Introduction

January 8, 2019

Overview

Why Study Education?

Simple answer:

- We spend over $ 1.2 trillion on education in the United States.
- Majority of economic output comes from labor
- Schools are thought to play an important role in training labor force

Not so simple answer:

- Schools play an important role in students lives and in society
- Goals of education are multi-dimensional
- Education in the US involves a complex mix of problems and decisions at the individual level (e.g. students and teachers), organizational level (schools and districts), and political level (departments of education, governing bodies)
- Education, like many social policy arenas, has a history of ongoing issues of inequality

Why Study Economics of Education

Alright, but why the economics of education?

- There are certainly other theories and methods that provide useful insights into education policy topics. But in this class we focus on the use of economics.

- Economic theories provide useful models to understand how individuals make decisions. For example, they help us understand:
  - how students and families choose schools
  - how peers influence student outcomes
  - who becomes a teacher and where do they choose to work
  - how to design policies that hold teachers and schools accountable for student outcomes
  - and so on ...

- Economists have also pushed the methodological envelope by refining and designing statistical techniques to estimate the causal impact of social policies and programs.

Important Economic Principles

Although a review for you, we will see a few classic economic ideas re-occur throughout the readings

- Scarcity
- Opportunity Costs
- Budget Constraints
- Trade-offs
- Diminishing Marginal Returns

Important Economic Principles

As mentioned in the book, economics tools and theories help us think about

- What should be produced
- How much should we produce
- And for whom should it be produced?

Important Building Blocks

In this class we will often talk about two key components of education policy and research

- **Inputs**: Any factors or resources that contribute to building an individual's ability or knowledge
  - Some inputs are both easy to measure and change with policies and/or incentivize (e.g. class-size, textbooks)
  - Other inputs we're starting to measure better but are hard to change with policy (e.g. teacher quality)
  - Others yet are both hard to measure and hard to change with policy (e.g. peers, neighborhoods, building quality)
- **Outputs**: Any knowledge, skill, or attribute that is a result of participation in the education process
  - Often there's two (or more) dimensions to the outputs of interest:
    - The amount of **time** that has lapsed since the exposure to a policy/practice/incentive of interest
    - The **specificity** of the output (e.g. multiplication of two-digit integers versus broader civic behavior).

Types of Education Policies

In this class we will read about three broad types of policies

- **Total Resource Policies** which increase the total amount of funding to schools (interestingly this is one of the most contentious literatures in education research)

- **Input-based policies** which focus on specific inputs such as class-size, teaching credentials, length of the school year. These were quite popular through NCLB.

- **Output-based policies** which tie the performance of students, teachers, or schools (or other entities) to incentives (e.g. rewards/sanctions). The use of these policies has exploded in the past 10 years.

In short, most policies can be seen as a set of incentives. Incentives often change behavior, but an important question is whether the behavioral change(s) was intended and the net effect was in the anticipated direction.

Markets in Education

Education is a unique marketplace:

- It is not perfectly competitive (e.g. typically large start up costs, imperfect information)
- Spillovers or externalities are quite common (we'll a number of interesting papers on this topic).
- Supply is often local, but this is changing with the use of virtual education
- Education is highly differentiated, both vertically (age) and horizontally (flavors of education for a given age)
- The quality of your education is influenced by the characteristics of other consumers (peers)

However a number of interesting education policies are based on near perfectly competitive market principles (e.g. school choice). We'll read about what happens in these settings.

Why Does the US Gov Participate in Education?

- Education is a consumption good. The market for consumption goods (movies, wine, education) generally has some degree of information asymmetry.
- Education often benefits from economics of scale (e.g. why is there a negative correlation between high school size and the # of AP classes offered?)
- Education has positive externalities, and in these cases people typically under consume goods.
- Individuals differ in their budget constraints which affects their ability to access credit.

Bias

Bias - The Difference Between Causal and Correlational

- In this class we will spend A LOT of time talking about the effect of policies/practice/interventions on a variety of outcomes.
- In order to talk about **effects**, we need to be fairly certain we've isolated causal relationships
- The extent to which an estimated impact is expected to differ from the true impact is statistical *bias*.
- In essences it is the difference between the measured correlation and the actual causal impact.

