

Example : VAR(1) with 2 variables

$$\underset{2 \times 1}{\tilde{X}_t} = \underset{2 \times 2}{\hat{\Phi}} \underset{2 \times 1}{\tilde{X}_{t-1}} + \underset{2 \times 1}{\tilde{\epsilon}_t} ; \tilde{\epsilon}_t \sim VWN(0, \Sigma)$$

$$\text{i.e. } \begin{pmatrix} X_{1,t} \\ X_{2,t} \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix} \begin{pmatrix} X_{1,t-1} \\ X_{2,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix}$$

$$\text{i.e. } \begin{pmatrix} \underline{X_{1,t}} \\ \underline{X_{2,t}} \end{pmatrix} = \begin{pmatrix} \underline{\phi_{11} X_{1,t-1} + \phi_{12} X_{2,t-1} + \underline{\epsilon_{1,t}}} \\ \underline{\phi_{21} X_{1,t-1} + \phi_{22} X_{2,t-1} + \underline{\epsilon_{2,t}}} \end{pmatrix}$$

Also

$$(\mathbf{I}_2 - \hat{\Phi} B) \underset{2 \times 1}{\tilde{X}_t} = \underset{2 \times 1}{\tilde{\epsilon}_t}$$

$$\text{i.e. } \hat{\Phi}(B) \underset{2 \times 1}{\tilde{X}_t} = \underset{2 \times 1}{\tilde{\epsilon}_t}$$

$$\hat{\Phi}(B) = \begin{pmatrix} 1 - \phi_{11}B & -\phi_{12}B \\ -\phi_{21}B & 1 - \phi_{22}B \end{pmatrix} \begin{matrix} \text{VAR matrix} \\ \text{polynomial} \end{matrix}$$

Condition for stationarity of VAR(p)

A K -variate VAR(p) process is covariance stationary if all values of z satisfying $|\Phi(z)| = 0$ ($|A|$ is determinant of A) all lie outside the unit circle

i.e. all z satisfying

$$|I_K - \Phi_1 z - \Phi_2 z^2 - \dots - \Phi_p z^p| = 0$$

lie outside the unit circle,

i.e. all y satisfying

$$|I_K y^p - \Phi_1 y^{p-1} - \dots - \Phi_p| = 0$$

lie inside the unit circle

Example VAR(1) with $K=2$

$$\begin{pmatrix} X_{1,t} \\ X_{2,t} \end{pmatrix} = \begin{pmatrix} 1 & -.6 \\ .5 & -.7 \end{pmatrix} \begin{pmatrix} X_{1,t-1} \\ X_{2,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix}$$

$$\Phi(B) = I_2 - \begin{pmatrix} 1 & -.6 \\ .5 & -.7 \end{pmatrix} B$$

$$\begin{aligned}
 |\Phi(z)| &= \begin{vmatrix} 1-z & .6z \\ -.5z & 1+.7z \end{vmatrix} = (1-z)(1+.7z) + .3z^2 \\
 &= (1+.7z - z - .7z^2) + .3z^2 \\
 &= 1 - .3z - .4z^2 \\
 &= (1 - .8z)(1 + .5z)
 \end{aligned}$$

Roots of $|\Phi(z)| = 0$ are $\frac{1}{.8}$, $-\frac{1}{.5}$

\Rightarrow all z satisfying $|\Phi(z)| = 0$ lie outside the unit circle

\Rightarrow the VAR(1) process is covariance stationary.

Remark: w.l.o.g. we can take mean vector of a covariance stationary VAR(1) as null vector, i.e. we take w.l.o.g. a VAR(1) (covariance stationary) without a const vector in the model,

$$\begin{aligned}
 \text{or } \underset{\sim}{Y}_t &= \underset{\sim}{\delta} + \underset{\sim}{\Phi}_1 \underset{\sim}{Y}_{t-1} + \dots + \underset{\sim}{\Phi}_p \underset{\sim}{Y}_{t-p} + \underset{\sim}{\epsilon}_t \\
 &\quad \underset{\sim}{Y}_t \sim_{K \times 1} \quad \underset{\sim}{\delta} \sim \quad \underset{\sim}{\Phi}_i \sim \quad \underset{\sim}{Y}_{t-i} \sim \quad \underset{\sim}{\epsilon}_t \sim \text{VWN}(0, I)
 \end{aligned}$$

