Economics 174/274

Global Poverty and Impact Evaluation

Professor Frederico Finan

February 11, 2011

Lecture 7

Today's lecture

The following lecture is based on the following readings:

- Duflo et al. article on Randomization

- Duflo, Esther (2001): "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment", AER, 91(4)

Supply-side interventions in education

- Last class, we focused on some experiments that sought to increase the demand for schooling among the poor

Supply-side interventions in education

- Last class, we focused on some experiments that sought to increase the demand for schooling among the poor
- Children of poor households are credit constrained $\longrightarrow$ they want to consume more school if they had the money

Supply-side interventions in education

- Last class, we focused on some experiments that sought to increase the demand for schooling among the poor
- Children of poor households are credit constrained $\longrightarrow$ they want to consume more school if they had the money
- Progresa (and other CCT's throughout the world) relaxes this constrain

Supply-side interventions in education

- Last class, we focused on some experiments that sought to increase the demand for schooling among the poor
- Children of poor households are credit constrained $\rightarrow$ they want to consume more school if they had the money
- Progresa (and other CCT's throughout the world) relaxes this constrain
- We saw that such programs have been useful in increasing the demand for school

Supply-side interventions in education

- Increasing demand is only part of the story.

Supply-side interventions in education

- Increasing demand is only part of the story.
- Another way of increasing schooling among the poor is to focus on the cost of schooling through the supply side

Supply-side interventions in education

- Increasing demand is only part of the story.
- Another way of increasing schooling among the poor is to focus on the cost of schooling through the supply side
  - School construction

Supply-side interventions in education

- Increasing demand is only part of the story.
- Another way of increasing schooling among the poor is to focus on the cost of schooling through the supply side
  - School construction
  - Improve transportation

Supply-side interventions in education

- Increasing demand is only part of the story.
- Another way of increasing schooling among the poor is to focus on the cost of schooling through the supply side
  - School construction
  - Improve transportation
  - Eliminate school fees (text books, uniforms, etc)

Supply-side interventions in education

- Increasing demand is only part of the story.
- Another way of increasing schooling among the poor is to focus on the cost of schooling through the supply side
  - School construction
  - Improve transportation
  - Eliminate school fees (text books, uniforms, etc)
  - Reduce child labor (opportunity costs)

Do we have any evidence that supply-side interventions work?

- This is a hard question to answer

Do we have any evidence that supply-side interventions work?

- This is a hard question to answer
- For example, suppose we wanted to know whether improving access to schools (say by constructing more schools) will increase school enrollment?

Do we have any evidence that supply-side interventions work?

- This is a hard question to answer
- For example, suppose we wanted to know whether improving access to schools (say by constructing more schools) will increase school enrollment?
- How would we design such an intervention and evaluation?

Do we have any evidence that supply-side interventions work?

- This is a hard question to answer
- For example, suppose we wanted to know whether improving access to schools (say by constructing more schools) will increase school enrollment?
- How would we design such an intervention and evaluation?
- The ideal design would be to randomize, of course! But how?

Unit of analysis

First, we need to define the unit of analysis

- Do we randomize at the village level or the district level?

Unit of analysis

First, we need to define the unit of analysis

- Do we randomize at the village level or the district level?

- What are some of the tradeoffs?

Unit of analysis

First, we need to define the unit of analysis

- Do we randomize at the village level or the district level?
- What are some of the tradeoffs?
  - Sample size - the smaller the sample the less statistical power we will have to detect the impact

Unit of analysis

First, we need to define the unit of analysis

- Do we randomize at the village level or the district level?
- What are some of the tradeoffs?
  - Sample size - the smaller the sample the less statistical power we will have to detect the impact
  - Spillover - children in non-treated villages may still benefit from a new school if it is constructed in a nearby village $\longrightarrow$ makes it harder to detect the effect

Assignment of the intervention

Suppose we decide that the unit of analysis the is village, how do we determine which villages gets a school?

- random assignment

Assignment of the intervention

Suppose we decide that the unit of analysis the is village, how do we determine which villages gets a school?

- random assignment

- is randomization politically feasible?

Assignment of the intervention

Suppose we decide that the unit of analysis the is village, how do we determine which villages gets a school?

