Small Cap Value and Momentum

MGMT 638: Data-Driven Investments: Equity

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Alternate Code to Access SQL Server

- Hopefully, "pip3 install" has solved the Mac problems (on a Mac always use pip3 instead of pip).
- If there continues to be a problem with pymssql, it is possible to use pyodbc instead.
- On a Mac,
    - Install Microsoft's ODBC Server
    - Then pip3 install pyodbc
    - Then create a connection with the following code.
- If this still doesn't work, we can install and use any SQL client, for example Azure Data Studio.

```
In [5]: """
        from sqlalchemy import create_engine

        server = 'fs.rice.edu'
        database = 'stocks'
        username = 'stocks'
        password = '6LAZH1'
        driver = 'SQL+Server'
        string = "mssql+pyodbc://" + username + ":" + password + "@" + server + "/" +
        conn = create_engine(string).connect()
        """
```

```
Out[5]: '\nfrom sqlalchemy import create_engine\n\nserver = \'fs.rice.edu\'\n
        database = \'stocks\'\nusername = \'stocks\'\npassword = \'6LAZH1\'\n
        driver = \'SQL+Server\'\nstring = "mssql+pyodbc://" + username + ":"
        + password + "@" + server + "/" + database + "?driver=" + driver\ncon
        n = create_engine(string).connect()\n'
```

Why Long and Short?

- Can do long and short and index ETF
    - earn index return + long return - short return - short borrowing fee
    - except cannot use short proceeds to buy index or long
- to get 100 index + 100 long - 100 short, must invest 200 or borrow 100
    - earn index return + long return - short return - short borrowing fee - margin loan rate
- or buy index futures
    - implicit interest rate in futures (spot-futures parity) will be less than margin loan rate
    - but maybe bad tax consequences (40% short-term gains $\approx$ ordinary income)

Small Cap Value and Growth

- small cap $\approx$ Russell 2000
- value usually measured by PB or PE
- some academic work (Fama-French) found PB is a better predictor of returns
- low PB = value, high PB = growth
- academics usually use BP instead of PB and call it book-to-market
- high BP = value, low BP = growth
- small-cap growth has historically had very poor returns

Value and Momentum Portfolios I

- get marketcap data in addition to prices
- calculate momentum
- keep stocks between 1,001 and 3,000 in market cap
- create 5x5 sort on value and momentum
- compute equally weighted portfolio returns

Value and Momentum Portfolios II

- rank each stock between 1,001 and 3,000 on value
    - low rank = best (low pb)
- rank each stock also on momentum
    - low rank = best (high momentum)
- add ranks to get a single combined rank
    - low combined rank = best
- go long best n and short worst n (e.g., n=50)

Value and Momentum Portfolios III

- For long only portfolio, choose best stocks in each sector and match sector weights to benchmark (e.g., Russell 2000).
- For long-short portfolio, match shorts and longs in each sector to get market-neutral and sector-neutral portfolio.

Value and Momentum Portfolios IV

- Use machine learning to find the optimal way to combine value and momentum
- And add other predictors (ROE, investment rate, short-term reversal, ...)

Data and Procedure

- Get sectors from tickers table
- Get marketcap and pb from weekly table
- Get closeadj and closeunadj from sep_weekly as before
- Calculate momentum as before
- Filter to 1,001-3,000 on marketcap each week
- Form portfolios

Create connection

Get data

Calculate momentum

Merge marketcap and pb

Save this week’s data

```
In [12]: today = df[df.date==df.date.max()]
         today.head(3)
```

Out[12]:

	ticker	date	ret	mom	closeunadj	marketcap	pb	sector
668	A	2023-10-27	-0.059141	-0.188863	102.77	30069.2	5.4	Healthcare
981	AA	2023-10-27	-0.020825	-0.256682	23.51	4195.9	0.9	Basic Materials
1644	AADI	2023-10-27	0.039120	-0.626255	4.25	104.2	0.8	Healthcare

Shift predictors and shift filtering variables to backtest

In [13]:
```
df = df.set_index(["ticker", "date"])
variables = ["mom", "pb", "marketcap", "closeunadj"]
df[variables] = df.groupby("ticker", group_keys=False)[variables].shift()
df = df.dropna()
df.head(3)
```

Out[13]:

		ret	mom	closeunadj	marketcap	pb	sector
ticker	**date**						
A	**2011-01-14**	0.008130	0.199287	41.88	14557.7	4.5	Healthcare
	2011-01-21	0.050456	0.270914	42.22	14675.8	4.5	Healthcare
	2011-01-28	-0.075973	0.337839	44.35	15416.2	4.8	Healthcare

