

## Canonical Correlations

$$X = \begin{pmatrix} X^1 \\ X^2 \end{pmatrix}_{\frac{m}{m}} \begin{matrix} m_1 \text{ components} \\ " \\ \text{TOTAL} \end{matrix} ; \mu = \begin{pmatrix} \mu^1 \\ \mu^2 \end{pmatrix}; \Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$$

Def

$$z = \alpha' X^1; w = \beta' X^2$$

with

$$g = \frac{\text{Cov}(z, w)}{\sqrt{\text{Var}(z) \text{Var}(w)}} = \frac{\text{Cov}(\alpha' X^1, \beta' X^2)}{\sqrt{[\alpha' \Sigma_{11} \alpha][\beta' \Sigma_{22} \beta]}}$$

If  $\alpha$  and  $\beta$  are chosen such as to maximize  $g$ , then  $g$  is termed the (first) canonical correlation between  $X^1$  and  $X^2$ , while  $z$  and  $w$  are called the (first set of) canonical variables associated to  $X^1$  and  $X^2$ .

Canonical correlations and variables are the solution of

$$\boxed{\text{Max}_{\alpha, \beta} \frac{\alpha' \Sigma_{12} \beta}{\sqrt{(\alpha' \Sigma_{11} \alpha)(\beta' \Sigma_{22} \beta)}}}$$

This maximized 1) homogeneous of degree zero, then we are faced with a scale problem. To eliminate this indeterminacy we impose

$$\alpha' \Sigma_{11} \alpha = 1 \text{ and } \beta' \Sigma_{22} \beta = 1$$

The mathematical form of the canonical correlation problem is

$$L = \alpha' \Sigma_{12} \beta + \frac{1}{2} \lambda_1 (1 - \alpha' \Sigma_{11} \alpha) + \frac{1}{2} \lambda_2 (1 - \beta' \Sigma_{22} \beta)$$

F.O.C.

$$\frac{\partial L}{\partial \alpha}$$

$$= \Sigma_{12} \beta - \lambda_1 \Sigma_{11} \alpha = 0 \Rightarrow \begin{cases} \text{The solution must} \\ \text{ satisfy} \end{cases}$$

$$\frac{\partial L}{\partial \beta}$$

$$= 0 \quad \lambda_1 = \lambda_2 \Rightarrow \begin{bmatrix} -\lambda \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\lambda \Sigma_{22} \end{bmatrix} \begin{pmatrix} \alpha \\ \beta \end{pmatrix} = 0$$

$$\frac{\partial L}{\partial \lambda_1}$$

$$= 0$$

This will have a non-trivial solution iff

$$\begin{vmatrix} -\lambda \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\lambda \Sigma_{22} \end{vmatrix} = 0.$$

How do we find the second set of canonical correlations?

$$L = \alpha' \Sigma_{12} \beta + \frac{1}{2} \lambda_1 (1 - \alpha' \Sigma_{11} \alpha) + \frac{1}{2} \lambda_2 (1 - \beta' \Sigma_{22} \beta) \\ + M_1 \underbrace{\alpha'_{(1)} \Sigma_{11} \alpha}_{''} + M_2 \underbrace{\beta'_{(1)} \Sigma_{22} \beta}_{''}$$

F.O.C.

The solution is again the vectors that satisfy

$$\begin{bmatrix} -\lambda \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\lambda \Sigma_{22} \end{bmatrix} \begin{pmatrix} \alpha \\ \beta \end{pmatrix} = 0$$

now linked to the second eigenvalue of  $\begin{vmatrix} -\lambda \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\lambda \Sigma_{22} \end{vmatrix} = 0$ .

## Proposition

$$X = \begin{pmatrix} X^1 \\ X^2 \end{pmatrix}; \quad M = \begin{pmatrix} M^1 \\ M^2 \end{pmatrix} \quad \text{and} \quad \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$$

The canonical correlations are obtained as the roots of

$$(*) \quad \begin{vmatrix} -\lambda \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\lambda \Sigma_{22} \end{vmatrix} = 0 \quad (\lambda^1, \lambda^2, \dots, \lambda^m)$$

while the canonical variables are obtained as the vectors that solve

$$\begin{bmatrix} -\lambda \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\lambda \Sigma_{22} \end{bmatrix} \begin{pmatrix} \alpha \\ \beta \end{pmatrix} = 0$$

## Some properties of the canonical correlations

- (1) They ought to be less than one
- (2) Their squares has an interpretation as a characteristic root of a certain positive semidefinite matrix

The determinant of a partitioned matrix

$$(*) \quad (-1)^{m_1 m_2} \lambda^{m_2 - m_1} |\Sigma_{22}| |\lambda^2 \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}| = 0$$

So (\*) has at least  $m_2 - m_1$  zero roots, and its nonzero roots are exactly the nonzero roots of

$$|\lambda^2 \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}| = 0$$

# Cointegration and Reduced Rank Regression

$$\Delta X_t = \alpha \beta' X_{t-1} + \sum_{i=1}^{K-1} \gamma_i \Delta X_{t-i} + \varepsilon_t, \quad t=1 \dots T$$

