

ECM 512 Lec 9

Note Title

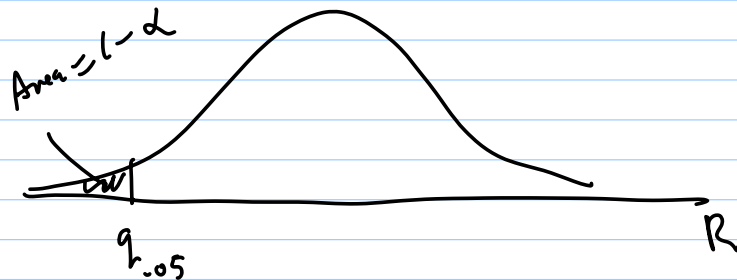
4/26/2010

VaR

$L = \text{losses}$



$R = \text{returns}$, $L = -R \cdot W_0$



Multivariate GARCH: CCC Model

$$\Sigma_x = \begin{bmatrix} \sigma_x^{11} & \sigma_x^{12} & \dots & \sigma_x^{1K} \\ & \sigma_x^{22} & & \\ & & \ddots & \\ & & & \sigma_x^{KK} \end{bmatrix}$$

Constant correlations

$$= \begin{bmatrix} (\sigma_x^{11})^{1/2} & 0 & & \\ & \ddots & & \\ 0 & & (\sigma_x^{KK})^{1/2} \end{bmatrix} \rightarrow \begin{bmatrix} 1 & \rho_{12} & \dots & \rho_{1K} \\ & \ddots & & \\ & & 1 & \\ \rho_{K1} & & & \ddots \end{bmatrix}$$

Univariate GARCH Models

$$\begin{bmatrix} (\sigma_t^{11})^{1/2} & 0 & \\ & \ddots & \\ 0 & & (\sigma_t^{KK})^{1/2} \end{bmatrix}$$

time varying volatility

$$\sigma_t^{12} = \sigma_t^{11} \cdot \rho_{12}$$

time invariant correlation

time varying conditional covariance

Aside

Factor Models

$$r_{jt} = \beta_{j0} r_{ft} + \beta_{jm} f_{mt} + u_{jt} \quad \begin{matrix} t=1, \dots, T \\ j=1, \dots, K \\ m=1, \dots, M \end{matrix}$$

$m \ll k \quad (\text{e.g. } M=2 \text{ or } 3)$

$$f_{jt} = \text{common factors} \quad j=1, \dots, M$$
$$\sim \text{GARN}(H(1,1))$$

$$u_{jt} = \text{residual} \sim \text{iid}(0, \sigma_u^2)$$

Method 2: use observable portfolios as factors

e.g. CAPM

$$r_{jt} = \beta_j r_{mt} + u_{jt}$$

r_{mt} = return on mkt index.

$$\text{Var}(r_{jt} | \mathcal{I}_{t-1}) = \beta_j^2 \text{Var}(r_{mt} | \mathcal{I}_{t-1})$$

$$+ \text{var}(u_{jt} | I_{t-1})$$

$$+ 2 \text{cov}(r_{mt}, u_{jt} | I_{t-1})$$

Assume: $\text{var}(u_{jt} | I_{t-1}) = \sigma_{ju}^2$ constant

$$\text{cov}(r_{mt}, u_{jt} | I_{t-1}) = 0$$

β_j is constant as well

Method 2: Principle Components

$$\tilde{r}_t \sim (0, \Sigma) \quad , \quad \tilde{r}_t = (r_{1t}, \dots, r_{kt})'$$

$100 \times 1 \qquad 100 \times 100$

$$\text{cov}(\tilde{r}_t) = \Sigma = \Lambda \Delta \Lambda = \text{spectral decomposition}$$

