AREC 345: Global Poverty & Economic Development

# Lecture 16:

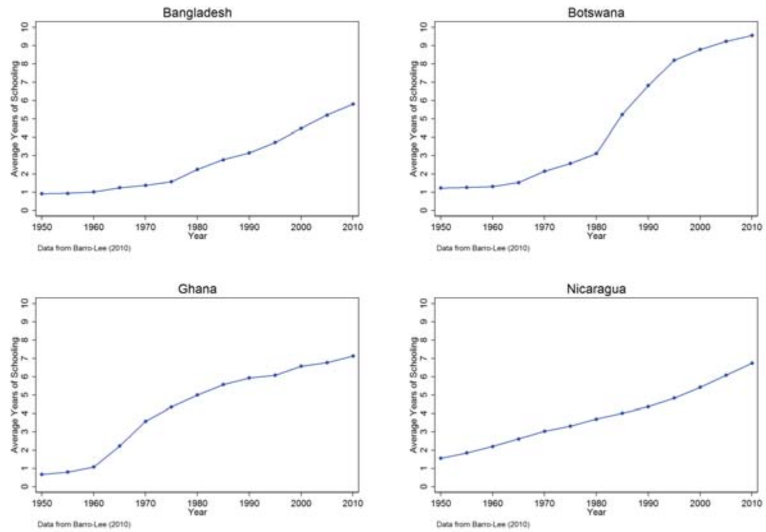
# The Returns to Education

Professor: Pamela Jakiela

Department of Agricultural and Resource Economics
University of Maryland, College Park

# Education: Successes and Failures

## Educational Attainment: A Major Success Story




Figures plot the average level of education of the adult population



## Education: Successes and Failures

**Good news:** school attainment has increased dramatically since 1950

- Between 1999 and 2006, primary school enrollment rates increased:
  - From 54 to 70 percent in Sub-Saharan Africa
  - From 75 to 88 percent in South Asia
- Well on the way to reaching MDG of universal primary education

**Bad news:** the quality of education if extremely low

- Recall PSDP test score results:
- In 2005, ASER study in India found that 60 percent of children aged 7–14 could not read a story from the Grade 2 curriculum
- Uwezo ("capability") studies in East Africa low levels of competency in both math and language skills in Kenya, Tanzania, and Uganda

# School Quality: Uwezo Methodology

**Methodology:** survey enumerators visit randomly-selected homes and children's basic literacy and numeracy skills using simple tests

**An example of a literacy test:**

STORY

**My name is Agaba. I have a friend. She is called Akello. Today my mother took us to school. She drove us in her car. It was very early in the morning. We were the first children to reach the school.**

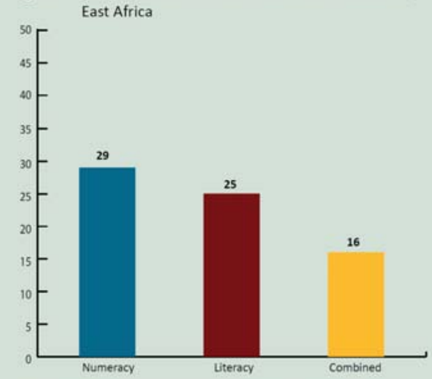
Sample story from Uganda that some Primary 7 children cannot read.



# School Quality: Uwezo Results

**Result 1:** most students in Grade 3 cannot pass Grade 2 tests

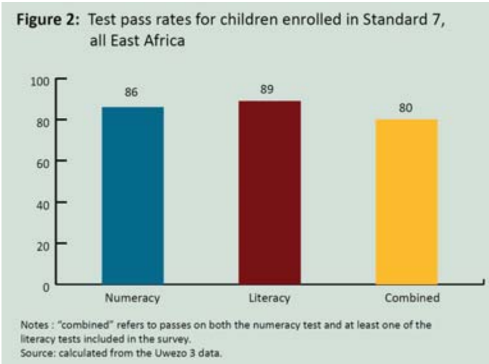
**Figure 1:** Test pass rates for children enrolled in Standard 3, East Africa




Notes: "combined" refers to passes on both the numeracy test and at least one of the literacy testsin the survey.
Source: calculated from the Uwezo 3 data.

