Small Cap Value and Momentum

MGMT 638: Data-Driven Investments: Equity

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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 50 and short worst 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 marketneutral 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





today = df[df.date==df.date.max()] today.head(3) closeunadj ticker date marketcap pb ret mom sector Out[7]: 2023-668 Α -0.059141 -0.188863 102.77 30069.2 5.4 Healthcare 10-27 2023-Basic -0.020825 -0.256682 981 AA 23.51 4195.9 0.9 10-27 Materials 2023-1644 0.039120 AADI -0.626255 4.25 104.2 0.8 Healthcare

10-27



Shift predictors and shift filtering variables to backtest





```
In [8]: 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[8]:

		ret	mom	closeunadj	marketcap	pb	sector
ticker	date						
Α	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 [9]: 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()
         date
Out[9]:
         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 [10]:
         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[10]:
          mom_group
                                         2
                                                   3
                                                                        5
          value_group
                                                              4
                 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
          2011-01-28 -0.026927 -0.021369 -0.030210 -0.027047
                                                                -0.030028
                                                                           -0.010046
```

3 rows × 25 columns





```
In [11]: (52*rets.mean()).unstack().round(3)
                                         4 _
         value_group
                       1 2
                                   3
                                                5
Out[11]:
         mom_group
                          0.038 0.060 0.052
                  1 0.040
                                            -0.003
                  2 0.114
                          0.087
                                0.076
                                      0.079
                                             0.066
                  3 0.129
                          0.092
                                0.094
                                      0.102
                                             0.097
                          0.095 0.094 0.117
                  4 0.143
                                             0.079
                  5 0.178
                          0.125 0.112
                                      0.104
                                             0.138
```





How many stocks are in the groups?





```
In [12]:
        counts = df.groupby(["date", "value_group", "mom_group"]).ret.count()
        counts = counts.unstack().unstack()
        counts.tail(3)
        mom_group
Out[12]:
         value_group
                          2
               date
                                       103 94
                                               57 53 60 ...
                                                             50 75 87 79 76
         2023-10-13
                    131
                         74 61
                                57 45
         2023-10-20
                    138
                         75 57
                                50 46
                                       108
                                            94
                                               59 47
                                                      58
                                                             58 71 80 66 91
                                                          ... 62 80 55
         2023-10-27 144 63 54 52 48
                                       107
                                            94
                                               52 57 50
```

 $3 \text{ rows} \times 25 \text{ columns}$



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









Test A: Deciles





```
In [14]: 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()
          decile
Out[14]:
                0.140782
                0.111245
                0.110181
                0.106055
                0.096709
                0.103076
                0.092262
                0.056943
          8
          9
                0.074983
          10
                0.034706
          dtype: float64
```





Test B: Top 50 and Bottom 50

- rank at each date on combined_rnk
- put best 50 in long portfolio at each date
- put worst 50 in short portfolio at each date
- compute equally weighted returns in each portfolio
- calculate long minus short return





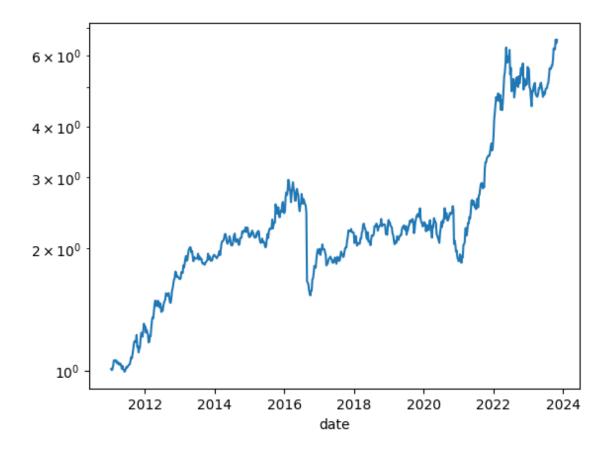
```
In [16]: print(f"annualized mean long return is {52*long_rets.mean():.2%}")
    print(f"annualized mean short return is {52*short_rets.mean():.2%}")
    annualized mean long return is 17.82%
    annualized mean short return is 0.23%
```





```
In [17]: (1+long_rets-short_rets).cumprod().plot(logy=True)
```

