Returns to Job-Skills Training, Entrepreneurship, and Microenterprise Support among the Youth: A Meta-analysis of Active Labor-Market Programs in Low and Middle-Income Countries.

By Paula Ochiel

Thesis Advisor: Professor Jeremy Magruder

(This is a summary ƻŧ my college thesis ǈǋƻɂŜŎű. It provides an overview of the project including the research question, data, methods, results, and a brief discussion)

Abstract

This paper explores evidence on how Active Labor Market Programs (ALMPs) affect labor-market outcomes among targeted beneficiaries. Using individual-level data aggregated from 10 RCTs, I conduct an empirical analysis of the effect of job-skills training, entrepreneurship/basic business training, and microenterprise support on earnings and employment outcomes. I show that ALMPs have large and highly significant effects on income, profits, savings, probability of employment, hours-worked, and number of employees. This finding contradicts results of other evaluations of ALMPs that typically find somewhat small estimates and insignificant results. There are large advantages to my methodological approach of integrating results across several of ALMP studies. Doing so increases statistical precision since we have a larger sample. I also test for heterogeneous treatment effects by preexisting education levels and gender and find that income, number of employees, and hours-worked are particularly large for more educated participants and women compared to less educated participants and men.

Introduction

According to the International Labor Organization's World Employment and Social Outlook 2017 estimates, the global youth unemployment rate is 13.1%. In middle income countries, the rate is 13.7% and in low-income countries it is 9.4%. Considering the consequences of youth unemployment, these high rates of unemployment have generated much concern among policy makers. Over the past few decades, ALMPs have been largely advocated by the OECD as a policy measure to curb high levels of youth unemployment (Card et al, 2010). ALMPs typically offer business skills training, job-market skills training, entrepreneurship training, job-search assistance, business and microenterprise support, wage subsidies, or a combination of two or multiple of the aforementioned trainings (Kluve et al. 2016).

I conducted a synthesis of the experimental literature on ALMPs in low-income and middle-income countries around the world to find out how ALMPs affect labor-market employment outcomes among different groups of participants. The research question evaluated how ALMPs affect labor-market outcomes among less educated youth who participate in them in low and middle-income countries. I was particularly interested in whether ALMPs have meaningful impacts for less educated youth because this group tends to have high levels of unemployment and low levels of employment in the formal sector. I focused on evaluations of job and business skills training programs and microenterprise support programs because they tend to be more popular in the geographical regions I studied and as such, have more data. Job-skills training programs usually teach skills relevant for formal employment such as administrative skills, while business training programs usually train participants in standard business practices like financial accounting, marketing, sales, and managerial skills(Card et al, 2015). Microenterprise support programs are similar to business training programs but offer on-the-job business support, and sometimes offer cash grants in addition (Yoonyoung and Honorati, 2013).

Prior Work

Existing research presents mixed views about the effectiveness of various active labor-market youth employment interventions. Prior work is divided into three categories: (1) Studies that find positive significant effects of youth employment interventions, (2) Studies that do not find any significant effect, (3) Studies that find negative significant effects. My research question and design were informed by these existing differences and attempted to fill gaps that have not yet been addressed by existing meta-analyses. Two prior studies were particularly important to this research. Kluve et al. (2016) and Card et al. (2015). In the first study, authors found that ALMPs had better outcomes in less developed countries and speculated that this may be because program investments are especially helpful for the most vulnerable populations – low skilled and low income. I explored that idea further by investigating whether the most disadvantaged groups among the poor benefit more from ALMPs than slightly "better of" participants. In the second study, the authors found systematic heterogeneity across gender and long-term unemployed participant groups. I adopted their methodologies to examine heterogeneity across pre-existing education levels and gender.

Data

From a database of research studies included in meta-analyses of ALMPs and a systematic internet search for experimental studies, I identified 32 potential studies to include in this study. From this sample, 10 studies met my preconditions of being experimental studies of ALMPs in low and middle-income countries with publicly accessible data that could be used to reproduce the research findings and I included them in the final set of studies in the meta-analysis. 4 studies were on job-skills training programs, 4 on business/entrepreneurship skills training, and 2 on micro-enterprise support.

Methods

I combined individual level-data of between 18,000 – 40,000 observations from 10 studies, conducted at different times in 7 countries, into 1 large sample and evaluated the sample as if it was one large experiment. For comparability of studies, I used the general regression equation below to evaluate treatment effects.

