#### Econometrics 1, Class Week 10

Back-up Video: Class week 10 video (click here)

Learning Outcomes

- (a) Vector Autoregressive (VAR) processes.
- (b) Forecasting.
- (c) Granger causality.
- (d) Vector Error Correction Model (VECM) representation.
- (e)-(f) Cointegration.
  - (g) ARDL model implied by VAR.

#### Prerequisites

- 1. Concepts and results of classes of weeks 7, 8 and 9.
- 2. Multivariate normal distribution (Distributional Handout): conditional vs. unconditional normal distribution.

### (a) VAR(1) Setting

Consider the vector-valued process  $\{\mathbf{y}_t\} = \{(y_{1t}, y_{2t})'\}$  which is assumed to be autoregressive of order one (VAR(1)),

$$\mathbf{y}_t = \mathbf{A}_0 + \mathbf{A}_1 \mathbf{y}_{t-1} + \epsilon_t \iff (\mathbf{I}_2 - \mathbf{A}_1 L) \mathbf{y}_t = \mathbf{A}_0 + \epsilon_t$$

for any t, where

$$\mathbf{A}_0 = \left[ egin{array}{c} a_1^0 \ a_2^0 \end{array} 
ight]$$
 ,  $\mathbf{A}_1 = \left[ egin{array}{cc} a_{11}^1 & a_{12}^1 \ a_{21}^1 & a_{22}^1 \end{array} 
ight]$  ,

and  $\epsilon_t$  is multivariate WN, i.e.

$$\epsilon_t = (\epsilon_{1t}, \epsilon_{2t})' \overset{i.i.d.}{\sim} N(\mathbf{0}, \Omega), \text{ with } \Omega = \begin{bmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & \omega_{22} \end{bmatrix} \text{ p.d.s.}$$

Written out in single equation form,

$$y_{1t} = a_1^0 + a_{11}^1 y_{1,t-1} + a_{12}^1 y_{2,t-1} + \epsilon_{1t},$$
  

$$y_{2t} = a_2^0 + a_{21}^1 y_{1,t-1} + a_{22}^1 y_{2,t-1} + \epsilon_{2t}.$$

Suppose data  $\{\mathbf{y}_t, t = 1, \dots, T\}$  are available for periods 1 to T. On the basis of such data, the parameters can be estimated by OLS:

- (i)  $a_1^0$ ,  $a_{11}^1$ ,  $a_{12}^1$  from an OLS regression of  $y_{1t}$  on a constant,  $y_{1,t-1}$  and  $y_{2,t-1}$ ;
- (ii)  $a_2^0$ ,  $a_{21}^1$ ,  $a_{22}^1$  from an OLS regression of  $y_{2t}$  on a constant,  $y_{1,t-1}$  and  $y_{2,t-1}$ ;
- (iii) and  $\omega_{ij}$  from the OLS residuals  $\{\hat{\epsilon}_{it}, t = 1, 2, t = 1, \dots, T\}$ , as  $\hat{\omega}_{ij} = \frac{1}{T} \sum_{t=1}^{T} \hat{\epsilon}_{it} \hat{\epsilon}_{jt}$ ,  $i, j \in \{1, 2\}$ .

### (b) Forecasting

Analogous to process (1) in the assignment for week 7, the first-order Markov property of the process  $\{y_t\}$  implies

$$\begin{split} \hat{\mathbf{y}}_{T+1|T} &= & \mathbb{E}[\mathbf{y}_{T+1}|\mathbf{y}_{t \leq T}] \\ &= & \mathbb{E}[\mathbf{y}_{T+1}|\mathbf{y}_{T}] = \mathbf{A}_{0} + \mathbf{A}_{1}\mathbf{y}_{T}, \\ \hat{\mathbf{y}}_{T+2|T} &= & \mathbb{E}[\mathbf{y}_{T+2}|\mathbf{y}_{t \leq T}] \\ &= & \mathbf{A}_{0} + \mathbf{A}_{1}\mathbb{E}[\mathbf{y}_{T+1}|\mathbf{y}_{T}] \\ &= & (\mathbf{I}_{2} + \mathbf{A}_{1})\mathbf{A}_{0} + \mathbf{A}_{1}^{2}\mathbf{y}_{T}, \end{split}$$

where  $I_2$  is the identity matrix of dimension 2. These conditional expectations can be estimated by replacing  $A_0$  and  $A_1$  by their estimates from part (a).

## (c) Granger Causality

Granger causality relates to usefulness in prediction.

 $y_{1t}$  is not Granger-causal with respect to  $y_{2t}$  if lagged values of  $y_{1t}$  do not help in the prediction of  $y_{2t}$ , i.e. when  $a_{21}^1 = 0$ .

Typically, economic causality and Granger causality run in opposite directions.

Example: A listed firm's earning determines the dividends its stockholder receive; and its dividends Granger cause the firm's earnings.

