



Chapter 5: VAR Models & Granger Causality

Multivariate Time Series



Lecture Outline

- 1 Introduction to Multivariate Time Series
- 2 Vector Autoregression (VAR)
- 3 Granger Causality
- 4 Impulse Response Functions
- 5 Forecast Error Variance Decomposition
- 6 Practical Example
- 7 Summary

Why Multivariate Analysis?

Limitations of Univariate Models

- ARIMA models each variable **in isolation**
- Ignores potential **interactions** between variables
- Cannot capture **feedback effects**

Economic Examples of Interdependence

- GDP and unemployment (Okun's law)
- Interest rates and inflation (Taylor rule)
- Stock prices and trading volume
- Exchange rates and trade balance

Multivariate Time Series Notation

Vector of Variables

Let $\mathbf{Y}_t = (Y_{1t}, Y_{2t}, \dots, Y_{Kt})'$ be a $K \times 1$ vector of time series.

Example with $K = 2$:

$$\mathbf{Y}_t = \begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} \text{GDP growth}_t \\ \text{Inflation}_t \end{pmatrix}$$

Key Questions

- 1 Does Y_1 help predict Y_2 ? (Granger causality)
- 2 How do shocks to Y_1 affect Y_2 ? (Impulse responses)
- 3 What proportion of Y_2 's variance is due to Y_1 ? (Variance decomposition)

The VAR(p) Model

Definition

A **VAR(p)** model for K variables:

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{A}_1 \mathbf{Y}_{t-1} + \mathbf{A}_2 \mathbf{Y}_{t-2} + \cdots + \mathbf{A}_p \mathbf{Y}_{t-p} + \boldsymbol{\varepsilon}_t$$

where:

- \mathbf{Y}_t : $K \times 1$ vector of endogenous variables
- \mathbf{c} : $K \times 1$ vector of constants
- \mathbf{A}_i : $K \times K$ coefficient matrices
- $\boldsymbol{\varepsilon}_t$: $K \times 1$ vector of error terms with $\mathbb{E}[\boldsymbol{\varepsilon}_t] = \mathbf{0}$, $\mathbb{E}[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'] = \boldsymbol{\Sigma}$

VAR(1) with Two Variables

Bivariate VAR(1)

$$\begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

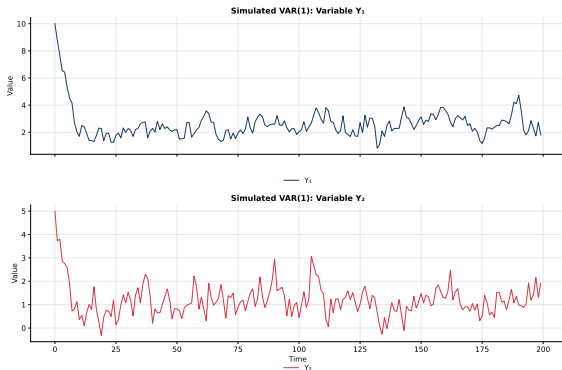
Equation by Equation

$$Y_{1t} = c_1 + a_{11} Y_{1,t-1} + a_{12} Y_{2,t-1} + \varepsilon_{1t}$$

$$Y_{2t} = c_2 + a_{21} Y_{1,t-1} + a_{22} Y_{2,t-1} + \varepsilon_{2t}$$

Key insight: Each equation includes lags of **all** variables!

Simulated VAR Process



- Two simulated series from a bivariate VAR(1) process showing interdependence
- Each variable responds to both its own past and the other variable's past
- Notice how the series co-move due to cross-equation dynamics

Stationarity of VAR

Stability Condition

VAR(p) is **stable** (stationary) if all roots of:

$$\det(\mathbf{I}_K - \mathbf{A}_1 z - \mathbf{A}_2 z^2 - \dots - \mathbf{A}_p z^p) = 0$$

lie **outside** the unit circle (i.e., $|z| > 1$).

For VAR(1)

The model is stable if all **eigenvalues** of \mathbf{A}_1 are less than 1 in absolute value.

Example: For $\mathbf{A}_1 = \begin{pmatrix} 0.5 & 0.1 \\ 0.2 & 0.3 \end{pmatrix}$, eigenvalues are $\lambda_1 = 0.6$ and $\lambda_2 = 0.2$.

Both $< 1 \Rightarrow$ stable!