- random assignment
- is randomization politically feasible?
- is randomization ethical?

Measuring the impact

Suppose that we are able to convince a government official to randomize across villages, how do we measure the impact? What kind of data do we collect?

- A baseline? Why would this be useful?

Measuring the impact

Suppose that we are able to convince a government official to randomize across villages, how do we measure the impact? What kind of data do we collect?

- A baseline? Why would this be useful?
- How long before the follow-up? How many follow ups?

Measuring the impact

Suppose that we are able to convince a government official to randomize across villages, how do we measure the impact? What kind of data do we collect?

- A baseline? Why would this be useful?
- How long before the follow-up? How many follow ups?
- Do we collect information at the households or the schools?

Measuring the impact

Suppose that we are able to convince a government official to randomize across villages, how do we measure the impact? What kind of data do we collect?

- A baseline? Why would this be useful?
- How long before the follow-up? How many follow ups?
- Do we collect information at the households or the schools?
- A well-designed randomized evaluation will take time

Difference-in-differences

- To conduct a randomized evaluation on these “bigger” questions is difficult, and often infeasible

Difference-in-differences

- To conduct a randomized evaluation on these "bigger" questions is difficult, and often infeasible
- But these are important questions, we need to think of alternative ways in which to estimate the impact

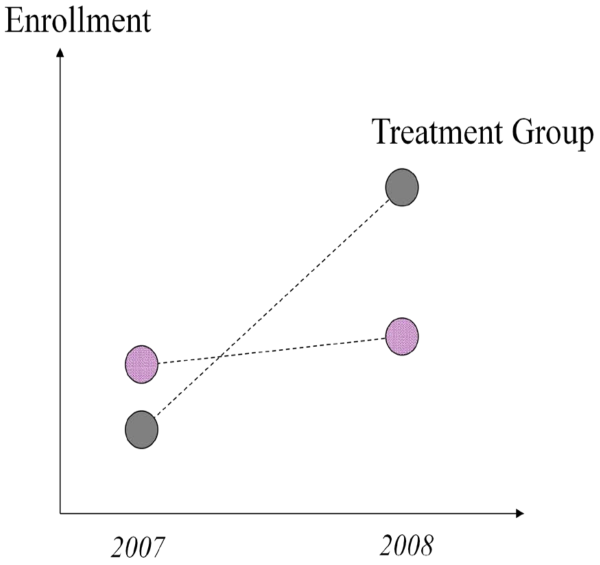
Difference-in-differences

- To conduct a randomized evaluation on these “bigger” questions is difficult, and often infeasible
- But these are important questions, we need to think of alternative ways in which to estimate the impact
- One alternative approach is called: **difference-in-differences**

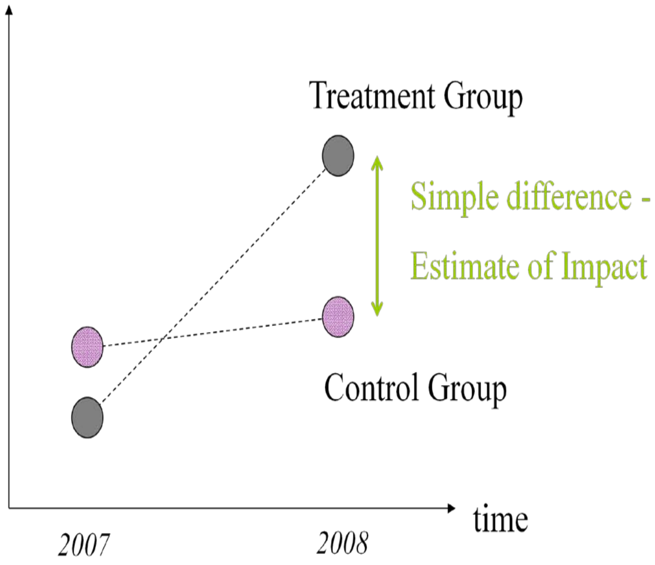
Difference-in-differences

- To conduct a randomized evaluation on these "bigger" questions is difficult, and often infeasible
- But these are important questions, we need to think of alternative ways in which to estimate the impact
- One alternative approach is called: **difference-in-differences**
  - Useful when we have a treatment and a control group, with data before and after the intervention

