

Vector Autoregression

A pth order vector autoregression generalizes a scalar AR(p):

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

where $y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ is an $n \times 1$ vector of variables, $\vec{c} = (c, c, \dots, c)'$ is an $n \times 1$ vector of constants Φ_j is an $n \times n$ matrix of autoregressive coefficients for $j = 1, \dots, p$

and $\vec{\varepsilon}_t = (\varepsilon_{1t}, \dots, \varepsilon_{nt})'$ s.t.

$$E[\vec{\varepsilon}_t] = \vec{0} \text{ and } E[\vec{\varepsilon}_t \vec{\varepsilon}_\tau'] = \begin{cases} \Omega & t = \tau \\ 0 & \text{o/w} \end{cases}$$

$\vec{\varepsilon}_t$ is a vector white noise process

\vec{y}_t is referred to as a VAR(p)

Recall, an AR(p) can be written as a VAR(1)

$$\vec{y}_t = \Phi \vec{y}_{t-1} + \vec{v}_t$$

$$\text{where } \vec{y}_t = \begin{bmatrix} y_t \\ \vdots \\ y_{t-p+1} \end{bmatrix}_{px1}, \quad \Phi = \begin{bmatrix} \phi_1 & \phi_2 & \dots & \phi_{p-1} & \phi_p \\ 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}_{p \times p} \quad \vec{v}_t = \begin{bmatrix} \varepsilon_t \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}_{px1}$$

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t$$

In lag operator notation,

$$[I_n - \Phi_1 L - \Phi_2 L^2 - \dots - \Phi_p L^p] \vec{y}_t = \vec{c} + \vec{\varepsilon}_t$$

Φ is a matrix where each component is a scalar lag polynomial.

The concept of weak stationarity is unchanged:

\vec{y}_t is weakly stationary if $E[\vec{y}_t] + E[\vec{y}_t \vec{y}_{t-j}']$ are independent of $t \forall j$

Weak stationarity results in:

$$E[\vec{y}_t] = \vec{\mu} = \vec{c} + \Phi_1 \vec{\mu} + \dots + \Phi_p \vec{\mu}$$

$$\implies \vec{\mu} = [I_n - \Phi_1 - \dots - \Phi_p]' \vec{c}_1$$

not necessarily

$$\text{where } \vec{\mu} = (\mu_1, \mu_2, \dots, \mu_n)' \neq (\mu, \mu, \dots, \mu)'$$

Alternatively,

$$(\vec{y}_t - \vec{\mu}) = \Phi_1 (\vec{y}_{t-1} - \vec{\mu}) + \dots + \Phi_p (\vec{y}_{t-p} - \vec{\mu}) + \vec{\varepsilon}_t$$

We can write a VAR(p) as a VAR(1):

$$\vec{\xi}_t = F \vec{\xi}_{t-1} + \vec{v}_t$$

where

$$\vec{\xi}_t = \begin{bmatrix} \vec{y}_t - \vec{\mu} \\ \vec{y}_{t-1} - \vec{\mu} \\ \vdots \\ \vec{y}_{t-p+1} - \vec{\mu} \end{bmatrix}_{npx1}$$

$$F = \begin{bmatrix} \Phi_1 & \Phi_2 & \Phi_3 & \dots & \Phi_{p-1} & \Phi_p \\ I_n & 0 & 0 \dots & 0 & 0 & \\ 0 & I_n & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & I_n \end{bmatrix}_{np \times np}$$

$$\vec{v}_t = \begin{bmatrix} \vec{\varepsilon}_t \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}_{px1}$$

Clearly,

$$E[\vec{v}_t \vec{v}_\tau'] = \begin{cases} Q & t = \tau \\ 0 & \text{o/w} \end{cases}$$

where

$$Q = \begin{bmatrix} \Omega & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix}_{np \times np}$$

Recursively iterating on the VAR(1):

$$\vec{\xi}_{t+s} = \vec{v}_{t+s} + F\vec{v}_{t+s-1} + F^2\vec{v}_{t+s-2} + \dots + F^{s-1}\vec{v}_{t+1} + F^s\vec{\xi}_t$$

Assuming F is nonsingular, it can be decomposed as

$$F = T\Lambda T^{-1}$$

where Λ is a diagonal matrix comprised of the np eigenvalues of F and T is a matrix of eigenvalues as columns