Estimation of VAR

OLS Estimation

Each equation can be estimated by **OLS separately**:

$$\hat{\mathbf{A}} = \left(\sum_{t=1}^T \mathbf{Y}_{t-1} \mathbf{Y}_{t-1}' \right)^{-1} \left(\sum_{t=1}^T \mathbf{Y}_{t-1} \mathbf{Y}_t' \right)$$

This is efficient because all equations have the **same regressors**.

Covariance Matrix

$$\hat{\Sigma} = \frac{1}{T - Kp - 1} \sum_{t=1}^T \hat{\varepsilon}_t \hat{\varepsilon}_t'$$

The errors ε_{1t} and ε_{2t} may be **contemporaneously correlated**.

Information Criteria

Choose p that minimizes:

$$\text{AIC}(p) = \ln |\hat{\Sigma}_p| + \frac{2pK^2}{T}$$

$$\text{BIC}(p) = \ln |\hat{\Sigma}_p| + \frac{pK^2 \ln T}{T}$$

$$\text{HQ}(p) = \ln |\hat{\Sigma}_p| + \frac{2pK^2 \ln \ln T}{T}$$

Guidelines

- AIC tends to select **larger** models (better for forecasting)
- BIC tends to select **smaller** models (consistent selection)
- Start with maximum p_{max} based on data frequency (e.g., 4 for quarterly, 12 for monthly)

What is Granger Causality?

Clive Granger (1969, Nobel Prize 2003)

“**X Granger-causes Y**” if past values of X help predict Y , **beyond** what past values of Y alone can predict.

Important Distinction

Granger causality \neq True causality

- Granger causality is about **predictive content**
- Does NOT imply economic/structural causation
- “**X Granger-causes Y**” means: X contains useful information for forecasting Y

Granger Causality

X **does not** Granger-cause Y if:

$$\mathbb{E}[Y_t | Y_{t-1}, Y_{t-2}, \dots, X_{t-1}, X_{t-2}, \dots] = \mathbb{E}[Y_t | Y_{t-1}, Y_{t-2}, \dots]$$

In other words: adding X 's history does not improve the prediction of Y .

In the VAR Context

For VAR(1): $Y_{1t} = c_1 + a_{11} Y_{1,t-1} + a_{12} Y_{2,t-1} + \varepsilon_{1t}$

Y_2 does **not** Granger-cause Y_1 if $a_{12} = 0$.

For VAR(p): Y_2 does not Granger-cause Y_1 if $a_{12}^{(1)} = a_{12}^{(2)} = \dots = a_{12}^{(p)} = 0$.

Testing for Granger Causality

Hypothesis Test

H_0 : Y_2 does **not** Granger-cause Y_1

$$H_0 : a_{12}^{(1)} = a_{12}^{(2)} = \dots = a_{12}^{(p)} = 0$$

H_1 : At least one $a_{12}^{(i)} \neq 0$ (Granger causality exists)

Test Statistic: Wald Test

$$F = \frac{(RSS_R - RSS_U)/p}{RSS_U/(T - 2p - 1)} \sim F_{p, T-2p-1}$$

where:

- RSS_R : Residual sum of squares from restricted model (without Y_2 lags)
- RSS_U : Residual sum of squares from unrestricted model (full VAR)

Types of Granger Causality



Unidirectional: $X \rightarrow Y$



Bidirectional: $X \leftrightarrow Y$



Unidirectional: $Y \rightarrow X$

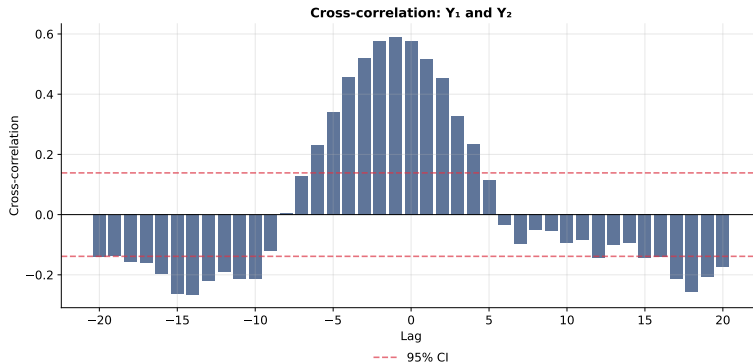


No causality

Economic Examples

- Money \rightarrow Output? (monetarist view)
- Stock prices \leftrightarrow Trading volume (bidirectional)
- Weather \rightarrow Crop yields (unidirectional, obvious)