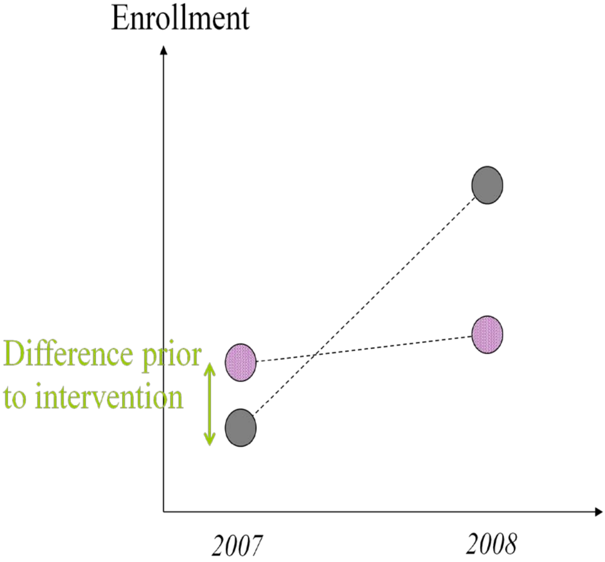
Difference-in-differences



Difference-in-differences



Difference-in-differences



Difference-in-differences

How do we control for this initial difference (selection bias)?

- Look at the change over time in the control group

Difference-in-differences

How do we control for this initial difference (selection bias)?

- Look at the change over time in the control group

- Assume that the same change over time would have happened in the treatment group

Difference-in-differences

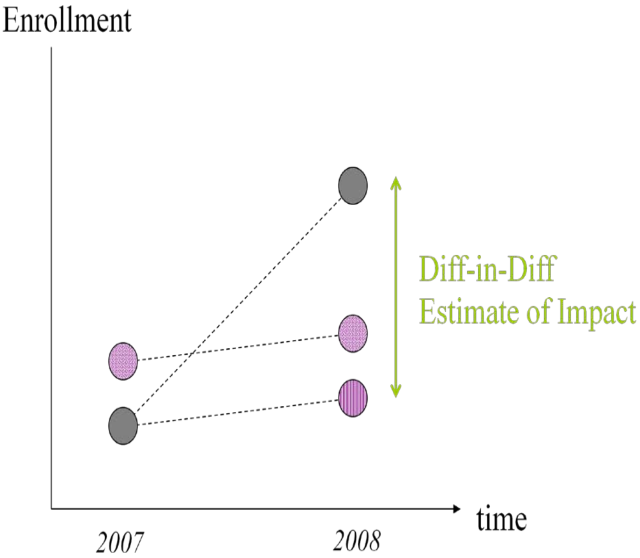
How do we control for this initial difference (selection bias)?

- Look at the change over time in the control group

- Assume that the same change over time would have happened in the treatment group

- Adjust the difference post intervention by difference prior to the intervention (hence the name difference-in-differences)

Difference-in-differences



Difference-in-differences

Mathematically,

- Y_1^T potential outcome if treated in period 1 (after treatment occurs)
- Y_1^C potential outcome if untreated in period 1
- Y_0^T potential outcome if treated in period 0 (before treatment occurs)
- Y_0^C potential outcome if untreated in period 0

We are interested in an estimate of the average treatment effect (ATE): Which is?

Difference-in-differences

Mathematically,

- Y_1^T potential outcome if treated in period 1 (after treatment occurs)
- Y_1^C potential outcome if untreated in period 1
- Y_0^T potential outcome if treated in period 0 (before treatment occurs)
- Y_0^C potential outcome if untreated in period 0

We are interested in an estimate of the average treatment effect (ATE): Which is?

$$ATE = E[Y_1^T|T] - E[Y_1^C|T]$$

T indicates group assignment. Recall we do not observe this difference?

