

9

(2 SLS)
(3 SLS)
STOCHASTIC

REGRESSORS

[x's not fixed]

3 cases: SUMMARY

- 1) $X \notin \epsilon$ independent;
OLS "OK", usual $\hat{\beta}$ unbiased, t -ratios OK, ...
- 2) $X \notin \epsilon$ contemporaneously uncorrelated;
OLS $\hat{\beta}$ biased, but consistent - be careful.
- 3) $X \notin \epsilon$ correlated;
OLS not OK. Big problem!

Case 1): $X \notin \epsilon$ independent.

i.e. x_{ti} is independent of ϵ_s , $\forall t, s = 1, \dots, T$
and $\forall i = 1, \dots, K$.

i.e. Allowing X to be random,
but uncorrelated with any disturbance.

Now X is a random variable,
with its own distribution and properties.

Now we must talk about all the other r. v.'s
[ϵ , estimates of β_i , σ^2 , ...]
conditional on X .

i.e. given X , we can discuss these.

e.g.

The independence implies,

$$f(\epsilon|x) = f(\epsilon) = N(0, \sigma^2 I) \text{ density}$$

✓ i.e. the conditional density of ϵ (given X)
= the unconditional density of ϵ .

This means that conditional on X ,
all the previous OLS properties hold.

✓ \rightarrow Conditional on X , $\hat{\beta}$ is nice,
 s^2 is nice,
 t & F statistics are nice

What if we want to talk about
the distribution of $\hat{\beta}$ not conditional on X ?

✓ Consider $\hat{\beta} = \beta + (X'X)^{-1} X'\epsilon$.

If X is random,
the distribution of this is weird
and not generally Normal.

Still, some properties hold. \Rightarrow

~~However, again,
we must talk about estimates
conditional on X .
Given X & its parameters, we have $\epsilon, \hat{\beta}, s^2$~~

xero

[To discuss these properties, need a Lemma.]

3

Lemma: Let x & y be random variables
and g be a function \rightarrow
 $E[g(x, y)]$ exists. Then

$$E[g(x, y)] = E_y [E_{x/y} [g(x, y)]]$$

$\underbrace{\hspace{10em}}$
($E[x, \text{conditional on } y]$)
— a function of y .)

Proof: Suppose $f(x, y) =$ joint density.

$$\text{Then } E[g(x, y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f(x, y) dx dy$$

$$= \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} \frac{g(x, y) f(x, y)}{f(y)} dx \right] f(y) dy$$

(where $f(y) =$ marginal density)

$$= E_y [E_{x/y} [g(x, y)]]$$

QED

Thm: If $E(\hat{\beta})$ exists, then $E(\hat{\beta}) = \beta$.

Proof: $\hat{\beta} = \beta + (X'X)^{-1}X'\epsilon$

$$E(\hat{\beta}) = \beta + E_x \left[\underbrace{E_{\epsilon|x} [(X'X)^{-1}X'\epsilon]} \right]$$

↓ (If $X \notin \epsilon$ independent, this = 0.)
= β

* The second step is just an applic. of the lemma with $x = \epsilon$, $y = X$, and $g(x, y) = (X'X)^{-1}X'\epsilon$.

Alternative Proof:

$$\begin{aligned} E(\hat{\beta}) &= \beta + E[(X'X)^{-1}X'\epsilon] \\ &= \beta + E[(X'X)^{-1}X'] E(\epsilon) \quad (\text{since } X \notin \epsilon \text{ independent}) \\ &= \beta \end{aligned}$$

Problem: What is $E[(X'X)^{-1}X']$?

It depends on the distribution of X !
— It may not exist (eg. Cauchy).

If it exists, $\hat{\beta}$ unbiased.

Thm.: The Covariance Matrix of $\hat{\beta}$ is $\sigma^2 E[(X'X)^{-1}]$.

(again, if it exists)

Proof:

$$\begin{aligned} \text{Cov}(\hat{\beta}) &= E(\hat{\beta} - \beta)(\hat{\beta} - \beta)' \\ &= E[(X'X)^{-1} X' \epsilon \epsilon' X (X'X)^{-1}] \\ &= E_x [E_{\epsilon/x} [(X'X)^{-1} X' \epsilon \epsilon' X (X'X)^{-1}]] \end{aligned}$$

(by Lemma)

$$= E_x [(X'X)^{-1} X' E_{\epsilon/x}(\epsilon \epsilon') X (X'X)^{-1}]$$

(since $X \notin \epsilon$ independent)

$$= E_x [(X'X)^{-1} X' (\sigma^2 I) X (X'X)^{-1}]$$

$$= \sigma^2 E[(X'X)^{-1}]$$

QED

Claim: The usual tests are valid.