## School Quality: Uwezo Results

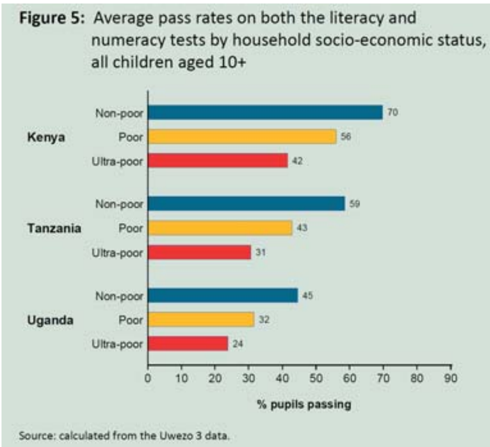
**Result 2:** quite a few students in Grade 7 cannot pass Grade 2 tests






## School Quality: Uwezo Results

**Result 3:** the poorest children are the furthest behind in all countries



## Education: Successes and Failures

To summarize:

- **Good news:** educational attainment has increased dramatically over the last 50 years, and is continuing to increase over time
- **Bad news:** the link between years of schooling and learning ("human capital") does not appear to be as strong as we would like

**Question:** What is holding back human capital accumulation?



## Supply vs. Demand Constraints in Education

## Supply vs. Demand Constraints

The **supply side of education**: provision of quality schools, teachers

- Are there enough schools?
  - Example: In Kenya, most villages have a primary school
  - There are, however, not enough places in high school for all students
- Are there enough well-trained teachers
- Are teachers physically present?
- Are class sizes too large?

**Supply wallahs** stress the importance of improving school quality

- Main problem:



## Supply vs. Demand Constraints

The **demand for education**: would parents send kids to school in the absence of compulsory schooling laws? Would kids exert sufficient effort?

- How large are the **returns to education**?
  - 
- Do parents understand the returns to education?
- Can HHs afford to pay for children to go to school?
  - What is the **opportunity cost** of education?
- Do HHs need children on the farm, working at home, etc?

**Demand wallahs** suggest that the problem is more about beliefs, HH dynamics, and the market return to additional years of schooling

# A "Natural" Experiment in Education

**Research question:** If the government builds more schools, how much will education levels, human capital increase? Will wages increase?

- How large are the **returns to education**?

In a famous paper in the *American Economic Review*, Esther Duflo examines the impacts of a large wave of school construction in Indonesia

Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment

By Esther Duflo*

*Between 1973 and 1978, the Indonesian government engaged in one of the largest school construction programs on record. Combining differences across regions in the number of schools constructed with differences across cohorts induced by the timing of the program suggests that each primary school constructed per 1,000 children led to an average increase of 0.12 to 0.19 years of education, as well as a 1.5 to 2.7 percent increase in wages. This implies estimates of economic returns to education ranging from 6.8 to 10.6 percent.* (JEL I2, J31, O15, O22)



# A "Natural" Experiment in Education

The **Sekolar Dasar INPRES program** (1974–1978):

- The mid-east oil crisis created a large windfall for Indonesia
- Indonesian President Suharto used oil money to fund school construction build schools
- Close to 62,000 primary schools built by national gov't
  - Approximately 1 school built per 500 school-age children
- More schools built in areas which started with less
- Schools intended to promote national identity

**Question:** How did these additional schools impact Indonesia's children?

# The Return to Education in Indonesia

Strategy: **difference-in-difference estimation**

- Data on children born before and after program (pre vs. post)
- Data on children born in communities where many schools were build (treatment), those where few schools were built (comparison)
- Difference-in-difference estimate of program impact compares pre vs. post differences in treatment vs. comparison communities

**Intuitively, difference-in-difference estimation asks:**

After controlling for time trends and fixed differences between treatment and control communities, do children who were born into areas with more newly built schools get more education? Do they earn more as adults?



