DuPont Analysis

Historically, the profitability factor was a strong driver of the cross-section of stock returns (see anomalies replication -- Profitability). The recent FF5 model even includes RMW factor, which is formed on operating profitability. The evidence motivates us to study ROE, an important profitability measure.

DuPont analysis breaks down a company's ROE into three parts: gross profit margin, asset turnover, and leverage. That is to say, a company can generate higher returns per unit of equity by

- Increasing earnings per unit of sales (e.g., better production methods to reduce COGS);
- Make more efficient use of its resources, i.e., total assets, to generate sales (e.g., import-export companies); or
- Borrowing more money (e.g., a commertial banks's revenue is critically dependent on the size of its balance sheet).

But at the end of the day, in a fundamental analysis, we want to compare after we have these ratios (both in the time-series and the cross-section) and make an investment decision. Notice that when constructing a factor portfolio we are also doing comparisons, though in a more systematic way, by ranking and comparing profitability ratios of companies in the whole investment universe.

Industry average seems to be a natural anchor in fundamental analysis, it's good to know how a company is doing among its peers. That's why when doing DuPont analysis, we need industry average (or median, to mitigate the impact of outliers).

Breaking down the ROE --

- Gross Profit Margin:
$$\text{Gross Profit Margin} = \frac{\text{Net Income}}{\text{Sales}}$$
- Asset Turnover:
$$\text{Asset Turnover} = \frac{\text{Sales}}{\text{Total Assets}}$$
- Leverage:
$$\text{Leverage} = \frac{\text{Total Assets}}{\text{Book Equity}}$$

and we can reconstruct ROE by multiplying these three ratios:

$$\begin{aligned}\text{Return on Equity} &= \frac{\text{Net Income}}{\text{Book Equity}}\\ &= \text{Gross Profit Margin} \times \text{Asset Turnover} \times \text{Leverage}.\end{aligned}$$

In the following, I use stocks in the NYSE, AMEX and NASDAQ to construct the investment universe. I calculated for each stock its gross profit margin (GPM), asset turnover (AsT), and leverage (Lev) at December end of each of its fiscal year. Then I classify them according to Fama-

French 12 industry definitions. At year ends, I selected the *median* ratios for every group of stocks in an industry; I didn't use mean (i.e. equal-weight) or market-cap-weighted mean to mitigate the effect of outliers. Finally, I calculated the 2016-2020 industry average of these ratios.

Some interesting facts.

Overall:

- Asset turnover is negatively correlated with gross profit margin and leverage;
- Leverage is weakly positively correlated with gross profit margin.

Specifics that shed some light on typical business models in different industries (when I say high/low, it means relative to other industries). For example:

- Shops: high turnover, low margin -- better sell more with smaller profits;
- Money: high leverage, high margin -- loading on debt (e.g., deposits) doesn't matter so much, but the financing costs matter;
- Utils: low turnover, high margin -- the sales of gas/water/highways are relatively fixed, there isn't much we can do.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:
```
df = pd.read_csv("DuPont.csv", index_col=0)
```

In [3]:
```
df
```

Out[3]:

ind	IndAbbr	PM	AsT	Lev
1	NoDur	0.049816	0.970883	2.030531
2	Durbl	0.032268	1.081833	2.179640
3	Manuf	0.038180	0.873129	2.160736
4	Enrgy	-0.114954	0.334616	1.950638
5	Chems	0.060008	0.720106	2.292029
6	BusEq	0.011803	0.665196	1.882411
7	Telcm	0.033755	0.431226	2.561428
8	Utils	0.108712	0.231352	2.561464
9	Shops	0.020943	1.699199	2.492847
10	Hlth	-0.600018	0.354148	1.650303
11	Money	0.137825	0.061631	6.423876
12	Other	0.033065	0.791900	2.248530

