

## ML Estimation

Example: Multiplicative Heteroskedasticity

$$y_i = \gamma_i^T \beta + \mu_i \quad \mu_i \sim N(0, \sigma_i^2)$$

$$\sigma_i^2 = \exp\{z_i^T \alpha\}$$

$\gamma_i^T$   $1 \times k$  exogenous variables.

$z_i^T$   $1 \times s$  exogenous variables.

$$z_i = \ln \sigma_i^2 \Rightarrow \sigma_i^2 = \sigma^2 \exp\{z_i^T \alpha\}$$

$$Q \equiv \ln(L) = -\frac{n}{2} \ln(2\pi) - \frac{1}{2} \sum_{i=1}^n \ln(\sigma_i^2) - \frac{1}{2} \sum_{i=1}^n \frac{\mu_i^2}{\sigma_i^2}$$

$$Q = -\frac{n}{2} \ln(2\pi) - \frac{1}{2} \sum_{i=1}^n z_i^T \alpha - \frac{1}{2} \sum_{i=1}^n \frac{(y_i - \gamma_i^T \beta)^2}{\exp\{z_i^T \alpha\}}$$

$$\frac{\partial Q}{\partial \beta} = \sum_{i=1}^n \gamma_i (y_i - \gamma_i^T \beta) / \exp\{z_i^T \alpha\} = 0$$

$$\begin{aligned} \frac{\partial Q}{\partial \alpha} &= -\frac{1}{2} \sum_{i=1}^n z_i + \frac{1}{2} \sum_{i=1}^n z_i (y_i - \gamma_i^T \beta)^2 / \exp\{z_i^T \alpha\} \\ &= \frac{1}{2} \sum_{i=1}^n z_i \left( \frac{(y_i - \gamma_i^T \beta)^2}{\exp\{z_i^T \alpha\}} - 1 \right) = 0 \end{aligned}$$

$$\frac{\partial^2 \ell}{\partial \beta \partial \beta^T} = - \sum_{i=1}^n \frac{1}{\exp\{z_i^T \alpha\}} \gamma_i \gamma_i^T = -X^T \Omega^{-1} X$$

$$\frac{\partial^2 \ell}{\partial \beta \partial \alpha^T} = - \sum_{i=1}^n \frac{(y_i - \gamma_i^T \beta)}{\exp\{z_i^T \alpha\}} \gamma_i z_i^T$$

$$\frac{\partial^2 \ell}{\partial \alpha \partial \alpha^T} = - \frac{1}{2} \sum_{i=1}^n \frac{(y_i - \gamma_i^T \beta)^2}{\exp\{z_i^T \alpha\}} z_i z_i^T$$

$$\text{Hessian} \begin{pmatrix} \beta \\ \alpha \end{pmatrix} = \begin{bmatrix} -X^T \Omega^{-1} X & - \sum_{i=1}^n \frac{y_i - \gamma_i^T \beta}{\exp\{z_i^T \alpha\}} \gamma_i z_i^T \\ & - \frac{1}{2} \sum_{i=1}^n \frac{(y_i - \gamma_i^T \beta)^2}{\exp\{z_i^T \alpha\}} z_i z_i^T \end{bmatrix}$$

$$-E[H] = \mathbb{I} \begin{pmatrix} \beta \\ \alpha \end{pmatrix} = \begin{bmatrix} -X^T \Omega^{-1} X & 0 \\ 0 & -\frac{1}{2} Z^T Z \end{bmatrix}$$

$$(1) E(y_i - \gamma_i^T \beta) = E[\mu_i | \gamma_i] = 0$$

$$(2) E\left(\frac{\mu_i^2}{\sigma_i^2} \mid \gamma_i, z_i\right) = 1$$

you can see that the Information matrix is much simpler than Hessian.

$$\theta_{j+1} = \theta_j - H_j^{-1} g_j$$

The method of scoring uses  $I_j$  instead of  $-H_j$ . It is block diagonal, which simplifies computation.