$Y_{ij} = \theta + \beta \text{ treatment}_{ij} + \pi \text{ study}_j + \varepsilon_{ij}$ (*Equation 1*)

where individual observations are indexed by i and studies are indexed by j. Y is a dependent variable of interest such as income or employment status, treatment is a dummy for treatment assignment and , π is a study fixed effect. β and θ are the parameters of interest (the constant term and treatment effect respectively) and ε the error term. To minimize bias and improve comparability across multiple studies with different variables and scales, I standardized the outcome variables to convert them into unit-less values, thus allowing for different studies to be pooled together and analyzed in one regression.

To test for treatment effect heterogeneity, particularly on pre-existing education levels, I used the regression equation:

$Y_{ij} = \theta + \beta \text{ treatment}_{ij} + \gamma \textit{ below educ}_{ij} + \delta \text{ treatment} * \textit{below educ} + \pi \text{ study}_j + \varepsilon_{ij}$ (*Equation 2*) *below educ* is a dummy for being below the median level of education in the sample. I used the median level of education as opposed to the mean or other measures because the median gives approximately equal proportions of participants into each group, which maximizes statistical power. Using the median worked especially well because there was a relatively even distribution of years of education, with observations for each level of education. Many participants in my sample had either completed high-school or dropped out before primary or secondary completion or had a few years of college education.

Results

Tables 1 presents aggregate treatment effect estimates (Equation 1) of training on 6 outcome variables (income, employment, hours-worked, number of employees, profits, and savings). On average, treated individuals earned 7.2% higher incomes than controls. They were also 5.8% more likely to be employed, worked 8.1% more hours, employed 16% more employees on average if they own a business, received 19% more in profits and saved 21.7% more. These estimates were all highly significant at the 1% level. This provided evidence that ALMPs did in fact increase labor-market outcomes for participants post-training.

To test whether there was variation in the treatment effects by levels of education, I used median levels of education in each study as a cut off for being either in the high or low education category. Table 2 presents treatment effects for participants with either below median level or above median level of education (Equation 2). I found that for individuals assigned to treatment who have levels of education above the median, training increased their incomes by 17.6% compared to controls. These individuals were also 5.3% more likely to be employed, worked 7.2% more hours when in employment, employed 47.9% more employees on average if they owned a business, earned 21%more in profits, and saved 32.1% more. All estimates were significant at 1% level. In contrast, individuals assigned to treatment that had below median level of education earned 18.5 % lower incomes (significant at 1%). They also employed 28% fewer employees if they are business owners, earned slightly less profits and saved less than treated individuals with above median education.

Estimating heterogeneous treatment effects on gender, females had similar incomes, employability, profits, and savings as men. However, they worked 15.8% more hours and female owned enterprises employed about 12% more people than male owned enterprises.

Discussion

This research provided evidence that ALMPs did in fact increase labor-market outcomes for participants post-training. This finding contradicted findings from previous ALMP meta-analyses (particularly meta-analyses of ALMPs in high-income countries that typically found small estimates and largely insignificant. A possible explanation for my finding is that ALMPs do have large employment effects in low and middle-income because returns to training are higher in these countries. My approach of integrating results across several of ALMP studies also increased statistical precision since I had a larger sample than a typical ALMP RCT would have.

The differential estimates in income, employees, profits, and savings effects between treated individuals with above median education and treated individuals with below median education highlights huge differences in labor-market outcomes based on participants' education levels. ALMPs are indeed boosting income and a variety of labor market characteristics, but that many of these effects are concentrated for the already advantaged within these developing countries, such as participants with above median education levels. However, certain disadvantaged groups actually benefit from ALMPs. Women experience better outcomes on labor supply variables, and statistically identical outcomes as a result of treatment on other variables. They work more hours and employ more people in their businesses, suggesting that training females in business and entrepreneurship is likely to result in more employment opportunities in low and middle-income countries.

The disadvantaged face a lot of hurdles in society - credit constraints, skills gaps, labor demand, discrimination, etc. It's possible that the skills that can be imbued in an ALMP are just not effective for the disadvantaged, but can be quite effective for the advantaged. If so, it may be the case that rather ALMPs should not be emphasized for their role in helping the (still poor) relatively advantaged people in developing countries rather than restructured to help the poorest. From the analysis here, one can't know which approach would be better. I'd suggest instead posing the question of the potential of targeted ALMPs for different groups as an exploratory idea for future research

Appendix

Figure 1 below shows estimated treatment effects for income by education level for each study. The horizontal dashed lines denote the average income or employment effect across all studies for individuals with above (red) and below (blue) median education level.) Post-training, there is a large gap between incomes for participants with below median education and participants with above median education (huge gap between dashed red line and dashed blue line). The red and blue dots show the income effect of above and below median education individuals for each study.