Filter out penny stocks and filter to small caps

```
In [14]: df = df[df.closeunadj>5]
         df["rnk"] = df.groupby("date").marketcap.rank(
             ascending=False,
             method="first"
         )
         df = df[(df.rnk>1000) & (df.rnk<=3000)]
         df.reset_index().groupby("date").ticker.count()
```

```
Out[14]: date
         2011-01-14    2000
         2011-01-21    2000
         2011-01-28    2000
         2011-02-04    2000
         2011-02-11    2000
                       ...
         2023-09-29    1865
         2023-10-06    1853
         2023-10-13    1837
         2023-10-20    1829
         2023-10-27    1802
         Name: ticker, Length: 668, dtype: int64
```

Value and Momentum Portfolios I

In [15]:

```python
df["value_group"] = df.groupby("date", group_keys=False).pb.apply(
    lambda x: pd.qcut(x, 5, labels=range(1, 6))
)
df["mom_group"] = df.groupby("date", group_keys=False).mom.apply(
    lambda x: pd.qcut(x, 5, labels=range(1, 6))
)
rets = df.groupby(["date", "value_group", "mom_group"]).ret.mean()
rets = rets.unstack().unstack()
rets.head(3)
```

Out[15]:

mom_group					**1**		
value_group	**1**	**2**	**3**	**4**	**5**	**1**	
date							
2011-01-14	-0.004985	-0.014070	-0.008452	-0.006321	-0.009538	-0.006124	-0.
2011-01-21	0.018622	0.018095	0.020878	0.013126	0.003709	0.013191	0.
2011-01-28	-0.026927	-0.021369	-0.030210	-0.027047	-0.030028	-0.010046	-0.

3 rows × 25 columns

```
In [16]: (52*rets.mean()).unstack().round(3)
```

Out[16]:

value_group	1	2	3	4	5
mom_group					
1	0.040	0.039	0.061	0.053	-0.004
2	0.114	0.087	0.076	0.079	0.067
3	0.129	0.093	0.094	0.101	0.098
4	0.145	0.095	0.094	0.117	0.078
5	0.176	0.125	0.113	0.104	0.138

How many stocks are in the groups?

In [17]:
```python
counts = df.groupby(["date", "value_group", "mom_group"]).ret.count()
counts = counts.unstack().unstack()
counts.tail(3)
```

Out[17]:

mom_group					**1**					**2**	**...**					**4**
value_group	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**...**	**1**	**2**	**3**	**4**	**5**
date																
2023-10-13	131	74	61	57	45	103	94	57	53	60	...	50	75	87	79	76
2023-10-20	138	75	57	50	46	108	94	59	47	58	...	58	71	80	66	91
2023-10-27	144	63	54	52	48	107	94	52	57	50	...	62	80	55	79	84

3 rows × 25 columns

Value and Momentum Portfolios II

- Rank stocks on momentum each week: 1=best, 2=next best, etc. (best=high momentum)
- Rank stocks on pb each week: 1=best, 2=next best, etc. (best=low pb)
- Add momentum and pb ranks: lowest combined ranks are best stocks
- Test A: sort into deciles on combined ranks and compute equally weighted returns
- Test B: go long best 50 stocks and short worst 50 stocks and compute returns

In [18]:

```
df["mom_rnk"] = df.groupby("date", group_keys=False).mom.rank(
    ascending=False,
    method="first"
)
df["pb_rnk"] = df.groupby("date", group_keys=False).pb.rank(
    ascending=True,
    method="first"
)
df["combined_rnk"] = df.mom_rnk + df.pb_rnk
```

Test A: Deciles

```
In [19]: df["decile"] = df.groupby("date", group_keys=False).combined_rnk.apply(
             lambda x: pd.qcut(x, 10, labels=range(1, 11))
         )
         rets = df.groupby(["date", "decile"]).ret.mean()
         rets = rets.unstack()
         52*rets.mean()
```

```
Out[19]: decile
         1     0.140992
         2     0.111454
         3     0.109872
         4     0.106887
         5     0.096466
         6     0.102888
         7     0.092114
         8     0.057470
         9     0.075204
         10    0.034701
         dtype: float64
```