$f(\text{t-ratio} | X)$ is distributed t
 \notin does not depend on X .

ie. Conditional on X , $\text{t-ratio} \sim t$.

Likewise, F is OK.

Bottom Line $\left\{ \begin{array}{l} X \notin \epsilon \text{ being independent is very similar} \\ \text{to } X \text{ being nonstochastic,} \\ \text{for all practical purposes} \end{array} \right.$

Case 2): $X \notin E$ contemporaneously uncorrelated.

Defn 1: $\text{Cov}(E_t, X_{ti}) = 0 \quad \forall t=1, \dots, T$ and
 $\forall i=1, \dots, K$

Says X 's in period t are uncorrelated
 with E 's in period t .

\therefore There may be correlation between
 X 's $\notin E$'s in different time periods,
 but not in the same time period.

Defn 2: $\text{plim} \frac{X'E}{T} = 0$.

This is like an asymptotic correlation coeff.
 (\therefore like Defn 1, for large samples)

Consider $\frac{1}{T} [X'E]_i = \frac{1}{T} \sum_{t=1}^T X_{ti} E_t \quad ; \quad i=1, \dots, K$
 $(K \times 1)$

If $X_{ti} \notin E_t$ are asymptotically uncorrelated,
 then these will have $\text{plim} = 0$.

\uparrow
contemporaneously

Defn 1 \notin Defn 2 are consistent with Case 2).
 They are not mathematically equivalent,
 but very similar.

[1 - uncorrel. in small samples as well as large ;
 2 - asymptotically uncorrel.]

Consider the OLS estimates.

Thm: $\hat{\beta}$ is biased.

Proof:
$$\hat{\beta} = \beta + (X'X)^{-1}X'\epsilon$$

$$\begin{aligned} E(\hat{\beta}) &= \beta + E[(X'X)^{-1}X'\epsilon] \\ &= \beta + E_x[E_{\epsilon|x}(X'X)^{-1}X'\epsilon] \quad (\text{by Lemma}) \\ &= \beta + E_x[(X'X)^{-1}X' E_{\epsilon|x}(\epsilon)] \end{aligned}$$

↑

This is not generally 0;
some ϵ 's can be correl. with
some x 's in different period.

For $E_{\epsilon|x}(\epsilon)$ to be zero,
all of x must be independent of
all of ϵ .

Alternative Proof:
$$E(\hat{\beta}) = \beta + E[(X'X)^{-1}X'\epsilon]$$

$$\neq \beta + E(X'X)^{-1}X' E(\epsilon),$$

since $x \notin \epsilon$ not
entirely independent.

\therefore \exists small sample problems with OLS.
 $\hat{\beta}$ biased. $\neq \beta$

Consider Large Sample Properties
of OLS $\hat{\beta}$ & s^2 in Case 2.

Thm: If $\text{plim} \left(\frac{X'X}{T} \right)$ is finite & nonsingular,
then $\hat{\beta}$ & s^2 are consistent.

$$\begin{aligned} \text{Proof: } \text{plim } \hat{\beta} &= \beta + \text{plim } (X'X)^{-1} X'E \\ &= \beta + \text{plim} \left(\frac{X'X}{T} \right)^{-1} \text{plim} \frac{X'E}{T} \\ &\downarrow \qquad \qquad \qquad \uparrow \text{ (finite) } \qquad \qquad \qquad \uparrow \text{ (= 0 by Defn 2 of Case 2.)} \\ &= \beta \qquad \qquad \qquad \text{QED} \end{aligned}$$

s^2 , similar.

Thm: If $\frac{X'E}{\sqrt{T}} \rightarrow N \left[0, \sigma^2 \text{plim} \left(\frac{X'X}{T} \right) \right]$,
then $\sqrt{T}(\hat{\beta} - \beta) \rightarrow N \left[0, \sigma^2 \text{plim} \left(\frac{X'X}{T} \right)^{-1} \right]$.

Proof: Recall Useful Fact; If $\xi \rightarrow N(0, \Omega)$,
then $A\xi \rightarrow N(0, \text{plim } A\Omega A')$

$$\begin{aligned} \text{Consider } \sqrt{T}(\hat{\beta} - \beta) &= \sqrt{T} (X'X)^{-1} X'E \\ &= \left(\frac{X'X}{T} \right)^{-1} \frac{X'E}{\sqrt{T}} \end{aligned}$$

$$\text{let } A = \left(\frac{X'X}{T} \right)^{-1}, \xi = \frac{X'E}{\sqrt{T}}; \quad A\xi = \sqrt{T}(\hat{\beta} - \beta).$$

$$\text{Then } \sqrt{T}(\hat{\beta} - \beta) \rightarrow N \left[0, \text{plim} \left(\frac{X'X}{T} \right)^{-1} \left(\sigma^2 \text{plim} \frac{X'X}{T} \right) \text{plim} \left(\frac{X'X}{T} \right) \right]$$

No!

