2026 ECONOMETRICS GAME PROMPT (PRELIMINARY ROUND)

OECONOMICA

1. Prompt

Your task is to identify and estimate a causal effect relating to education at any stage of the lifecycle. Some examples are discussed below.

A few papers which quantify the effect of early-childhood programs on outcomes such as earnings, health and cognitive and personality skills include García et al. (2020), Heckman et al. (2013) and Heckman and Raut (2016).

In the context of primary education, Duflo et al. (2011) and Card and Giuliano (2016) find a positive effect of 'tracking' students into separate classes by prior achievement, and Duflo et al. (2011) use a randomized experiment and structural model to examine whether monitoring and financial incentives can reduce teacher absence and increase learning in India. They find a drop in absenteeism, an increase in test scores, and, using their structural model, find that teachers respond strongly to financial incentives.

In the context of higher education, Chetty et al. (2020) constructs statistics on parental and student earnings for colleges in the U.S. and estimate the variation in students' earnings outcomes due to college enrollment. They find that children of low- and high-income parents who attend the same college have relatively similar earnings outcomes, but children from more affluent families are much more likely to attend colleges with high earnings outcomes. They argue that a change in how students are allocated to colleges may increase intergenerational mobility. In a randomized trial, Angrist et al. (2009) evaluate interventions such as offering academic support services and financial incentives for good grades among college freshmen and find persistent effects on grades and academic standing for female students.

Some authors investigate factors that influence educational decisions. For example, Wiswall and Zafar (2015) uses an information experiment to study the effects of earnings expectations, perceived ability and heterogeneous preference on major choice. Heckman et al. (2018) estimates the effect of higher education on earnings, health, and smoking using a dynamic model of educational choice.

2. Data

The datasets from Angrist et al. (2009) and Chetty et al. (2020) are linked below. For a brief description of each dataset:

- Angrist et al. (2009) uses a cross-sectional dataset consisting of 1656 observations for 48 variables, including gender, age, academic performance, and family characteristics. The individuals in the study were undergraduate students at a large Canadian university. Click here for complete data and replication files.
- Chetty et al. (2020) uses a cross-sectional dataset consisting of 2202 observations at the college level for 85 variables, including measures of intergenerational mobility and college characteristics such as proportion of female students and proportion of married students. Click here for complete data and replication files.

Feel free to supplement these datasets with others:

- Click here for partial data and replication files for Duflo et al. (2011).
- Click here for partial data and replication files for Duflo et al. (2012).

3. AI Use Policy

As with any nascent technology, publicly accessible AI interfaces such as ChatGPT present opportunities both to augment the learning experience and to facilitate unethical behavior. While the specific nuances of the ethics of AI interface use in academic work are still a matter of debate, the following guidelines will be used in this competition.

It is ethical to use an AI interface to assist with organizing and communicating your thoughts and ideas. Examples include obtaining recommendations of word choice and sentence structure, summarizing sections of technical writing, or outlining key points to address in an argument. To ensure transparency, you must include a written acknowledgement or include an in-text citation or footnote any time you use AI during the competition or during the preliminary round.

It is unethical to use an AI interface to produce a response and then present this response as if it contained original ideas and insights. Not only are most platforms unable to assess the veracity of the content they generate, but this practice is unambiguously plagiarism. Prompt questions are written to ensure robustness to AI generated answers, but it is imperative to remember that submitting AI produced responses misleads others about your knowledge and skills and is antithetical to the principles of a fair competition in general.

Given the aforementioned ethical uncertainties surrounding AI interfaces, violation of these guidelines will result in a clarifying discussion with the game organizers and potential disqualification.

References

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