Test B: Top 44 and Bottom 44

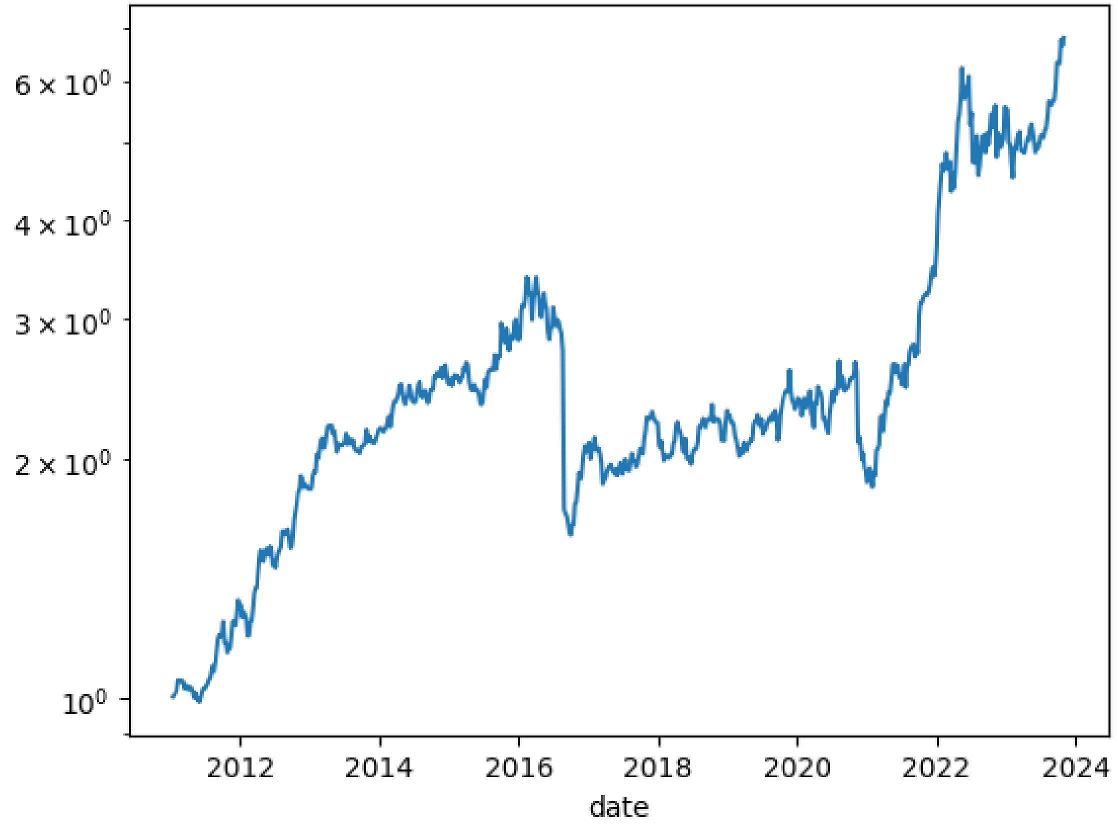
- rank at each date on combined_rnk
- put best 44 in long portfolio at each date
- put worst 44 in short portfolio at each date
- compute equally weighted returns in each portfolio
- calculate long minus short return

```
In [21]: print(f"annualized mean long return is {52*long_rets.mean():.2%}")
         print(f"annualized mean short return is {52*short_rets.mean():.2%}")
```

```
annualized mean long return is 18.68%
annualized mean short return is 0.47%
```

```
In [22]: (1+long_rets-short_rets).cumprod().plot(logy=True)
```

```
Out[22]: <AxesSubplot: xlabel='date'>
```



What are the top 44 and bottom 44 today?

- Apply penny stock and size filters to today dataframe
- Rank on momentum (low rank = high momentum = best)
- Rank on value (low rank = low pb = best)
- Add ranks
- Find best 44 and worst 44 stocks today

In [25]:
```
long
```

Out[25]:

	ticker	sector	mom_rnk	pb_rnk	combined_rnk	closeunadj
772871	EHTH	Financial Services	26	32	58	7.860
427948	CBUS	Healthcare	30	69	99	10.270
2367118	TRML	Healthcare	78	53	131	14.000
1429651	LSEA	Real Estate	97	39	136	7.240
2197648	SPHR	Communication Services	100	51	151	33.470
387833	BZH	Consumer Cyclical	48	221	269	23.430
2449388	USAP	Basic Materials	102	197	299	14.020
1761051	OPRT	Financial Services	272	44	316	5.510
1597522	MUX	Basic Materials	99	267	366	7.090
1488461	MDV	Real Estate	125	260	385	15.210
1139786	HOV	Consumer Cyclical	29	362	391	66.360
1593141	MTW	Industrials	128	266	394	12.320

```
In [26]: short
```