Difference-in-differences

Average treatment effect

$$ATE = E[Y_1^T | T] - E[Y_1^C | T]$$

Difference-in-differences

Average treatment effect

$$ATE = E[Y_1^T | T] - E[Y_1^C | T]$$

Let's add zero

$$\begin{aligned} ATE &= E[Y_1^T | T] - E[Y_1^C | T] \\ &= E[Y_1^T | T] - E[Y_1^C | C] + E[Y_1^C | C] - E[Y_1^C | T] \end{aligned}$$

Difference-in-differences

Let's add zero again

$$
\begin{aligned}
ATE &= E[Y_1^T|T] - E[Y_1^C|C] \\
&+ E[Y_1^C|C] - E[Y_1^C|T] + E[Y_0^C|T] - E[Y_0^C|T]
\end{aligned}
$$

Difference-in-differences

Let's add zero again

$$\begin{aligned} ATE &= E[Y_1^T|T] - E[Y_1^C|C] \\ &+ E[Y_1^C|C] - E[Y_1^C|T] + E[Y_0^C|T] - E[Y_0^C|T] \end{aligned}$$

One more time and rearrange

$$\begin{aligned} ATE &= \{E[Y_1^T|T] - E[Y_1^C|C]\} - \{E[Y_0^C|T] - E[Y_0^C|C]\} \\ &+ E[Y_1^C|C] - E[Y_0^C|C] + E[Y_0^C|T] - E[Y_1^C|T] \end{aligned}$$

Difference-in-differences

What does this equation mean?

$$\begin{aligned} ATE &= \underbrace{\{E[Y_1^T|T] - E[Y_1^C|C]\} - \{E[Y_0^C|T] - E[Y_0^C|C]\}}_{\text{Difference-in-differences}} \\ &+ E[Y_1^C|C] - E[Y_0^C|C] + E[Y_0^C|T] - E[Y_1^C|T] \end{aligned}$$

Difference-in-differences

What does this equation mean?

$$\begin{aligned} ATE &= \underbrace{\{E[Y_1^T|T] - E[Y_1^C|C]\} - \{E[Y_0^C|T] - E[Y_0^C|C]\}}_{\text{Difference-in-differences}} \\ &+ E[Y_1^C|C] - E[Y_0^C|C] + E[Y_0^C|T] - E[Y_1^C|T] \end{aligned}$$

So for a causal interpretation we need the second quantity to equal zero, or

$$E[Y_1^C|C] - E[Y_0^C|C] = E[Y_1^C|T] - E[Y_0^C|T]$$

What does this mean?

Difference-in-differences

Counterfactual assumption of the difference-in-differences estimate:

- "Parallel trends" - change in outcome in the control group would be the same as the treatment group, if the treatment never took place

Difference-in-differences

Counterfactual assumption of the difference-in-differences estimate:

- "Parallel trends" - change in outcome in the control group would be the same as the treatment group, if the treatment never took place

- The method fails if the comparison group is on a different trajectory

Difference-in-differences

Counterfactual assumption of the difference-in-differences estimate:

- "Parallel trends" - change in outcome in the control group would be the same as the treatment group, if the treatment never took place
- The method fails if the comparison group is on a different trajectory
  - Suppose the government targeted the schools at villages with the poor school enrollment

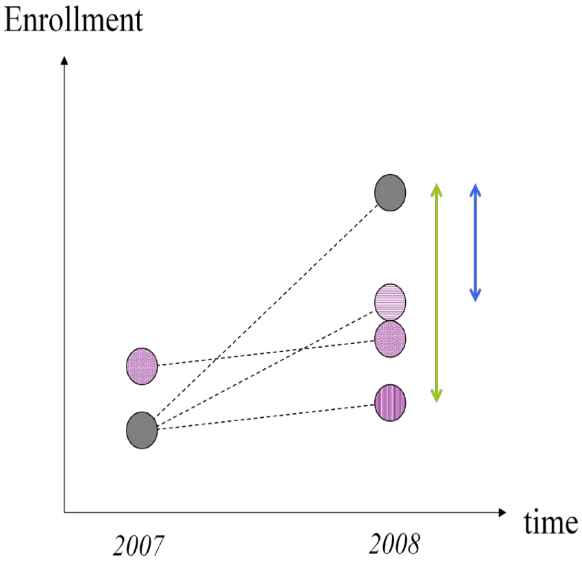
Difference-in-differences

Counterfactual assumption of the difference-in-differences estimate:

- "Parallel trends" - change in outcome in the control group would be the same as the treatment group, if the treatment never took place

- The method fails if the comparison group is on a different trajectory
  - Suppose the government targeted the schools at villages with the poor school enrollment
  - Places with lowest enrollment rates will have a tendency to grow faster than high enrollment rate places (reversion to the mean)