Out[17]: <Axes: xlabel='date'>



What are the top 50 and bottom 50 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 50 and worst 50 stocks today





In [20]: long

Out[20]:		ticker sector		mom_rnk	pb_rnk	combined_rnk	closeun	
	772071	FLITLI	Financial	26	22	Γ0	7	

	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
050525	EDD	Dania Mataviala	276	1.47	422	0.710

In [21]: short

short						
	ticker	sector	mom_rnk	pb_rnk	combined_rnk	closeunadj
2425203	UG	Consumer Defensive	1664	1382	3046	6.180
1121494	HLIT	Technology	1596	1456	3052	9.890
1570573	MRVI	Healthcare	1623	1431	3054	6.220
124978	AMLX	Healthcare	1701	1354	3055	15.740
1869626	PLMR	Financial Services	1625	1433	3058	49.360
229881	AUID	Technology	1460	1599	3059	6.000
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
	2425203 1121494 1570573 124978 1869626 229881 291701 1903132 260770 244448 1447625 1217100 1253736	ticker 2425203 UG 1121494 HLIT 1570573 MRVI 124978 AMLX 1869626 PLMR 229881 AUID 291701 BE 1903132 PRCT 260770 AYX 244448 AVXL 1447625 LYFT 1217100 IMXI 1253736 IRTC	2425203UGConsumer Defensive1121494HLITTechnology1570573MRVIHealthcare124978AMLXHealthcare1869626PLMRFinancial Services229881AUIDTechnology291701BEIndustrials1903132PRCTHealthcare260770AYXTechnology244448AVXLHealthcare1447625LYFTTechnology1217100IMXITechnology1253736IRTCHealthcare	ticker sector mom_rnk 2425203 UG Consumer Defensive 1664 1121494 HLIT Technology 1596 1570573 MRVI Healthcare 1623 124978 AMLX Healthcare 1701 1869626 PLMR Financial Services 1625 229881 AUID Technology 1460 291701 BE Industrials 1409 1903132 PRCT Healthcare 1393 260770 AYX Technology 1304 244448 AVXL Healthcare 1685 1447625 LYFT Technology 1366 1253736 IRTC Healthcare 1378	ticker sector mom_rnk pb_rnk 2425203 UG Consumer Defensive 1664 1382 1121494 HLIT Technology 1596 1456 1570573 MRVI Healthcare 1623 1431 124978 AMLX Healthcare 1701 1354 1869626 PLMR Financial Services 1625 1433 229881 AUID Technology 1460 1599 291701 BE Industrials 1409 1654 1903132 PRCT Healthcare 1393 1678 260770 AYX Technology 1304 1767 244448 AVXL Healthcare 1685 1399 1447625 LYFT Technology 1366 1524 1217100 IMXI Technology 1566 1524 1253736 IRTC Healthcare 1378 1716	ticker sector mom_rnk pb_rnk combined_rnk 2425203 UG Consumer Defensive 1664 1382 3046 1121494 HLIT Technology 1596 1456 3052 1570573 MRVI Healthcare 1623 1431 3054 124978 AMLX Healthcare 1701 1354 3055 1869626 PLMR Financial Services 1625 1433 3058 229881 AUID Technology 1460 1599 3059 291701 BE Industrials 1409 1654 3063 1903132 PRCT Healthcare 1393 1678 3071 260770 AYX Technology 1304 1767 3071 244448 AVXL Healthcare 1685 1399 3084 1447625 LYFT Technology 1367 1701 3088 1217100 IMXI Technology 1566 1524

