# Selecting the Cointegration Rank and the Form of the Intercept when the Time Trends are not cointegrated

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# 1.Introduction

- In this paper, we propose a procedure to test the cointegration rank, the number of lags and the form adopted by the deterministic terms of a multivariate dynamic system using an Information Criterion (IC).
- Extension of the paper "Selecting the rank of the cointegration space and the form of the intercept using an information criterion" By A. Aznar and M. Salvador (2002)
   Econometric Theory, 18, 926-947

### 2. Models

Consider the following four models

$$M_{3,r,k} : \Delta X_{t} = \alpha \beta' X_{t-1} + \mu_{0} + \alpha \rho_{1} t + \sum_{i=1}^{k-1} \Gamma_{i} \Delta X_{t-i} + \varepsilon_{t}$$

$$M_{2,r,k} : \Delta X_{t} = \alpha \beta' X_{t-1} + \mu_{0} + \sum_{i=1}^{k-1} \Gamma_{i} \Delta X_{t-i} + \varepsilon_{t}$$

$$M_{1,r,k} : \Delta X_{t} = \alpha \beta' X_{t-1} + \alpha \rho_{0} + \sum_{i=1}^{k-1} \Gamma_{i} \Delta X_{t-i} + \varepsilon_{t}$$

$$M_{0,r,k} : \Delta X_{t} = \alpha \beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_{i} \Delta X_{t-i} + \varepsilon_{t}$$

### 2. Models

- X<sub>t</sub> is a vector of p I(1) variables.
- $\beta$  is a p×r matrix of the cointegrating vectors.
- $\alpha$  is a p<sub>x</sub>r matrix of adjustment coefficients.
- p is the number of variables, r is the cointegration rank and k is the number of lags.
- $\rho_0$  and  $\rho_1$  are vectors of r elements
- $\mu_0$  is a vector of p elements.

 $\varepsilon_t i.i.d. E[\varepsilon_t] = 0, Cov(\varepsilon_t) = \Omega$ 

### 2. Models

# **Reduced Rank Regression**

$$R_{0t} = \alpha \beta' R_{1t} + \tilde{\varepsilon}_{t}$$

$$R_{0t} \text{ residuals of } \Delta x_{t} \text{ on } (1, \Delta x_{t-1}, \dots \Delta x_{t-k+1})$$

$$R_{1t} \text{ residuals of } X_{t-1} \text{ on } (1, \Delta x_{t-1}, \dots \Delta x_{t-k+1})$$
Since  $\hat{\alpha} = S_{01}\beta (\beta' S_{11}\beta)^{-1}$  we have
$$Var(\tilde{\varepsilon}) = \frac{1}{T} \sum_{1}^{T} (R_{0t} - \hat{\alpha}\beta' R_{1t}) (R_{0t} - \hat{\alpha}\beta' R_{1t})' =$$

$$= \left( S_{00} - S_{01}\beta (\beta' S_{11}\beta)^{-1} \beta' S_{10} \right)$$
Where
$$S_{ij} = \frac{1}{T} \sum_{1}^{T} R_{it}R_{jt}'$$

# 3. The Information Criterion (IC)

• We will use an IC that chooses the model that minimizes the expression

$$IC(M) = -2\log \tilde{L}(M) + c_T n_p(M)$$

Where  $\tilde{L}(M)$  is the maximized likelihood function,  $n_P(M)$  is the number of parameters and  $C_T$  is a deterministic sequence that imposes a penalty to encourage the selection of a parsimonious model. We assume

$$c_T \to \infty \text{ and } c_T = o(T) \text{ as } T \to \infty$$
 (1)