# Difference-in-Difference Estimation

Difference-in-difference (or "diff-in-diff" or "DD") impact evaluations combine the pre vs. post and enrolled vs. not enrolled approaches

- The difference-in-difference approach can **sometimes** overcome the twin problems plaguing the two types of false counterfactuals
  - Selection bias
  - Time trends
- The basic idea is to observe the treatment group and a comparison group (for example, the not enrolled) before and after the program

The diff-in-diff estimator is:

$$DD = \underbrace{\bar{Y}^{treatment}_{post} - \bar{Y}^{treatment}_{pre}}_{\text{pre-post estimate for treatment}} - (\underbrace{\bar{Y}^{comparison}_{post} - \bar{Y}^{comparison}_{pre}}_{\text{pre-post estimate for control}})$$

## Difference-in-Difference Estimation

| | Treatment | Comparison |
|---|---|---|
| **Pre-Program** | $\bar{Y}^{treatment}_{pre}$ | $\bar{Y}^{comparison}_{pre}$ |
| **Post-Program** | $\bar{Y}^{treatment}_{post}$ | $\bar{Y}^{comparison}_{post}$ |

Intuitively, diff-in-diff estimation is just a comparison of 4 cell-level means



## Difference-in-Difference Estimation

| | Treatment | Comparison |
|---|---|---|
| **Pre-Program** | $\bar{Y}^{treatment}_{pre}$ | $\bar{Y}^{comparison}_{pre}$ |
| **Post-Program** | $\bar{Y}^{treatment}_{post}$ | $\bar{Y}^{comparison}_{post}$ |

Only one of the 4 cells is **treated** (i.e. has received the program)

## Difference-in-Difference Estimation

| | Treatment | Comparison |
|---|---|---|
| **Pre-Program** | $\bar{Y}^{treatment}_{pre}$ | $\bar{Y}^{comparison}_{pre}$ |
| **Post-Program** | $\bar{Y}^{treatment}_{post}$ | $\bar{Y}^{comparison}_{post}$ |

Comparing treatment vs. comparison pre-program measures selection bias



## Difference-in-Difference Estimation

| | Treatment | Comparison |
|---|---|---|
| **Pre-Program** | $\bar{Y}^{treatment}_{pre}$ | $\bar{Y}^{comparison}_{pre}$ |
| **Post-Program** | $\bar{Y}^{treatment}_{post}$ | $\bar{Y}^{comparison}_{post}$ |

Comparing before vs. after in comparison group measures time trend

## Difference-in-Difference Estimation

The assumption underlying diff-in-diff estimation is that, in the absence of the program, individual $i$'s outcome at time $t$ is given by:

$$E[Y_i|P_i = 0, t] = Ability_i + YearEffect_t$$

There are two implicit identifying assumptions here:

- Selection bias relates to fixed characteristics of individuals ($Ability_i$)
  - The magnitude of the selection bias term isn't changing over time
- Time trend ($YearEffect_t$) same for treatment and control groups

These two necessary conditions for identification in diff-in-diff estimation are often referred to (collectively) as the **common trends** assumption



## The Return to Education in Indonesia

In practice, the difference-in-difference estimator is:

$$DD = \bar{Y}_{post}^{treatment} - \bar{Y}_{pre}^{treatment} - \left(\bar{Y}_{post}^{comparison} - \bar{Y}_{pre}^{comparison}\right)$$

**Dependent Variable: Years of Schooling**

| | **Many Schools Built** | **Few Schools Built** | **Difference** |
|---|---|---|---|
| **Over 11 in 1974** | 8.02 | 9.40 | -1.38 |
| **Under 7 in 1974** | 8.49 | 9.76 | -1.27 |
| **Difference** | 0.47 | 0.36 | 0.12 |

Younger children (who reached school age after INPRES) in areas where the program built a large number of schools are the treatment group

- Who is the comparison group?