Do this!

EKP

Note: These 2 Thm's \Rightarrow

$\hat{\beta}$ & s^2 are consistent, and

$\hat{\beta}$ has the same asymptotic distribution as it did under the full ideal conditions!

— (when X is non stochastic.)

\Rightarrow Asymptotically nice! (eff.)

\Rightarrow Even though $\hat{\beta}$ is biased in small samples, it becomes nice as T increases.

* How big must T be, for OLS to be nice?

Answer: It depends on the distribution of the X 's.

\rightarrow How weird are the X 's?

If the distributions of estimates become "Normal" quickly (as T reaches 30-50), then you're OK with that many observations.

Example: Autoregressive Model

- y_t depends on lagged y 's.

$$y_t = \beta_1 x_{t1} + \dots + \beta_k x_{tk} + \gamma_1 y_{t-1} + \dots + \gamma_p y_{t-p} + \epsilon_t$$

This is a Case 2 problem.

The lagged y 's are stochastic regressors!

They depend on past ϵ 's,
but are uncorrelated with the current ϵ_t .

→ Contemporaneously uncorrelated.

The X matrix (of regressors) looks like;

$$t^{\text{th}} \text{ row} \rightarrow X_t = [x_{t1} \dots x_{tk} y_{t-1} \dots y_{t-p}]$$

$$\text{And } X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{bmatrix} \rightarrow T \times (K+p)$$

Case 2 implications apply;

$\hat{\beta}$ biased but consistent; nice with large samples

Note: If you have Autocorrelated ϵ_t 's
 in this example,
 then $\epsilon_t = \rho\epsilon_{t-1} + u_t$,
 and ϵ_t is correlated with y_{t-1} !

i.e. you do have contemporaneous correlation.

— See Case 3, example 3, following.

Case 3): $X \neq \epsilon$ are correlated.

$\text{Cov}(x_{ti}, \epsilon_t) \neq 0$ for some i and some t ;

equivalently, $\text{plim} \frac{1}{T} X'E \neq 0$.

Problem: $\hat{\beta}$ is biased \neq inconsistent.

a) Already shown $\hat{\beta}$ is biased [Case 2].

$$\begin{aligned} \text{b) } \text{plim } \hat{\beta} &= \beta + \text{plim } (X'X)^{-1} X'E \\ &= \beta + \text{plim } \left(\frac{X'X}{T} \right)^{-1} \text{plim } \frac{X'E}{T} \end{aligned}$$

\uparrow (finite) \uparrow ($\neq 0$)

$\neq \beta$

Thus t 's, F 's are not good.

Same magnitude of problem as in Specification Error by Omitted Variables.

→ This is a big problem!

EXAMPLES

Example 1: Simultaneous Equation Problem
[more next term!]

$$\begin{array}{l}
 (1) \quad C_t = \alpha + \beta(y_t) + \epsilon_t \\
 (2) \quad C_t + I_t = y_t
 \end{array}$$

$C_t =$ Consumption
 $y_t =$ Income
 $I_t =$ Investment

Endogenous Variables; C_t, y_t
[determined in the model]

Exogenous Variable; I_t



Intuitively, $y_t \rightarrow C_t$ and $C_t \rightarrow y_t$; they are determined simultaneously!

If this is the case, then y_t is correlated with ϵ_t , and OLS yields biased and inconsistent estimates → Called Simultaneous Equation Bias.

To show that y_t & ϵ_t are correlated,
solve this structural system
for the reduced form.

[for the equilibrium y_t]

Substituting (1) into (2);

$$\alpha + \beta y_t + \epsilon_t + I_t = y_t$$

$$\Rightarrow y_t = \frac{\alpha}{1-\beta} + \frac{1}{1-\beta} I_t + \frac{1}{1-\beta} \epsilon_t$$

From this it is obvious that

y_t & ϵ_t are correlated.

Again, OLS $\hat{\beta}$ is bad.

Example 2: Measurement Error

The model; $y_t = \alpha + \beta X_t + \epsilon_t$

Suppose we don't observe X_t ;
but some proxy of X_t , X_t^* .

Assume $X_t^* = X_t + v_t$, with v_t iid $N(0, \sigma_v^2)$
and v 's indep of ϵ 's.

v_t is the measurement error.

