2011-02-11	0.015693	0.022936	0.020645	0.020812	0.025529	0.016449	

5 rows × 25 columns

In [17]:

```python
mean_sorted_rets = sorted_rets.mean()
mean_sorted_rets = mean_sorted_rets.unstack()
(52*mean_sorted_rets).round(3)
```

Out[17]:

mom_quintile	1	2	3	4	5
pb_quintile					
1	0.038	0.134	0.159	0.163	0.140
2	0.057	0.105	0.116	0.110	0.128
3	0.068	0.095	0.106	0.103	0.132
4	0.084	0.091	0.109	0.127	0.128
5	0.001	0.077	0.110	0.094	0.152

Example strategy

- Compute momentum rank each week (1 = highest = best)
- Compute value rank each week (1 = lowest = best)
- Average ranks
- Hold 50 stocks with best (1 = best) ranks each week, equally weighted
- Compare to 50 stocks with worst ranks each week, equally weighted and compare to all stocks

Best stocks

In [18]:

```
mom_rank = df.groupby("date", group_keys=False).mom.rank(ascending=False)
pb_rank = df.groupby("date", group_keys=False).pb.rank()
avg_rank = (mom_rank + pb_rank) / 2

starting_from_best = avg_rank.groupby("date", group_keys=False).rank()
best = df[starting_from_best <= 50]
best_rets = best.groupby("date", group_keys=True).ret.mean()
best_rets.index = pd.to_datetime(best_rets.index)
```

Worst and all stocks

In [19]:

```
starting_from_worst = avg_rank.groupby(
    "date",
    group_keys=False
).rank(ascending=False)
worst = df[starting_from_worst <= 50]
worst_rets = worst.groupby("date", group_keys=True).ret.mean()
worst_rets.index = pd.to_datetime(worst_rets.index)

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

Cumulative returns

In [20]:

```
import matplotlib.pyplot as plt
(1+best_rets).cumprod().plot(label="best")
(1+worst_rets).cumprod().plot(label="worst")
(1+all_rets).cumprod().plot(label="all")
plt.legend()
plt.show()
```