# (d) VECM

Analogous to ECM studied in week 9.

The form in (d) is a vector error correction model (VECM) which follows from

$$\Delta \mathbf{y}_{t} = \mathbf{A}_{0} + (\mathbf{A}_{1} - \mathbf{I}_{2})\mathbf{y}_{t-1} + \epsilon_{t}$$

$$\Rightarrow \Pi = \mathbf{A}_{1} - \mathbf{I}_{2}$$

$$\Delta \mathbf{y}_{t} = \mathbf{A}_{0} + \Pi \mathbf{y}_{t-1} + \epsilon_{t}.$$

### (e) Cointegration

General principle: In VECM, order of integration of the LHS = order of integration of the RHS. And note: In this example, the rank of  $\Pi$  can be 0, 1 or 2. Consider three cases:

(iii)  $y_{it}$ , i=1,2, are both I(1), i.e. contain a unit root, and not cointegrated. Then, the term  $\Pi \mathbf{y}_t$  in the VECM must disappear for all realizations of  $\mathbf{y}_t$ . Hence,  $\Pi = \mathbf{0}$ , i.e.  $\mathbf{A}_1 = \mathbf{I}_2$ , and so  $\mathrm{rk}(\Pi) = 0$ .

(ii)  $y_{it}$ , i=1,2, are both I(1), i.e. contain a unit root, and cointegrated. Then,  $rk(\Pi)$  equals the number of cointegrating vectors, so in this case  $rk(\Pi) = 1$ .

To see that unit roots imply rank deficiency of  $\Pi$ , note that

$$0 = |\mathbf{I}_{2} - \mathbf{A}_{1}z|$$

$$= \left| \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} a_{11}^{1}z & a_{12}^{1}z \\ a_{21}^{1}z & a_{22}^{1}z \end{bmatrix} \right|$$

$$= \left| \begin{vmatrix} 1 - a_{11}^{1}z & -a_{12}^{1}z \\ -a_{21}^{1}z & 1 - a_{22}^{1}z \end{vmatrix} \right|$$

$$= (1 - a_{11}^{1}z)(1 - a_{22}^{1}z) - a_{12}^{1}a_{21}^{1}z^{2},$$

so a unit root, i.e. z=1 solving the preceding equality, implies

$$(1-a_{11}^1)(1-a_{22}^1)-a_{12}^1a_{21}^1=0,$$

which is equivalent to  $\frac{a_{12}^1}{1-a_{11}^1}=\frac{1-a_{22}^1}{a_{21}^1}$  (\*). But this implies that

$$\operatorname{rk}(\Pi) = \operatorname{rk}\left(\left[\begin{array}{cc} a_{11}^1 - 1 & a_{12}^1 \\ a_{21}^1 & a_{22}^1 - 1 \end{array}\right]\right) = 1.$$

(Multiplying the first row by  $\frac{a_{21}^1}{a_{11}^1-1}$  yields  $[a_{21}^1, \frac{a_{21}^1 a_{12}^1}{a_{11}^1-1}]$ , which is equal to the second row, using the equality  $(\star)$ .)

In this case,  $\Pi$  can be expressed as  $\Pi = \beta \mathbf{r}'$ , for  $\beta$ ,  $\mathbf{r} \in \mathbb{R}^2$ , where  $\mathbf{r}$  is a cointegrating vector, i.e. the scalar random variable  $z_t = \mathbf{r}'\mathbf{y}_t$ , a linear combination of  $y_{1t}$  and  $y_{2t}$ , is I(0). Then,

$$\Delta \mathbf{y}_t = \mathbf{A}_0 + \beta z_{t-1} + \epsilon_t.$$

(i)  $y_{it}$ , i=1,2, are both stationary. Then,  $|\mathbf{I}_2 - \mathbf{A}_1 z| = 0$  has both roots outside the unit circle, and  $\Pi$  has full rank 2.

Informal argument: To see this, suppose to the contrary that  $rk(\Pi) < 2$ :

$$\exists \mathbf{w} \in \mathbb{R}^2 : \mathbf{w}'\Pi = \mathbf{0}'$$

$$\Rightarrow \mathbf{w}'\Delta\mathbf{y}_t = \mathbf{w}'\mathbf{A}_0 + \mathbf{w}'\Pi\mathbf{y}_{t-1} + \mathbf{w}'\epsilon_t = \mathbf{w}'\mathbf{A}_0 + \mathbf{w}'\epsilon_t$$

$$\Rightarrow \mathbf{w}'\Delta\mathbf{y}_t \quad \text{is } I(0), \text{ i.e. stationary.}$$

The last implication is consistent with  $\mathbf{w}'\mathbf{y}_t$  being I(1), i.e. at least one series contains a unit root. This contradicts that  $y_{it}$ , i=1,2, are both stationary. So stationary requires that  $\Pi$  have full rank.

