# FACTOR MODEL

### Xie zejian

xiezej@gmail.com

November 3, 2020

## 1 CAPM

## 1.1 Beta representation

Recall the tangency portfolio is  $\omega_D = \frac{\mathbf{V}^-(\overline{\mathbf{r}} - r_f \mathbf{e})}{\mathbf{e}' \mathbf{V}^-(\overline{\mathbf{r}} - r_f \mathbf{e})}$ . Write  $\omega_D = m \mathbf{V}^-(\overline{\mathbf{r}} - r_f \mathbf{e})$  where  $m = \frac{1}{\mathbf{e}' \mathbf{V}^-(\overline{\mathbf{r}} - r_f \mathbf{e})}$ , then we have

$$\bar{r} - r_f \mathbf{e} = \frac{1}{m} \mathbf{V} \omega_D$$

Note  $Cov(\mathbf{r}, \omega'\mathbf{r}) = \mathbf{V}\omega$  and

$$\sigma_D^2 = \omega_D' \mathbf{V} \omega_D = m \omega_D' (\overline{\mathbf{r}} - r_f \mathbf{e}) = m r_D - m r_f$$

we have

$$\overline{\mathbf{r}} - r_f \mathbf{e} = \frac{r_D - r_f}{\sigma_D^2} \operatorname{Cov}(\mathbf{r}, r_D)$$

Denote  $\frac{\mathrm{Cov}(\mathbf{r},r_D)}{\sigma_D^2}=\beta_D$ , we have

$$\overline{\mathbf{r}} - r_f \mathbf{e} = \beta_D (r_D - r_f)$$

Similar results also holds for any portfolio  $\overline{r}_p$  in the MVF:

$$\overline{\mathbf{r}} - \overline{r}_q \mathbf{e} = \beta_p (\overline{r}_p - \overline{r}_q)$$

It's clear in the view of every portfolio  $\overline{r}_p$  is also a tangency portfolio by selecting proper  $r_f$ . One can also check it in a dirty way:

**Proof** Suppose  $r_p$  and  $r_q$  both in the MVF without risk-free asset, recall

$$\omega_p' \mathbf{V} \omega_q = \frac{1}{\delta} + \frac{\delta(\overline{r}_p - \frac{\alpha}{\delta})(\overline{r}_q - \frac{\alpha}{\delta})}{\delta \xi - \alpha^2}$$

If the covariance is 0, we have

$$\overline{r}_q = \frac{\alpha}{\delta} - \frac{\delta \xi - \alpha^2}{\delta^2 (\overline{r}_p - \alpha/\delta)}$$

Then

$$\begin{split} \overline{\mathbf{r}} - \overline{r}_q \mathbf{e} &= \overline{\mathbf{r}} - (\frac{\alpha}{\delta} - \frac{\delta \xi - \alpha^2}{\delta^2 (\overline{r}_p - \alpha/\delta)}) \mathbf{e} \\ &= \frac{1}{\delta^2 (\overline{r}_p - \alpha/\delta)} (\delta^2 (\overline{r}_p - \alpha/\delta)) (\overline{\mathbf{r}} - (\frac{\alpha}{\delta} - \frac{\delta \xi - \alpha^2}{\delta^2 (\overline{r}_p - \alpha/\delta)}) \mathbf{e}) \\ &= \frac{1}{\delta^2 (\overline{r}_p - \alpha/\delta)} (\overline{\mathbf{r}} (\delta^2 (\overline{r}_p - \alpha/\delta)) - (\alpha \delta (\overline{r}_p - \alpha/\delta) - (\delta \xi - \alpha^2)) \mathbf{e}) \\ &= \frac{1}{\delta^2 (\overline{r}_p - \alpha/\delta)} (\overline{\mathbf{r}} (\delta^2 (\overline{r}_p - \alpha/\delta)) - (\alpha \delta \overline{r}_p - \delta \xi) \mathbf{e} \\ &= \frac{(\delta^2 \overline{r}_p \overline{\mathbf{r}} - \alpha \delta \overline{\mathbf{r}}) - (\alpha \delta \overline{r}_p - \delta \xi) \mathbf{e}}{\delta^2 (\overline{r}_p - \alpha/\delta)} \\ &= \frac{(\delta \overline{r}_p - \alpha) \overline{\mathbf{r}} - (\alpha \overline{r}_p - \xi) \mathbf{e}}{\delta (\overline{r}_p - \alpha/\delta)} \end{split}$$