$$E(\underset{\sim}{Y}_t) = E(\underset{\sim}{\delta} + \underset{\sim}{\Phi}_1 \underset{\sim}{Y}_{t-1} + \dots + \underset{\sim}{\Phi}_p \underset{\sim}{Y}_{t-p} + \underset{\sim}{\epsilon}_t)$$

$$\text{i.e. } \underset{\sim}{\mu} = \underset{\sim}{\delta} + \underset{\sim}{\Phi}_1 \underset{\sim}{\mu} + \dots + \underset{\sim}{\Phi}_p \underset{\sim}{\mu}$$

$$\Rightarrow (\mathbf{I}_k - \hat{\Phi}_1 - \dots - \hat{\Phi}_p) \underline{\mu} = \underline{\delta}$$

$$\Rightarrow \underline{\mu} = (\mathbf{I}_k - \hat{\Phi}_1 - \dots - \hat{\Phi}_p)^{-1} \underline{\delta}$$

$$\text{i.e. } \underline{\mu} = (\hat{\Phi}(1))^{-1} \underline{\delta}$$

$$\left(\begin{array}{l} \text{Note that } \hat{\Phi}(z) = \mathbf{I}_k - \hat{\Phi}_1 z - \dots - \hat{\Phi}_p z^p \\ \hat{\Phi}(1) = \mathbf{I}_k - \hat{\Phi}_1 - \dots - \hat{\Phi}_p \\ \& \hat{\Phi}(1) \text{ is non singular} \\ \text{as } |\hat{\Phi}(1)| \neq 0 \text{ for stationary process.} \end{array} \right)$$

$$\underline{\delta} = \hat{\Phi}(1) \underline{\mu}$$

$$\Rightarrow y_t - \underline{\mu} = \hat{\Phi}_1 (y_{t-1} - \underline{\mu}) + \dots + \hat{\Phi}_p (y_{t-p} - \underline{\mu}) + \epsilon_t$$

$$\text{let } x_t = y_t - \underline{\mu}$$

$$\Rightarrow x_t = \hat{\Phi}_1 (x_{t-1}) + \dots + \hat{\Phi}_p x_{t-p} + \epsilon_t$$

Equivalent VAR(p) with same VWN and

$\hat{\Phi}_1, \dots, \hat{\Phi}_p$ and without const vector

A. Mean vector & covariance stationary VAR(p)

$$x_t = \hat{\Phi}_1 x_{t-1} + \dots + \hat{\Phi}_p x_{t-p} + \epsilon_t$$

$$\hat{\Phi}_p \neq 0, \epsilon_t \sim \text{VWN}(0, \Sigma)$$

$$\text{Cov}(\epsilon_t, x_{t-j}) = 0 \quad \forall j > 0$$

$$\tilde{x}_t = \Phi_1 \tilde{x}_{t-1} + \dots + \Phi_p \tilde{x}_{t-p} + \epsilon_t$$

$$\Rightarrow \mu = E(\tilde{x}_t) = \Phi_1 E(\tilde{x}_{t-1}) + \dots + \Phi_p E(\tilde{x}_{t-p}) + 0$$

$$\text{i.e. } \mu = \Phi_1 \mu + \dots + \Phi_p \mu$$

$$\text{i.e. } (\mathbf{I}_K - \Phi_1 - \dots - \Phi_p) \mu = 0$$

$$\text{i.e. } \Phi(1) \mu = 0$$

$$\Rightarrow \mu = 0 \quad (|\Phi(1)| \neq 0).$$

Auto covariance matrix function

$$\Gamma_0 = \text{Cov}(\tilde{x}_t, \tilde{x}_t) = E(\tilde{x}_t \tilde{x}_t')$$

$$= E(\tilde{x}_t (\Phi_1 \tilde{x}_{t-1} + \dots + \Phi_p \tilde{x}_{t-p} + \epsilon_t)')$$

$$= E(\tilde{x}_t \tilde{x}_{t-1}') \Phi_1' + E(\tilde{x}_t \tilde{x}_{t-2}') \Phi_2' + \dots$$