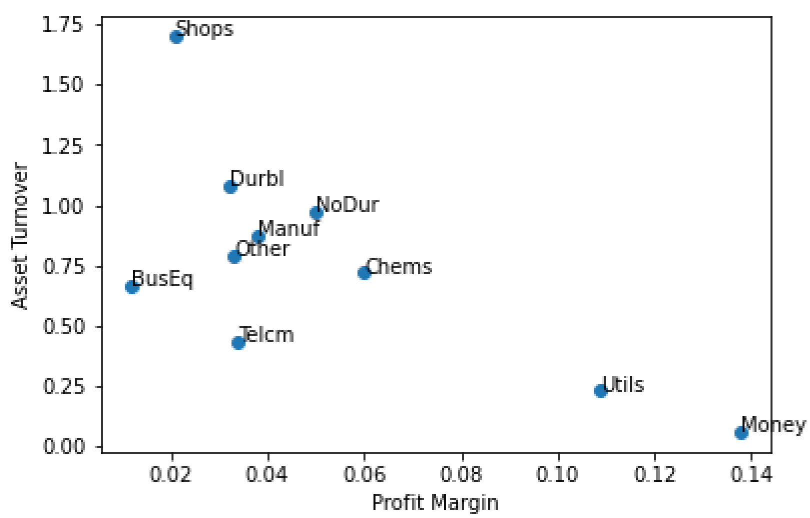
In [4]:
```
df = df.drop(index=[4, 10])
```

In [5]:
```
df['PM'] * df['AsT'] * df['Lev']
```

Out[5]:
```
ind
1     0.098208
2     0.076089
3     0.072030
5     0.099044
6     0.014779
7     0.037284
8     0.064423
9     0.088712
11    0.054566
12    0.058876
dtype: float64
```

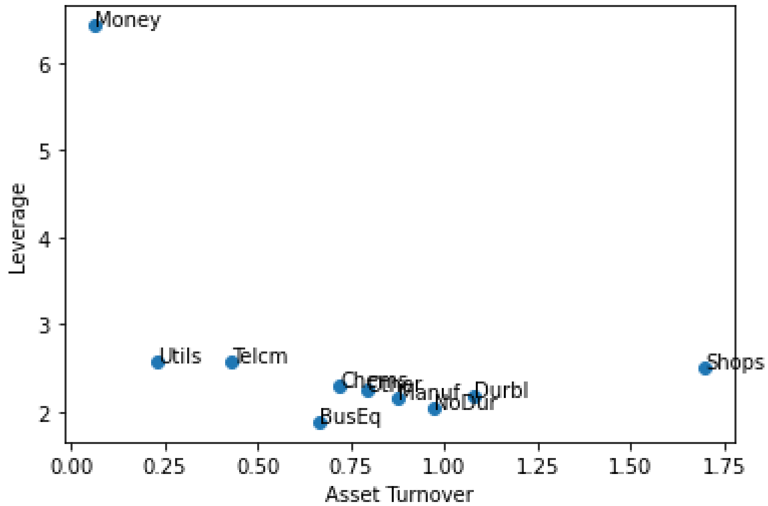
In [6]:
```
fig, ax = plt.subplots()
z, y = df['PM'].values, df['AsT'].values
ax.scatter(z, y)
ax.set_xlabel("Profit Margin")
ax.set_ylabel("Asset Turnover")

for i, txt in enumerate(df['IndAbbr']):
    ax.annotate(txt, (z[i], y[i]))
```



In [7]:
```
fig, ax = plt.subplots()
z, y = df['AsT'].values, df['Lev'].values
ax.scatter(z, y)
ax.set_xlabel("Asset Turnover")
ax.set_ylabel("Leverage")

for i, txt in enumerate(df['IndAbbr']):
    ax.annotate(txt, (z[i], y[i]))
```



In [8]:

```
fig, ax = plt.subplots()
z, y = df['PM'].values, df['Lev'].values
ax.scatter(z, y)
ax.set_xlabel("Profit Margin")
ax.set_ylabel("Leverage")

for i, txt in enumerate(df['IndAbbr']):
    ax.annotate(txt, (z[i], y[i]))
```