

Intstrumental Variables

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Identifying assumptions

Second stage: $Y_i = \alpha_0 + \alpha_1 D_i + \epsilon_i$

First stage: $D_i = \beta_0 + \beta_1 Z_i + \mu_i$

- ▶ Exogenous instrument
 - ▶ $\text{Cov}(Z_i, \mu_i) = 0$ i.e., $D_0, D_1 \perp\!\!\!\perp Z$
- ▶ Exclusion restriction
 - ▶ $\text{Cov}(Z_i, \epsilon_i) = 0$ i.e., $Y_0, Y_1 \perp\!\!\!\perp Z$
- ▶ First stage
 - ▶ $\beta_1 \neq 0$ i.e., $0 < P(Z = 1) < 1$ and $P(D_1 = 1) \neq P(D_1 = 0)$
- ▶ Monotonicity ($D_1 \geq D_0$)

Overview

- ▶ Wald estimator
 - ▶ Constant treatment effects & binary instrument
 - ▶ Tests for first stage
 - ▶ Placebo regressions for exclusion restriction
- ▶ Preliminaries on 2SLS estimator
 - ▶ More in class
 - ▶ Heterogeneous treatment effects
 - ▶ Two papers

Paper 1: Bloom et al 1997

- ▶ What is the effect of participation in job training programs on earnings?
- ▶ Leverage random assignment of admission to training program
 - ▶ 21,000 person RCT commissioned by US Dept of Labor in 1986
 - ▶ 16 local areas across the country between 1987 and 1989
 - ▶ Sample consists of economically disadvantaged adults and out-of-school youths
- ▶ Outcomes: total earnings and educational attainment
- ▶ Problems with compliance (not a perfect experiment)

Load the Data

```
library(haven)
library(estimatr)
rm(list=ls())
setwd("C:\\Users\\Sidak Yntiso\\Dropbox\\CI\\Week 10\\Lab")
load("jtpa.RDA")
```

```
#imperfect compliance
```

```
mean(d$training[d$assignmt==1])
```

```
## [1] 0.6415976
```

```
mean(d$training[d$assignmt==0])
```

```
## [1] 0.01452785
```

```
#naive OLS maybe biased
```

```
summary(lm_robust(earnings~training,data=d))$coefficients
```

```
##               Estimate Std. Error   t value    Pr(>|t|)
## (Intercept) 14605.085    206.8771  70.597879 0.00000e+00
```

First stage effect

#regression effect of Z on D

```
summary(lm_robust(training~assignmt,data=d))$coefficients
```

```
##              Estimate Std. Error    t value    Pr(>|t|)
## (Intercept) 0.01452785 0.001962840    7.401441 1.443646e-
## assignmt    0.62706980 0.005879983 106.644835 0.000000e-
##              CI Upper      DF
## (Intercept) 0.01837536 11201
## assignmt    0.63859560 11201
```

#\$\frac{Cov(D,Z)}{Var(Z)}\$

```
vmat <- cov(d[,c("earnings","training","assignmt")])
vmat[3,2]/vmat[3,3]
```

```
## [1] 0.6270698
```

Reduced form/Intent to Treat Effect

#regression effect of Z on Y

```
summary(lm_robust(earnings~assignmt,data=d))$coefficients
```

##		Estimate	Std. Error	t value	Pr(> t)
##	(Intercept)	15040.504	265.3927	56.67264	0.0000000000
##	assignmt	1161.417	330.4793	3.51434	0.0004425883
##		DF			
##	(Intercept)	11201			
##	assignmt	11201			

#\$\frac{Cov(Y,Z)}{Var(Z)}\$

```
vmat[1,3]/vmat[3,3]
```

```
## [1] 1161.417
```

Wald Estimator

- Effect of D on Y using only exogenous variation in D induced by Z:

$$\begin{aligned}\rho &= \frac{\frac{Cov(Y, Z)}{Var(Z)}}{\frac{Cov(D, Z)}{Var(Z)}} = \frac{\text{Reduced form}}{\text{First stage}} \\ &= \frac{Cov(Y, Z)}{Cov(D, Z)} = \frac{\sum_{i=1}^N (z_i - \bar{z})(y_i - \bar{y})}{\sum_{i=1}^N (z_i - \bar{z})(D_i - \bar{D})}\end{aligned}$$

Estimation

Focusing on the numerator...

$$\begin{aligned}\sum_{i=1}^N (z_i - \bar{z})(y_i - \bar{y}) &= \sum_{i=1}^N z_i(y_i - \bar{y}) - \left(\sum_{i=1}^N \bar{z}(y_i - \bar{y})\right) \\ &= \sum_{i=1}^N (z_i y_i - z_i \bar{y}) - \bar{z} \left(\sum_{i=1}^N (y_i - \bar{y})\right) \\ &= \sum_{z_i=1} (z_i y_i - z_i \bar{y}) - \bar{z}(n\bar{y} - n\bar{y}) \\ &= \sum_{z_i=1} (z_i y_i - z_i \bar{y})\end{aligned}$$

