# 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:
$$\text{Gross Profit Margin} = \frac{\text{Gross Profit}}{\text{Sales}} = \frac{\text{Revenue} - \text{COGS}}{\text{Sales}}$$
- 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:

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

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]:

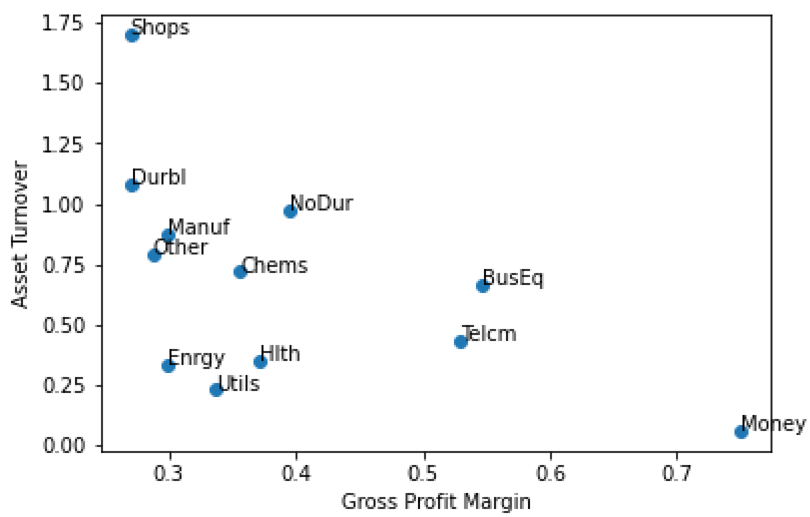
| ind | IndAbbr | GPM | AsT | Lev |
|---|---|---|---|---|
| 1 | NoDur | 0.394934 | 0.970883 | 2.030531 |
| 2 | Durbl | 0.270073 | 1.081833 | 2.179640 |
| 3 | Manuf | 0.298646 | 0.873129 | 2.160736 |
| 4 | Enrgy | 0.297949 | 0.334616 | 1.950638 |
| 5 | Chems | 0.356142 | 0.720106 | 2.292029 |
| 6 | BusEq | 0.546194 | 0.665196 | 1.882411 |
| 7 | Telcm | 0.528838 | 0.431226 | 2.561428 |
| 8 | Utils | 0.336360 | 0.231352 | 2.561464 |
| 9 | Shops | 0.269943 | 1.699199 | 2.492847 |
| 10 | Hlth | 0.370903 | 0.354148 | 1.650303 |
| 11 | Money | 0.750309 | 0.061631 | 6.423876 |
| 12 | Other | 0.287629 | 0.791900 | 2.248530 |

In [4]:
```python
df['GPM'] * df['AsT'] * df['Lev']
```

Out[4]:
```
ind
1     0.778575
2     0.636835
3     0.563426
4     0.194476
5     0.587814
6     0.683928
7     0.584130
8     0.199327
9     1.143438
10    0.216775
11    0.297053
12    0.512156
dtype: float64
```

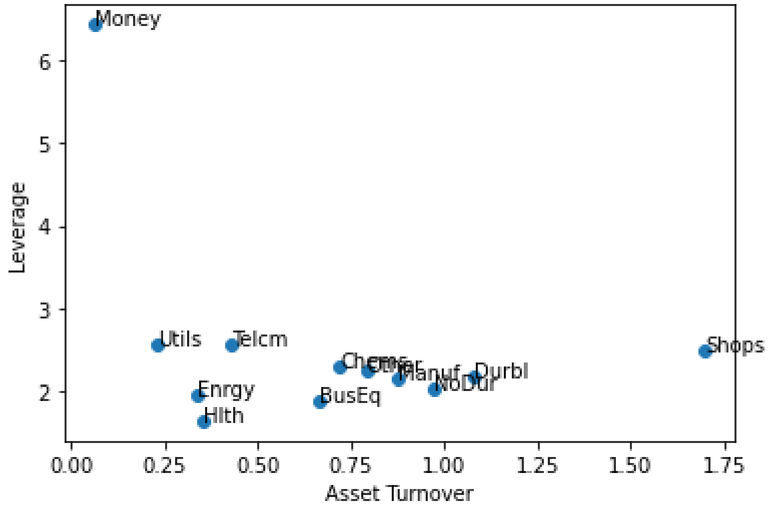
In [5]:
```python
fig, ax = plt.subplots()
z, y = df['GPM'].values, df['AsT'].values
ax.scatter(z, y)
ax.set_xlabel("Gross Profit Margin")
ax.set_ylabel("Asset Turnover")

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



In [6]:
```python
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 [7]:
```
fig, ax = plt.subplots()
z, y = df['GPM'].values, df['Lev'].values
ax.scatter(z, y)
ax.set_xlabel("Gross Profit Margin")
ax.set_ylabel("Leverage")

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