

8 General filtering

expected returns

$$p = P\bar{r} + e$$

model P $m \times n$ matrix

\bar{r} n -dimensional vector

p and e are m -dimensional vectors

vector p - set of observation values

vector e - a vector of error having zero mean

Q - error vector's covariance matrix

the best (minimum variance) estimate of \bar{r}

$$\hat{\bar{r}} = (P^T Q^{-1} P)^{-1} P^T Q^{-1} p$$

a) $p = \bar{r} + e$

which means $P = 1 \therefore P^T = 1$

$$\hat{\bar{r}} = (1 Q^{-1} 1)^{-1} (1) Q^{-1} p$$

$$= Q Q^{-1} p$$

$$\hat{\bar{r}} = p$$

b) two uncorrelated measurements with values p_1 and p_2 , having variances σ_1^2 and σ_2^2

$$Q = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} \therefore Q^{-1} = \frac{1}{\sigma_1^2 \sigma_2^2} \begin{bmatrix} \sigma_2^2 & 0 \\ 0 & \sigma_1^2 \end{bmatrix}$$

we let $p = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \therefore P^T = [1 \ 1]$

$$\hat{\bar{r}} = \left([1 \ 1] \frac{1}{\sigma_1^2 \sigma_2^2} \begin{bmatrix} \sigma_2^2 & 0 \\ 0 & \sigma_1^2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right)^{-1} [1 \ 1] \frac{1}{\sigma_1^2 \sigma_2^2} \begin{bmatrix} \sigma_2^2 & 0 \\ 0 & \sigma_1^2 \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \end{bmatrix}$$

$$= \left(\frac{1}{\sigma_1^2 \sigma_2^2} [\sigma_2^2 \ \sigma_1^2] \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right)^{-1} [\sigma_2^2 \ \sigma_1^2] \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} \frac{1}{\sigma_1^2 \sigma_2^2}$$

$$= \left(\frac{1}{\sigma_1^2 \sigma_2^2} (\sigma_2^2 + \sigma_1^2) \right)^{-1} \frac{1}{\sigma_1^2 \sigma_2^2} (p_1 \sigma_2^2 + p_2 \sigma_1^2)$$

$$\hat{\bar{r}} = \left(\frac{p_1}{\sigma_1^2} + \frac{p_2}{\sigma_2^2} \right) \left(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} \right)^{-1}$$

2. APT Factors

Two stocks are believed to satisfy the two-factor model

$$r_1 = a_1 + 2f_1 + f_2$$

$$r_2 = a_2 + 3f_1 + 4f_2$$

$$r_f = 10\%$$

$$\bar{r}_1 = 15\%$$

$$\bar{r}_2 = 20\%$$

$$\bar{r}_1 = \lambda_0 + 2\lambda_1 + \lambda_2$$

$$\bar{r}_2 = \lambda_0 + 3\lambda_1 + 4\lambda_2$$

From Simple APT

$$\bar{r}_i = \lambda_0 + \sum_{j=1}^n b_{ij} \lambda_j$$

for $i=1, 2, \dots, n$

$$\lambda_0 = 0.10$$

$$0.15 = 0.10 + 2\lambda_1 + \lambda_2 \quad \text{--- (1)}$$

$$0.20 = 0.10 + 3\lambda_1 + 4\lambda_2 \quad \text{--- (2)}$$

$$0.60 = 0.40 + 8\lambda_1 + 4\lambda_2$$

$$0.20 = 0.10 + 3\lambda_1 + 4\lambda_2 \quad \text{---}$$

$$0.40 = 0.30 + 5\lambda_1$$

$$0.10 = 5\lambda_1$$

$$\lambda_1 = 0.02$$

$$0.20 = 0.10 + 3(0.02) + 4\lambda_2$$

$$0.20 - 0.16 = 4\lambda_2$$

$$\lambda_2 = 0.01$$

$$\therefore, \lambda_0 = 0.10$$

$$\lambda_1 = 0.02$$

$$\lambda_2 = 0.01$$

4. Variance estimate

Let r_i , for $i = 1, 2, \dots, n$ be independent samples of a return r of mean \bar{r} and variance σ^2 .

Define the estimates $\hat{r} = \frac{1}{n} \sum_{i=1}^n r_i$

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (r_i - \hat{r})^2$$

Show that $E(s^2) = \sigma^2$

$$\bar{r} = E\left(\frac{1}{n} \sum_{i=1}^n r_i\right)$$

$$\begin{aligned} E(s^2) &= E\left(\frac{1}{n-1} \sum_{i=1}^n (r_i - \hat{r})^2\right) \\ &= E\left(\frac{1}{n-1} \sum_{i=1}^n \left(r_i - \frac{1}{n} \sum_{j=1}^n r_j\right)^2\right) \\ &= E\left(\frac{1}{n-1} \sum_{i=1}^n \left((r_i - \bar{r}) - \frac{1}{n} \sum_{j=1}^n (r_j - \bar{r})\right)^2\right) \end{aligned}$$

we know, $E\left[\frac{1}{n} \sum_{i=1}^n (r_i - \bar{r})\right]^2 = \frac{1}{n} \sigma^2$

$$\begin{aligned} &= \frac{1}{n-1} E\left(\sum_{i=1}^n \left(\left(\frac{n-1}{n}\right)(r_i - \bar{r}) - \frac{1}{n} \sum_{j \neq i} (r_j - \bar{r})\right)^2\right) \\ &= \frac{1}{n-1} \left(\left(\frac{n-1}{n}\right)^2 + \frac{n-1}{n^2}\right) n \sigma^2 \\ &= \frac{n \sigma^2}{n-1} \left(\frac{(n-1)^2 + (n-1)}{n^2}\right) = \frac{n \sigma^2}{n-1} \cdot \frac{(n-1)(n-1+1)}{n^2} = \sigma^2 \cdot \frac{n}{n-1} \end{aligned}$$

$$E(s^2) = \sigma^2$$