14.74 Foundations of Development Policy
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Lecture 5: The Determinants of Educational Choice

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There are enormous disparities in educational outcomes:

- Around the world
- Across regions in the same country
- By gender within countries
- By income levels
- By urban/rural residence

Why do some children get an education and others do not?

We will answer this question using a simple model of how parents make educational decisions for their children. We will be thinking of education as an investment, with costs and benefits.

1 A simple model of educational choice

Parents make schooling decisions for their child. Their utility function as a function of schooling (S) and earnings of the child when he grows up (y) is:

$$U(y, S) = m * ln(y) - h(S), \tag{1}$$

where:

-S is :

- $h(S)$ is :

-$ln(y)$ is :

-m is:

-What is the interpretation of this equation?

-What does this equation miss?

The earnings of the child when he grows will be:

$$ln(y) = a + b * S \tag{2}$$

To understand this formulation, derive both sides with respect to S.

This formulation (which is very general in economics) is saying that for each new year of education, the future wage will go up by $b\%$. b is called the *economic returns to education.*

The formulation assumes that it is the same for each year, i.e that returns to education are *linear*. Is it a reasonable assumption? How does it relate to the capacity curve debate?

Finally, we need to specify what the cost of education function looks like. Is it likely to be convex or concave? Is it likely that each year of education costs more or less than the next?

$$h'(S) = r + \phi(S) \tag{3}$$

We are now ready to solve the maximization problem of the parents:

replace equation (2) and (3) in equation (1), and take the derivative.

$$S^* = \frac{mb - r}{\phi} \tag{4}$$

Comment on this equation:

We are now in a position to think about what motivates parents in, or prevents them from sending their children to school: we have to think about what determines m, b, r, and ϕ.

2 What determines the returns to education?

- The market: Demand and Supply for educated labor

  How will it differ for boys vs girls, urban vs Rural, Rich vs poor

- The quality of education
  - Resources
  - Pedagogy
  - Incentives

If parents are indeed sensitive to the returns to education, insuring a quality education will be important for two reasons:

- There is no point getting children into school if they don't learn anything
- Parents will stop sending their children to school if they feel that they are not learning.

3 What determines the parental share (m)

Why do parents value children's earnings? Do they value it as much as the child does?
It is going to differ for boys and girls. Why? What is m likely to be for a girl? To answer this question, we need to understand how the marriage market works (more on this later!).

4 What determines the cost of education

- Direct costs
- Indirect costs: *Opportunity costs*
  Definition:
- Ability to attend: Health.

5 What programs are effective to increase educational attainment?

This conversations has given us many ideas to increase educational attainment. How can we evaluate them on a consistent basis, and compare their effectiveness?

Difficulty with program evaluation. Suppose you want to evaluate the impact of scholarship of needy children. How would you go about it? what would be the difficulties?

Using only data from observations, we can form intelligent hypotheses, but not resolve them. Before spending all of our money on something, how do we find out whether or not it will work? Why do we have problems teasing out causal relationship in real-life data?

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To address these, we need to compare comparable people, some of whom were exposed to a particular policy and some of whom were not.

How would we do it to test a new drug?

Why not do it to test an intervention in this context?

To test the effect of a policy, we can use *randomized evaluation*, where a randomly selected *treatment group* receives a treatment, while the other group does not (this is the comparison group). We will collect data on both the treatment and the comparison group, and compare the result. Because the treatment and the comparison groups have been randomly selected, any difference between them after the intervention should be due to the intervention itself.

Now, a more formal introduction to this problem, with school uniform as an example:

Let us call Y_i^T the education level of an individual i who receives a free uniform and Y_i^{NT} the education of the same individual i if he does not have a free school uniform. Can we observe Y_i^T and Y_i^{NT} at the same time?

Y_i^T and Y_i^{NT} are called *potential outcomes*.

We are interested in the difference:

$$Y_i^T - Y_i^{NT}$$

The effect of receiving a free uniform on education.