## The Return to Education in Indonesia

In practice, the difference-in-difference estimator is:

$$DD = \bar{Y}_{post}^{treatment} - \bar{Y}_{pre}^{treatment} - \left(\bar{Y}_{post}^{comparison} - \bar{Y}_{pre}^{comparison}\right)$$

**Dependent Variable: Years of Schooling**

| | Many Schools Built | Few Schools Built | Difference |
|---|---|---|---|
| **Over 11 in 1974** | 8.02 | 9.40 | -1.38 |
| **Under 7 in 1974** | 8.49 | 9.76 | -1.27 |
| **Difference** | 0.47 | 0.36 | 0.12 |

Pre vs. post analysis does not control for time trends

- Indonesia is getting wealthier over time, so younger children (those entering school after the program) may get more education anyway



## The Return to Education in Indonesia

In practice, the difference-in-difference estimator is:

$$DD = \bar{Y}_{post}^{treatment} - \bar{Y}_{pre}^{treatment} - \left(\bar{Y}_{post}^{comparison} - \bar{Y}_{pre}^{comparison}\right)$$

**Dependent Variable: Years of Schooling**

| | Many Schools Built | Few Schools Built | Difference |
|---|---|---|---|
| **Over 11 in 1974** | 8.02 | 9.40 | -1.38 |
| **Under 7 in 1974** | 8.49 | 9.76 | -1.27 |
| **Difference** | 0.47 | 0.36 | 0.12 |

Treatment vs. comparison analysis does not control for selection bias

- More schools were built in those areas that were initially lagging behind — poorer, more remote, less developed communities

## The Return to Education in Indonesia

In practice, the difference-in-difference estimator is:

$$DD = \bar{Y}^{treatment}_{post} - \bar{Y}^{treatment}_{pre} - \left(\bar{Y}^{comparison}_{post} - \bar{Y}^{comparison}_{pre}\right)$$

**Dependent Variable: Years of Schooling**

| | Many Schools Built | Few Schools Built | Difference |
|---|---|---|---|
| **Over 11 in 1974** | 8.02 | 9.40 | -1.38 |
| **Under 7 in 1974** | 8.49 | 9.76 | -1.27 |
| **Difference** | 0.47 | 0.36 | 0.12 |

Difference-in-difference estimation compares the change in years of schooling (i.e. the pre vs. post estimate) in treatment, control areas

- Program areas increased faster than comparison areas



## The Return to Education in Indonesia

In practice, the difference-in-difference estimator is:

$$DD = \bar{Y}^{treatment}_{post} - \bar{Y}^{treatment}_{pre} - \left(\bar{Y}^{comparison}_{post} - \bar{Y}^{comparison}_{pre}\right)$$

**Dependent Variable: Years of Schooling**

| | Many Schools Built | Few Schools Built | Difference |
|---|---|---|---|
| **Over 11 in 1974** | 8.02 | 9.40 | -1.38 |
| **Under 7 in 1974** | 8.49 | 9.76 | -1.27 |
| **Difference** | 0.47 | 0.36 | 0.12 |

Difference-in-difference estimation compares the change in years of schooling (i.e. the pre vs. post estimate) in treatment, control areas

- **Diff-in-diff estimate:**

## The Return to Education in Indonesia

In practice, the difference-in-difference estimator is:

$$DD = \bar{Y}^{treatment}_{post} - \bar{Y}^{treatment}_{pre} - \left(\bar{Y}^{comparison}_{post} - \bar{Y}^{comparison}_{pre}\right)$$

**Dependent Variable: Log (Wages)**

| | **Many Schools Built** | **Few Schools Built** | **Difference** |
|---|---|---|---|
| **Over 11 in 1974** | 6.87 | 7.02 | -0.15 |
| **Under 7 in 1974** | 6.61 | 6.73 | -0.12 |
| **Difference** | -0.26 | -0.29 | 0.026 |

Difference-in-difference estimation compares the change in years of schooling (i.e. the pre vs. post estimate) in treatment, control areas

- **Diff-in-diff estimate:**



## Diff-in-Diff in a Regression Framework

To implement diff-in-diff in a regression framework, we estimate:

$$Y_{i,t} = \alpha + \beta D_i + \zeta Post_t + \delta\left(D_i * Post_t\right) + \varepsilon_{i,t}$$

where:

- $Post_i$ is an indicator equal to 1 if $t = 2$
- $\delta$ is the coefficient of interest (the treatment effect)
- $\alpha = E[\gamma_i|D_i = 0] + \lambda_1$ — pre-program mean in comparison group
- $\beta = E[\gamma_i|D_i = 1] - E[\gamma_i|D_i = 0]$ — selection bias
- $\zeta = \lambda_2 - \lambda_1$ — time trend