We can add & subtract βX_t^* ;

$$y_t = \alpha + \beta X_t + \epsilon_t + \beta X_t^* - \beta X_t^*$$

OR
$$y_t = \alpha + \beta X_t^* + \epsilon_t + \beta(X_t - X_t^*)$$

$$= \alpha + \beta X_t^* + (\epsilon_t - \beta v_t)$$

This is the model that is run.

Problem: $\text{Cov}(X_t^*, \epsilon_t - \beta v_t) \neq 0$.

↑
(has v_t in it)

Result: OLS yields biased & inconsistent estimates.

The extent of the inconsistency depends on the extent of the measurement error, v_t , and its variance, σ_v^2 .

$$\begin{aligned} \text{Here, } \text{plim } \hat{\beta} &= \beta - \beta \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\epsilon^2} \\ &= \beta \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_v^2} \end{aligned}$$

[See Kmenta, Johnston
for algebra.]

Note: This biases $\hat{\beta}$ toward zero under this assumption. "attenuating bias"

* Note: Measurement Error in y_t is not a problem.

$$y_t = \alpha + \beta x_t + \epsilon_t ; \text{ observe } y_t^* = y_t + v_t$$

$$\Rightarrow y_t^* = \alpha + \beta x_t + (\epsilon_t + v_t)$$

$$\text{Cov}(x_t, \epsilon_t + v_t) = 0.$$

This simply results in more randomness in y_t .
OLS $\hat{\beta}$ is still good.

What can be done about this?

Generally, nothing, unless you can eliminate the measurement error.

If you knew σ_v^2 ,
then you could correct $\hat{\beta}$
to get consistent estimates.

\Rightarrow Multiply it by $\left(\frac{\sigma_e^2 + \sigma_v^2}{\sigma_e^2}\right)$.

BUT in economics,
things like σ_v^2 are rarely known!

In something like Physics,
we may know something like this...

— Johnston shows how to manipulate $\hat{\beta}$
to get consistent estimates.

Schmidt argues that you can't do this
given the assumptions as to v_t ,
the parameters of the model
are not identified.

Identification -- (next term)

Example 3: Autoregressive Model with Auto correlated Errors

$$y_t = \alpha + \beta x_t + \gamma y_{t-1} + \epsilon_t$$

where $\epsilon_t = \rho \epsilon_{t-1} + u_t$

Note: y_{t-1} is correlated with ϵ_{t-1} and \therefore with ϵ_t .

All estimates are biased and inconsistent.

This is a very complicated case;

3 Other Problems:

- (i) Usual tests for Autocorrelation don't work. e.g. D-W statistic is biased towards 2 (Against finding Autocorrelation).

Intuition; OLS $\hat{\beta}, \hat{\gamma}$ are bad;
 \therefore OLS e_t are bad;
 $\therefore \hat{\rho} \neq DW$ are bad!

See Durbin, ECON, 1970 & Johnston for other tests that do work in this case.



e.g. —

SK

e.g. Regress e_t on e_{t-1} plus other rhs variables.
 Then use t-test on coefficient of e_{t-1} ... $\rightarrow (\hat{\rho})$
 This is asymptotically OK.

Note: this is like the C-O method (*2)
 for estimating $\hat{\rho}$.

Given this problem, what to do?

GLS? Yes, but I problems with GLS.

(ii) Estimates of $\hat{\rho}$ are inconsistent.

Again, Intuition: OLS $\hat{\beta}$, $\hat{\gamma}$ are bad;
 \therefore OLS e_t are bad;
 $\therefore \hat{\rho}$ & DW are bad!

Solutions:

a) Use MLE (Hildreth-Lu) procedure.

b) estimate $\hat{\rho}$ like before,
 but use Instrumental Variables residual
 instead of OLS residuals.

-(more in a minute!)

(iii) —

(iii) GLS estimates [of β & γ]

based on a consistent estimate of ρ
need not be asymptotically efficient
in this case (not as good as MLE).

Solution c) \exists an asymptotically efficient
2-step procedure;

Define: $y_t^* = y_t - \hat{\rho} y_{t-1}$; $x_t^* = x_t - \hat{\rho} x_{t-1}$

Summary of Stochastic Regressors

\exists 3 cases: $Y = X\beta + \epsilon$

Case (1) $X \nsubseteq \epsilon$ independent.

OLS "OK"; usual $\hat{\beta}$ unbiased, t-ratios OK,

Case (2) $X \nsubseteq \epsilon$ contemporaneously uncorrelated.

OLS $\hat{\beta}$ biased but consistent;
Be careful!