Examples: HQ:  $c_T = 2 \log \log T$ BIC:  $c_T = \log T$ 

# 3. The Information Criterion

$$\begin{split} M_{2,r,k} : Z_{0t} &= \alpha \beta' Z_{1t} + \theta_1' Z_{2t} + \varepsilon_t \\ Z_{0t} &= \Delta X_t, Z_{1t} = (X_{t-1}), Z_{2t} = (1, \Delta X_{t-1}, \dots \Delta X_{t-k+1}) \quad \theta_1' = (\mu_0, \Gamma_1, \dots \Gamma_{k-1}) \\ X_t &= C \sum_{i=1}^t \varepsilon_i + \tau t + \tau_0 + Y_t \quad C = \beta_\perp (\alpha_\perp' \Gamma \beta_\perp)^{-1} \alpha_\perp' \text{ with } \beta' \tau = 0 \\ \tilde{L}(M_2)^{-(2/T)} &= \left| S_{00} - S_{01} \tilde{\beta}^* (\tilde{\beta}^* S_{11} \tilde{\beta}^*)^{-1} \tilde{\beta}^* S_{10} \right| = |S_{00}| \prod_{i=1}^r (1 - \hat{\lambda}_i^*) = U_{2,r,k} (\tilde{\beta}^*) \\ &1 \geq \hat{\lambda}_1^* \geq \dots \geq \hat{\lambda}_p^* \quad roots \text{ of } \quad \left| \hat{\lambda}^* S_{11} - S_{10} S_{00}^{-1} S_{01} \right| = 0 \\ \hat{\beta}^* &= (\hat{v}_1^*, \dots \hat{v}_r^*) \text{ is the } MLE \text{ of } \beta. \text{ The } v's \text{ eigenvectors} \\ S_{ij} &= \frac{1}{T} \sum R_{it} R_{jt}' \text{ } i, j = 0, 1 \qquad R_{it} \text{ } i = 0, 1 \text{ are the residuals of } Z_{it} \text{ on } Z_{2t} \\ n_p(M_2) &= \frac{p(p+1)}{2} + (k-1) p^2 + pr + (p-r)r + p \end{split}$$

# 3. The Information Criterion

$$\begin{split} M_{3,r,k} : Z_{0t} &= \alpha \beta_{1}' Z_{11t} + \theta_{1}' Z_{2t} + \varepsilon_{t} \text{ with} \\ Z_{0t} &= \Delta X_{t}, Z_{11t} = (X_{t-1}, t) \quad \beta_{1}' = (\beta', \rho_{1}) \\ X_{t} &= C \sum_{i=1}^{t} \varepsilon_{i} + \tau_{1} t + \tau_{0} + Y_{t} \quad C = \beta_{\perp} (\alpha_{\perp} \Gamma \beta_{\perp}) \quad \alpha_{\perp}' \text{ with } \beta' \tau_{1} = -\rho_{1} \\ \tilde{L} (M_{3})^{-(2/T)} &= \left| S_{00} - S_{0,1b} \tilde{\beta}_{1} (\tilde{\beta}_{1}' S_{11,bb} \tilde{\beta}_{1})^{-1} \tilde{\beta}_{1} S_{1b,0} \right| = \left| S_{00} \right| \prod_{i=1}^{r} (1 - \hat{\lambda}_{i}) = U_{3,r,k} (\tilde{\beta}_{1}) \\ 1 \geq \hat{\lambda}_{1} \geq \dots \geq \hat{\lambda}_{p} \quad roots \text{ of } \left| \hat{\lambda} S_{11,bb} - S_{1b,0} S_{00}^{-1} S_{0,1b} \right| = 0 \\ \hat{\beta} &= (\hat{v}_{1}, \dots, \hat{v}_{r}) \text{ is the MLE of } \beta. \text{ The } v' \text{ s eigenvectors} \\ \text{Let } R_{1bt} &= (R_{1t}, b_{t}) \text{ where } b_{t} \text{ residuals of } t \text{ on } Z_{2t} \\ S_{0,1b} &= \frac{1}{T} \sum_{t} R_{0t} R_{1bt} \quad \text{and} \quad S_{11,bb} = \frac{1}{T} \sum_{t} R_{1bt} R_{1bt} \\ n_{p} (M_{3}) &= \frac{p(p+1)}{2} + (k-1) p^{2} + p + (rp-r)r + (p+r) \end{split}$$

# 4. Proposed Strategy

1. Determine the cointegration rank

 $IC_{3,r_{out},k} = \min_{r} IC_{3,r,k}$  where  $r \in \{0, 1, ..., p\}$ 

2. Determine the number of lags

$$IC_{3,r_{opt},k_{opt}} = \min_{k} IC_{3,r_{opt},k} \quad where \ k \in \{1,...,k_{max}\}$$

3. Determine the deterministic terms.

$$IC_{j_{opt},r_{opt},k} = \min_{j} IC_{j,r_{opt},k_{opt}} \quad where \ j \in \{0,1,2,3\}$$

The model finally chosen will be

 $M_{j_{opt},r_{opt},k_{opt}}$ 

5. Cointegration Rank Identificatio Rules

 In this paper, we use alternatively two of the three identification rules considered in chapter 13 of Johansen. The first one satisfies

$$\hat{\beta}' S_{11} \hat{\beta} = I \text{ or } \hat{\beta}_1' S_{11,bb} \hat{\beta}_1 = I$$