$$+ E(\tilde{x}_t \tilde{x}_{t-p}') \Phi_p' + E(\tilde{x}_t \epsilon_t')$$

Note that

$$E(\tilde{x}_t \epsilon_t') = E(\tilde{x}_t (\Phi_1 \tilde{x}_{t-1} + \dots + \Phi_p \tilde{x}_{t-p} + \epsilon_t) \epsilon_t')$$

$$= \Phi_1 \text{Cov}(\tilde{x}_{t-1}, \epsilon_t) + \dots + \Phi_p \text{Cov}(\tilde{x}_{t-p}, \epsilon_t)$$

$$+ \text{Cov}(\epsilon_t, \epsilon_t)$$

$$= \sum (\text{Cov}(\tilde{x}_{t-j}, \epsilon_t) = 0 \quad \forall j > 0)$$

$$\Rightarrow \Gamma_0 = \Gamma(-1) \Phi_1' + \Gamma(-2) \Phi_2' + \dots + \Gamma(-p) \Phi_p' + \sum \quad (*)'$$

Note further that

$$\begin{aligned} \Gamma_0 &= E(\underline{X}_t \underline{X}_t') \quad \text{can be derived through} \\ &= E(\Phi_1 \underline{X}_{t-1} + \dots + \Phi_p \underline{X}_{t-p} + \epsilon_t) \underline{X}_t' \\ &= \Phi_1 E(\underline{X}_{t-1} \underline{X}_t') + \dots + \Phi_p E(\underline{X}_{t-p} \underline{X}_t') + E(\epsilon_t \underline{X}_t') \\ &= \Phi_1 (E(\underline{X}_t \underline{X}_{t-1}'))' + \dots + \Phi_p (E(\underline{X}_t \underline{X}_{t-p}'))' + \sum \end{aligned}$$

i.e $\Gamma_0 = \Phi_1 (\Gamma(-1))' + \dots + \Phi_p (\Gamma(-p))' + \sum$

i.e $\Gamma_0 = \Phi_1 \Gamma(1) + \dots + \Phi_p \Gamma(p) + \sum \quad ((\Gamma(-h))' = \Gamma(h)) \quad (*)^2$

$(*)' = (*)^2$ - Γ_0 is anyway symmetric matrix

$$\text{Cov}(\underline{X}_t, \underline{X}_{t+h}) = E(\underline{X}_t \underline{X}_{t+h}')$$

$$= E(\underline{X}_t (\underline{\Phi}_1 \underline{X}_{t+h-1} + \dots + \underline{\Phi}_p \underline{X}_{t+h-p} + \underline{\epsilon}_{t+h})')$$

$$\forall h > 0$$

$$\Gamma_h = \text{Cov}(\underline{X}_t, \underline{X}_{t+h})$$

$$= E(\underline{X}_t \underline{X}_{t+h-1}') \underline{\Phi}_1' + \dots + E(\underline{X}_t \underline{X}_{t+h-p}') \underline{\Phi}_p'$$

$$\left(E(\underline{X}_t \underline{\epsilon}_{t+h}') = \text{Cov}(\underline{X}_t, \underline{\epsilon}_{t+h}) = 0 \text{ as } h > 0 \right)$$

$$\Rightarrow \Gamma(h) = \Gamma(h-1) \underline{\Phi}_1' + \dots + \Gamma(h-p) \underline{\Phi}_p'$$

matrix Yule-Walker eqⁿ

$$\text{Further } \Gamma(-h) = (\Gamma(h))'$$

Causal VAR process

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Defⁿ: A VAR(p) process is said to be Causal if it can be expressed in terms of a VWN sequence as a VMA(∞) form