Case (3) $X \nsubseteq \epsilon$ correlated.

OLS not OK;
 $\hat{\beta}$ biased & inconsistent;
big problem.

INSTRUMENTAL Variables

A way to deal with Case 3.

- Given $X \notin \epsilon$ correlated,
this is a method for getting consistent estimates.

INTUITION: $Y = X\beta + \epsilon$

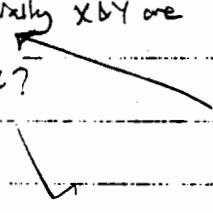
X is highly correlated with Y ;
this is the relationship we wish to measure.

X is correlated with ϵ ;
this inhibits our attempt to measure the rel.

If we can transform X into
a matrix of instruments, Z ,
that are highly correlated with X
(and \therefore still highly correlated with Y),
but not correlated with ϵ ;

then we can get consistent estimates.

Highly correlated?
What if initially X & Y are
not highly
correlated?



Thm.: Suppose Z a $(T \times K)$ matrix, Z, Y

(1) $\text{plim} \frac{Z'X}{T}$ is finite and nonsingular,

(2) $\text{plim} \frac{Z'E}{T} = 0$.

Then the Instrumental Variables Estimator,

$$\tilde{\beta} = (Z'X)^{-1} Z'Y \text{ is consistent.}$$

(3) Furthermore, if $\frac{1}{\sqrt{T}} Z'E \rightarrow N(0, \sigma^2 \text{plim} \frac{ZZ'}{T})$, then

$$\sqrt{T}(\tilde{\beta} - \beta) \rightarrow N\left[0, \sigma^2 \text{plim} \left(\frac{Z'X}{T}\right)^{-1} \left(\frac{ZZ'}{T}\right) \left(\frac{X'Z}{T}\right)^{-1}\right]$$

Proof:

$$\begin{aligned} \tilde{\beta} &= (Z'X)^{-1} Z'Y \\ &= (Z'X)^{-1} Z'(X\beta + E) \\ &= \beta + (Z'X)^{-1} Z'E \end{aligned}$$

$$\begin{aligned} \text{plim} \tilde{\beta} &= \beta + \text{plim} \left(\frac{Z'X}{T}\right)^{-1} \text{plim} \frac{Z'E}{T} \\ &= \beta \quad \begin{matrix} \uparrow \\ \text{(finite)} \end{matrix} \quad \begin{matrix} \uparrow \\ (0) \end{matrix} \quad \left[\begin{array}{l} \text{Assumptions} \\ (1) \ \& \ (2) \end{array} \right] \end{aligned}$$

$$\text{Then, } \sqrt{T}(\tilde{\beta} - \beta) = \left(\frac{Z'X}{T}\right)^{-1} \frac{Z'E}{\sqrt{T}};$$

and given assumption (3),

and the useful fact, if $\xi \rightarrow N(0, \Omega)$
then $A\xi \rightarrow N[0, (\text{plim } A)\Omega]$

$$\sqrt{T}(\tilde{\beta} - \beta) \rightarrow N\left[0, \sigma^2 \text{plim} \left(\frac{Z'X}{T}\right)^{-1} \left(\frac{ZZ'}{T}\right) \left(\frac{X'Z}{T}\right)^{-1}\right].$$

QED

Discussion :

Z is a matrix of Instruments.

Assumption (1) says that Z must be correlated with X.

[ie we want the instruments to be correlated with the variables of interest.]

Assumption (2) says that Z must not be correlated with ϵ .

If we can find such a Z, we've solved the problem.

* If we want the asymptotic distribution, we need assumption (3).

— [but no one worries about that...]

Example:

$$y_t = \alpha + \beta X_t + \gamma y_{t-1} + \epsilon_t$$

$$\text{where } \epsilon_t = \rho \epsilon_{t-1} + u_t$$

⇒ [Case 3 problem!]

— y_{t-1} correlated with ϵ_t .

— we need an instrument for y_{t-1} ;

use X_{t-1} !

— highly correlated with y_{t-1} ,
uncorrelated with ϵ_t .

Thus let $Z_t = [1, X_t, X_{t-1}]$

correl. with α
uncorrel. with ϵ_t

correl. with X_t
uncorrel. with ϵ_t

correl. with y_{t-1}
uncorrel. with ϵ_t

* We want something as highly correlated with y_{t-1} as possible; this will get us better estimates.

→ Then $\text{plim } \frac{Z'X}{T}$ is finite, $\text{plim } \frac{Z'\epsilon}{T} = 0 \dots$

Another possible instrument: $Z = [1, X, u_{t-1}]$