The ratio

$$\begin{aligned}\rho &= \frac{\sum_{z_i=1}(z_i y_i - z_i \bar{y})}{n_1} / \frac{\sum_{z_i=1}(z_i D_i - z_i \bar{D})}{n_1} \\ &= \frac{\bar{y}_1 - \bar{y}}{\bar{D}_1 - \bar{D}}\end{aligned}$$

Using the fact that $\bar{y} = \frac{n_1 \bar{y}_1 + n_0 \bar{y}_0}{n}$

$$\rho = \frac{\bar{y}_1 - \bar{y}_0}{\bar{D}_1 - \bar{D}_0}$$

Converges in probability to...

$$= \frac{E[Y_i | Z_i = 1] - E[Y_i | Z_i = 0]}{E[D_i | Z_i = 1] - E[D_i | Z_i = 0]}$$

Wald Estimate

```
##  $\frac{\text{Cov}(Y,Z)}{\text{Var}(Z)} / \frac{\text{Cov}(D,Z)}{\text{Var}(Z)}$   
(vmat[1,3]/vmat[3,3])/(vmat[2,3]/vmat[3,3])
```

```
## [1] 1852.133
```

Variance

- ▶ The asymptotic standard error of the Wald estimates is derived from the limiting distribution of $\sqrt{n} \frac{(\bar{y}_1 - \bar{y}_0)}{(\bar{D}_1 - \bar{D}_0)}$.
- ▶ The numerator has a nondegenerate limiting distribution, while $(\bar{D}_1 - \bar{D}_0)$ converges to a constant.
- ▶ The standard error is therefore equal to $1/(\bar{D}_1 - \bar{D}_0)$ times the standard error of the numerator

Standard Error of Wald Estimate

```
#variance of Y1
```

```
var1 = var(d$earnings[d$assignmt==1])/(length(d$earnings[d$
```

```
#variance of Y0
```

```
var0 = var(d$earnings[d$assignmt==0])/(length(d$earnings[d$
```

```
#difference in compliance
```

```
diffcom = mean(d$training[d$assignmt==1]) - mean(d$training
```

```
#variance of wald estimate
```

```
(var1+var0)^0.5/diffcom
```

```
## [1] 527.0215
```

Test for first stage

- ▶ In contrast to OLS, the IV estimator is not unbiased in small (finite) samples even when instrument is perfectly exogenous
- ▶ Because of sampling variability in first stage estimation of fitted values, some part of the correlation between errors in first and second stage seeps into 2SLS estimates (correlation disappears in large samples)
- ▶ Finite sample bias can be considerable (e.g., 20 - 30%), even when the sample size is over 100,000 if the instrument is weak

Empirical papers typically report first-stage F-statistics

```
library(lmtest,quietly = T)
fs1 <- lm_robust(training~ sex + age2225+age2629+age3035+
                  age3644+age4554+married +assignmt,data=d)
fs2 <- lm_robust(training~ sex +age2225+age2629+age3035+
                  age3644+age4554+married,data=d)
waldtest(fs1, fs2)
```

```
## Wald test
```

```
##
```

```
## Model 1: training ~ sex + age2225 + age2629 + age3035 +
##      married + assignmt
```

```
## Model 2: training ~ sex + age2225 + age2629 + age3035 +
##      married
```

```
##   Res.Df Df Chisq Pr(>Chisq)
```

```
## 1  11194
```

```
## 2  11195 -1 11314  < 2.2e-16 ***
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
```

Continuous IV example

- ▶ For our example with IV, we will start with AJR (2001) - Colonial Origins of Comparative Development
- ▶ Treatment is average protection from expropriation
- ▶ Exogenous covariates are dummies for British/French colonial presence
- ▶ Instrument is settler mortality
- ▶ Outcome is $\log(\text{GDP})$ in 1995

Continuous IV example

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```
require(foreign,quietly=TRUE)
dat <- read.dta("AJR 2001\maketable5.dta")
dat <- subset(dat, baseco==1)
```

2SLS Estimator

- ▶ Fit first stage and obtain fitted values $E[D|Z]$
- ▶ Plug into second stage: $Y = \alpha_0 + \alpha_1 E[D|Z] + \epsilon_i$
- ▶ Standard errors incorrect (ignore estimation uncertainty in first stage).
- ▶ Canned packages estimate 2SLS in one step

Estimate IV via 2SLS

```
#first stage
```

```
first <- lm_robust(avexpr~logem4+f_brit+f_french,dat)
```

```
#IV
```

```
iv2sls<-iv_robust(logpgp95~avexpr+f_brit+f_french|logem4+f_
```

Examine First Stage

