

IN4402: Applied statistics for management and economics

Estimating Instrumental Variables

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- To capture this, we can run OLS in two **stages**:

first stage:

$$X_i = \pi_0 + \pi_1 Z_i + v_i$$

second stage:

$$Y_i = \beta_0 + \beta_1 \widehat{X}_i + u_i$$

- There is a method for estimating both stages using the same variance-covariance matrix: **two-stages least square (2SLS)**.

- If we have many instruments ($Z_1, Z_2, \dots$), we use all in the first stage:

$$X_i = \pi_0 + \pi_1 Z_1 + \pi_2 Z_2 + \pi_3 Z_3 + v_i$$

- We should add covariates (W_i) in the first stage and then control for that effect in the second stage:

$$X_i = \pi_0 + \pi_1 Z_1 + \pi_2 Z_2 + \pi_3 Z_3 + \pi_4 W_i + v_i$$

$$Y_i = \beta_0 + \beta_1 \widehat{X}_i + \beta_2 W_i + u_i$$

INSTRUMENTAL VARIABLES ESTIMATING

CUASI AND NON EXPERIMENTAL METHODS

```
> summary(lm(Y~X+Q))$coefficients #Endogeneous regression -> X is biased
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.0122637	0.04507074	-0.272099	7.857349e-01
X	5.4670276	0.03247571	168.342041	1.047603e-296
Q	0.4682528	0.05499298	8.514774	8.441462e-16

```
> summary(lm(X~Z+Q))$coefficients #First Stage where Z is instrument and Q covariate
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.04826532	0.05742495	-0.840494	4.013076e-01
Z	1.02455989	0.06032526	16.983929	1.119680e-45
Q	0.99795394	0.05570610	17.914626	3.593973e-49

```
> X_hat <- predict.lm(lm(X~Z+Q))
```

```
> summary(lm(Y~X_hat+Q))$coefficients #Second stage -> Unbiased estimation
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.01266232	0.3377340	-0.037492	9.701179e-01
X_hat	5.05959752	0.3466945	14.593822	9.672448e-37
Q	0.88619541	0.4837122	1.832072	6.794201e-02

- Real 2SLS-IV method (instead of OLS two times) estimates just one variance-covariance matrix so S.E. are lower