The second one that is convenient for the mathematical analysis satisfies

$$\tilde{\beta} = \hat{\beta} \left( \overline{\beta}' \hat{\beta} \right)^{-1} \text{ or } \tilde{\beta}_1 = \hat{\beta}_1 \left( \overline{\beta}_1' \hat{\beta}_1 \right)^{-1}$$

#### 5. Cointegration Rank

• Lemma 4.1. Let 0 < r < p and let  $Q(M_{3,r,k} / M_{3,p,k})$  be the likelihood ratio of  $M_{3,r,k}$  and  $M_{3,p,k}$ . We then have  $M = M_{i,r,k_0}$ , i = 0,1,2,3, and let  $M_{i,r,k_0} \subseteq M_{3,r,k_0}$ .

$$-2\log Q(M_{3,r,k} / M_{3,p,k}) = O_P(1)$$

Notice that the result is valid **independently of**  $k_0$ . Next, Theorem 4.1 proves that The IC criterion selects the cointegration rank, **independently of the number of lags**, when the form of the drift is overspecified.

**Theorem 4.1.** Let  $M = M_{i,r,k_0}$ , i = 0, 1, 2, 3, be the true DGP with  $M_{i,r,k_0} \subseteq M_{3,r,k_0}$ Then, for  $r' \neq r$  and k, the following holds

$$P(IC_{3,r,k} < IC_{3,r',k}) \to 1 \text{ as } T \to \infty$$

if  $c_T$  satisfies (21).

• Lemma 4.2 Let  $U_{3,r,k}(\beta_1)$  be defined as before assuming that  $\beta_1$  is known. Then, for any k', we have that if  $M_{i,r,k'}$ , i = 0, 1, 2, 3, is the true DGP, then  $U_{3,r,k'}(\tilde{\beta}_1) = U_{3,r,k'}(\theta_i^*) + o_p(\frac{1}{T})$ , where  $\theta_i^* = (\beta, 0)'$  if  $i \in \{0, 2\}$ ,  $\theta_1^{*'} = (\beta', \rho_0)$  and  $\theta_3^{*'} = (\beta', \rho_1)$  Lemma 4.2 permits to continue the analysis assuming that  $\theta_i$  is known. Note

$$U_{3,r,k}(\tilde{\beta}_1) = \left| S_{00} - S_{0,1b} \tilde{\beta}_1 \left( \tilde{\beta}_1' S_{11,bb} \tilde{\beta}_1 \right)^{-1} \tilde{\beta}_1 S_{1b,0} \right|$$
  
**Proof:** First, let  $M_{2,r,k}$  be the true DGP. In this case,  $\beta_1 = \beta^* = \begin{pmatrix} \beta \\ 0_{1 \times r} \end{pmatrix}$ 

Define  $A_{32T} = \left(\beta^*, T^{-1/2}\overline{\gamma}^*, T^{-1}\overline{\tau}^*\right) \quad \gamma^* \text{ is orthogonal to } \beta^* \text{ and } \tau^*$ 

With 
$$\gamma^* = \begin{pmatrix} \gamma \\ 0_{1 \times (p-r)} \end{pmatrix}, \tau^* = \begin{pmatrix} \tau \\ -1 \end{pmatrix} \overline{\beta}^* = \beta^* \left( \beta^{*'} \beta^* \right)^{-1}, etc.$$

$$\tilde{\beta}_{1} = \beta_{1} + \overline{\gamma}^{*} \gamma^{*'} \tilde{\beta}_{1} + \overline{\tau}^{*} \tau^{*'} \tilde{\beta}_{1} = \beta_{1} + B_{32T} U_{32T}$$
$$B_{32T} = \left(\overline{\gamma}^{*}, T^{-1/2} \overline{\tau}^{*}\right) and U_{32T} = \left(\gamma^{*}, T^{1/2} \tau^{*}\right)' \tilde{\beta}_{1}$$

• The roots of  $|\lambda A_{32T} S_{11,bb} A_{32T} - A_{32T} S_{1b,0} S_{00}^{-1} S_{0,1b} A_{32T}|$  (2) are those of  $|\lambda S_{11} - S_{10} S_{00}^{-1} S_{01}|$  (3) and the eigenvectors of (2) are  $A_{32T}^{-1} V$  where V is the matrix of eigenvectors of (3).

Remember that  $\tilde{\beta}_1$  are the first eigenvectors of (3) and that the space spanned by the first eigenvectors of (2) is  $A^{-1}\hat{\beta}_1 = A^{-1}\tilde{\beta}_1$ .