The problem: we don't observe individual i both with and without the free uniform at the same time. What can we do? We will never know the effect of a free uniform on a particular individual. We may hope to learn the *average* effect of a free uniform.

$$E[Y_i^T - Y_i^{NT}]$$

Imagine we have access to data on lots of individuals in the regions. Some individuals receive a free uniform and others do not. We may think of taking the average in both groups, and the difference between the two. Why does it make sense?

$$E[Y_i^T|\text{uniform}] - [Y_i^{NT}|\text{no uniform}] = E[Y_i^T|T] - E[Y_i^{NT}/NT]$$

Subtract and add $E[Y_i^{NT}|T]$

$$E[Y_i^T/T] - E[Y_i^{NT}|T] - E[Y_i^{NT}|NT] + E[Y_i^{NT}|T] = E[Y_i^T - Y_i^{NT}|T] + E[Y_i^{NT}|T] - E[Y_i^{NT}|NT]$$

- The first term $E[Y_i^T - Y_i^{NT}|T]$ is the *treatment effect* that we try to isolate: on average, among all the people I give a uniform to, what will be the effect of the uniform on their enrollment?
- What is:

  -$E[Y_i^{NT}|T]$?

  -$E[Y_i^{NT}|NT]$?

  - The difference $E[Y_i^{NT}|T] - E[Y_i^{NT}|NT]$?

  - Which is likely to be bigger? Why?

The difference is the *selection bias.* It tells me that beside the effect of the uniform, there may be systematic differences between those who receive a free uniforms and those who do not.

5.1 What happens when we randomly allocate the treatment?

Suppose that we select the individuals to whom we give the free uniforms randomly within a population of individuals. We observe school participation both in a treatment group (those to whom we gave a uniform) and to those we have not given a uniform to, which will form our *control (or comparison) group.*

On average, what do we expect to find if we compare treated individuals and untreated individuals before the intervention? If we compare other characteristics of these individuals that are not likely to be affected by iron (e.g. how much land they have)?

Compare $E[Y^{NT}|NT]$ and $E[Y^{NT}|T]$

$\rightarrow$ What is $E[Y^T|T] - E[Y^{NT}|NT]$ equal to?

5.2 Example: Free Uniforms In Kenya

- Since 2002 primary education (grades 1 to 8) is free in Kenya, at \$6, uniform remains the main cost of education.
- 163 treatment primary schools were randomly chosen, 165 schools are control.
- In treatment primary school, all children received a uniform is grade 6 in spring of 2003, and 18 months later.
- Note: level of randomization.
  - The randomization is a the *school level*, not individual level. Would it work if we had 2 schools (one treatment, one control). Why or why not?
  - We need to adjust for this in our standard errors (we can average enrollment at the school level, so we only have 328 observations, or we can tell Stata to adjust for us, using the "cluster" option).
- Note: the sample
  - Can we just compare overall school enrollment in T and C schools after the program starts? Why or why not?
  - We need to fix the affected cohort, and look at them.
  - And we need to make sure we have all of them: *Attrition* would bias our results. Why and how?
- Compiling results:
  - We can look at simple difference between treatment and control groups:
    * Drop out for girls: 18% in control, 12% in treatment
    * Drop out for boys: 13% in control, 9% in treatment
  - Or we can run a regression:

    $$y = \alpha + \beta T + \epsilon$$

    where T is 1 if in the treatment group, 0 otherwise.

* What is $\hat{beta}$ equal to?

- In this case, we had another treatment: teacher training in HIV AIDS prevention
- Intervention design has 4 boxes (see handout). To find out the effect of all combinations, we can run:

$$y = \alpha + \beta_1 U + \beta_2 TT + \beta_3 (U and TT) + \epsilon$$

where U is if in schools that receive uniform (0 otherwise), TT is 1 in schools that receive teacher training (0 otherwise), and (U and TT) is one if the schools gets both, 0 otherwise.

  * What is β_1 equal to?
  * What is β_2 equal to?
  * What is β_3 equal to?

- In fact, since the uniform program is only for grade 6 students in 2003, we further refine the regression:

$$y = \alpha + \gamma_1 U + \gamma_2 TT + \gamma_3 U * G6 + +\gamma_4 (U and TT) * G6 + \gamma_5 G6 + \epsilon$$

where $G6$ is 1 if student was in grade 6 in 2003.

- What do we expect for γ_2 (which is the effect of uniform on students in other grade?)
- What do we expect for γ_3 (which is the *additional* effect of the uniform in grade 6.

Using Randomized evaluation to compare cost effectiveness

The same methodology can be used (and has been used), to evaluate various projects to try to get children into schools:

- Scholarships
- School health (deworming)
- Conditional Cash transfers: providing money to parents if their children attend school.

Normally, the cost of policy is evaluated by cost by child reached. Now we can evaluate the cost per additional year of education due to the program: cost that it would be to run the program for, say 1,000 people, and the extra years of education these 1,000 people would get.

You get interesting comparisons...(see figure in handout).