Regress  $\Delta X_t$  on  $\Delta X_{t-1}, \dots, \Delta X_{t-K+1} \rightarrow R_{\text{ct}}$

Regress  $X_{t-1}$  on  $\Delta X_{t-1}, \dots, \Delta X_{t-K+1} \rightarrow R_{1K}$

$$\text{Log } L(\alpha, \beta, \sigma) = -\frac{1}{2}T \log |\Sigma| - \frac{1}{2} \sum_{t=1}^T (\mathbf{R}_{\text{ct}} - \alpha \beta' \mathbf{R}_{1t})' \Sigma^{-1} (\mathbf{R}_{\text{ct}} - \alpha \beta' \mathbf{R}_{1t})$$

Define

$$S_{ij} = T^{-1} \sum_{t=1}^T \mathbf{R}_{it} \mathbf{R}_{jt}' \quad i, j = 0, 1$$

Note that for fixed  $\beta$

$$\hat{\alpha}(\beta) = S_{01} \beta (\beta' S_{11} \beta)^{-1} \quad \text{and}$$

$$\hat{\Sigma}(\beta) = S_{00} - S_{01} \beta (\beta' S_{11} \beta)^{-1} \beta' S_{10}$$

$$= S_{00} - \hat{\alpha}(\beta) (\beta' S_{11} \beta) \hat{\alpha}(\beta)'$$

$$L_{\max}^{-2} (\hat{\alpha}(\beta), \beta, \hat{\Sigma}(\beta)) = L_{\max}^{-2/T} (\beta) = |\hat{\Sigma}(\beta)| = |S_{00} - S_{01} \beta (\beta' S_{11} \beta)^{-1} \beta' S_{10}|$$

$$= |S_{00}| \frac{|\hat{\beta}' (S_{11} - S_{10} S_{00}^{-1} S_{01}) \hat{\beta}|}{|\hat{\beta}' S_{11} \hat{\beta}|} = |S_{00}| \prod_{i=1}^r (1 - \hat{\lambda}_i)$$

since by the choice of  $\hat{\beta}' S_{11} \hat{\beta} = I$ , as well as,  
 $\hat{\beta}' S_{10} S_{00}^{-1} S_{01} \hat{\beta} = \text{diag}(\hat{\lambda}_1, \dots, \hat{\lambda}_r)$

The likelihood ratio test of rank  $r$   
 vs  
 rank  $p$

$$Q(H(r) | H(p))^{-\frac{2}{T}} = \frac{|S_{00}| \prod_{i=1}^r (1 - \hat{\lambda}_i)}{|S_{00}| \prod_{i=1}^p (1 - \hat{\lambda}_i)}$$

$$-2 \log Q(H(r) | H(p)) = -T \sum_{i=r+1}^p \log (1 - \hat{\lambda}_i)$$

Theorem: Under the hypothesis

$$H(r): \Pi = \alpha \beta'$$

the ML estimator of  $\beta$  is found by the following procedure

(1) Solve

$$\lambda S_{11} - S_{10} S_{00}^{-1} S_{01} = 0$$

for the eigenvalues  $1 > \hat{\lambda}_1 > \dots > \hat{\lambda}_p > 0$

and eigenvector

$$\hat{V} = (\hat{v}_1, \dots, \hat{v}_p) \text{ which normalize}$$

$$\hat{V}' S_{11} \hat{V} = I$$

The cointegrating relations are estimated by

$$\hat{\beta} = (\hat{v}_1, \dots, \hat{v}_r),$$

and

$$L_{\max}^{-2/T}(H(r)) = |S_{00}| \prod_{i=1}^r (1 - \hat{\lambda}_i)$$

Theorem: Under hypothesis  $H_0: \beta = H\hat{\beta}$  we find the maximum likelihood estimator of  $\beta$  by reduced rank regression of  $\Delta X_t$  on  $H'X_{t-1}$

(corrected by lagged differences), that is, first we solve

$$(\lambda H'S_{11}H - H'S_{10}S_{00}'S_{01}H) = 0$$

for  $1 > d_1^* > \dots > d_s^* > 0$  and  $V = (v_1, \dots, v_s)$  which we normalize by  $V' H' S_{11} H V = I$ . Then choose

$$\hat{\beta} = (v_1, \dots, v_r) \text{ and } \hat{\beta} = H\hat{\beta}$$

and find the estimates of the remaining parameters by OLS for  $\beta = \hat{\beta}$ . Then

$$L_{\max}^{-2/T}(H_0) = |S_{00}| \prod_{i=1}^r (1 - \lambda_i^*)$$

and the likelihood ratio test  $Q(H_0|H(r))$  of the hypothesis  $H_0$  in  $H(r)$  is

$$-2 \log Q(H_0|H(r)) = T \sum_{i=1}^r \log \left\{ (1 - \lambda_i^*) / (1 - \hat{\lambda}_i) \right\}$$

which is asymptotically  $\chi^2$  with  $r(s-r)$ .