```
> summary(lm(Y~X_hat+Q))$coefficients #Second Stage -> Unbiased estimation
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.01266232	0.3377340	-0.037492	9.701179e-01
X_hat	5.05959752	0.3466945	14.593822	9.672448e-37
Q	0.88619541	0.4837122	1.832072	6.794201e-02

```
> summary(ivreg(Y~X+Q|Z+Q))$coefficients #Estimation using 2SLS method
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.01266232	0.05574847	-0.2271332	8.204765e-01
X	5.05959752	0.05722753	88.4119488	2.284416e-215
Q	0.88619541	0.07984452	11.0990136	3.557419e-24

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Checking the estimation of Instrumental Variables

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- It's important to understand the IV method:
 - Avoid **weak** instruments
 - **Interpret** the effect estimate (β_1^{2SLS})
 - Have in mind that **standard errors** will be higher

- What happens if the relevance is not strong enough??

$$\widehat{\beta_1^{2SLS}} = \frac{Cov(Y_i, Z_i)}{Cov(X_i, Z_i)} =$$

- Validity of the effect coefficient
 - The estimation can be interpreted as local effect conditioned on the instrumental variable
 - This means that external validity might be low
 - IV uses a subgroup for the estimation so errors might be larger

- When we have non-compliance, random-assignment can be a good instrument because it's exogenous and relevant
 - The IV effect can be interpreted as CACE (remember CACE= ITT / ITTd)

$$Treated_i = \pi_0 + \pi_1 Assigned_i + v_i$$

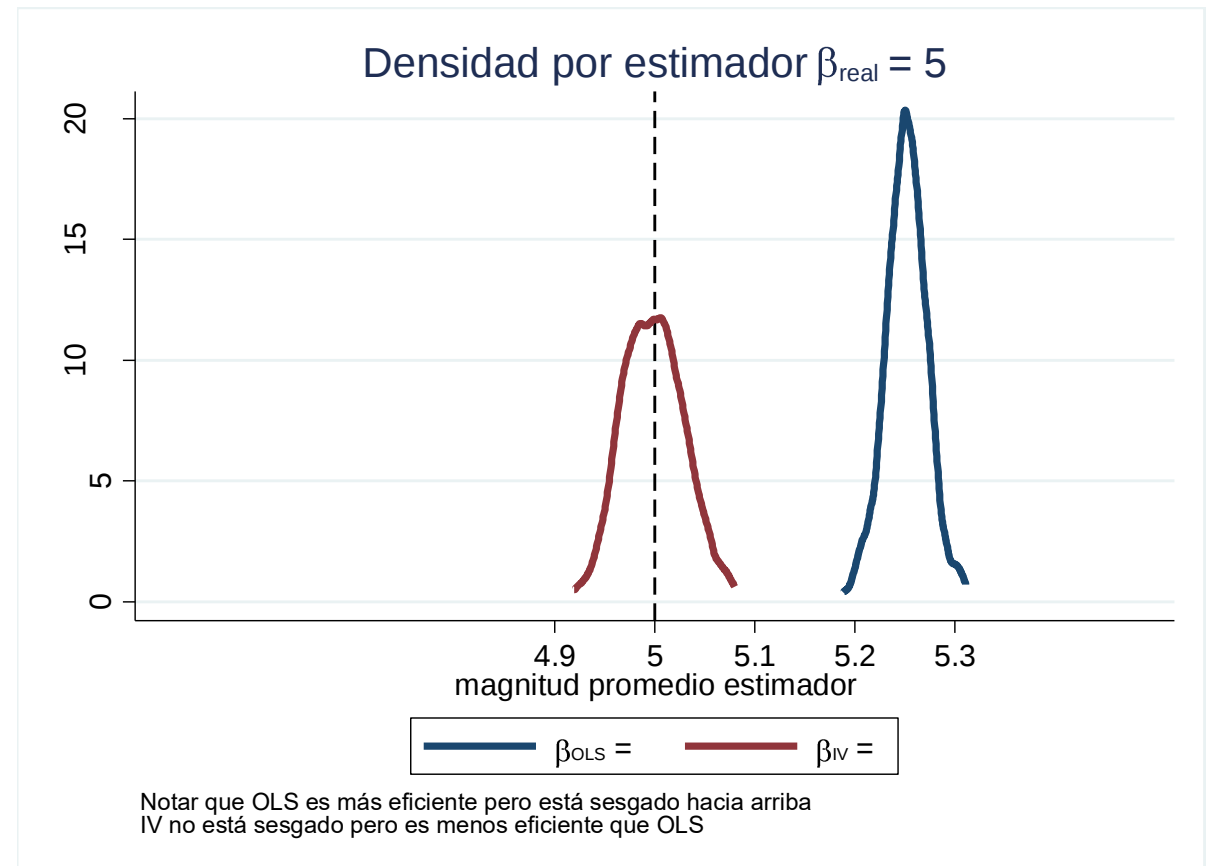
$$Result_i = \beta_0 + \underbrace{\beta_1}_{\text{CACE}} \widehat{Treated}_i + u_i$$

$$CACE = \underbrace{E[Y_i(d=1) - Y_i(d=0)]}_{\text{Average Treatment Effect}} \underbrace{d_i(1)=1}_{\text{Among compliers}}$$

INSTRUMENTAL VARIABLES: BIAS AND ERRORS

CUASI AND NON EXPERIMENTAL METHODS

- Under endogeneity:
 - OLS is biased and inconsistent
 - IV is unbiased
 - less efficient than OLS



- Let's see a comparison on the effect of **Job trainings**:

TABLE 4.4.1

Results from the JTPA experiment: OLS and IV estimates of training impacts

	Comparisons by Training Status (OLS)		Comparisons by Assignment Status (ITT)		Instrumental Variable Estimates (IV)	
	Without Covariates (1)	With Covariates (2)	Without Covariates (3)	With Covariates (4)	Without Covariates (5)	With Covariates (6)