Why Do We Need to Know Causal Information?

- Much of microeconometrics today involves the pursuit of *causal inference*.
  - The ability to establish a causal relationship between two factors.
  - This is opposed to *correlation* which is an estimate of a statistical relationship between two factors.
- Consider the following example
  - A matter of much controversy in educating English Language Learners (ELLs) is whether it is better to provide immersive English instruction or a bilingual instructional environment.
  - How can one figure out which is better?
  - Tempting to simply compare students in English immersion to those in bilingual education.

Bad Causality Leads to Bad Policy

- It's clear from a statistical perspective we want to get to the "truth."

- But from a practical perspective why is this so important? So what if we are off a bit in the policy impact estimates?

- What's the worst that can happen?

Formula for OLS Coefficients

- Remember the formula for an OLS regression coefficient
- The simple algebra formula for a single regression coefficient is

$$\hat{\beta} = \frac{cov(X, Y)}{var(X)} \tag{1}$$

- The matrix algebra formula for multiple regression coefficients is

$$\hat{\boldsymbol{\beta}} = \frac{\mathbf{X'Y}}{\mathbf{X'X}} = (\mathbf{X'X})^{-1} \mathbf{X'Y} \tag{2}$$

Consistency vs. Unbiasedness

- While consistency and unbiasedness are technically distinct, an unbiased estimator is almost always consistent (and will be consistent in any context we learn in this class).

- Thus our focus today (and mostly in your readings as well) will be more on unbiasedness.

- Before we talk about when an OLS estimate is unbiased, let's talk through a thought experiment from our textbook: ability bias in our estimated relationship between earnings and education.

Ability Bias

- Many studies find a positive a positive relationship between education and labor productivity.

- Does this mean that our simple bivariate regression coefficient ($\hat{\beta}$) represents a causal estimate of the returns to education?
  - Are there other factors that are both correlated with education and labor market productivity?

- The answer to this question has important implications to how we may design future education policies.

Ability Bias

- Let's take ability as an example of a factor related to both years of education and labor market productivity.

- In most scenarios, we have to rely on proxies for ability, in this case individuals' SAT scores.

- It is likely that higher ability people not only are more likely to extend their education, but are also likely to earn more in the labor market.

- If this is true, our simple bivariate regression coefficient then includes both the true return to education as well as the impact of ability on earnings.
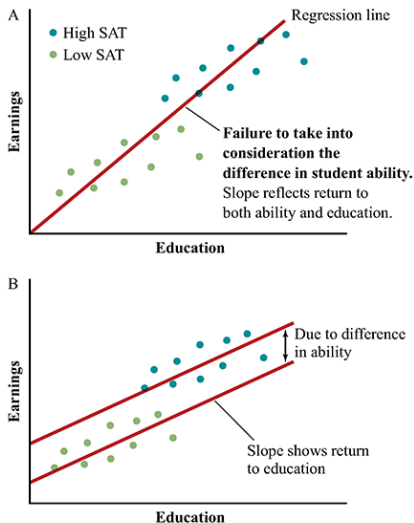
Figure 3.2
Lovenheim/Turner, *Economics of Education*, 1e,
© 2018 Worth Publishers

- The Figures show that for the same education level, individuals with higher ability earn more than individuals with lower ability

- We also see that the true returns to education (Figure B) is flatter than the biased estimate in Figure A

When is OLS unbiased?

- There are a few conditions under which we can assume that OLS is unbiased.

1. The model is of the correct functional form
   - This just means that we have correctly specified the model, e.g. that we include the correct variables and that they are in the model in the appropriate fashion (e.g. x, x^2, xz, etc).

   - This also implies that the true model is linearly additive. That is, it has the form $y = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k + \varepsilon$ instead of something nonlinear like $y = \beta_0 x^{\beta_1} \varepsilon$.

   - In practice, in economics of education research tends to use additively linear models and this is a routine assumption.

