Chapter 18: SIMULTANEOUS EQUATION MODELS

NATURE OF SIMULTANEOUS EQUATION SYSTEMS

- STK 310 / RAL 780 / EKT 713 Single equation models
- Basic assumptions NB!!!!
- ullet Prediction of Y conditional on fixed values of the X variables.
- Unidirectional causal realtionship
- EKT 720 Part II Simultaneous equation systems
- ullet Two-way or simultaneous relationship between the X and Y variables
- Move away frome dependent and independent variables to endogenous and exogenous variables
- Do not estimate the parameters of a single equation without taking into account the information provided by the other equations of the system.
- OLS ????

Crucial assumption - the explanatory variables are non stochastic, or if stochastic are distributed independently from the stochastic disturbance term.

- If neither of these hold then estimators are **biased** and **inconsistent**
- Examples of Simulataneous Equation models
 - (a) Demand and Supply model
 - (b) National Income model
 - (c) Wage Price model
 - (d) IS Model of macro-economics
 - (e) LM Model of macro-economics

THE SIMULTANEOUS-EQUATION BIAS: INCONSISTENCY OF OLS ESTIMATORS

• Consider the Keynesian National Income model

Consumption
$$C_t = \beta_0 + \beta_1 Y_t + u_t \ 0 < \beta_1 < 1$$
 function

Income
$$Y_t = C_t + I_t$$
 identity

where

C = consumption expenditure

Y = income

I =exogenous investment

t = time

u = stochastic disturbance term

 β_0 and β_1 = parameters

Assume that

$$E(u_t) = 0$$

$$E(u_t^2) = \sigma^2$$

$$E(u_t; u_{t+j}) = 0$$
 for $i \neq j$

$$Cov(I_t, u_t) = 0$$

Correlation between u_t and Y_t :

$$Y_{t} = \beta_{0} + \beta_{1}Y_{t} + u_{t} + I_{t}$$

$$Y_{t} = \frac{\beta_{0}}{1 - \beta_{1}} + \frac{1}{1 - \beta_{1}}I_{t} + \frac{1}{1 - \beta_{1}}u_{t}$$
Now
$$E(Y_{t}) = \frac{\beta_{0}}{1 - \beta_{1}} + \frac{1}{1 - \beta_{1}}I_{t}$$
Therefore
$$Y_{t} - E(Y_{t}) = \frac{u_{t}}{1 - \beta_{1}}$$
and
$$u_{t} - E(u_{t}) = u_{t}$$
yielding
$$Cov(Y_{t}, u_{t}) = E[Y_{t} - E(Y_{t})][u_{t} - E(u_{t})]$$

$$= E[\frac{u_{t}}{1 - \beta_{1}}][u_{t}]$$

$$= \frac{E(u_{t}^{2})}{1 - \beta_{1}}$$

$$= \frac{\sigma^{2}}{1 - \beta_{1}}$$

indicating a non-zero correlation between u_t and Y_t :

Inconsistency of the estimator $\hat{\beta}_1$:

$$\hat{\beta}_{1} = \frac{\sum (C_{t} - \overline{C})(Y_{t} - \overline{Y})}{\sum (Y_{t} - \overline{Y})^{2}}$$

$$= \frac{\sum c_{t}y_{t}}{\sum y_{t}^{2}}$$

$$= \frac{\sum C_{t}y_{t}}{\sum y_{t}^{2}}$$

where the lowercase letters indicate deviation form

$$\hat{\beta}_1 = \frac{\sum (\beta_0 + \beta_1 Y_t + u_t) y_t}{\sum y_t^2}$$

$$= \beta_1 + \frac{\sum y_t u_t}{\sum y_t^2}$$

If we take expectations on both sides:

$$E(\hat{\beta}_1) = \beta_1 + E\left(\frac{\sum y_t u_t}{\sum y_t^2}\right)$$

Unfortunately we cannot evaluate $E\left(\frac{\sum y_t u_t}{\sum y_t^2}\right)$ since the expectations operator is a linear operator.

Intuitively: If $\left(\frac{\sum y_t u_t}{\sum y_t^2}\right) = 0$ the the estimator is unbiased.

Compare - What did we prove in the previous section??????

$$Cov(Y_t, u_t) \neq 0$$

- sample versus population !!!!!!

But if the sample increases the sample measure will tend toward the population measure.

Use the large sample properties - probability limit:

$$plim(\hat{\beta}_{1}) = plim(\beta_{1}) + plim\left(\frac{\sum y_{t}u_{t}}{\sum y_{t}^{2}}\right)$$

$$= plim(\beta_{1}) + plim\left(\frac{\sum y_{t}u_{t}/n}{\sum y_{t}^{2}/n}\right)$$

$$= plim(\beta_{1}) + \left(\frac{plim(\sum y_{t}u_{t})/n}{plim(\sum y_{t}^{2})/n}\right)$$

$$= \beta_{1} + \left(\frac{\sigma^{2}/(1-\beta_{1})}{\sigma_{Y}^{2}}\right)$$

$$= \beta_{1} + \frac{1}{1-\beta_{1}}\left(\frac{\sigma^{2}}{\sigma_{Y}^{2}}\right)$$

Yielding a biased and inconsitent estimator.