## Diff-in-Diff in a Regression Framework

When treatment intensity is a continuous variable:

$$Y_{i,t} = \alpha + \beta Intensity_i + \zeta Post_t + \delta\left(Intensity_i * Post_t\right) + \varepsilon_{i,t}$$

We can also implement diff-in-diff in a panel data framework when more than two periods of data are available; this can increase statistical power*

$$Y_{i,t} = \alpha + \eta_i + \nu_t + \gamma D_{i,t} + \varepsilon_{i,t}$$



## Example: A Natural Experiment in Education

Main empirical specification in Duflo (2001):

$$S_{ijk} = \alpha + \eta_j + \beta_k + \gamma\left(Intensity_j * Young_i\right) + \boldsymbol{C}_j\delta + \varepsilon_{ijk}$$

where:

- $S_{ijk}$ = education of individual $i$ born in region $j$ in year $k$
- $\eta_j$ = region of birth fixed effect
- $\beta_k$ = year of birth fixed effect
- $Young_i$ = dummy for being 6 or younger in 1974 (treatment group)
- $Intensity_j$ = INPRES schools per thousand school-aged children
- $\boldsymbol{C}_j$ = a vector of region-specific controls (that change over time)

# Example: A Natural Experiment in Education

**Dependent Variable: Years of Education**

| | Obs. | OLS (1) | OLS (2) | OLS (3) |
|---|---|---|---|---|
| *Panel A: Entire Sample* | | | | |
| $Intensity_j * Young_i$ | 78,470 | 0.124 | 0.150 | 0.188 |
| | | (0.025) | (0.026) | (0.029) |
| *Panel B: Sample of Wage Earners* | | | | |
| $Intensity_j * Young_i$ | 31,061 | 0.196 | 0.199 | 0.259 |
| | | (0.042) | (0.043) | (0.050) |
| *Controls Included:* | | | | |
| YOB∗enrollment rate in 1971 | | No | Yes | Yes |
| YOB∗other INPRES programs | | No | No | Yes |

Sample includes individuals aged 2 to 6 or 12 to 17 in 1974. All Specifications include region of birth dummies, year of birth dummies, and interactions between the year of birth dummis and the number of children in the region of birth (in 1971). Standard errors are in parentheses.



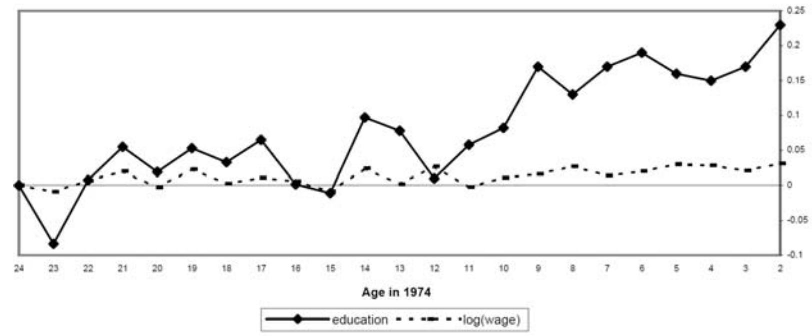
# Example: A Natural Experiment in Education

**Dependent Variable: Log Hourly Wages (as Adults)**

| | Obs. | OLS (1) | OLS (2) | OLS (3) |
|---|---|---|---|---|
| *Panel A: Sample of Wage Earners* | | | | |
| $Intensity_j * Young_i$ | 31,061 | 0.0147 | 0.0172 | 0.027 |
| | | (0.007) | (0.007) | (0.008) |
| *Controls Included:* | | | | |
| YOB∗enrollment rate in 1971 | | No | Yes | Yes |
| YOB∗other INPRES programs | | No | No | Yes |

Sample includes individuals aged 2 to 6 or 12 to 17 in 1974. All Specifications include region of birth dummies, year of birth dummies, and interactions between the year of birth dummis and the number of children in the region of birth (in 1971). Standard errors are in parentheses.