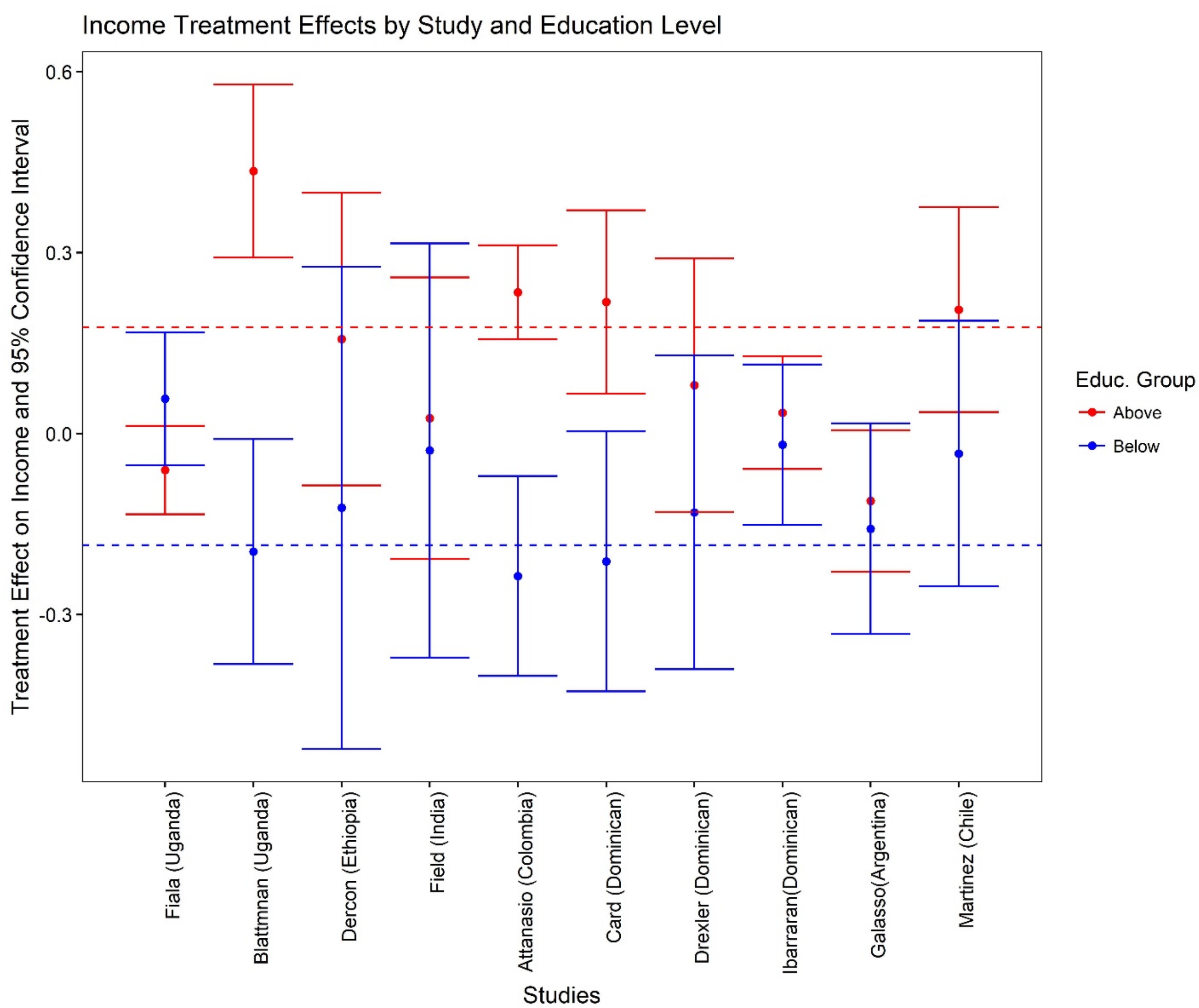

Figure 1: Treatment Effect on Income with 95% Confidence intervals for 10 RCTs.