A. Men	3,970 (555)	3,754 (536)	1,117 (569)	970 (546)	1,825 (928)	1,593 (895)
B. Women	2,133 (345)	2,215 (334)	1,243 (359)	1,139 (341)	1,942 (560)	1,780 (532)

Notes: Authors' tabulation of JTPA study data. The table reports OLS, ITT, and IV estimates of the effect of subsidized training on earnings in the JTPA experiment. Columns 1

- Summary:
 - Discuss whether is a strong or **weak** instrument
 - Bias might be larger than before
 - Discuss **heterogeneity** assumptions
 - The estimate has a local effect interpretation
 - Discuss **error estimation**
 - Discuss standard error estimation (higher for IV)

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Instrumental Variables Application II

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AMÉRICA LATINA

Alarma en Chile por el aumento de la violencia narco: muertes, peleas y disparos en funerales

Decenas de muertes en un fin de semana y cuatro tiroteos en 48 horas. Según los expertos está relacionada con el aumento del tráfico de drogas

- Can prisons and incarceration be a good option?

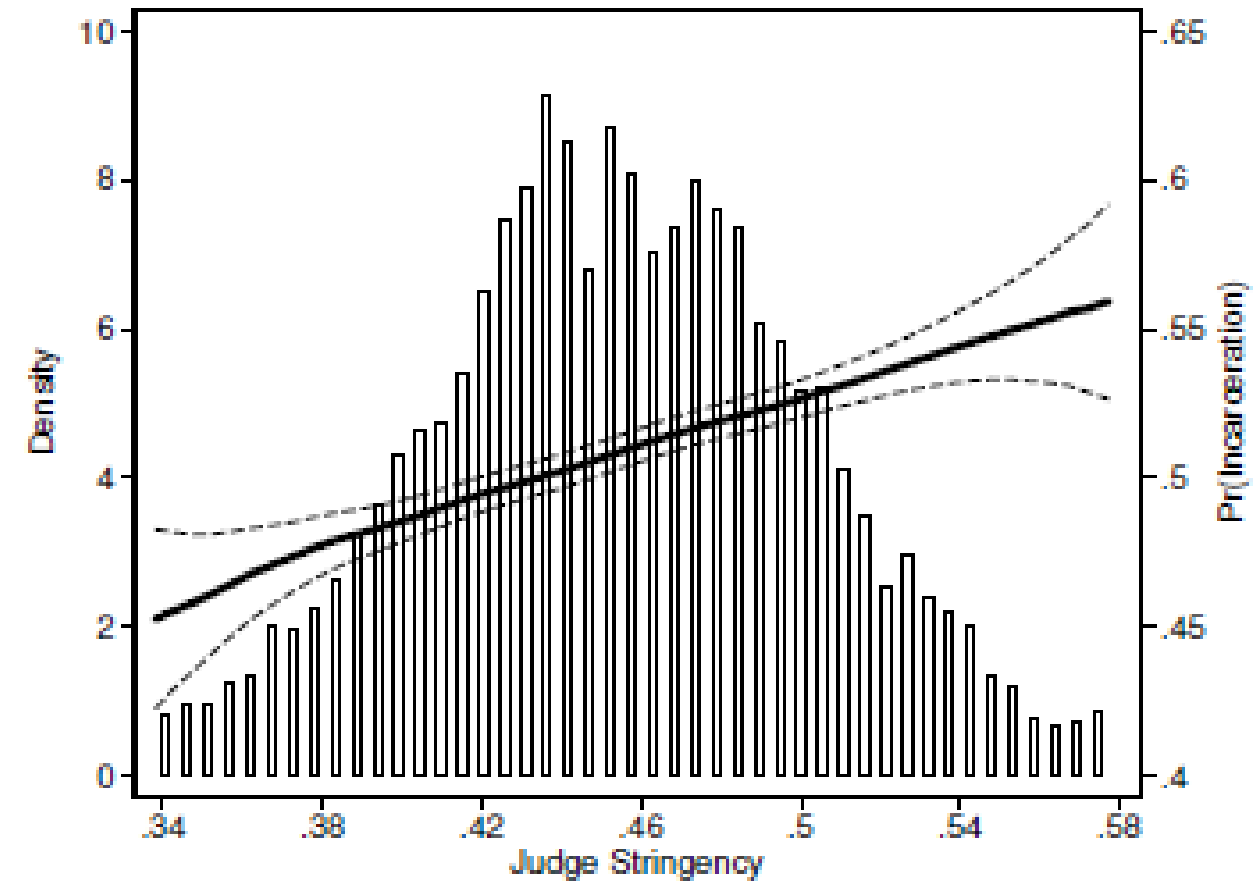
- Can prisons and incarceration be a good option?

$$ProbCrime_i = \beta_0 + \beta_1 Incarcerated_i + \varepsilon_i$$

- Bhuller and others (2020) use that
 - judges stringency (how frequent a judge sends to prison) is *distribued near as random*
 - judges are *randomly assigned* to cases in Norway

- Could it be a good instrument?

$$\text{Incarcerated}_i = \pi_0 + \pi_1 \text{JudgesStringency}_i + v_i$$



For example, a judge at the 90th percentile incarcerates about 54% of cases as compared to approximately 37% for a judge at the 10th percentile (p. 17)

$$Incarcerated_i = \pi_0 + \pi_1 JudgesStringency_i + v_i$$

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Estimation Sample:</i>	Time of Decision	Month 12 after Decision	Month 24 after Decision	Month 36 after Decision	Month 48 after Decision	Month 60 after Decision
<i>Dependent Variable:</i>	Pr(Incarcerated)					
Judge Stringency	0.4897*** (0.0665)	0.4922*** (0.0661)	0.4887*** (0.0662)	0.4818*** (0.0659)	0.4795*** (0.0661)	0.4699*** (0.0669)
F-stat. (Instrument)	53.56	54.67	53.69	52.79	51.89	48.61
Dependent mean	0.5083	0.5077	0.5066	0.5055	0.5047	0.5045
Number of cases	33,548	33,275	32,786	32,341	31,870	31,428

INSTRUMENTAL VARIABLES APPLICATION

