

# Multivariate Models Summary

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## Simultaneous Equations Models

All the models we have looked at thus far have been single equations models of the form:

$$(ARMAX) \quad y\phi(L) = X\beta + \theta(L)u \quad (1)$$

*outside the model* (pointing to  $y\phi(L)$ ) *inside the model* (pointing to  $\theta(L)u$ )

where  $X$  contains exogenous variables, and  $y$  is an endogenous variable. In a simultaneous equations model, we consider systems of equations such as the demand and supply of a good:

$$\begin{cases} Q_d = \alpha_1 + \beta_1 P + \gamma_1 S + u_d & (2) \\ Q_s = \alpha_2 + \beta_2 P + \gamma_2 T + u_s & (3) \\ Q_d = Q_s & (4) \end{cases}$$

*price* (pointing to  $P$ ) *"state of technology"* (pointing to  $T$ )

Here,  $P$  and  $Q$  are endogenous, while  $S$  and  $T$  are exogenous.

## Structural Form and Reduced Form

The structural form of the simultaneous equations model is given by:

*assuming equilibrium of the market:*

$$\begin{cases} Q_d = \alpha_1 + \beta_1 P + \gamma_1 S + u_d & (5) \\ Q_s = \alpha_2 + \beta_2 P + \gamma_2 T + u_s & (6) \end{cases}$$

By solving these equations for the endogenous variables, we obtain the reduced form:

$$\begin{cases} P = \pi_{10} + \pi_{11}S + \pi_{12}T + v_1 & (7) \\ Q = \pi_{20} + \pi_{21}S + \pi_{22}T + v_2 & (8) \end{cases}$$

## Simultaneous Equations Bias

Estimating the structural form using OLS will lead to **biased** and **inconsistent coefficient estimates** due to the endogeneity of  $P$ . This is known as simultaneous equations bias.

↳ both equations depend on  $P$ .



not possible to use OLS directly on structural form.

## Identification of Simultaneous Equations

To identify an equation, it must satisfy certain conditions:

necessary but not sufficient.

"naïve"

- **Order Condition:** An equation is exactly identified if the number of excluded variables from that equation is equal to the number of endogenous variables minus one. *Over-id. if more than G-1 are absent. Under if less.*
- **Rank Condition:** A **necessary and sufficient** condition for identification, involving the rank of a matrix of coefficients.

In finance: often over-identified.

## Tests for Exogeneity

The Hausman test can be used **to determine whether variables should be treated as endogenous**. This involves estimating reduced form equations, obtaining fitted values and residuals, and testing the inclusion of these residuals in the original equation.

## Recursive Systems

In recursive systems, equations can be estimated individually using OLS **if the error terms are uncorrelated** and the equations are ordered such that each endogenous variable is determined only by previously determined endogenous variables and exogenous variables.

↳ not many systems will be recursive.

**RECURSIVE** or **TRIANGULAR SYSTEM.**

## Estimation Techniques

### Indirect Least Squares (ILS)

ILS involves **estimating reduced form equations using OLS** and substituting back to obtain structural parameters. This method is valid but not commonly used due to its complexity.

### Two-Stage Least Squares (2SLS)

2SLS is a more practical approach, involving two stages:

- **Stage 1:** Estimate the reduced form equations using OLS and obtain fitted values. *every RHS*
- **Stage 2:** Replace endogenous variables in the structural equations with their fitted values from Stage 1 and estimate the structural equations using OLS.

## Instrumental Variables (IV)

IV methods involve using instruments that are correlated with endogenous variables but uncorrelated with the error terms. These "instruments" replace the endogenous variables in the structural equations.