$100 \times 100 \quad 100 \times 100 \quad 100 \times 100 \quad 100 \times 100$

Δ = diagonal matrix with eigen-values
(sorted from largest to smallest)

$$\Sigma = \begin{bmatrix} \Delta_1 & & & 0 \\ & \Delta_2 & & \\ & & \ddots & \\ 0 & & & \Delta_{100} \end{bmatrix}$$

$$\Delta_1 > \Delta_2 > \dots > \Delta_{100}$$

$$\Lambda = \begin{bmatrix} \underbrace{\lambda_1}_{100 \times 1} & \dots & \underbrace{\lambda_{100}}_{100 \times 1} \end{bmatrix}_{100 \times 100} = \text{orthogonal matrix of eigenvectors}$$

$$\underbrace{\lambda_i}_{\sim} = \begin{bmatrix} \lambda_{i1} \\ \vdots \\ \lambda_{i,100} \end{bmatrix}$$

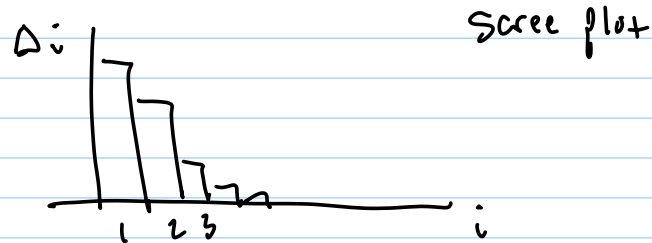
$$\Lambda \text{ orthogonal} \Rightarrow \Lambda = \Lambda' = \Lambda^{-1}$$

$$\Rightarrow \|\lambda_i\|^2 = 1 \text{ and } \lambda_i' \lambda_j = 0$$

$$\lambda_i = \text{principle components } i=1, \dots, 100$$

$$\Sigma = \Lambda \Delta \Lambda' = \sum_{i=1}^{100} \underbrace{\Delta_i}_{\text{scalar}} \underbrace{\lambda_i \lambda_i'}_{K \times 1 \text{ and } 1 \times K}$$

If there is a factor structure with m common factors then exactly m eigenvalues will be non-zero and $k-m$ eigenvalues will be zero.



$$f_{1t} = \lambda_1' r_t = \sum_{i=1}^k \lambda_{1i} \cdot r_{it}$$

$$f_{2t} = \lambda_2' r_t = \sum_{i=1}^k \lambda_{2i} r_{it}$$

f_{1t} is uncorrelated with f_{2t}

1st principle component f.e. solves

$$\max_w w' \Sigma w \quad \text{s.t.} \quad w'w = 1$$

2nd principle component

$$\max_x x' \Sigma x \quad \text{s.t.} \quad x'x = 1 \quad \text{and} \quad x'w = 0$$

$$\Sigma_x = A_0 + A_1 \odot G_x G_x' + h_1 \odot \Sigma_{x-1}$$

$$G_x = \Sigma_x^{1/2} z_x, \quad z_x \sim N(0, I_K)$$

$$G_x G_x' = \Sigma_x^{1/2} z_x z_x' \Sigma_x^{1/2}$$

$$\begin{aligned} E[G_x G_x' | \Sigma_{x-1}] &= \Sigma_x^{1/2} E[z_x z_x' | \Sigma_x] \Sigma_x^{1/2} \\ &= \Sigma_x^{1/2} \cdot I_K \Sigma_x^{1/2} \\ &= \Sigma_x \end{aligned}$$

$$r_t = \beta_1 f_{1t} + \dots + \beta_m f_{mt} + u_t$$

PCA estimate factors by eigen-vectors

$$r_t = \beta_1 \hat{f}_{1t} + \dots + \beta_m \hat{f}_{mt} + u_t$$

↑
estimated
factor from principal
components analysis

$$\hat{f}_{it} = \hat{\Delta}_i' r_t$$

$$E[\sigma_t^4] = ?$$

$$\text{var}(x) = E[x^2] - E[x]^2$$

$$x = \sigma_t^2$$

$$\text{var}(\sigma_t^2) = E[\sigma_t^4] - E[\sigma_t^2]^2$$

$$\Rightarrow E[\sigma_t^4] = \text{var}(\sigma_t^2) + E[\sigma_t^2]^2$$