

①

16 April 03

Regression in the complex case.

$$Y_j = \beta x_j + \epsilon_j, \quad j = 1, \dots, n$$

$x$ 's fixed

$$\epsilon_j: \text{IN}^c(0, \sigma^2)$$

$$EY_j = \beta x_j \quad \text{var } Y_j = \sigma_j^2$$

$$\begin{aligned} \text{LSE } \hat{\beta} &= \frac{\sum_j Y_j \bar{x}_j}{\sum_j |x_j|^2} \\ &= \beta + \frac{\sum_j \epsilon_j \bar{x}_j}{\sum_j |x_j|^2} \end{aligned}$$

$$\hat{\beta} \sim N^c(\beta, \sigma^2 / \sum_j |x_j|^2)$$

$$\begin{aligned} \hat{\sigma}^2 &= \frac{\sum_j |Y_j - \hat{\beta} x_j|^2}{n-1} \\ &\sim \sigma^2 \chi_{2(n-1)}^2 / 2(n-1) \end{aligned}$$

$$\hat{\beta} \perp \hat{\sigma}^2$$

$$1 - |\hat{R}|^2 = \frac{\sum_j |Y_j - \hat{\beta} x_j|^2}{\sum_j |Y_j|^2}$$

$$0 \leq |\hat{R}|^2 \leq 1$$

(2)

16 April 2003

Cross-spectral analysis

Separate regression at each frequency

Model

$$Y(t) = \mu + \sum_u a(u)X(t-u) + \epsilon(t) \quad (*)$$

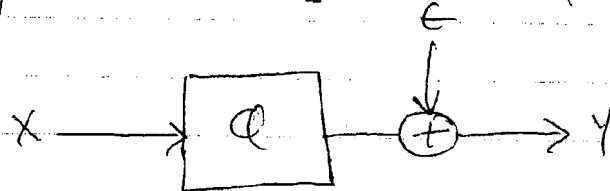
{ $\epsilon(\cdot)$ } 0 mean, stationary

$$EY(t) = \mu + \sum_u a(u)X(t-u)$$

nonstationary

{ $a(\cdot)$ } impulse response

$$A(\lambda) = \sum_u e^{-i\lambda u} a(u) \quad \underline{\text{transfer function}}$$

 $|A(\lambda)|$ : gain       $\arg A(\lambda)$ : phase
System identification

Estimate { $a(\cdot)$ }, { $A(\cdot)$ },  $f_{\epsilon\epsilon}(\lambda)$  from  
 data  $(X(t), Y(t)), t=0, \dots, T-1$

(3)

16 April 03

Pick  $n$  distinct  $\frac{2\pi j}{T}$  near  $\lambda$

FT (\*)

$$d_y^T(\lambda) \approx A(\lambda) d_x^T(\lambda) + d_\epsilon^T(\lambda)$$

$$d_y^T\left(\frac{2\pi j}{T}\right) \approx A(\lambda) d_x^T\left(\frac{2\pi j}{T}\right) + d_\epsilon^T\left(\frac{2\pi j}{T}\right)$$

cp.  $y_j = \beta x_j + \epsilon_j$

CLT for  $d_\epsilon^T\left(\frac{2\pi j}{T}\right)$ :  $IN(0, 2\pi T f_{\epsilon\epsilon}(\lambda))$

$$y_j \approx d_y^T\left(\frac{2\pi j}{T}\right); \quad x_j \approx d_x^T\left(\frac{2\pi j}{T}\right); \quad \epsilon_j \approx d_\epsilon^T\left(\frac{2\pi j}{T}\right)$$

$$\beta \approx A(\lambda); \quad \sigma^2 \approx 2\pi T f_{\epsilon\epsilon}(\lambda)$$

(4)

16 April 03

$$A^T(\lambda) = \frac{\sum_j d_Y^T\left(\frac{2\pi j}{T}\right) d_X^T\left(\frac{2\pi j}{T}\right)}{\sum_j |d_X^T\left(\frac{2\pi j}{T}\right)|^2}$$

$$\sim N^c\left(A(\lambda), 2\pi T f_{ee}(\lambda) / \sum_j |d_X^T\left(\frac{2\pi j}{T}\right)|^2\right)$$

II

$$f_{ee}^T(\lambda) = \frac{\sum_j |d_Y^T\left(\frac{2\pi j}{T}\right) - A^T(\lambda) d_X^T\left(\frac{2\pi j}{T}\right)|^2}{2\pi T (n-1)}$$

$$\sim f_{ee}(\lambda) \chi_{2(n-1)}^2 / 2(n-1)$$

$$\sum_j |d_X^T\left(\frac{2\pi j}{T}\right)|^2 \sim 2\pi T n f_{xx}^T(\lambda)$$

$$|R_{yx}^T(\lambda)|^2 = 1 - f_{ee}^T(\lambda) / f_{yy}^T(\lambda)$$

$$= |f_{yx}^T(\lambda)|^2 / f_{xx}^T(\lambda) f_{yy}^T(\lambda)$$

$$E |R_{yx}^T(\lambda)|^2 \sim 1/(n-1)$$

$$100\% \text{ pt } 1 - (1-\alpha)^{1/(n-1)}$$

$$f_{ee}^T(\lambda) = [1 - |R_{yx}^T(\lambda)|^2] f_{yy}^T(\lambda)$$

⑤

16 April 03

$$f_{YX}^T(\omega) = \frac{1}{2\pi T} \frac{1}{m} \sum_j d_Y^T\left(\frac{2\pi j}{T}\right) \overline{d_X^T\left(\frac{2\pi j}{T}\right)}$$

Plot  $|R_{YX}^T(\omega)|^2$

$\log |A^T(\omega)|$

$\arg A^T(\omega)$

$$AV(\log |A^T(\omega)|) \sim \frac{1}{2m} [ |R_{YX}^T(\omega)|^{-2} - 1 ]$$

See DRB book Chapter 6

$m$  can be  $m_T \rightarrow \infty$ ,  $\frac{m_T}{T} \rightarrow 0$

(6)

16 April 03

## Splitting approach

Suppose  $T = LV$  having in mind  
 $V \rightarrow \infty$ ,  $L$  fixed

Let  $j = 1, \dots, L$

Compute

$$g_j = d_y^v(\lambda, j) = \sum_{n=0}^{v-1} e^{-i\lambda n} \gamma(n+j-1, V)$$

$$x_j = d_x^v(\lambda, j) =$$

Better for higher-order spectra

$L$  can be  $L_T$

16 April 03

## Importance of pre filtering

$$Y(t) = \alpha X(t-\tau) + \epsilon(t)$$

$$\begin{aligned} E f_{YX}^T(\omega) &\approx \frac{1}{2\pi T} \frac{1}{n} \sum_j A\left(\frac{2\pi j}{T}\right) |d_X^T\left(\frac{2\pi j}{T}\right)|^2 \\ &\approx \frac{1}{2\pi T} \frac{1}{n} \sum_j e^{i\frac{2\pi j\tau}{T}} |d_X^T\left(\frac{2\pi j}{T}\right)|^2 \end{aligned}$$