# ECDN 480 -3 <br> LECTURE 4: ENDOGENEITY 

Ivan A. Canay

Northwestern University


## So FAR

- Three Interpretations of $\beta$
- Solving and estimating sub-vectors of $\beta$
- Properties of LS
- Estimating $\mathbb{V}$
- Classical Problems that lead to $E[X U] \neq 0$


## TODAY

- Instrumental Variables
- The IV Estimator
- The 2SLS Estimator
- Properties of 2SLS
- Estimating $\mathbb{V}$



## Instrumental Variables

- Let $(Y, X, U)$ be a random vector where $Y$ and $U$ take values in $\mathbf{R}$ and $X$ takes values in $\mathbf{R}^{k+1}$. Assume further that the first component of $X$ is constant and equal to one, i.e., $X=\left(X_{0}, X_{1}, \ldots, X_{k}\right)^{\prime}$ with $X_{0}=1$. Let $\beta=\left(\beta_{0}, \beta_{1}, \ldots, \beta_{k}\right)^{\prime} \in \mathbf{R}^{k+1}$ be such that

$$
Y=X^{\prime} \beta+U
$$

- We do not assume $E[X U]=0$. Any $X_{j}$ such that $E\left[X_{j} U\right]=0$ is said to be exogenous; any $X_{j}$ such that $E\left[X_{j} U\right] \neq 0$ is said to be endogenous. Normalizing $\beta_{0}$ if necessary, we view $X_{0}$ as exogenous.
- Instrument: to overcome the difficulty associated with $E[X U] \neq 0$, we assume that there is an additional random vector $Z$ taking values in $\mathbf{R}^{\ell+1}$ with $\ell+1 \geqslant k+1$ such that $E[Z U]=0$.
- Any exogenous component of $X$ is contained in $Z$ (the so-called included instruments). In particular, we assume the first component of $Z$ is constant equal to one, i.e., $Z=\left(Z_{0}, Z_{1}, \ldots, Z_{\ell}\right)^{\prime}$ with $Z_{0}=1$.
- We also assume that $E\left[Z X^{\prime}\right]<\infty, E\left[Z Z^{\prime}\right]<\infty$ and that there is no perfect collinearity in $Z$.
- We assume (1) $E[Z U]=0$, (2) $E\left[Z X^{\prime}\right]<\infty$, (3) $E\left[Z Z^{\prime}\right]<\infty$, and (4) there is no perfect collinearity in Z.
- The requirement that $E[Z U]=0$ is termed instrument exogeneity.
- We further assume (5) the rank of $E\left[Z X^{\prime}\right]$ is $k+1$. This is termed instrument relevance or rank condition.
- A necessary condition for (5) to be true is $\ell \geqslant k$. This is referred to as the order condition.
- Using that $U=Y-X^{\prime} \beta$ and $E[Z U]=0$, we see that $\beta$ solves the system of equations

$$
E[Z Y]=E\left[Z X^{\prime}\right] \beta .
$$

- Since $\ell+1 \geqslant k+1$, this may be an over-determined system of equations.


## LEMMA

Suppose there is no perfect collinearity in $Z$ and let $\Pi$ be such that $B L P(X \mid Z)=\Pi^{\prime} Z$. $E\left[Z X^{\prime}\right]$ has rank $k+1$ if and only if $\Pi$ has rank $k+1$. Moreover, the matrix $\Pi^{\prime} E\left[Z X^{\prime}\right]$ is invertible.

## Soliving fort $\beta$

$$
\beta \text { solves: } E[Z Y]=E\left[Z X^{\prime}\right] \beta \text { or } \quad \Pi^{\prime} E[Z Y]=\Pi^{\prime} E\left[Z X^{\prime}\right] \beta
$$

Using the previous lemma and $\Pi=E\left[Z Z^{\prime}\right]^{-1} E\left[Z X^{\prime}\right]$, we can derive three formulae for $\beta$

Interpretation: Consider the case where $k=\ell$ and only $X_{k}$ is endogenous. Let $Z_{j}=X_{j}$ for all $0 \leqslant j \leqslant k-1$. In this case,

$$
\Pi^{\prime}=\left(\begin{array}{ccccc}
1 & 0 & \cdots & 0 & 0 \\
0 & 1 & \cdots & 0 & 0 \\
\vdots & \vdots & & \vdots & \vdots \\
0 & 0 & \cdots & 1 & 0 \\
\pi_{0} & \pi_{1} & \cdots & \pi_{\ell-1} & \pi_{\ell}
\end{array}\right)
$$

The rank condition therefore requires $\pi_{\ell} \neq 0$ : the instrument $Z_{\ell}$ must be "correlated with $X_{k}$ after controlling for $X_{0}, X_{1}, \ldots, X_{k-1}$."

