

Time Series Analysis

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An economic example: Using the Structural VAR (SVAR) model to analyse stock market returns from Tokyo, Singapore, Korea.

$$\begin{aligned}
 r_t^T &= k^T && + \beta_{12}^{(0)} r_t^S + \beta_{13}^{(0)} r_t^K + \beta_{11}^{(1)} r_{t-1}^T + \beta_{12}^{(1)} r_{t-1}^S + \beta_{13}^{(1)} r_{t-1}^K + u_t^T \\
 r_t^S &= k^S && + \beta_{21}^{(0)} r_t^T + \beta_{23}^{(0)} r_t^K + \beta_{21}^{(1)} r_{t-1}^T + \beta_{22}^{(1)} r_{t-1}^S + \beta_{23}^{(1)} r_{t-1}^K + u_t^S \\
 r_t^K &= k^K && + \beta_{31}^{(0)} r_t^T + \beta_{32}^{(0)} r_t^S + \beta_{31}^{(1)} r_{t-1}^T + \beta_{32}^{(1)} r_{t-1}^S + \beta_{33}^{(1)} r_{t-1}^K + u_t^K
 \end{aligned}$$

$$\mathbf{y}_t = \begin{bmatrix} r_t^T \\ r_t^S \\ r_t^K \end{bmatrix} \quad \mathbf{k} = \begin{bmatrix} k^T \\ k^S \\ k^K \end{bmatrix} \quad \mathbf{B}_0 = \begin{bmatrix} 1 & -\beta_{12}^{(0)} & -\beta_{13}^{(0)} \\ -\beta_{21}^{(0)} & 1 & -\beta_{23}^{(0)} \\ -\beta_{31}^{(0)} & -\beta_{32}^{(0)} & 1 \end{bmatrix} \quad \mathbf{u}_t = \begin{bmatrix} u_t^T \\ u_t^S \\ u_t^K \end{bmatrix}$$

$$\mathbf{B}_0 \mathbf{y}_t = \mathbf{k} + \mathbf{B}_1 \mathbf{y}_{t-1} + \mathbf{u}_t$$

A structural VAR in a primitive form

$$\mathbf{B}_0 \mathbf{y}_t = \mathbf{k} + \mathbf{B}_1 \mathbf{y}_{t-1} + \mathbf{B}_2 \mathbf{y}_{t-2} + \dots + \mathbf{B}_p \mathbf{y}_{t-p} + \mathbf{u}_t$$

$$\mathbb{E}(\mathbf{u}_t \mathbf{u}_t') = \mathbf{D}$$

$$\mathbb{E}(\mathbf{u}_t \mathbf{u}_{t-\tau}') = \mathbf{0} \quad \text{for } t \neq \tau$$

with \mathbf{D} a diagonal matrix, ensuring that the elements of \mathbf{u}_t are mutually uncorrelated. The (j, j) element of \mathbf{D} gives the variance of u_{jt} .

*p*th-order vector autoregression VAR(*p*) in standard form

$$\mathbf{y}_t = \mathbf{c} + \Phi_1 \mathbf{y}_{t-1} + \Phi_2 \mathbf{y}_{t-2} + \dots + \Phi_p \mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t$$

$\mathbf{c} = \mathbf{B}_0^{-1} \mathbf{k}$ ($n \times 1$) vector of constants

$\Phi_s = \mathbf{B}_0^{-1} \mathbf{B}_s$ ($n \times n$) matrix of AR coefficients for $s = 1, \dots, p$

$\boldsymbol{\varepsilon}_t = \mathbf{B}_0^{-1} \mathbf{u}_t$ ($n \times 1$) vector generalization of white noise.

$$\mathbb{E}(\boldsymbol{\varepsilon}_t) = \mathbf{0}$$

$$\mathbb{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_{\tau}) = \begin{cases} \boldsymbol{\Omega} & \text{for } t = \tau \\ \mathbf{0} & \text{otherwise.} \end{cases}$$

since $\mathbb{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_{t-\tau}) = \mathbf{0}$ follows $\mathbb{E}(\mathbf{u}_t \mathbf{u}'_{t-\tau}) = \mathbf{0}$ for $t \neq \tau$.

The VMA(∞) Representation

$$y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \Psi_3 \varepsilon_{t-3} + \dots$$

The interpretation of Ψ_s is

$$\frac{\partial y_{t+s}}{\partial \varepsilon'_t} = \Psi_s$$

i.e. row i , column j element of Ψ_s identifies the consequences of a one-unit increase in the j th variable's innovation at date t (ε_{jt}) for the value of the i th variable at time $(t + s)$ ($y_{i,t+s}$), holding all other innovations at all dates constant.

Impulse Responses using the MA coefficients. A plot of row i , column j element of Ψ_s as a function of s is called impulse response function: response of $y_{i,t+s}$ to a one-time impulse in $y_{j,t}$ with all other variables dated t or earlier held constant. $\frac{\partial y_{i,t+s}}{\partial \epsilon_{jt}}$