When is OLS unbiased?

2. All independent variables are linearly independent.
   - Basically this says that no set of variables in the regression can come together in the form $x_0 = b_0 + b_1 x_1 + ... + b_j x_j$.
   - In practice you do not need to worry much about this as most statistical programs will take care of this for you by dropping one of the variables.
   - Most often this occurs when you have a mutually exclusive categorical variable.
   - For example say you want to regress test scores on race, where race can be black, white or other $\rightarrow Black_i = 0/1$; $White_i = 0/1$; $Other_i = 0/1$ where only one category can equal 1 for a person.

   $$Score_i = \beta_0 + \beta_1 White_i + \beta_2 Black_i + \beta_3 Other_i + \varepsilon$$

   is not permissible. Instead you would estimate

   $$Score_i = \beta_0 + \beta_1 White_i + \beta_2 Black_i + \varepsilon$$

   and β_1 will be the relationship between test scores and being black *relative* to other, and similarly for β_2 and white.

When is OLS unbiased?

3. The third and most important assumption is that the independent variables X are exogenous - they are uncorrelated with ε.

   - This leads to the following condition

   $$E(\varepsilon|\mathbf{X}) = 0 \tag{5}$$

   - This says that conditional on the X the error terms have expected values of 0. This is also sometimes called the "exogeneity assumption."
   - This condition also holds if and only if the covariance of each x_j with ε is zero:

   $$Cov(x_j, \varepsilon) = 0 \tag{6}$$

   - Note that if ε is normally distributed with a mean of 0, the exogeneity condition holds.

What happens when the Exogeneity Condition Doesn't Hold?

- Let's assume that an individual's outcome Y_i is a function of her years of education (Ed_i) and ability ($Ability_i$)

$$Y_i = \beta_0 + \beta_1 Ed_i + \beta_2 Ability_i + \epsilon \tag{7}$$

- What happens if we just estimate our original model, omitting ability?

$$Y_i = \gamma_0 + \gamma_1 Ed_i + \mu \tag{8}$$

- Using our formula for a regression coefficient $E(\hat{\gamma_1}) = \frac{cov(Y, Ed_i)}{var(Ed_i)}$, and substituting $\alpha + \beta_1 Ed_i + \beta_2 Ability_i + \epsilon$ for Y_i, we get:

$$E(\hat{\gamma_1}) = \frac{cov(\alpha + \beta_1 Ed_i + \beta_2 Ability_i + \epsilon, Ed_i)}{var(Ed_i)} \tag{9}$$

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What happens when the Exogeneity Condition Doesn't Hold?

$$= \frac{cov(\beta_0, Ed_i)}{var(Ed_i)} + \beta_1 + \beta_2 \frac{cov(Ability_i, Ed_i)}{var(Ed_i)} + \frac{cov(\epsilon, Ed_i)}{var(Ed_i)} \qquad (10)$$

- The first term is zero since β_0 is a constant and the last term is also zero given the main OLS assumptions ($cov(\epsilon, X_i) = 0$)

- This leaves us with the omitted variable bias formula:

$$E(\hat{\gamma_1}) = +\beta_1 + \beta_2 \frac{cov(Ability_i, Ed_i)}{var(Ed_i)} \qquad (11)$$

- Note that the last term $\frac{cov(Ability_i, Ed_i)}{var(Ed_i)}$ is the coefficient from a bivariate regression of $Ability_i$ on Ed_i

- OVB is driven by factor(s) that are more correlated with your independent variables of interest and your dependent variable.

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What happens when the Exogeneity Condition Doesn't Hold?

- We are left with two options to deal with selection or omitted variable bias
    1. Include all of the variables in our OLS regression that are related to treatment and outcome (very difficult to do in practice)
    2. Find a source of exogenous variation in the treatment variable that removes selection bias from our statistical analysis

- Throughout the course we will now discuss common methods used to find exogenous variation in treatment assignment. We will provide refreshers for the methods as they come up in the readings. We can also suggest a number of useful books to use as a reference (e.g Mostly Harmless Econometrics).