

# Instrumental Variables

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Quantitative Political Methodology (L32 363)

November 20, 2017

# Road map

Where we have been:

- What is regression?
- How to interpret coefficients?
- Interactions/Dummies
- Regression assumptions
- Using regression for causal inference
- Using difference-in-differences to make causal claims
- Regression discontinuity

Today:

- Instrumental variables

# Instrumental variables (IV) analysis: Two frameworks

- How to handle non-compliance in experiments

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- How to make causal inference in the presence of endogenous regressors

# Instrumental variables (IV) analysis: Two frameworks

- How to handle non-compliance in experiments
  - ▶ What do you do if some people in an experiment don't do what they are told?
- How to make causal inference in the presence of endogenous regressors
  - ▶ An approach that can sometimes work when you can't do anything else

# Framework 1: Who get's the milk?



# A non-hypothetical example: The setup

Let's imagine a nutrition intervention:

- Randomly assign schools to get extra provisions of school milk at lunch
- At all schools teachers allocate milk and keep track of who gets it
- After one year, follow up and measure weights of all children



# A non-hypothetical example: The hitch

## Two-sided noncompliance

- People in the treatment condition failed to receive the treatment

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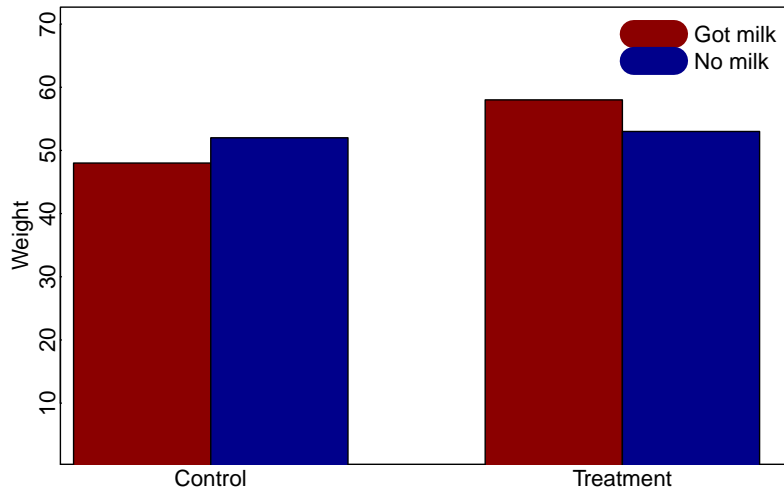
- People in the treatment condition failed to receive the treatment
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- People in the control condition receive the treatment
  - ▶ Some people have cows

# A non-hypothetical example: The hitch

## Two-sided noncompliance

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  - ▶ Some kids don't like milk
  - ▶ More importantly, who would you give milk to?
- People in the control condition receive the treatment
  - ▶ Some people have cows
  - ▶ Rich people

# Hypothetical experimental results



# Instrumental variables

We are going to solve two equations at the same time:

$$x_i = \tau + T_i\gamma + \epsilon_{i1} \quad (1)$$

$$y_i = \alpha + x_i\beta + \epsilon_{i2} \quad (2)$$

$$\begin{pmatrix} \epsilon_{i1} \\ \epsilon_{i2} \end{pmatrix} \sim N(\mathbf{0}, \Sigma)$$



# How does this work? In the abstract

- 1 We have an endogenous regressor  $x$  and we want to know how it affect  $y$ .
- 2 We have a randomly assigned variable  $T$  that has a strong effect on  $x$
- 3  $T$  only affects  $y$  through  $x$  (exclusion restriction)
- 4 No one does the opposite on purpose (no defiers)

If we have all of these, we can correctly estimate  $\beta \dots$

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... but only for the subset of observations that are compliers.

# How does this work? In our example

- 1 We have an endogenous regressor  $x$  (milk consumption) and we want to know how it affect  $y$  (weight).
- 2 We have a randomly assigned variable  $T$  (which schools get lunch) that has a strong effect on  $x$  (milk consumption)
- 3  $T$  only affects  $y$  through  $x$  (assignment not related to weight except through milk)
- 4 No one does the opposite on purpose (no one drinks extra milk because their school was added to the control)

If we have all of these, we can correctly estimate  $\beta$ .

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## Framework 2: Guns and money



# Some things can't be randomized

- Bad economy  $\rightarrow$  more war

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- More war  $\rightarrow$  bad economy

# Some things can't be randomized

- Bad economy  $\rightarrow$  more war
- More war  $\rightarrow$  bad economy
- Bad government  $\rightarrow$  more war, bad economy



# Instrumental variables

We are going to solve two equations at the same time:

$$x_i = \tau + T_i\gamma + \epsilon_{i1} \quad (3)$$

$$y_i = \alpha + x_i\beta + \epsilon_{i2} \quad (4)$$

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# Using rainfall as an instrument



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# How does this work? In our example

- 1 We have an endogenous regressor  $x$  (economy) and we want to know how it affect  $y$  (civil war).
- 2 We have a randomly assigned variable  $T$  (rainfall in the previous year) that has a strong effect on  $x$  (economic growth)
- 3  $T$  only affects  $y$  through  $x$  (rain does not directly affect civil war)
- 4 No one does the opposite on purpose (countries do not have negative economic growth as a consequence of lot's of rain)

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# R code for two staged least squares

```
library(AER)
ivreg(y ~ x | T, data = myData)
```



# Negative ads and turnout



Ansolabehere, Iyengar, and Simon (1999), "Replicating Experiments Using Aggregate and Survey Data: The Case of Negative Advertising and Turnout," *American Political Science Review*.

# The basic approach

Using survey data from the 1992 election

- $y$ : Self-reported probability of voting

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Using survey data from the 1992 election

- $y$ : Self-reported probability of voting
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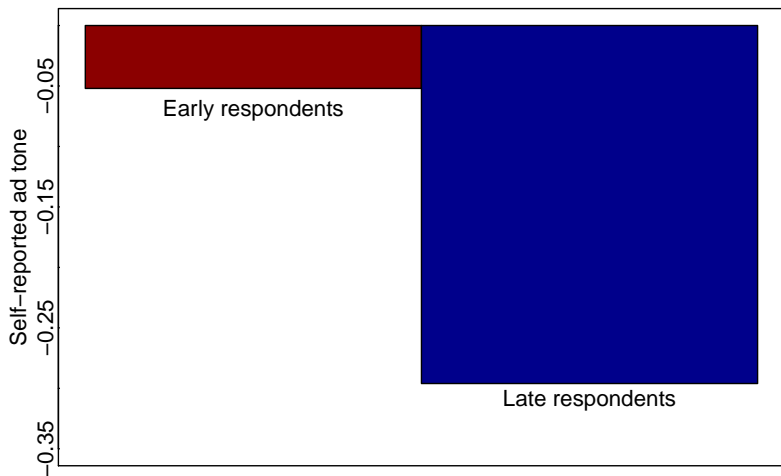
# The basic approach

Using survey data from the 1992 election

- $y$ : Self-reported probability of voting
- $x$ : Self-reported ad tone
- $T$ : Date of the interview

# Check our assumptions

Assumption 1: We have a randomly assigned variable  $T$  that has a strong effect on  $x$



# Check our assumptions

- $T$  only affects  $y$  through  $x$
- No one does the opposite on purpose

## 2SLS Results

	2SLS	
	Instrumental Variables for Pos & Neg	Neg Only
Recall of positive ad	.527 (.496)	.017 (.022)
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Remember, this is the effect of the treatment on compliers.