Consumer

Sector weights







```
short.groupby("sector").ticker.count()
In [23]:
          sector
Out[23]:
          Basic Materials
          Communication Services
          Consumer Cyclical
          Consumer Defensive
          Energy
          Financial Services
          Healthcare
                                    19
          Industrials
          Technology
                                    15
          Utilities
          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 5 and short worst 5 in each sector to get sector neutrality
- Compute equally weighted returns for long and short portfolios
- Compute long minus short return





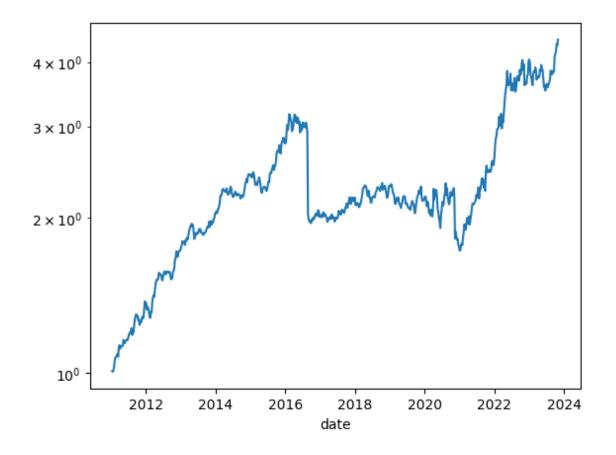
```
In [25]: print(f"annualized mean long return is {52*long_rets.mean():.2%}")
    print(f"annualized mean short return is {52*short_rets.mean():.2%}")
    annualized mean long return is 15.07%
    annualized mean short return is 1.82%
```





```
In [26]: (1+long_rets-short_rets).cumprod().plot(logy=True)
```

Out[26]: <Axes: xlabel='date'>



Best and worst stocks today in sector-neutral strategy

- Just group by sector when ranking
- Choose top 5 and bottom 5 in each sector





In [28]: long_neutral

Out[28]:

•		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 Ma		Basic Materials	276	147	423	9.710
	2638060	ZEUS	Basic Materials	47	636	683	49.430
	986128	GATO	Basic Materials	182	579	761	5.010
	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
	2116089	SGA	Communication Services	751	195	946	19.150
	387833	Consume BZH Cyclica		48	221	269	23.430
Consumer							

In [29]: short_neutral

Out[29]:

		ticker	sector	mom_rnk	pb_rnk	combined_rnk	closeunadj
	1433593	LTHM	Basic Materials	1633	986	2619	15.110
	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
	1195703	IDT	Communication Services	1159	1501	2660	27.790
	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
•	425453	CBRL	Consumer Cyclical	1611	1418	3029	64.620
Consumer							





```
In [30]: long_neutral.groupby("sector").ticker.count()
          sector
Out[30]:
          Basic Materials
          Communication Services
          Consumer Cyclical
          Consumer Defensive
          Energy
          Financial Services
          Healthcare
          Industrials
          Real Estate
          Technology
          Utilities
          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 [32]: long_neutral["shares"] = (1000000/long_neutral.shape[0])/long_neutral.closeum
long_neutral["shares"] = long_neutral.shares.round(0).astype(int)
long_neutral

Out[32]:		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
	986128	GATO	Basic Materials	182	579	761	5.010
	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
	2116089	SGA	Communication Services	751	195	946	19.150
	387833	BZH	Consumer	48	221	269	23.430

Short side





In [33]:

short_neutral["shares"] = (1000000/short_neutral.shape[0])/short_neutral.close short_neutral["shares"] = short_neutral.shares.round(0).astype(int) short_neutral

Out[33]:

•		ticker	sector	mom_rnk	pb_rnk	combined_rnk	closeunadj
	1433593	LTHM	Basic Materials	1633	986	2619	15.110
	1573351	MSB	Basic Materials	950	1725	2675	20.170
	2165284	SMID	Basic Materials	1242	1447	2689	19.366
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	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
	425453	CBRL	Consumer	1611	1418	3029	64.620

```
In [35]: with pd.ExcelWriter("portfolios 2023-11-01.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)
```