- Partition $X$ into $X_{1}$ and $X_{2}$, where $X_{2}$ is exogenous. Partition $Z$ into $Z_{1}$ and $Z_{2}$ and $\beta$ into $\beta_{1}$ and $\beta_{2}$ analogously.
- Note that $Z_{2}=X_{2}$ are included instruments and $Z_{1}$ are excluded instruments. Then,

$$
Y=X_{1}^{\prime} \beta_{1}+X_{2}^{\prime} \beta_{2}+U
$$

- We can conveniently re-write this by projecting (BLP) on $Z_{2}=X_{2}$. Consider the case $k=\ell$

$$
\operatorname{BLP}\left(Y \mid Z_{2}\right)=\operatorname{BLP}\left(X_{1} \mid Z_{2}\right)^{\prime} \beta_{1}+X_{2}^{\prime} \beta_{2}
$$

- Define $Y^{*}=Y-\operatorname{BLP}\left(Y \mid Z_{2}\right)$ and $X_{1}^{*}=X_{1}-\operatorname{BLP}\left(X_{1} \mid Z_{2}\right)$ so that

$$
E\left[Z_{1} Y^{*}\right]=E\left[Z_{1} X_{1}^{* \prime}\right] \beta_{1}+E\left[Z_{1} U\right]
$$

- It follows that

$$
\beta_{1}=E\left[Z_{1} X_{1}^{* \prime}\right]^{-1} E\left[Z_{1} Y^{*}\right]
$$

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## Estimating $\beta$ : The IV Estimator

- Just identified case: $k=\ell$. Denote by $P$ the marginal distribution of $(Y, X, Z)$.
- Let $\left(Y_{1}, X_{1}, Z_{1}\right), \ldots,\left(Y_{n}, X_{n}, Z_{n}\right)$ be an i.i.d. sequence of random variables with distribution $P$.
- By analogy with $\beta=E\left[Z X^{\prime}\right]^{-1} E[Z Y]$, the natural estimator of $\beta$ is simply

$$
\hat{\beta}_{n}=\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} X_{i}^{\prime}\right)^{-1}\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} Y_{i}\right) .
$$

- This estimator is called the instrumental variables (IV) estimator of $\beta$. Note that $\hat{\beta}_{n}$ satisfies

$$
\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i}\left(Y_{i}-X_{i}^{\prime} \hat{\beta}_{n}\right)=0 .
$$

In particular, $\hat{U}_{i}=Y_{i}-X_{i}^{\prime} \hat{\beta}_{n}$ satisfies

$$
\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} \hat{U}_{i}=0 .
$$

## THE MV ESTIMATOR

Insight on the IV estimator: assume $X_{0}=1$ and $X_{1} \in \mathbf{R}$. An interesting interpretation of the IV estimator of $\beta_{1}$ is obtained by multiplying and dividing by $\frac{1}{n} \sum_{i=1}^{n}\left(Z_{1, i}-\bar{Z}_{1, n}\right)^{2}$, i.e.,

$$
\hat{\beta}_{1, n}=\frac{\frac{1}{n} \sum_{i=1}^{n}\left(Z_{1, i}-\bar{Z}_{1, n}\right) Y_{i} / \frac{1}{n} \sum_{i=1}^{n}\left(Z_{1, i}-\bar{Z}_{1, n}\right)^{2}}{\frac{1}{n} \sum_{i=1}^{n}\left(Z_{1, i}-\bar{Z}_{1, n}\right) X_{1, i} / \frac{1}{n} \sum_{i=1}^{n}\left(Z_{1, i}-\bar{Z}_{1, n}\right)^{2}}
$$