Difference-in-differences



Another issue with D-D approach

Functional form

	0	1	
T	1.3	2.1	0.8
C	1.1	1.8	0.7
			0.1

	0	1	
T	$\ln(1.3)$	$\ln(2.1)$	0.479
C	$\ln(1.1)$	$\ln(1.8)$	0.492
			-0.013

Difference-in-differences: Regression

How would we estimate the difference-in-differences in a regression?

$$
\begin{aligned}
Y_{it} &= \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{Program}_i \\
&+ \beta_3 \text{Post} \times \text{Program}_{it} + \epsilon_{it}
\end{aligned}
$$

- Post_t - indicator if observation is in post period
- Program_i - indicator if observation is in treatment group
- $\text{Post} \times \text{Program}_{it}$ - interaction (multiplication) of the post indicator with the program indicator, i.e. indicator if observation is in the treatment group *and* in the post period

Claim: β_3 is the difference-in-differences estimate. Why?

Difference-in-differences: Regression

Suppose there are two time periods $t = 0, 1$ and the intervention happens in $t = 1$.

$$Y_{it} \quad = \quad \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{Program}_i + \beta_3 \text{Post X Program}_{it} + \epsilon_{it}$$

- $E[Y_{i1}|\text{Program} = 1] =?$
- $E[Y_{i0}|\text{Program} = 1] =?$
- $E[Y_{i1}|\text{Program} = 0] =?$
- $E[Y_{i0}|\text{Program} = 0] =?$

Difference-in-differences: Regression

$$Y_{it} = \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{Program}_i + \beta_3 \text{Post X Program}_{it} + \epsilon_{it}$$

- $E[Y_{i1}|\text{Program} = 1] = \beta_0 + \beta_1 + \beta_2 + \beta_3$
- $E[Y_{i0}|\text{Program} = 1] = \beta_0 + \beta_2$
- $E[Y_{i1}|\text{Program} = 0] = \beta_0 + \beta_1$
- $E[Y_{i0}|\text{Program} = 0] = \beta_0$

Difference-in-differences: Regression

$$Y_{it} = \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{Program}_i + \beta_3 \text{Post X Program}_{it} + \epsilon_{it}$$

- $E[Y_{i1}|\text{Program} = 1] = \beta_0 + \beta_1 + \beta_2 + \beta_3$
- $E[Y_{i0}|\text{Program} = 1] = \beta_0 + \beta_2$
- $E[Y_{i1}|\text{Program} = 0] = \beta_0 + \beta_1$
- $E[Y_{i0}|\text{Program} = 0] = \beta_0$

Difference-in-differences estimator (DID):

$$\begin{aligned} DID &= E[Y_{i1}|\text{Program} = 1] - E[Y_{i0}|\text{Program} = 1] \\ &- [E[Y_{i1}|\text{Program} = 0] - E[Y_{i0}|\text{Program} = 0]] \\ &= \beta_3 \end{aligned}$$

Progresa Redux

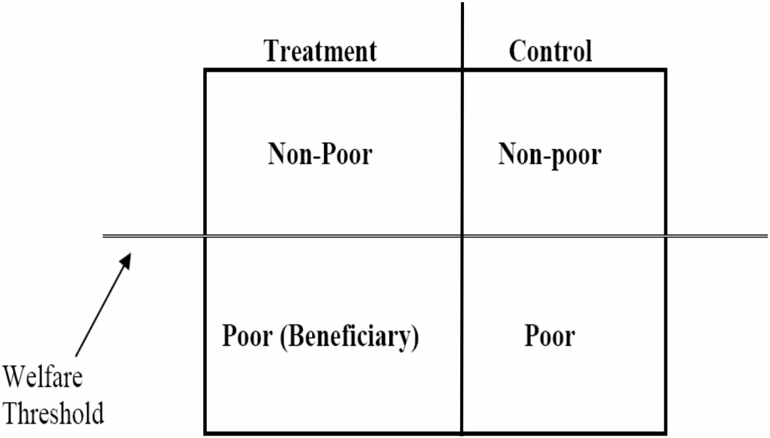


Figure 1: Program Evaluation Design