

# Generalized IV Estimator

Consider a set of instruments  $W$  where  $W_{n \times l}$  and  $l > k$ . Here we have more instruments than needed.

- overidentified.

Basically, ~~we~~ there is more than one way to specify the moment condition

$$E[W^T(y - X\beta)] = 0$$

$$(l \times n) [\tilde{w}^T \times (1) \quad \tilde{w}^T \times (k \times 1)] = 0 \times e_1$$

(i.e., there are  $l$  equations

and only  $k$  unknowns.

# Asymptotic Cov Matrix

$$\sigma^2 \text{plim}_{n \rightarrow \infty} \left( \frac{1}{n} X^T W (W^T W)^{-1} W^T X \right)^{-1} \quad (8-17) \\ \text{ETM}$$

optimal choice of instruments,  $W$   
is the set that minimizes  
this.

Note: suppose  $W = X$  and  
 $E[u|x] = 0$

$$\sigma^2 \text{plim}_{n \rightarrow \infty} \left( \frac{1}{n} X^T X (X^T X)^{-1} X^T X \right)^{-1} \\ = \sigma^2 \text{plim}_{n \rightarrow \infty} \left( \frac{X^T X}{n} \right)^{-1}$$

Asy. Cov of LS which is BLUE  
 $X$  is optimal!

When  $l = k \equiv$  Just Identified

$l < k \equiv$  underidentified  
not identified<sup>o.</sup>

### ~~Problems~~ Solutions

(1) Drop instruments

This discards information which is almost never a good idea, especially if instruments are strong

(2) Take a linear combination of instruments

Take  $k$  linear combination of  $l$  columns

$$\begin{array}{l}
 WJ \\
 = \\
 n \times l \quad l \times k \quad n \times k
 \end{array}
 \quad \text{where } J \text{ is } l \times k$$

The trick is to find the optimal  $J$ !

### Optimal $J$

Choose  $J$  that minimizes  
The Asymptotic Covariance  
Matrix of the IV Estimator.

$$(WJ)^T (y - X\beta) = 0$$

$$\text{Let } WJ = W(W^T W)^{-1} W^T X$$

$$\text{So, } J = (W^T W)^{-1} W^T X$$

which is LS applied to

$$X = W\tilde{J} + v$$

$$\text{So, } WJ = \hat{X} = W(W^T W)^{-1} W^T X$$

from their Regression.

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$$WJ = w(w^T w)^{-1} w^T X = P_w X = \hat{X}$$

$$= \hat{\cdot}$$

Then

$$(WJ)^T (y - X\beta) = 0$$

$$X^T P_w (y - X\beta) = 0$$

$$X^T P_w y - X^T P_w X \hat{\beta}_{IV} = 0$$

$$\hat{\beta}_{IV} = (X^T P_w X)^{-1} X^T P_w y$$

$$= (X^T w (w^T w)^{-1} w^T X)^{-1} X^T w (w^T w)^{-1} w^T y$$

SAME AS GLS estimator.

Also,

$$\hat{X}^T (y - X\beta) = 0$$

$\hat{X}$  Maximizes "Fit" Between

$X$  &  $w$  (Because its least

squares). For Instruments  $w$ ,

This choice of  $J$  is

optimal.

2SLS

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$$\begin{aligned}\hat{\beta}_{IV} &= (X^T P_w X)^{-1} X^T P_w y \\ &= (X^T P_w^T P_w X)^{-1} X^T P_w^T y\end{aligned}$$

$$P_w X = W(W^T W)^{-1} W^T X = \hat{X}$$

$$\hat{\beta}_{IV} = (\hat{X}^T \hat{X})^{-1} \hat{X}^T y$$

$\hat{X}$  is the result of  
A Regression

$$y = \hat{X} \beta + u$$

This means that you can  
get the same result by  
Running 2 Regressions

$$(1) \quad X = WJ + v$$

stage 1

$$J = (W^T W)^{-1} W^T X$$

$$\hat{X} = WJ$$

$$(2) \quad y = \hat{X}\beta + u$$

$$\text{stage 2} \quad \hat{\beta}_{2SLS} = (\hat{X}^T \hat{X})^{-1} \hat{X}^T y$$

Hence the name:  
Two Stage Least Squares

## Warning

The correct covariance matrix is estimated

$$\hat{\sigma}^2 (X^T P_w X)^{-1} = \hat{\sigma}^2 (\hat{X}^T \hat{X})^{-1}$$

$$\hat{\sigma}^2 (X^T W (W^T W)^{-1} W^T X)^{-1}$$

where 
$$\hat{\sigma}^2 = \frac{(y - X \hat{\beta}_{IV})^T (y - X \hat{\beta}_{IV})}{n - k}$$

Note: This is NOT THE SAME AS what would be produced by a regression package if you use  $\hat{X}$  in place of  $X$ .

wrong 
$$\hat{\sigma}^2 = (y - \hat{X} \hat{\beta}_{IV})^T (y - \hat{X} \hat{\beta}_{IV}) / n - k$$

correct 
$$\hat{\sigma}^2 = (y - X \hat{\beta}_{IV})^T (y - X \hat{\beta}_{IV}) / n - k.$$

So, Use Proper IV SOFTWARE AND don't do this in 2 Steps.