```
summary(first)
```

```
##
```

```
## Call:
```

```
## lm_robust(formula = avexpr ~ logem4 + f_brit + f_french,
```

```
##
```

```
## Standard error type: HC2
```

```
##
```

```
## Coefficients:
```

```
##           Estimate Std. Error t value Pr(>|t|) CI Low
```

```
## (Intercept)   8.7466     0.7639  11.4502 9.909e-17  7.21
```

```
## logem4        -0.5344     0.1612  -3.3148 1.559e-03 -0.85
```

```
## f_brit         0.6293     0.3740   1.6825 9.766e-02 -0.11
```

```
## f_french       0.0474     0.4044   0.1172 9.071e-01 -0.76
```

```
##
```

```
## Multiple R-squared:  0.3081 ,    Adjusted R-squared:  0.
```

```
## F-statistic: 7.762 on 3 and 60 DF,  p-value: 0.0001837
```

Examine Output

```
summary(iv2sls)
```

```
##
```

```
## Call:
```

```
## iv_robust(formula = logpgp95 ~ avexpr + f_brit + f_french
```

```
##       f_brit + f_french, data = dat)
```

```
##
```

```
## Standard error type:  HC2
```

```
##
```

```
## Coefficients:
```

```
##           Estimate Std. Error t value Pr(>|t|) CI Low
```

```
## (Intercept)   1.3724     1.6481  0.8327 4.083e-01 -1.92
```

```
## avexpr        1.0779     0.2553  4.2214 8.353e-05  0.56
```

```
## f_brit        -0.7777     0.3852 -2.0188 4.798e-02 -1.54
```

```
## f_french      -0.1170     0.3484 -0.3358 7.382e-01 -0.81
```

```
##
```

```
## Multiple R-squared:  0.04833 ,    Adjusted R-squared:  0
```

```
## F-statistic: 8.342 on 3 and 60 DF,  p-value: 0.0001011
```

Final example

- ▶ We're going to be looking at Ananat (2011) in AEJ
- ▶ This study looks at the effect of racial segregation on economic outcomes.
- ▶ Outcome: Poverty rate & Inequality (Gini index)
- ▶ Treatment: Segregation (level of dissimilarity)
 - ▶ What percentage of blacks (or nonblacks) would have to move to another census tract in order for the proportion black in equal tract to be constant
 - ▶ $dism = 1/2 |(blacks\ in\ i / blacks\ total) - (non\ blacks\ in\ i / nonblacks\ total)|$
- ▶ Instrument: "railroad division index"
 - ▶ $herf = 1 - (\sum (Area\ of\ Neighborhood\ i) / (Area\ Total))^2$
- ▶ Main covariate of note: railroad length in a town

```
require(foreign)
d<-read.dta("Ananat 2011\\aej_maintdata.dta")
```

Main effects for Black Subsample

#OLS

```
ols <- lm_robust(lngini_b ~ dism1990 +lenper,d)
```

#first stage for all areas

```
first.stage <- lm_robust(dism1990~herf+lenper,d)
```

#IV for gini and poverty

```
gini.iv <- iv_robust(lngini_b~dism1990+lenper|herf+lenper,c
```

```
pov.iv <- iv_robust(povrate_b~dism1990+lenper|herf+lenper,c
```

Base Results

```
round(summary(ols)$coefficients[2,],3)
```

##	Estimate	Std. Error	t value	Pr(> t)	CI Lower
##	0.449	0.095	4.704	0.000	0.260

```
round(summary(first.stage)$coefficients[2,],3)
```

##	Estimate	Std. Error	t value	Pr(> t)	CI Lower
##	0.357	0.114	3.139	0.002	0.132

```
round(summary(gini.iv)$coefficients[2,],3)
```

##	Estimate	Std. Error	t value	Pr(> t)	CI Lower
##	0.875	0.441	1.982	0.050	0.001

```
round(summary(pov.iv)$coefficients[2,],3)
```

##	Estimate	Std. Error	t value	Pr(> t)	CI Lower
##	0.258	0.112	2.302	0.023	0.036

Effects for whites

```
ols.v2 <- lm_robust(lngini_w~dism1990+lenper,d)

first.stage.v2 <- lm_robust(dism1990~herf+lenper,d)

gini.iv.v2 <- iv_robust(lngini_w~dism1990+lenper|herf+lenper)

pov.iv.v2 <- iv_robust(povrate_w~dism1990+lenper|herf+lenper)
```

Base Results for White Subsample

```
round(summary(ols.v2)$coefficients[2,],3)
```

##	Estimate	Std. Error	t value	Pr(> t)	CI Lower
##	-0.075	0.039	-1.912	0.058	-0.152

```
round(summary(first.stage.v2)$coefficients[2,],3)
```

##	Estimate	Std. Error	t value	Pr(> t)	CI Lower
##	0.357	0.114	3.139	0.002	0.132

```
round(summary(gini.iv.v2)$coefficients[2,],3)
```

##	Estimate	Std. Error	t value	Pr(> t)	CI Lower
##	-0.334	0.129	-2.591	0.011	-0.590

```
round(summary(pov.iv.v2)$coefficients[2,],3)
```

##	Estimate	Std. Error	t value	Pr(> t)	CI Lower
##	-0.196	0.070	-2.811	0.006	-0.334