• We have

$$A_{32T}^{-1}\tilde{\beta}_{1} = \left(\overline{\beta}^{*}, T^{1/2}\gamma^{*}, T\tau^{*}\right)'\tilde{\beta}_{1} = \left(I, T^{1/2}U_{32T}'\right)'$$
  
so that  $T^{1/2}U_{32T} \xrightarrow{P} 0$ 

because the space spanned by the r first eigenvectors of (2) converges to the space spanned by the first r unit vectors or equivalently the space spanned by vectors with zeros in the last p-r+1 coordinates.

Now we have

 $\tilde{\beta}_{1}'S_{11,bb}\tilde{\beta}_{1} = \beta_{1}'S_{11,bb}\beta_{1} + U_{32T}'B_{32T}'S_{11,bb}\beta_{1} + \beta_{1}'S_{11,bb}B_{32T}U_{32T} + U_{32T}'B_{32T}'S_{11,bb}B_{32T}U_{32T} = \beta_{1}'S_{11,bb}\beta_{1} + o_{P}(1)$ 

Because  $B'_{32T}S_{11,bb}\beta_1$  is  $O_P(1)$   $T_{, 32T}^{-1}B'_{32T}S_{11,bb}B_{32T}$  is  $O_P(1)$ and  $T^{1/2}U_{32T} \xrightarrow{P} 0$ Similarly,  $\tilde{\beta}'_1S_{1b,0} = \beta'_1S_{1b,0} + U'_{32T}B'_{32T}S_{1b,0} = \beta'_1S_{1b,0} + o_P(T^{-1/2})$ The analysis can continue assuming  $\beta_1$ known

• Let M<sub>3,r,k</sub> be the true DGP. Then,

$$A_{33T} = \left(\beta_{1}, T^{-1/2} \overline{\gamma}_{1}^{*}, T^{-1} \overline{\tau}_{1}^{*}\right), B_{33T} = \left(\overline{\gamma}_{1}^{*}, T^{-1/2} \overline{\tau}_{1}^{*}\right), U_{33T} = \left(\gamma_{1}^{*}, T^{1/2} \tau_{1}^{*}\right)^{'} \tilde{\beta}_{1}$$

with 
$$\gamma_1^* = \begin{pmatrix} \gamma \\ 0 \end{pmatrix}, \tau_1^* = \begin{pmatrix} \tau_1 \\ 1 \end{pmatrix}$$
  
In this case,  $\gamma$  is orthogonal to  $\beta$  and  $\tau_1$ 

For the same reasons given previously

$$T^{1/2}U_{33T} \longrightarrow 0$$

• Then, we have

$$\tilde{\beta}_{1}'S_{11,bb}\tilde{\beta}_{1} = \beta_{1}'S_{11,bb}\beta_{1} + U_{33T}'B_{33T}'S_{11,bb}\beta_{1} + \beta_{1}'S_{11,bb}B_{33T}U_{33T} + U_{33T}'B_{33T}'S_{11,bb}B_{33T}U_{33T}$$
$$= \beta_{1}'S_{11,bb}\beta_{1} + o_{P}(1)$$

Because  $B'_{32T}S_{11,bb}\beta_1$  is  $O_P(1)$   $T^{-1}B'_{32T}S_{11,bb}B_{32T}$  is  $O_P(1)$ and  $T^{1/2}U_{32T} \xrightarrow{P} 0$ Similarly,  $\tilde{\beta}'_1S_{1b,0} = \beta'_1S_{1b,0} + U'_{32T}B'_{32T}S_{1b,0} = \beta'_1S_{1b,0} + o_P(T^{-1/2})$ 

and the result follows.

- Theorem 4.2. Let  $M_0 = M_{3,r,k}$  and  $M_1 = M_{3,r,k'}$  with a matrix of cointegrating vectors that is known and k<k'. If  $c_T$  satisfies (21), then

a) If  $M_0$  is the true DGP then  $P(IC_0 < IC_1) \rightarrow 1 \text{ as } T \rightarrow \infty$ b) If  $M_1$  is the true DGP then  $P(IC_0 > IC_1) \rightarrow 1 \text{ as } T \rightarrow \infty$ 

# The number of lags is consistently estimated

- In this section, we will show how the use of the IC criterion allows us to consistently estimate the form of the drift of the model.
- To discriminate between  $M_{0,r,k}, M_{1,r,k}, M_{2,r,k}$  against  $M_{3,r,k}$  when 0 < r < p we are going to introduce an slight modification of the IC criterion when this is calculated for the three more restrictive models .
- For these three models, the likelihood is estimated substituting their parameters by their estimators obtained from  $M_{3,r,k}$  and we will use  $IC^*(M)$ .