VMA(∞) representation of VAR

VAR(1) $\tilde{X}_t = \Phi \tilde{X}_{t-1} + \tilde{\epsilon}_t ; \tilde{\epsilon}_t \sim \text{VWN}(0, \Sigma)$

$$\Phi(B) \tilde{X}_t = \tilde{\epsilon}_t$$

$$\Phi(B) = I_K - \Phi B$$

Suppose $\Phi(B)^{-1}$ is the inverse of the operator $\Phi(B)$

$$\text{i.e. } \Phi(B)^{-1} \Phi(B) = I_K$$

Then $\tilde{X}_t = \Phi(B)^{-1} \tilde{\epsilon}_t = \Psi(B) \tilde{\epsilon}_t$, say

where $\Psi(B) = \Psi_0 + \Psi_1 B + \Psi_2 B^2 + \dots$

$$\Phi(B)^{-1} = \Psi(B)$$

$$\text{i.e. } I_K = \Phi(B) \Psi(B)$$

$$\begin{aligned} \text{i.e. } I_K &= (I_K - \Phi B) (\Psi_0 + \Psi_1 B + \Psi_2 B^2 + \dots) \\ &= (\Psi_0 + \Psi_1 B + \Psi_2 B^2 + \dots) \\ &\quad - (\Phi \Psi_0 B + \Phi \Psi_1 B^2 + \dots) \end{aligned}$$

$$\text{i.e. } I_K = \Psi_0 + (\Psi_1 - \Phi \Psi_0) B + (\Psi_2 - \Phi \Psi_1) B^2 + \dots$$

Comparing coefficient of B^j

$$B^0 : \quad \Psi_0 = I_K$$

$$B^1 : \quad \Psi_1 = \Phi$$

$$B^2 : \quad \Psi_2 = \Phi \Psi_1 = \Phi^2$$

$$B^j : \quad \Psi_j = \Phi^j$$

$$\Rightarrow \underline{X}_t = \sum_{j=0}^{\infty} \Phi^j \underline{\epsilon}_{t-j}$$

This is the causal representation a covariance stationary VAR(1)

VAR(p) Suppose $\{X_t\}$ is covariance stationary VAR(p)

$$\underline{X}_t = \Phi_1 \underline{X}_{t-1} + \dots + \Phi_p \underline{X}_{t-p} + \underline{\epsilon}_t$$

$$\underline{\epsilon}_t \sim \text{VWN}(\underline{0}, \Sigma)$$

Suppose $\underline{\Phi}(B) \underline{X}_t = \underline{\epsilon}_t$; $\underline{\Phi}(B) = I_K - \sum_{i=1}^p \Phi_i B^i$

$$\underline{X}_t = \underline{\Phi}(B)^{-1} \underline{\epsilon}_t = \underline{\Psi}(B) \underline{\epsilon}_t = \sum_{j=0}^{\infty} \Psi_j \underline{\epsilon}_{t-j}$$

$$\underline{\Psi}(B) \text{ is } \ni \underline{\Phi}(B) \underline{\Psi}(B) = I_K$$

$$\text{i.e.} \left(I_K - \sum_{i=1}^p \Phi_i B^i \right) \left(\sum_{j=0}^{\infty} \Psi_j B^j \right) = I_K$$

$$\text{i.e. } (I_K - \Phi_1 B - \Phi_2 B^2 - \dots - \Phi_p B^p)$$

$$(\Psi_0 + \Psi_1 B + \Psi_2 B^2 + \dots) = I_K$$

$$\begin{aligned} \text{i.e. } \Psi_0 B^0 + (\Psi_1 - \Phi_1 \Psi_0) B + (\Psi_2 - \Phi_1 \Psi_1 - \Phi_2 \Psi_0) B^2 \\ + (\Psi_3 - \Phi_1 \Psi_2 - \Phi_2 \Psi_1 - \Phi_3 \Psi_0) B^3 + \dots \\ = I_K \end{aligned}$$

Comparing coefficients, we have

$$\Psi_0 = I_K$$

$$\Psi_1 = \Phi_1$$

$$\Psi_2 = \Phi_1 \Psi_1 + \Phi_2 \Psi_0$$

$$\Psi_3 = \Phi_1 \Psi_2 + \Phi_2 \Psi_1 + \Phi_3 \Psi_0$$

In general, $\forall s \geq 2$

$$\Psi_s = \Phi_1 \Psi_{s-1} + \Phi_2 \Psi_{s-2} + \dots + \Phi_p \Psi_{s-p}$$

$$\text{with } \Psi_0 = I_K \text{ \& } \Psi_l = 0 \quad \forall l < 0$$

$\Psi_0, \Psi_1, \Psi_2, \dots$ gives the Causal VMA(∞) representation of VAR(p).