CUASI AND NON EXPERIMENTAL METHODS

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Estimation Sample:</i>	Time of Decision	Month 12 after Decision	Month 24 after Decision	Month 36 after Decision	Month 48 after Decision	Month 60 after Decision
<i>Dependent Variable:</i>	Pr(Incarcerated)					
C. Add Controls for Demographics, Type of Crime, Past Work and Criminal History						
Judge Stringency	0.4705*** (0.0632)	0.4723*** (0.0627)	0.4667*** (0.0624)	0.4622*** (0.0622)	0.4606*** (0.0627)	0.4525*** (0.0634)
F-stat. (Instrument)	54.67	55.95	55.09	54.38	53.18	50.24
Dependent mean	0.5083	0.5077	0.5066	0.5055	0.5047	0.5045
Number of cases	33,548	33,275	32,786	32,341	31,870	31,428

INSTRUMENTAL VARIABLES APPLICATION

CUASI AND NON EXPERIMENTAL METHODS

<i>Dependent Variable:</i>	<i>Pr(Ever Charged)</i>			<i>Number of</i>
	<i>Months 1-24</i>	<i>Months 25-60</i>	<i>Months 1-60</i>	<i>Charges</i>
	<i>after Decision</i>	<i>after Decision</i>	<i>after Decision</i>	<i>Months 1-60</i>
	(1)	(2)	(3)	(4)
OLS: Incarcerated	0.130***	0.115***	0.113***	5.275***
<i>No controls</i>	(0.007)	(0.007)	(0.006)	(0.321)
OLS: Incarcerated	0.126***	0.109***	0.105***	5.369***
<i>Demographics & Type of Crime</i>	(0.007)	(0.007)	(0.006)	(0.310)
OLS: Incarcerated	0.068***	0.050***	0.052***	2.917***
<i>All controls</i>	(0.006)	(0.007)	(0.006)	(0.278)
Dependent mean	0.57	0.57	0.70	10.21
Complier mean if not incarcerated	0.56	0.57	0.73	13.62
Number of cases	31,428			

INSTRUMENTAL VARIABLES APPLICATION

CUASI AND NON EXPERIMENTAL METHODS

<i>Dependent Variable:</i>	<i>Pr(Ever Charged)</i>			<i>Number of</i>
				<i>Charges</i>
	<i>Months 1-24</i> <i>after Decision</i>	<i>Months 25-60</i> <i>after Decision</i>	<i>Months 1-60</i> <i>after Decision</i>	<i>Months 1-60</i> <i>after Decision</i>
	(1)	(2)	(3)	(4)
IV: Incarcerated	-0.239**	-0.245**	-0.293***	-11.482**
<i>All controls</i>	(0.113)	(0.113)	(0.106)	(5.705)
Dependent mean	0.57	0.57	0.70	10.21
Complier mean if not incarcerated	0.56	0.57	0.73	13.62
Number of cases	31,428			

- Summary: according to Bhuller et al. (2020):
 - The instrument of judges stringency is relevant and exogenous
 - OLS was biasing results
 - IV shows that incarcerating people reduces probability of repeating crimes and number of crimes
 - At least in people with strict judges that get sent to prison