**Lemma 5.1** Let  $U_{i,r,k}(\theta_i), i = 0, 1, 2, 3$  be defined as in Section 2 assuming that the values of the parameters are known. Denote  $\theta_i = \beta$  if  $i \in \{0, 2\}$ ,  $\theta_1 = (\beta', \rho_0)$  and  $\theta_3 = (\beta', \rho_1)$ . Let  $\tilde{\theta}_{i,3,r,k}$  the estimator of  $\theta_i$  calculated from  $M_{3,r,k}$ . Then, if  $M_{i,r,k'}, i = 0, 1, 2, 3$ , is the true DGP we have  $U_{j,r,k}(\tilde{\theta}_{j3,r,k}) = U_{j,r,k}(\theta_j) + o_P\left(\frac{1}{T}\right)$ 

**Proof:** Similar to that presented for Lemma 4.2

• Theorem 5.1. Let  $M_0 = M_{0,r,k}$  and  $M_1 = M_{3,r,k}$  with r and k fixed If  $C_T$  satisfies (21) then a) If  $M_0$  is the true DGP then  $P(IC_0^* < IC_1) \rightarrow 1$  as  $T \rightarrow \infty$ b) If  $M_1$  is the true DGP then  $P(IC_0^* > IC_1) \rightarrow 1$  as  $T \rightarrow \infty$ 

**Theorem 5.2** Let  $M_0 = M_{1,r,k}$  and  $M_1 = M_{3,r,k}$  with r and k fixed If  $C_T$  satisfies (21) then **a)** If  $M_0$  is the true DGP then  $P(IC_0^* < IC_1) \rightarrow 1$  as  $T \rightarrow \infty$ **b)** If  $M_1$  is the true DGP then  $P(IC_0^* > IC_1) \rightarrow 1$  as  $T \rightarrow \infty$ 

- **Theorem 5.3** Let  $M_0 = M_{2,r,k}$  and  $M_1 = M_{3,r,k}$  with r and k fixed If  $C_T$  satisfies (21), then
  - a) If  $M_0$  is the true DGP then b) If  $M_1$  is the true DGP then  $P(IC_0^* < IC_1) \rightarrow 1 \text{ as } T \rightarrow \infty$  $P(IC_0^* > IC_1) \rightarrow 1 \text{ as } T \rightarrow \infty$

**Proof of Theorem 5.3:** a)  $M_{2,r,k}$  is the true DGP. If we estimate using the same model it is the case treated by Johansen (1995) Lemma 13.1. If we use  $M_{3,r,k}$  to estimate the likelihood the results have been derived in Lemma 4.2. We have to compare  $L(M_1)^{-2/T}$  and  $L(M_0)^{-2/T}$  Since, in this case,  $\rho_1 = 0$  we have

$$L(M_{1})^{-2/T} = |S_{00} - S_{01}\beta(\beta'S_{11}\beta)^{-1}\beta'S_{10}| = L(M_{0})^{-2/T}$$

and hence  $IC^*(M_0) - IC(M_1) = -rc_T \rightarrow -\infty$ 

### **b)** $M_{3,r,k}$ is the true DGP. We have

$$L(M_0)^{-2/T} = \left| S_{00} - T^{-1/2} S_{01} \beta \frac{1}{T} \left( \frac{1}{T^2} \beta' S_{11} \beta \right)^{-1} T^{-1/2} \beta' S_{10} \right| \xrightarrow{p} \left| \Sigma_{00} \right|$$

• On the other hand

$$L(M_{1})^{-2/T} = \left| S_{00} - S_{01}\beta_{1} \left( \beta_{1} S_{11}\beta_{1} \right)^{-1} \beta_{1} S_{10} \right| \xrightarrow{P} \left| \Sigma_{00} - \Sigma_{0\beta} \Sigma_{\beta\beta} \Sigma_{\beta0} \right|$$

We obtain

$$IC_0^* - IC_1 = -2\log L(M_0) + 2\log L(M_1) + o_p(T) - rc_T$$
$$= -T\log \frac{\left|\Sigma_{00} - \Sigma_{0\beta}\Sigma_{\beta\beta}^{-1}\Sigma_{\beta0}\right|}{\left|\Sigma_{00}\right|} + o_p(T) - rc_T \to \infty$$

using

$$|A - BB'| = |A| |I - B'A^{-1}B| < |A|$$
if  $B \neq 0$ 

- 1. To carry out simulation exercises to confirm the theoretical results.
- **2. Key question**: In the first step, is the determination of the cointegration rank really independent of the number of lags?
- 3. To derive the results in the third step estimating the maximum likelihood of each model with the estimators calculated with the corresponding model and not with the estimators derived from the less restrictive model.