Thus,

$$F = FF = (T\Lambda T^{-1})T\Lambda T^{-1} = T\Lambda^2 T^{-1}$$

$$\implies F^s = T\Lambda^s T^{-1} \rightarrow 0 \text{ if } |\lambda_k| < 1 \text{ for } k = 1, \dots, np$$

If $F^s \rightarrow 0$ as $s \rightarrow \infty$, the effect of $\vec{\varepsilon}_t$ on $\vec{\xi}_{t+s}$ dies out as $s \rightarrow \infty$, which is necessary for stationarity and causality

Alternatively, \vec{y}_t is stationary and causal if the roots of $[I_n - \Phi_1 z - \Phi_2 z^2 - \dots - \Phi_p z^p]$ all lie outside the unit circle.

Vector MA(∞) Representation

If $F^s \rightarrow 0$ as $s \rightarrow 0$, then

$$\vec{\xi}_{t+s} = \vec{v}_{t+s} + F\vec{v}_{t+s-1} + F^2\vec{v}_{t+s-2} + \dots + F^{s-1}\vec{v}_{t+1} + F^s\vec{\xi}_t$$

which is a vector of MA(∞) process

We can also write \vec{y}_t alone as a vector MA(∞)

First, recognize

$$\vec{y}_{t+s} = \vec{\mu} + \vec{\varepsilon}_{t+s} + \Psi_1 \vec{\varepsilon}_{t+s-1} + \Psi_2 \vec{\varepsilon}_{t+s-2} + \dots + \Psi_{s-1} \vec{\varepsilon}_{t+1} + F_{11}^{(s)}(\vec{y}_t - \vec{\mu}) + F_{12}^{(s)}(\vec{y}_{t-1} - \vec{\mu}) + \dots + F_{1p}^{(s)}(\vec{y}_{t-p+1} - \vec{\mu})$$

where $\Psi_j = F_{11}^{(j)}$ and $F_{1k}^{(j)}$ is comprised of rows 1 to n and columns (k-1)n+1 + 1 to kn of matrix F^j

Side note:

$$\left. \begin{array}{l} (Fx F)[1:n, 1:n] \\ F[1:n, 1:n] x F[1:n, 1:n] \end{array} \right\} \text{not the same}$$

If all eigenvalues of F are inside the unit circle, $F^s \rightarrow 0$ as $s \rightarrow \infty$, which means $F_{1k}^{(s)} \rightarrow 0$ as $s \rightarrow \infty$.

In the limit

$$\vec{y}_{t+s} = \vec{\mu} + \vec{\varepsilon}_{t+s} + \Psi_1 \vec{\varepsilon}_{t+s-1} + \Psi_2 \vec{\varepsilon}_{t+s-2} + \dots = \vec{\mu} + \Psi(L)\varepsilon_t$$

In this case $\Psi(L) = \Phi(L)^{-1}$ or $[1 - \Phi_1 L - \Phi_2 L^2 - \dots - \Phi_p L^p][1 + \Psi_1 L + \Psi_2 L^2 + \dots] = I_n$

$$E[\varepsilon_t] = 0$$

$$E[\varepsilon_t \varepsilon_\tau'] = \begin{cases} \Omega & t = \tau \\ 0 & \text{o/w} \end{cases}$$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$$

Note that we can always write a stationary and causal VAR(p) as a vector MA(∞) with a mutually uncorrelated white noise vector:

$$\text{Define } \vec{u}_t = H \vec{\varepsilon}_t \quad \text{s.t. } H \Lambda H' = D$$

Then

$$\vec{y}_t = \vec{\mu} + H^{-1} H \vec{\varepsilon}_t + \Psi_1 (H^{-1} H) \vec{\varepsilon}_{t-1} + \dots = \vec{\mu} + J_0 \vec{u}_t + J_1 \vec{u}_{t-1} + J_2 \vec{u}_{t-2} + \dots \quad \text{where } J_s = \Psi_s H^{-1}$$

In this case the leading matrix $J_0 \neq I_n$

$$E[u_t u_t'] = E[H \varepsilon_t \varepsilon_t' H'] = H E[\varepsilon_t \varepsilon_t'] H' = H \Omega H'$$

$$H' \Lambda H = \mathcal{H}' \mathcal{H} \Omega \mathcal{H}' \mathcal{H}$$