Cross-Correlation Analysis



- Cross-correlation function measures linear dependence at different lags
- Significant correlations at negative lags suggest X leads Y ; positive lags suggest Y leads X
- Useful for preliminary analysis before formal Granger causality testing

Common Pitfalls

- 1 **Omitted variables:** A third variable Z may cause both X and Y
- 2 **Non-stationarity:** Test requires stationary data (or cointegration)
- 3 **Lag selection:** Results can be sensitive to p
- 4 **Sample size:** Need sufficient observations

Best Practices

- Test for unit roots first
- Use multiple lag selection criteria
- Check robustness to different lag lengths
- Report results for both directions

What are Impulse Response Functions?

Definition

An **Impulse Response Function (IRF)** traces the effect of a one-time shock to one variable on the current and future values of all variables.

Question IRFs Answer

"If there is an unexpected 1-unit shock to Y_1 today, what happens to Y_1 and Y_2 over the next h periods?"

MA(∞) Representation

A stable VAR(p) can be written as:

$$\mathbf{Y}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\Phi}_i \boldsymbol{\varepsilon}_{t-i}$$

The matrices $\boldsymbol{\Phi}_i$ are the **impulse responses** at horizon i .

Computing IRFs for VAR(1)

For VAR(1): $\mathbf{Y}_t = \mathbf{c} + \mathbf{A}\mathbf{Y}_{t-1} + \varepsilon_t$

The impulse response matrices are:

$$\Phi_0 = \mathbf{I}_K, \quad \Phi_1 = \mathbf{A}, \quad \Phi_2 = \mathbf{A}^2, \quad \dots, \quad \Phi_h = \mathbf{A}^h$$

Interpretation

$[\Phi_h]_{ij}$ = Effect on Y_i at time $t + h$ of a unit shock to Y_j at time t

For stable VAR: $\Phi_h \rightarrow \mathbf{0}$ as $h \rightarrow \infty$ (shocks die out)

Orthogonalized IRFs

Problem: Correlated Errors

If Σ is not diagonal, shocks ε_{1t} and ε_{2t} are correlated.

A shock to “ Y_1 ” also involves a shock to “ Y_2 ”.

Solution: Cholesky Decomposition

Factor $\Sigma = \mathbf{P}\mathbf{P}'$ where \mathbf{P} is lower triangular.

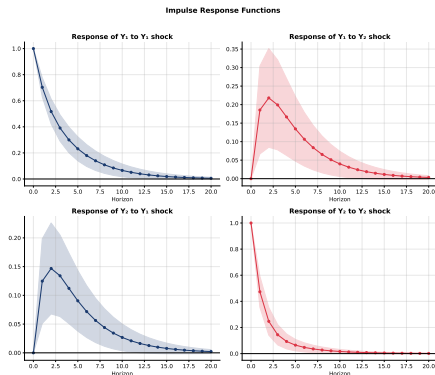
Define orthogonalized shocks: $\mathbf{u}_t = \mathbf{P}^{-1}\varepsilon_t$ with $\mathbb{E}[\mathbf{u}_t\mathbf{u}_t'] = \mathbf{I}$

Orthogonalized IRFs: $\Theta_h = \Phi_h\mathbf{P}$

Ordering Matters!

Cholesky assumes variables ordered from “most exogenous” to “most endogenous”. Results depend on this ordering.

Impulse Response Functions: Example



- IRFs show how each variable responds to a one-unit shock over time
- Shaded regions represent confidence intervals (uncertainty in estimates)
- For stable VAR models, responses converge to zero as the horizon increases

Variance Decomposition

Question

What proportion of the forecast error variance of Y_i at horizon h is due to shocks to Y_j ?

