MFE 230G
Key Formulas: Valuation, Behavioral Finance, Forecasting, Information Analysis

Valuation

We started out with a return decomposition:

$$r(t,t+\Delta t)+i_F=\frac{d(t+\Delta t)}{p(t)}+\frac{\Delta e}{e}+\frac{\Delta\left(p/e\right)}{\left(p/e\right)} \tag{1}$$

This decomposes returns into three sources: dividend yield, cashflow news, and discount rate (or multiple) news. We then discussed several approaches to valuation, from those firmly grounded in theory, to those more ad hoc in nature. We also discussed approaches focused on the stock price, and approaches focused on stock returns.

Stock Price: Theory

In theory, today's stock price represents the present value of all future dividend payments. One approach to implementing that theory is the constant growth dividend discount model (constant growth DDM). This model assumes that dividends grow at a constant growth rate, *gr*; and that we discount future dividends at a constant internal rate of return, *y*:

$$p(0)=\frac{d(1)}{y-gr} \tag{2}$$

In Equation (2) we represent current price at $p(0)$, and assume a dividend payment of $d(1)$ at the end of 1 year. We can rewrite Equation (2) in terms of the internal rate of return:

$$y=i_F+\beta\cdot f_B+\alpha=gr+\frac{d(1)}{p(0)} \tag{3}$$

We discussed how to model growth, assuming that growth follows from reinvesting earning in the company at the same return on equity, ROE. If κ represents the constant payout ratio (the fraction of earnings paid out as dividends) then:

$$gr=ROE\cdot(1-\kappa) \tag{4}$$

There are two ways we can use the DDM:

- Internal Rate of Return: For each stock, back out the internal rate of return, *y*, that equates $p(0)$ to the market price. Then use Equation (3) to estimate an alpha. This approach assumes that market mispricings remain forever.
- Net Present Value: For each stock, calculate the fair internal rate of return ($i_F+\beta\cdot f_B$), and the growth rate, and then estimate the fair price. Estimate

a time over which the market price will return to fair value. This leads to an alpha estimate.

We also discussed returns to value investing under several different circumstances. We start at t=0 with a market price and a true price (Equation (2)). We used the payout ratio to replace the dividends with the payout ratio times earnings, so that we could discuss both the true price/earnings ratio and the market's current price/earnings ratio. At t=1, our returns are:

$$r = \frac{d(1) + p_{mkt}(1)}{p_{mkt}(0)} - 1 \tag{5}$$

We calculated this under two different circumstances:

- At t=1, the market price matched the t=1 true price.
- At t=1, the market multiple was the same as at t=0.

Stock Price: Ad Hoc

We also discussed comparative valuation approaches. These extended Equation (2), assuming that stock prices we based on multiples of various fundamentals:

$$\begin{aligned} p_{DDM}(0) &= \frac{d(1)}{y - gr} = c \cdot d(1) \\ p_{CV}(0) &\Rightarrow c_1 \cdot d + c_2 \cdot earnings + c_3 \cdot book + \ldots \end{aligned} \tag{6}$$

Stock Return: Theory

We discussed the arbitrage pricing theory (APT). This theory started from a factor model and imposed no-arbitrage conditions to assert that expected specific returns must be zero. Hence, expected returns must arise from expected factor returns, where the factors represent sources of risk that some market participants must bear. Under this model, expected returns hence have the form:

$$\begin{aligned} \mathbf{f} &= \mathbf{X} \cdot \mathbf{m} \\ \mathbf{m} &= E\{\mathbf{b}\} \end{aligned} \tag{7}$$

"Smart Beta" products ultimately follow from this framework.

Stock Return: Ad Hoc

The most general approach is to extend the APT framework to also allow us to forecast specific returns. In general, we construct models that look like:

$$\mathbf{r} = \mathbf{X} \cdot \mathbf{b} + \mathbf{A} \cdot \mathbf{c} + \boldsymbol{\varepsilon} \tag{8}$$

We can forecast the factor returns as in Equation (7). We can also forecast the coefficients **c**. In fact, we typically pick signals **A** such that **c** are relatively constant. So if **A** represented analyst estimate revisions, the coefficient c would tell us the expected return given such revisions.

Behavioral Finance

Behavioral finance research has uncovered several types of systematic irrationality:

- Social interactions (conforming, follow-the-crowd behavior)
- Heuristic simplification (generalizing from personal experience and recent events)
- Self-deception (over-confidence)

Behavioral finance has two implications for active management:

- It helps make active management possible.
- In principle, it can lead us to develop new active strategies.

One example of behavioral research was Sloan's work, "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings." Part of that research was econometric: cash flows are more persistent than accruals. But another part—and the part that made this of interest to active managers—was that the market didn't understand this difference.

Forecasting:

Basic Forecasting Formula:

$$E\left\{\mathbf{r}\middle|\mathbf{g}\right\} = E\left\{\mathbf{r}\right\} + Cov\left\{\mathbf{r},\mathbf{g}\right\} \cdot Var^{-1}\left\{\mathbf{g}\right\} \cdot \left(\mathbf{g} - E\left\{\mathbf{g}\right\}\right). \qquad (9)$$

Note that in principal, **r** and **g** are vectors, and so $Var\{\mathbf{g}\}$ is a covariance matrix.

Forecasting Rule of Thumb:

$$\alpha = IC \cdot \omega \cdot z \qquad (10)$$

This is a central result of the section. You should understand each term. You should understand what we mean by a z-score. You should understand that it is a "time-series" score. You should understand conceptually what to do if you are given a set of cross-sectional scores. That is, whether you should multiply them by volatility or not depends on whether the raw signal volatility does not, or does vary linearly with asset volatility respectively. You don't need to memorize formulas from that section however.

Binary Model:

This provides some insight into the active management forecasting process, by assuming that residual returns consist of a number of independent binary elements:

$$\theta = \sum_{n=1}^{N} \phi_n \qquad (11)$$

$$\begin{aligned} Var\left\{\phi_n\right\} &= 1\% \\ Var\left\{\theta\right\} &= N \end{aligned} \qquad (12)$$

We then model our signal as a sum of some of the binary elements in θ, some elements of noise, and possibly a mean. For example:

$$g = \phi_1 + \phi_3 + \sum_{i=1}^{I} \eta_i + c \tag{13}$$

You should understand how to calculate:

- The standard deviations of the residual return and the signal,
- the covariance of the residual return and signal,
- the *IC*.

You should also know how to convert the signal into an alpha, as in Equation (10).

Information Analysis:

This section is less formula-rich than other sections we have covered. The concepts are quite important. You should understand how to interpret the information analysis results I showed in class—especially the cumulative return plots, the horizon *IR*s, and the event studies.

The probability of observing a t-statistic greater than 2 in magnitude after N tests of independent random data:

$$p = 1 - (0.95)^N . \tag{14}$$

So this probability is only 5% after one test. But it rises to 64% after 20 tests.

In testing hypotheses, the positive predictive value (*PPV*, i.e. the fraction of positive test results that are actually true) is:

$$PPV = \frac{R_{pn} \cdot (1 - f_{fn})}{R_{pn} \cdot (1 - f_{fn}) + f_{fp}} , \tag{15}$$

where R measures the ex ante expected ratio of true to false (it's a measure of the rarity of the effect in question), f_{fp} measures the false positive rate, and f_{fn} measures the false negative rate. You should understand how to apply this formula, though you need not memorize the embellishments of this formula to account for investigator bias or the impact of multiple tests.