On the other hand:

$$\beta_{p} = \frac{\mathbf{V}\omega_{\mathbf{p}}}{\omega_{p}'\mathbf{V}\omega_{p}}$$

$$= \frac{1}{\omega_{p}'\mathbf{V}\omega_{p}}(\lambda_{p}\overline{\mathbf{r}} + \gamma\mathbf{e})$$

$$= \frac{1}{\omega_{p}'\mathbf{V}\omega_{p}}(\frac{\xi\mathbf{e} - \alpha\overline{\mathbf{r}}}{\delta\xi - \alpha^{2}} + \frac{-\alpha\mathbf{e} + \delta\overline{\mathbf{r}}}{\delta\xi - \alpha^{2}}\overline{r}_{p})$$

$$= \frac{1}{\omega_{p}'\mathbf{V}\omega_{p}}(\frac{(\delta\overline{r}_{p} - \alpha)\overline{\mathbf{r}} - (\alpha\overline{r}_{p} - \xi)\mathbf{e}}{\Delta})$$

Then it's remain to show that

$$(\overline{r}_p - \overline{r}_q)\delta(\overline{r}_p - \alpha/\delta) = \omega' \mathbf{V}\omega\Delta$$

It's clear since

$$\omega' \mathbf{V} \omega \Delta = \sigma_p^2 \Delta = \frac{\Delta}{\delta} + \delta (\overline{r}_p - \frac{\alpha}{\delta})^2$$

and

$$(\overline{r}_p - \overline{r}_q)\delta(\overline{r}_p - \alpha/\delta) = ((\overline{r}_p - \frac{\alpha}{\delta}) + \frac{\delta\xi - \alpha^2}{\delta^2(\overline{r}_p - \alpha/\delta)})\delta(\overline{r}_p - \alpha/\delta)$$
$$= \frac{\Delta}{\delta} + \delta(\overline{r}_p - \frac{\alpha}{\delta})^2$$

#### **1.2 CAPM**

In capital market equilibrium, the market portfolio is tangecy portfolio  $r_D = r_m$ , then

$$\overline{\mathbf{r}} - r_f \mathbf{e} = \beta_m (r_m - r_f)$$

where

$$\beta_m = \begin{bmatrix} \frac{\operatorname{Cov}(r_1, r_m)}{\sigma_m^2} \\ \frac{\operatorname{Cov}(r_2, r_m)}{\sigma_m^2} \\ \vdots \\ \frac{\operatorname{Cov}(r_n, r_m)}{\sigma_n^2} \end{bmatrix}$$

this equation is called **Sharpe-Lintner CAPM**.  $r_m - r_f$  is called **market risk premium** and  $\frac{r_m - r_f}{\sigma_m}$  is called **market sharpe ratio**. Translate it from vector form, we get the **Security Market Line**:

$$r_i - r_f = \beta_{i,m}(r_m - r_f)$$

#### 1.2.1 Realized return

Now consider both  $r_i$  and  $r_m$  is random variable, let  $\epsilon$  be a random vector with zero expection and zero covariance with  $r_i$  and  $r_m$ , then

$$r_i - r_f = \beta_{i,m}(r_m - r_f) + \epsilon_i$$

This is a regression equation, if one include an intercept, then the model

$$r_i - r_f = \alpha_i + \beta_{i,m}(r_m - r_f) + \epsilon_i$$

is called **market model**, such  $\alpha$  is called **Jensen's alpha**.

#### 1.2.2 Variance decomposition

Decomposition the variance as:

$$\operatorname{Var}(r_i) = \underbrace{\beta_i \sigma_m^2 + \operatorname{Var}(\epsilon_i)}_{\text{Systematic risk}} + \underbrace{\operatorname{Var}(\epsilon_i)}_{\text{Idiosyncratic risk}}$$

The  $R^2$  is just the proportion of systematic risk

$$R^2 = \frac{\beta_i^2 \sigma_m^2}{\beta_i^2 \sigma_m^2 + \sigma^2}$$

since Fraction of variance unexplained.

#### 1.2.3 Testing CAPM

Suppose we run time series regressions for each of the n risky assets

$$\mathbf{r_t^e} = \alpha + \beta r_{m.t}^e + \nu_t$$

where  $\alpha$ ,  $\mathbf{r_t^e}$ ,  $\beta$ ,  $\nu_t$  are  $n \times 1$  vector and  $r_{m,t}^e$  is scalar.

By the discussion above,  $\alpha = \mathbf{0}$  when CAPM holds. Assume  $\{\nu_t\}_{t=1}^T$  i.i.d with  $N(0, \Sigma)$ , we have  $\mathbf{r_t^e} \mid r_{m,t}^e \sim N(\alpha + \beta r_{m,t}^e, \Sigma)$ .