FEVD Formula

$$\text{FEVD}_{ij}(h) = \frac{\sum_{s=0}^{h-1} [\Theta_s]_{ij}^2}{\sum_{s=0}^{h-1} \sum_{k=1}^K [\Theta_s]_{ik}^2}$$

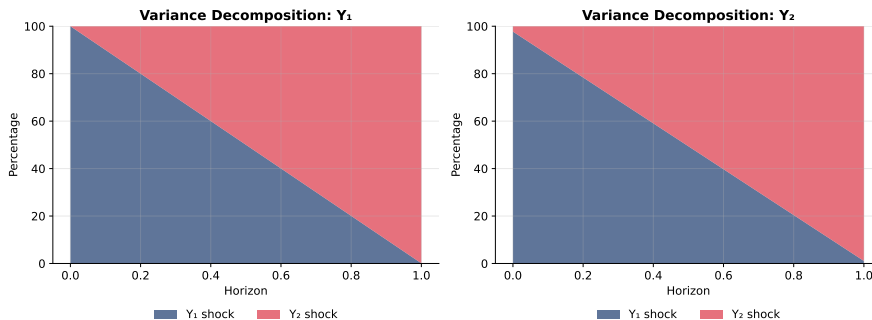
This gives the **percentage** of Y_i 's h -step forecast variance explained by shocks to Y_j .

Properties

- $0 \leq \text{FEVD}_{ij}(h) \leq 1$
- $\sum_{j=1}^K \text{FEVD}_{ij}(h) = 1$ (sums to 100%)
- At $h = 1$: Own shocks dominate (by construction with Cholesky)

FEVD: Example

Forecast Error Variance Decomposition



- FEVD shows the proportion of forecast variance attributable to each shock
- At short horizons, own shocks dominate; cross-variable effects grow over time
- Useful for understanding the relative importance of different shocks in the system

Example: GDP and Unemployment

Okun's Law

There is a negative relationship between GDP growth and unemployment:

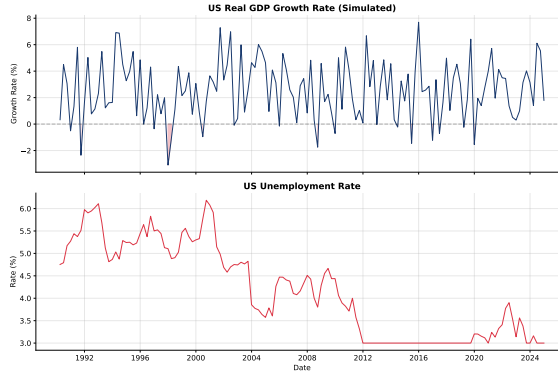
$$\Delta U_t \approx -\beta(\Delta Y_t - \bar{g})$$

where \bar{g} is trend GDP growth and $\beta \approx 0.4$.

VAR Analysis Questions

- 1 Does GDP growth Granger-cause unemployment changes?
- 2 Does unemployment Granger-cause GDP growth?
- 3 How do shocks propagate between variables?

GDP and Unemployment: Data



- GDP growth and unemployment rate show clear negative correlation (Okun's Law)
- Both series exhibit cyclical patterns related to business cycle fluctuations
- This bivariate system is ideal for VAR analysis and Granger causality testing

① Data preparation

- Check for stationarity (unit root tests)
- Transform if necessary (differences, logs)

② Lag selection

- Use AIC, BIC, HQ criteria
- Check residual autocorrelation

③ Estimation

- OLS equation by equation
- Check stability (eigenvalues)

④ Analysis

- Granger causality tests
- Impulse response functions
- Variance decomposition

⑤ Forecasting

VAR in Python (statsmodels)

```
from statsmodels.tsa.api import VAR
from statsmodels.tsa.stattools import grangercausalitytests

# Fit VAR model
model = VAR(data)
results = model.fit(maxlags=4, ic='aic')

# Granger causality test
granger_test = grangercausalitytests(data[['Y1', 'Y2']],
                                     maxlag=4)

# Impulse response functions
irf = results.irf(periods=20)
irf.plot()

# Variance decomposition
fevd = results.fevd(periods=20)
fevd.plot()
```

Key Takeaways

VAR Models

- Model **multiple** time series jointly
- Each variable depends on its own lags AND lags of other variables
- Estimated by OLS equation by equation
- Requires stationarity (or differencing)

Granger Causality

- Tests whether X helps predict Y beyond Y 's own history
- **Not** the same as true causality
- F-test on coefficient restrictions

IRF and FEVD

- IRF: How shocks propagate through the system
- FEVD: What proportion of variance is due to each shock
- Both depend on variable ordering (Cholesky)

What's Next?

Topics for Further Study

- **Cointegration:** Long-run relationships between non-stationary variables
- **VECM:** Error correction models for cointegrated systems
- **Structural VAR:** Imposing economic theory restrictions
- **Panel VAR:** VAR for panel data

Questions?