Out[26]:

	ticker	sector	mom_rnk	pb_rnk	combined_rnk	closeunadj
291701	BE	Industrials	1409	1654	3063	9.780
1903132	PRCT	Healthcare	1393	1678	3071	26.090
260770	AYX	Technology	1304	1767	3071	31.460
244448	AVXL	Healthcare	1685	1399	3084	5.200
1447625	LYFT	Technology	1387	1701	3088	9.260
1217100	IMXI	Technology	1566	1524	3090	16.200
1253736	IRTC	Healthcare	1378	1716	3094	78.190
2107199	SEMR	Technology	1463	1635	3098	8.050
2418352	UDMY	Consumer Defensive	1551	1551	3102	8.770
2375532	TRUP	Financial Services	1665	1438	3103	20.690
804166	ENVX	Industrials	1494	1628	3122	8.770
1569788	MRTX	Healthcare	1557	1579	3136	55.370
2630788	YOU	Technology	1433	1704	3137	16.520
1298662	JYNT	Healthcare	1690	1471	3161	7.890
2227119	SSTI	Technology	1722	1449	3171	14.790

Sector weights

```
In [27]: long.groupby("sector").ticker.count()
```

```
Out[27]: sector
         Basic Materials           3
         Communication Services    2
         Consumer Cyclical         8
         Energy                    1
         Financial Services       16
         Healthcare                4
         Industrials               5
         Real Estate               5
         Name: ticker, dtype: int64
```

```
In [28]: short.groupby("sector").ticker.count()
```

```
Out[28]: sector
         Basic Materials            1
         Communication Services     1
         Consumer Cyclical          3
         Consumer Defensive         1
         Energy                     2
         Financial Services         2
         Healthcare                17
         Industrials                3
         Technology                13
         Utilities                  1
         Name: ticker, dtype: int64
```

Value and Momentum Portfolios III

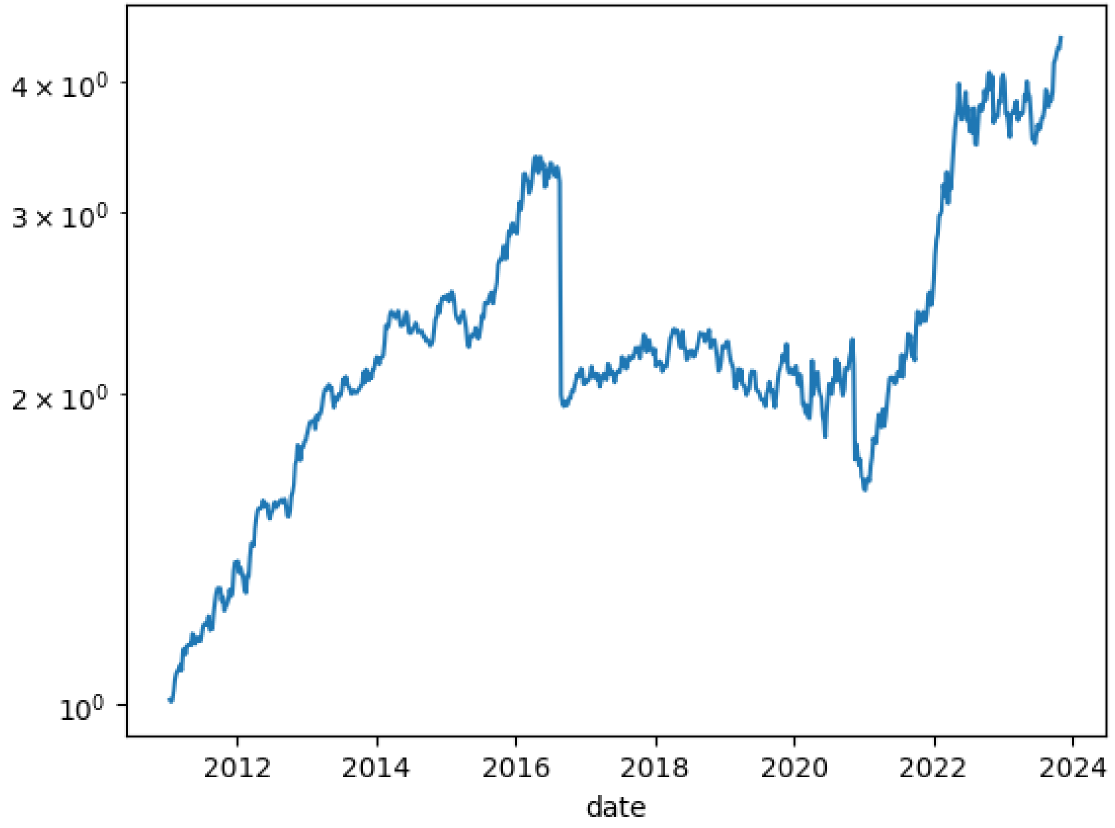
- Rank on combined rank separately in each sector
- Do that by grouping by date and sector instead of just date
- Go long best 4 and short worst 4 in each sector to get sector neutrality
- Compute equally weighted returns for long and short portfolios
- Compute long minus short return

```
In [30]: print(f"annualized mean long return is {52*long_rets.mean():.2%}")
         print(f"annualized mean short return is {52*short_rets.mean():.2%}")
```

```
annualized mean long return is 15.32%
annualized mean short return is 1.54%
```

```
In [31]: (1+long_rets-short_rets).cumprod().plot(logy=True)

Out[31]: <AxesSubplot: xlabel='date'>
```