Hence the p.d.f is

$$f(\mathbf{r}_t^e) = (2\pi)^{-n/2} |\Sigma|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2} (\mathbf{r}_t^e - \alpha - \beta r_{m,t}^e)' \Sigma^{-1} (\mathbf{r}_t^e - \alpha - \beta r_{m,t}^e)\right\}$$

By the indepedence, from t=1 to t=T, the joint p.d.f is  $L=\prod_{t=1}^T f(\mathbf{r}_t^e)=$ .

$$\log L = \sum_{t=1}^{T} \log f(\mathbf{r_t^e}) = -\frac{-nT}{2} \ln(2\pi) - \frac{T}{2} \ln|\Sigma| - \frac{1}{2} \sum_{t=1}^{T} (\mathbf{r_t^e} - \alpha - \beta r_{m,t}^e)' \Sigma^{-1} (\mathbf{r_t^e} - \alpha - \beta r_{m,t}^e)$$

MLE for  $(\alpha, \beta, \Sigma)$  is found by maximize  $\log L$ , W.r.t.  $\beta$ , it's the same as minimize

$$\sum_{t=1}^{T} (\mathbf{r_t^e} - \alpha - \beta r_{m,t}^e)' \Sigma^{-1} (\mathbf{r_t^e} - \alpha - \beta r_{m,t}^e)$$

FOC with  $\beta$  and recall  $\frac{\partial \mathbf{x}' \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = (\mathbf{A} + \mathbf{A}') \mathbf{x}, \frac{\partial \mathbf{f}}{\partial \mathbf{X}} = \mathbf{A}' \frac{\partial \mathbf{f}}{\partial \mathbf{A} \mathbf{X} \mathbf{B}} \mathbf{B}'$ 

$$\begin{split} \frac{\partial \log L}{\partial \beta} &= \sum_{t=1}^{T} (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e})' \Sigma^{-1} (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e}) \\ &= \sum_{t=1}^{T} \frac{\partial (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e})' \Sigma^{-1} (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e})}{\partial \beta} \\ &= \sum_{t=1}^{T} (\frac{\partial (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e})' \Sigma^{-1} (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e})}{\partial \mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e}} \frac{\partial \mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e}}{\partial \beta}) \\ &= \sum_{t=1}^{T} (-2r_{m,t}^{e} \Sigma^{-1} (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e})) = 0 \end{split}$$

since  $\Sigma^{-1}$  is clearly invertible,  $\sum_{t=1}^T r_{m,t}^e(\mathbf{r_t^e} - \hat{\alpha} - \hat{\beta}r_{m,t}^e) = \mathbf{0}$ Similarly, FOC w.r.t  $\alpha$ , we get

$$\sum_{t=1}^{T} \mathbf{r_t^e} - \hat{\alpha} - \hat{\beta} r_{m,t}^e = \mathbf{0}$$

By the truth  $\frac{\partial |\mathbf{X}|}{\mathbf{X}} = |\mathbf{X}|\mathbf{X}'^-$  and  $\frac{\partial \mathbf{a}'\mathbf{X}^-\mathbf{b}}{\partial \mathbf{X}} = -\mathbf{X}'^-\mathbf{a}\mathbf{b}'\mathbf{X}'^-$ , we have

$$\frac{\partial \log L}{\partial \Sigma} = \sum_{t=1}^{T} \left(-\frac{\Sigma^{-}}{2} - +\frac{\Sigma^{-}}{2} (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e}) (\mathbf{r_{t}^{e}} - \alpha - \beta r_{m,t}^{e})' \Sigma^{-}\right)$$

thus have

$$\hat{\Sigma} = \sum_{t=1}^{T} (\mathbf{r_t^e} - \hat{\alpha} - \hat{\beta}r_{m,t}^e) (\mathbf{r_t^e} - \hat{\alpha} - \hat{\beta}r_{m,t}^e)' / T$$

Suppose

$$\mathbf{r} = \begin{bmatrix} \mathbf{r_1^e}' \\ \mathbf{r_2^e}' \\ \mathbf{r_3^e}' \\ \vdots \\ \mathbf{r_T^e}' \end{bmatrix}, \mathbf{r_m} = \begin{bmatrix} r_{m,1}^e \\ r_{m,2}^e \\ r_{m,3}^e \\ \vdots \\ r_{m,T}^e \end{bmatrix}$$

Now

$$(\mathbf{r}' - \hat{\alpha}\mathbf{e}' - \hat{\beta}\mathbf{r}_{\mathbf{m}}')\mathbf{r}_{\mathbf{m}} = \mathbf{0}$$
$$(\mathbf{r}' - \hat{\alpha}\mathbf{e}' - \hat{\beta}\mathbf{r}_{\mathbf{m}}')\mathbf{e} = \mathbf{0}$$

which leads to a linear equation

$$\begin{bmatrix} \mathbf{e'r_m} & \mathbf{r'_mr_m} \\ \mathbf{e'e} & \mathbf{r'_me} \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \mathbf{r'r_m} \\ \mathbf{r'e} \end{bmatrix}$$

hence

$$\begin{cases} \alpha = \mathbf{r'r_m}(\mathbf{r'_m}\mathbf{e} - \mathbf{e'e})/(\mathbf{r'_m}\mathbf{e}\mathbf{e'r_m} - \mathbf{e'er'_m}\mathbf{r_m}) \\ \beta = \mathbf{r'e}(\mathbf{r'_m}\mathbf{r_m} - \mathbf{e'r_m}) \end{cases}$$