Lecture 10B: IV: Heterogeneous Effects

Introduction ot Econometrics,Fall 2017

Zhaopeng Qu

Nanjing University

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Review the last lecture

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  - When IV satisify these two assumptions,the causal effect of coefficients of interest,TSLS estimator,β_{TSLS} can be NOT unbiased but **consistent**.
  - The sampling distribution of the TSLS estimator is also normal in large samples,so the general procedures for statistical inference in OLS can be used.

IV with Heterogeneous Causal Effects: Simple Case

Introduction :

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- While the lottery didn't completely determine veteran status, it certainly mattered: relevance.
- The lottery outcome was random and seems reasonable to suppose that its only effect was on veteran status: exogenous.

Example: Angrist(1990): heterogeneous effects

- We can classify individuals according to assignment(Z) an treatment(X) into four parts

		Z=0	
		D=0	D=1
Z=1	D=0	Never-taker	Defier
	D=1	Complier	Always-taker

Figure 1:

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- Angrist and Imbens(1994) called it as **Local Average Treatment Effect(LATE)**, thus the treatment effect on those that change their behavior under the instrument.

IV with Heterogeneous Causal Effects: Generalization

Introduction

- If the population is *heterogeneous*, then the i^{th} individual now has his or her own causal effect, β_{1i},then the population regression equation can be written

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- β_{1i} is a random variable that,just like u_i, reflects unobserved variation across individuals.
- The average causal effect is the population mean value of the causal effect,$E(\beta_{1i})$ which is the expected causal effect of a randomly selected member of the population.

OLS with Heterogeneous Causal Effects

- If there is heterogeneity in the causal effect and if X_i is randomly assigned, then the differences estimator is a consistent estimator of the average causal effect.

$$
\begin{aligned}
\hat{\beta}_{ols} = \frac{s_{XY}}{s_X^2} \xrightarrow{p} \frac{Cov(Y_i, X_i)}{Var(X_i)} &= \frac{Cov(\beta_{0i} + \beta_{1i}X_i + u_i, X_i)}{Var(X_i)} \\
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- Thus, if X_i is randomly assigned, $\hat{\beta}_1$ is a *consistent* estimator of the average causal effect $E(\beta_{1i})$.

IV Regression with Heterogeneous Causal Effects

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- where the coefficients π_{0i} and π_{1i} vary from one individual to the next. And it is the first-stage equation of TSLS with the modification of heterogeneous effect of Z on X.

IV Regression with Heterogeneous Causal Effects

- Then TSLS estimator becomes

$$\hat{\beta}_{2SLS} = \frac{s_{ZY}}{s_{ZX}} \xrightarrow{p} \frac{\sigma_{ZY}}{\sigma_{ZX}} = \frac{E(\beta_{1i}\pi_{1i})}{E(\pi_{1i})}$$

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- The TSLS estimator converges in probability to the ratio of the expected value of the product of β_{1i} and π_{1i} to the expected value of π_{1i}.
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- It is a **weighted** average of the individual causal effects β_{1i}, The weights are $\frac{\pi_{1i}}{E(\pi_{1i})}$, which measure the relative degree to which the instrument influences whether the i_{th} individual receives treatment,
- In other words,TSLS estimator is a consistent estimator of a *weighted average of the individual causal effects*, where the individuals who receive the *most weight* are those for *whom the instrument is most influential*.

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- Aside from these three special cases, in general the local average treatment effect differs from the average treatment effect.

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- The difference arises because each researcher is implicitly estimating a different weighted average of the individual causal effects in the population.
- Recall: **J-test of overidentifying restrictions** can reject if the two instruments estimate different local average treatment effects,even if both instruments are valid. In general neither estimator is a consistent estimator of the average causal effect.

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- The answer to these questions is usually: **NO**, at least without additional assumptions.

Some Practical Guides by Angrist and Pischke(2012)

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   - *Falsification test*: Test the reduced form effect of Zi on Yi in situations where it is impossible or extremely unlikely that Zi could affect Xi.Because Zi can't affect Xi, then the exclusion restriction

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   - Worry if it is substantially different from what you get using multiple instruments.
   - Check over-identified 2SLS estimates with LIML. LIML is less than precise than 2SIS but also less biased. If the results come out similar, be happy. If not, worry, and try to find stronger instruments.

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    - Would other LATEs possible yield different estimates?

Where Do Valid Instruments Come From?

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  2. Exogenous Source of Variation in X(natural experiments)

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- Result: The estimated effect was three times larger than the effect estimated using OLS.

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- Result: the effect on test scores of class size is small.

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- Angrist & Evans(1998): have same sex or different sex children used to estimate the impact of an additional birth on women labor supply.

Several Applications in China Studies

Fang et al. (2012)

- Feng et al.(2012) "The Returns to Education in China: Evidence from the 1986 Compulsory Education Law".

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- Li and Zhang(2007),Liu(2012)- "One Child policy"
- Fang and Zhao(2008)- "Christian in China": The number of children enrollment in Christian's primary school per one thousand persons across cities.
- Ying Bai and Ruixue Jia(2014)-"keju" and "the number of small rivers"