Best and worst stocks today in sector-neutral strategy

- Just group by sector when ranking
- Choose best 4 and worst 4 in each sector

In [33]:

```
long_neutral
```

Out[33]:

	ticker	sector	mom_rnk	pb_rnk	combined_rnk	closeunadj
2449388	USAP	Basic Materials	102	197	299	14.020
1597522	MUX	Basic Materials	99	267	366	7.090
950535	FRD	Basic Materials	276	147	423	9.710
2638060	ZEUS	Basic Materials	47	636	683	49.430
2197648	SPHR	Communication Services	100	51	151	33.470
2300744	TDS	Communication Services	504	24	528	17.800
2455127	USM	Communication Services	274	430	704	41.390
1177442	IAC	Communication Services	704	159	863	41.840
387833	BZH	Consumer Cyclical	48	221	269	23.430
1139786	HOV	Consumer Cyclical	29	362	391	66.360
925188	FLXS	Consumer Cyclical	239	241	480	19.750

In [34]:

```python
short_neutral
```

Out[34]:

	ticker	sector	mom_rnk	pb_rnk	combined_rnk	closeunadj
1573351	MSB	Basic Materials	950	1725	2675	20.170
2165284	SMID	Basic Materials	1242	1447	2689	19.366
1555752	MP	Basic Materials	1572	1207	2779	16.500
2379344	TSE	Basic Materials	1735	1708	3443	5.990
1755960	OOMA	Communication Services	1203	1535	2738	10.740
934187	FNGR	Communication Services	1019	1749	2768	5.650
1042555	GOGO	Communication Services	1113	1776	2889	10.650
2388282	TTGT	Communication Services	1732	1497	3229	25.260
1492207	MED	Consumer Cyclical	1480	1561	3041	69.580
350200	BOWL	Consumer Cyclical	1518	1718	3236	10.340
1374556	LEE	Consumer Cyclical	1658	1578	3236	8.960

```
In [35]: long_neutral.groupby("sector").ticker.count()

Out[35]: sector
         Basic Materials           4
         Communication Services    4
         Consumer Cyclical         4
         Consumer Defensive        4
         Energy                    4
         Financial Services        4
         Healthcare                4
         Industrials               4
         Real Estate               4
         Technology                4
         Utilities                 4
         Name: ticker, dtype: int64
```

```
In [36]: short_neutral.groupby("sector").ticker.count()
```

```
Out[36]: sector
         Basic Materials           4
         Communication Services    4
         Consumer Cyclical         4
         Consumer Defensive        4
         Energy                    4
         Financial Services        4
         Healthcare                4
         Industrials               4
         Real Estate               4
         Technology                4
         Utilities                 4
         Name: ticker, dtype: int64
```

How many shares to buy/sell?

- Can do this either for long and short or long_neutral and short_neutral
- $1,000,000 to invest long and short
- Divide by number of stocks to get $ per stock
- Divide by price to get shares per stock

Long side

```
In [38]: long_neutral["shares"] = (1000000/long_neutral.shape[0])/long_neutral.closeun
         long_neutral["shares"] = long_neutral.shares.round(0).astype(int)

         long["shares"] = (1000000/long.shape[0])/long.closeunadj
         long["shares"] = long.shares.round(0).astype(int)
```

Short side

```
In [39]: short_neutral["shares"] = (1000000/short_neutral.shape[0])/short_neutral.clos
         short_neutral["shares"] = short_neutral.shares.round(0).astype(int)

         short["shares"] = (1000000/short.shape[0])/short.closeunadj
         short["shares"] = short.shares.round(0).astype(int)
```

```
In [ ]: with pd.ExcelWriter("portfolios 2023-11-02.xlsx") as writer:
            long.to_excel(writer, "long", index=False)
            short.to_excel(writer, "short", index=False)
            long_neutral.to_excel(writer, "long neutral", index=False)
            short_neutral.to_excel(writer, "short neutral", index=False)
            today.to_excel(writer, "today", index=False)
```