This estimator may be expressed more compactly using matrix notation. Define

$$
\begin{aligned}
\mathbb{Z} & =\left(Z_{1}, \ldots, Z_{n}\right)^{\prime} \\
\mathbb{X} & =\left(X_{1}, \ldots, X_{n}\right)^{\prime} \\
\mathbb{Y} & =\left(Y_{1}, \ldots, Y_{n}\right)^{\prime} .
\end{aligned}
$$

In this notation, we have

$$
\hat{\beta}_{n}=\left(\mathbb{Z}^{\prime} \mathbb{X}\right)^{-1}\left(\mathbb{Z}^{\prime} \mathbb{Y}\right)
$$

- Over-identified case: $\ell>k$
- The expressions we derived for $\beta$ in this case, like

$$
\beta=E\left[\Pi^{\prime} E\left[Z X^{\prime}\right]\right]^{-1} \Pi^{\prime} E[Z Y]
$$

all involved the matrix $\Pi$, where

$$
\operatorname{BLP}(X \mid Z)=\Pi^{\prime} Z
$$

- An estimate of $\Pi$ can be obtained by OLS.
- Since $\Pi=E\left[Z Z^{\prime}\right]^{-1} E\left[Z X^{\prime}\right]$, a natural estimator of $\Pi$ is

$$
\hat{\Pi}_{n}=\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} Z_{i}^{\prime}\right)^{-1}\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} X_{i}^{\prime}\right)
$$

## The Two-Stage Least Squares (TSLS) Estimator

$$
\text { Let } X_{i}=\hat{\Pi}_{n}^{\prime} Z_{i}+\hat{V}_{i} \quad \text { where } \quad \hat{\Pi}_{n}=\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} Z_{i}^{\prime}\right)^{-1}\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} X_{i}^{\prime}\right)
$$

With this estimator of $\Pi$, a natural estimator of $\beta$ is simply

- Note that $\hat{\beta}_{n}$ satisfies

$$
\frac{1}{n} \sum_{1 \leqslant i \leqslant n} \hat{\Pi}_{n}^{\prime} Z_{i}\left(Y_{i}-X_{i}^{\prime} \hat{\beta}_{n}\right)=0
$$

- In particular, $\hat{U}_{i}=Y_{i}-X_{i}^{\prime} \hat{\beta}_{n}$ satisfies

$$
\frac{1}{n} \sum_{1 \leqslant i \leqslant n} \hat{\Pi}_{n}^{\prime} Z_{i} \hat{U}_{i}=0
$$

- This implies that $\hat{U}_{i}$ is orthogonal to all of the instruments equal to an exogenous regressors, but may not be orthogonal to the other regressors.
- It is termed the TSLS estimator because it may be obtained in the following way:
(1) regress (each component of) $X_{i}$ on $Z_{i}$ to obtain $\hat{X}_{i}=\hat{\Pi}_{n}^{\prime} Z_{i}$;
(2) regress $Y_{i}$ on $\hat{X}_{i}$ to obtain $\hat{\beta}_{n}$. However, in order to obtain proper standard errors, it is recommended to compute the estimator in one step (see the following section).

This estimator may be expressed more compactly using matrix notation. Define

$$
\begin{aligned}
\mathbb{Z} & =\left(Z_{1}, \ldots, Z_{n}\right)^{\prime} \\
\mathbb{X} & =\left(X_{1}, \ldots, X_{n}\right)^{\prime} \\
\mathbb{Y} & =\left(Y_{1}, \ldots, Y_{n}\right)^{\prime} \\
\hat{\mathbb{X}} & =\left(\hat{X}_{1}, \ldots, \hat{X}_{n}\right)^{\prime} \\
& =\mathbb{P}_{Z} \mathbb{X},
\end{aligned}
$$

where

$$
\mathbb{P}_{Z}=\mathbb{Z}\left(\mathbb{Z}^{\prime} \mathbb{Z}\right)^{-1} \mathbb{Z}^{\prime}
$$

is the projection matrix onto the column space of $\mathbb{Z}$. In this notation, we have

$$
\begin{aligned}
\hat{\beta}_{n} & =\left(\hat{\mathbb{X}}^{\prime} \mathbb{X}\right)^{-1}\left(\hat{\mathbb{X}}^{\prime} \mathbb{Y}\right) \\
& =\left(\hat{\mathbb{X}}^{\prime} \hat{\mathbb{X}}\right)^{-1}\left(\hat{\mathbb{X}}^{\prime} \mathbb{Y}\right) \\
& =\left(\mathbb{X}^{\prime} \mathbb{P}_{Z} \mathbb{X}\right)^{-1}\left(\mathbb{X}^{\prime} \mathbb{P}_{Z} \mathbb{Y}\right)
\end{aligned}
$$