### Example of 2SLS

Consider the following system:

$$\begin{cases} Y_1 = \alpha_0 + \alpha_1 Y_2 + \alpha_2 Y_3 + \alpha_3 X_1 + \alpha_4 X_2 + u_1 & (9) \\ Y_2 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + u_2 & (10) \\ Y_3 = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + u_3 & (11) \end{cases}$$

- **Stage 1:** Estimate the reduced form equations for  $Y_2$  and  $Y_3$  using OLS to obtain fitted values  $\hat{Y}_2$  and  $\hat{Y}_3$ .
- **Stage 2:** Replace  $Y_2$  and  $Y_3$  in the first equation with  $\hat{Y}_2$  and  $\hat{Y}_3$  and estimate using OLS.

## Other Estimation Techniques

- **Three-Stage Least Squares (3SLS):** Allows for non-zero covariances between error terms.
- **Limited Information Maximum Likelihood (LIML):** Estimates reduced form equations by maximum likelihood.
- **Full Information Maximum Likelihood (FIML):** Estimates all equations simultaneously using maximum likelihood.

→ see article of George & Longstaff (1993): modelling the bid-ask spread & volume for options.  
↳ 2SLS

Simultaneous models → NOT USED ANYMORE.

Recall that OLS directly on the struct. eq. is IMPOSSIBLE because the endogenous var. are correlated with the errors.

→ we don't use "directly" the instruments in the structural equation: but run regressions of the form:  $\begin{cases} Y_2 = \lambda_1 + \lambda_2 z_2 + \varepsilon_1 \\ Y_3 = \lambda_3 + \lambda_4 z_3 + \varepsilon_2 \end{cases}$   $z_i$ : instruments for  $z_i$ .

What do Fi. Econometrics are using when they deal w/ multivariate time series?

• Vector Autoregressive Models: generalization of autoreg. models (~1980).

↳ more than 1 dependent variable.

↳  $\begin{cases} y_{1t} = \dots \\ y_{2t} = \dots \end{cases}$   $y_{1t}$  depends NOT ONLY on its previous values BUT ALSO on the previous values of the 2nd time series.

can be extended to the case with  $k$  lags.

↳ Can be extended to a VAR( $g$ ) model:  $g$  variables &  $g$  eq.

$$\underset{g \times 1}{y_t} = \underset{g \times 1}{\beta_0} + \underset{g \times g}{\beta_1} \underset{g \times 1}{y_{t-1}} + \underset{g \times 1}{u_t}$$

Compactness of notation.

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} \\ \beta_{21} & \alpha_{21} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} \quad \begin{cases} y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + \alpha_{11} y_{2t-1} + u_{1t} \\ y_{2t} = \beta_{20} + \beta_{21} y_{2t-1} + \alpha_{21} y_{1t-1} + u_{2t} \end{cases}$$

**Advantages of VAR:** - no need to specify which variables are endo: all are endogenous!

- more general than ARMA.

- can use OLS.

- Forecasts are often better than "traditional structural" models: you can put together "key" time-series to get better predictions.

**Problems:** - a-theoretical.

- how to decide the appropriate lag?  $\Rightarrow$  I.C again (to be min.).

- Many params.

- how to interpret the coefficients?

→ standard form of VAR: you can put contemporary terms on the left side & invert the matrix... :  $y_t = A^{-1}\beta_0 + A^{-1}\beta_1 y_{t-1} + A^{-1}u_t$ .

→ see article Brooks & Tsolacos (1999): use VAR methodology to investigate the interaction between the UK property mkt & various macroeconomic variables.

Method: how to work w/ multivariate stat. time-series?  $\left\{ \begin{array}{l} ① \text{ decide which endogenous variables you are interested in. Test for exogeneity w/ Hausman.} \\ ② \text{ decide simultaneous equations VS VAR.} \\ ③ \text{ estimate the sim. system (2SLS) + stat. Test.} \\ ④ \text{ use VAR or VARX : } \begin{array}{l} a) \text{ find opti. lag with I.C.} \\ b) \text{ estimate the selected model.} \\ c) \text{ statistical analysis ...} \end{array} \end{array} \right.$