# (f) VECM s.t. Cointegration Restriction

This is case (ii) in part (e) above, with  $\Pi = \beta \mathbf{r}'$  for some  $\beta$ ,  $\mathbf{r} \in \mathbb{R}^2$ . Note: For any non-zero scalar Q:

$$\Pi = \beta \mathbf{r}' = \beta Q Q^{-1} \mathbf{r}' = \tilde{\beta} \tilde{\mathbf{r}}'$$

for  $\tilde{\beta} = \beta Q$  and  $\tilde{\mathbf{r}}' = Q^{-1}\mathbf{r}'$ , so that  $\tilde{\mathbf{r}}$  is also a cointegrating vector. Hence, the cointegrating vector is not identified (unique), unless a restriction is imposed (which is equivalent of choosing a specific Q).

One possible restriction is to have  $\mathbf{r}$  normalized to have its first component equal to one. Then,  $\mathbf{r}' = [1, b]$  for some b, so that  $z_t = \mathbf{r}'\mathbf{y}_t = y_{1t} + by_{2t}$ . From above,

$$\Delta y_{1t} = a_1^0 + (a_{11}^1 - 1)y_{1,t-1} + a_{12}^1 y_{2,t-1} + \epsilon_{1t}$$

$$= a_1^0 + (a_{11}^1 - 1) \left( y_{1,t-1} + \frac{a_{12}^1}{a_{11}^1 - 1} y_{2,t-1} \right) + \epsilon_{1t}$$

$$\Delta y_{2t} = a_2^0 + a_{21}^1 y_{1,t-1} + (a_{22}^1 - 1) y_{2,t-1} + \epsilon_{2t}$$

$$= a_2^0 + a_{21}^1 \left( y_{1,t-1} + \frac{a_{22}^1 - 1}{a_{21}^1} y_{2,t-1} \right) + \epsilon_{1t},$$

and from the unit root condition that implies the rank deficiency of  $\Pi$ , it follows that

$$b = \frac{a_{12}^1}{a_{11}^1 - 1} = \frac{a_{22}^1 - 1}{a_{21}^1},$$

while  $\beta = [a_{11}^1 - 1, a_{21}^1]'$ .

#### ARDL implied by VAR

Starting from

$$y_{1t} = a_1^0 + a_{11}^1 y_{1,t-1} + a_{12}^1 y_{2,t-1} + \epsilon_{1t},$$

with  $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t})'$  satisfying  $\epsilon_t \sim N(\mathbf{0}, \Omega)$ , the conditional distribution of  $\epsilon_{1t}$ , given  $\epsilon_{2t}$ , is

$$|\epsilon_{1t}|\epsilon_{2t} \sim N\left(\frac{\omega_{12}}{\omega_{22}}\epsilon_{2t}, \omega_{11} - \frac{\omega_{12}^2}{\omega_{22}}\right),$$

so that  $\epsilon_{2t} = y_{2t} - a_2^0 - a_{21}^1 y_{1,t-1} - a_{22}^1 y_{2,t-1}$  implies

$$\mathbb{E}[y_{1t}|y_{2t}, \mathbf{y}_{t-1}] = a_1^0 + a_{11}^1 y_{1,t-1} + a_{12}^1 y_{2,t-1} + \mathbb{E}[\epsilon_{1t}|y_{2t}, \mathbf{y}_{t-1}] 
= a_1^0 + a_{11}^1 y_{1,t-1} + a_{12}^1 y_{2,t-1} 
+ \frac{\omega_{12}}{\omega_{22}} \left( y_{2t} - a_2^0 - a_{21}^1 y_{1,t-1} - a_{22}^1 y_{2,t-1} \right) 
= a_1^0 - \frac{\omega_{12}}{\omega_{22}} a_2^0 + \frac{\omega_{12}}{\omega_{22}} y_{2t} + \left( a_{11}^1 - \frac{\omega_{12}}{\omega_{22}} a_{21}^1 \right) y_{1,t-1} 
+ \left( a_{12}^1 - \frac{\omega_{12}}{\omega_{22}} a_{22}^1 \right) y_{2,t-1}.$$

Therefore, the ARDL(1,1) model  $y_{1t}=\alpha_0+\beta_0y_{2t}+\beta_1y_{2,t-1}+\alpha_1y_{1,t-1}+u_t$  has

$$\alpha_0 = a_1^0 - \frac{\omega_{12}}{\omega_{22}} a_2^0, \ \alpha_1 = a_{11}^1 - \frac{\omega_{12}}{\omega_{22}} a_{21}^1,$$
 $\beta_0 = \frac{\omega_{12}}{\omega_{22}}, \ \beta_1 = a_{12}^1 - \frac{\omega_{12}}{\omega_{22}} a_{22}^1$ 

and  $u_t \stackrel{i.i.d.}{\sim} N(0, \omega_{11} - \omega_{12}^2/\omega_{22})$ .