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- Let $(Y, X, U)$ be a random vector where $Y$ and $U$ take values in $\mathbf{R}$ and $X$ takes values in $\mathbf{R}^{k+1}$. Assume further that the first component of $X$ is constant and equal to one, i.e., $X=\left(X_{0}, X_{1}, \ldots, X_{k}\right)^{\prime}$ with $X_{0}=1$. Let $\beta=\left(\beta_{0}, \beta_{1}, \ldots, \beta_{k}\right)^{\prime} \in \mathbf{R}^{k+1}$ be such that

$$
Y=X^{\prime} \beta+U .
$$

- We assume (1) $E[Z U]=0$, (2) $E\left[Z X^{\prime}\right]<\infty$, (3) $E\left[Z Z^{\prime}\right]<\infty$, and (4) there is no perfect collinearity in $Z$, and (5) the rank of $E\left[Z X^{\prime}\right]$ is $k+1$
- Let $\left(Y_{1}, X_{1}, Z_{1}\right), \ldots,\left(Y_{n}, X_{n}, Z_{n}\right)$ be an i.i.d. sequence of random variables with distribution $P$.
- Under these assumptions the TSLS estimator is consistent for $\beta$, and under the additional requirement that $\operatorname{Var}[Z U]<\infty$, it is asymptotically normal with limiting variance

$$
\mathbb{V}=E\left[\Pi^{\prime} Z Z^{\prime} \Pi\right]^{-1} \Pi^{\prime} \operatorname{Var}[Z U] \Pi E\left[\Pi^{\prime} Z Z^{\prime} \Pi\right]^{-1} .
$$

## Consistency of TSLS

$$
\hat{\beta}_{n}=\left(\hat{\Pi}_{n}^{\prime}\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} X_{i}^{\prime}\right)\right)^{-1} \hat{\Pi}_{n}^{\prime}\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} Y_{i}\right) \xrightarrow{p} \beta \text { as } n \rightarrow \infty .
$$

## Asymptotic Normality df TSLS

$$
\begin{aligned}
& \text { Assume that } \operatorname{Var}[Z U]=E\left[Z Z^{\prime} U^{2}\right]<\infty . \text { Then, as } n \rightarrow \infty, \\
& \qquad \sqrt{n}\left(\hat{\beta}_{n}-\beta\right) \xrightarrow{d} N(0, \mathbb{V}) .
\end{aligned}
$$

## Estimation of V

A natural estimator of $\mathbb{V}$ is given by

$$
\hat{\mathbb{V}}_{n}=\left(\hat{\Pi}_{n}^{\prime}\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} Z_{i}^{\prime}\right) \hat{\Pi}_{n}\right)^{-1} \times \hat{\Pi}_{n}^{\prime}\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} Z_{i}^{\prime} \hat{U}_{i}^{2}\right) \hat{\Pi}_{n} \times\left(\hat{\Pi}_{n}^{\prime}\left(\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} Z_{i}^{\prime}\right) \hat{\Pi}_{n}\right)^{-1},
$$

where $\hat{U}_{i}=Y_{i}-X_{i}^{\prime} \hat{\beta}_{n}$.

- Primary difficulty in establishing the consistency of this estimator lies in showing that

$$
\frac{1}{n} \sum_{1 \leqslant i \leqslant n} Z_{i} Z_{i}^{\prime} \hat{U}_{i}^{2} \xrightarrow{P} \operatorname{Var}[Z U]
$$

as $n \rightarrow \infty$. The complication lies in the fact that we do not observe $U_{i}$ and therefore have to use $\hat{U}_{i}$.

- However, the desired result can be shown by arguing exactly as in the second part of this class.
- Note: $\hat{U}_{i}=Y_{i}-X_{i}^{\prime} \hat{\beta}_{n} \neq Y_{i}-\hat{X}_{i}^{\prime} \hat{\beta}_{n}$, so the standard errors from two repeated applications of OLS will be incorrect.
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