## The Return to Education in Indonesia



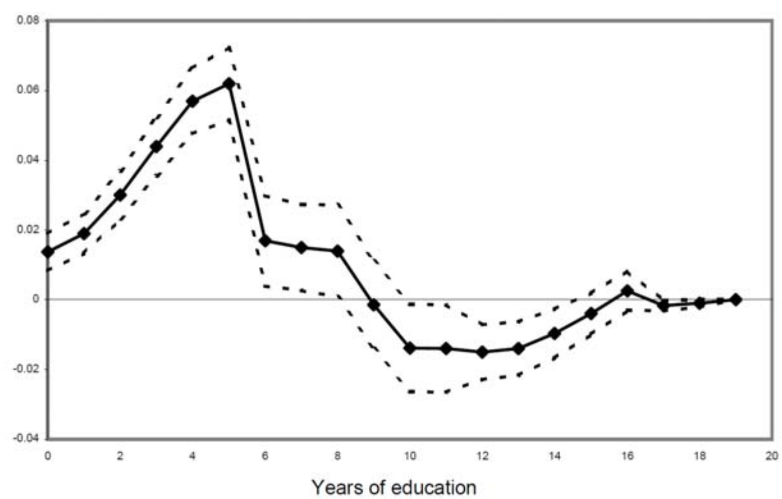

Another way of looking at the data:

- Interact year of birth with schools built per 1000 students (intensity)
- We observe impacts for children under 10 when program started



## The Return to Education in Indonesia

How much additional schooling did impacted children complete?



## Testing the Common Trends Assumption

The **common trends** assumption underlying the DD approach is that areas with fewer schools pre-program were not already catching up

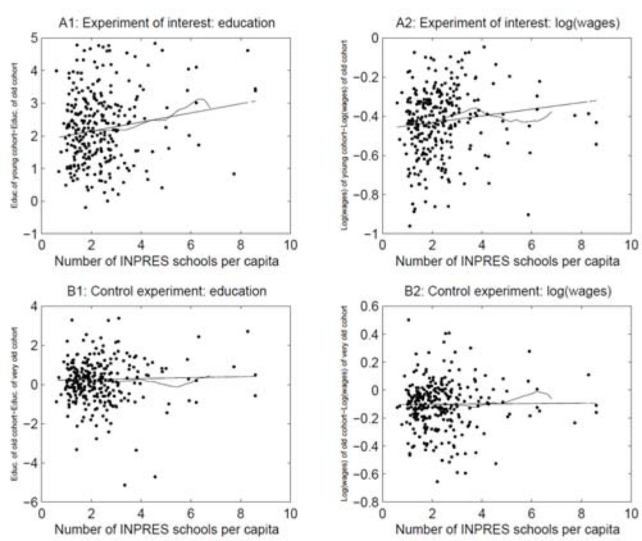
- Educational attainment, wages would have improved at the same rate in treatment, comparison areas in the absence of the program
- Estimates would be biased, for example, if other government programs were also targeting those areas with the fewest schools

**Q:** How can we test the common trends assumption?

- **A:**



## Testing the Common Trends Assumption



# The Return to Education in Indonesia

**Summarizing the evidence:**

- Total education attainment and adult wages grew faster in areas where more schools were built as part of the INPRES program
  - Schools caused an increase in education
  - Increases in education caused an increase in wages
- Results suggest that each additional year of primary schooling leads to about an 8 percentage point increase in adult wages
- Returns to education are large, supply side interventions can work!
  - Supply wallahs 1, demand wallahs 0



# The Return to Education: Additional Evidence

Evidence from other countries:

- Taiwan made schooling compulsory in 1968
  - Educational attainment increased for boys and girls
  - Infant mortality also declined in the most impacted areas
- Like Indonesia, Nigeria used oil money to fund school construction
  - Impacted regions saw significant declines in fertility among young women (because they were staying in school longer)

# Study Guide: Key Terms

- Uwezo
- human capital
- supply vs. demand constraints (in education)
- return to education
- opportunity cost
- difference-in-difference estimation