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Degree Project

Master

Education and Earnings for Poverty Reduction

Short-Term Evidence of Pro-Poor Growth from the Mexican *Oportunidades* Program

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Abstract

Education, as an indispensable component of human capital, has been acknowledged to play a critical role in economic growth, which is theoretically elaborated by human capital theory and empirically confirmed by evidence from different parts of the world. The educational impact on growth is especially valuable and meaningful when it is for the sake of poverty reduction and pro-poorness of growth. The paper re-explores the precious link between human capital development and poverty reduction by investigating the causal effect of education accumulation on earnings enhancement for anti-poverty and pro-poor growth. The analysis takes the evidence from a well-known conditional cash transfer (CCT) program — *Oportunidades* in Mexico. Aiming at alleviating poverty and promoting a better future by investing in human capital for children and youth in poverty, this CCT program has been recognized producing significant outcomes. The study investigates a short-term impact of education on earnings of the economically disadvantaged youth, taking the data of both the program's treated and untreated youth from urban areas in Mexico from 2002 to 2004. Two econometric techniques, i.e. difference-in-differences and difference-in-differences propensity score matching approach are applied for estimation. The empirical analysis first identifies that youth who under the program's schooling intervention possess an advantage in educational attainment over their non-intervention peers; with this identification of education discrepancy as a prerequisite, further results then present that earnings of the education advantaged youth increase at a higher rate about 20 percent than earnings of their education disadvantaged peers over the two years. This result indicates a confirmation that education accumulation for the economically disadvantaged young has a positive impact on their earnings enhancement and thus inferring a contribution to poverty reduction and pro-poorness of growth.

***Keywords*:** Human capital development, Pro-poor growth, Difference-in-differences, Propensity score matching, Causal inference.

This thesis is dedicated to my parents
for their love and support
throughout my life.

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1. Introduction

"An investment in knowledge pays the best interest."

Benjamin Franklin, *Poor Richard's Almanack*

Education as a fundamental component of human capital has been widely acknowledged to have a significant impact on individual development and economic growth. This educational impact becomes especially essential and vital when it comes to the personal development for children and youth from economically disadvantaged conditions and to the pro-poorness of growth in developing countries. Education performs as a critical booster for poverty reduction and economic growth chiefly through the accumulation in human capital. And human capital, which includes the investment of education, the general health and nutrition condition of working labour, and a wide range of informal training, has been considered having an indispensable nexus with economic development (see e.g. Schultz 1961; Becker 1964). The issue of human capital development for the economically disadvantaged children and youth has become an increasingly emphasized topic for the demand of developing nations seeking economic growth and more equal opportunities for advancement; for the calling of the movement — Education for All (EFA) of UNESCO committing to meet the needs of schooling for all children, youth and adults by 2015[1]; and for the mission of the well-recognized Millennium Development Goals of the United Nations to achieve objectives of halving poverty, universal primary schooling and equal opportunities for education and employment between genders, etc. by 2015[2].

Generally, the research into the effect of education on economic growth and poverty reduction has been carried out from both the macro-level and micro-level perspectives. Macro-level research takes the cross- countries evidence to explore the relationship between aggregated human capital investments and the growth rate of GDP, casting light on endogenous growth theories and external returns to human capital (Krueger and Lindahl 2001). Besides, evidence presents that in general countries with low per capita incomes have comparatively low enrolment rates of schooling (Oxaal 1997). Microeconomic research

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[1] A complete description of the goals of Education for All (EFA) can be found in the website of the UNESCO. Available from: http://www.unesco.org/new/en/education/themes/leading-the-international-agenda/education-for-all/.

[2] A complete description of the Millennium Development Goals can be found in the website of the United Nations. Available from: http://www.un.org/millenniumgoals/bkgd.shtml.

focuses on the household level, in some cases called as "micro-development" research (Rosenzweig 2010). Studies in this field take empirical methods to illustrate and quantify the effect of education on individuals' earnings and thus inferring anti-poverty and growth. Some research works on testing and improving the effectiveness of poverty reduction policies that provide development opportunities for the economically disadvantaged individuals by enhancing and enriching their education attainment. These evaluation studies are typically conducted by randomized design for experimental micro-data and difference-in-differences design for non-experimental micro-data (Card *et al.* 2011).

Recognizing the important link between human capital development and economic growth, the purpose of this study is to investigate the causal effect of education accumulation on earnings enhancement for poverty reduction and pro-poor growth from a micro-level perspective of research. To facilitate this research objective, depending on the theoretical guidance of human capital theory, the empirical study follows a strategy of first identifying an educational discrepancy among the economically disadvantaged youth, and then examining whether there exists a disparity in the increases of earnings during the research period between the education advantaged and the education disadvantaged for a causal inference. In order to implement this research strategy, evidence of the schooling impact from an anti-poverty program *Oportunidades* is taken advantage for empirical study.

Oportunidades is a pioneer conditional cash transfer program in Mexico, aiming to alleviate poverty and invest in human capital especially for children and youth from extreme poverty and social deprivation conditions. The program has shown remarkable results since its first launch in 1997 in rural areas of Mexico and has progressively expanded the influence to the impoverished families in urban areas since 2002. The empirical research in this paper takes the evidence from the program's intervention in urban settings, and centres on a short-term impact study of the causal effect of education on earnings for the economically disadvantaged young people, exploiting the data of the program's treated and untreated youth from 2002 to 2004. Methods of difference-in-differences estimator and difference-in-differences propensity score matching estimator are applied respectively for estimation. Both of the methods are common practices for causal inference with an effect on correcting the potential selection bias problems caused by the non-experimental design features of this program in urban areas.

The thesis contributes to the literature on micro-development research, conducting a household level analysis to answer a causal inference question about the causal effect of education on earnings for the economically disadvantaged. Household-level data from the Mexican anti-poverty program *Oportunidades* lends support for empirical estimation. Other than most previous studies on *Oportunidades*, which work on direct assessment or evaluation of the impact or effectiveness of the program itself, research in this paper focuses on exploring the causal link between education accumulation and earnings enhancement for youth from impoverished households by taking advantage of the evident schooling impacts from the program to facilitate this research strategy. The study in this paper limits the empirical examination to a short-term research, focusing on the data of youth from urban areas in Mexico, who were 14 to 20 in the baseline year 2002 and 16 to 22 in the post program intervention year 2004, in attempting to explore the evidence inferring the relationship between education and earnings for poverty reduction and pro- poor growth.

An outline of the remainder of this paper is as follows: chapter 2 gives a brief review of previous research on education, economic growth and poverty reduction, as well as an introduction of the research background; chapter 3 presents theoretical analyses of the concerning economic theories and model, besides the econometric framework of methodology; chapter 4 describes the empirical study of data, estimation specification and presents results; and chapter 5 discusses the results and presents the conclusions of this study.

2. Literature Review and Research Background

2.1 Previous Research on Education, Economic Growth and Poverty Reduction

2.1.1 Education and Economic Growth

Many theoretical and empirical studies have confirmed that education plays a critical role in economic growth, especially in the determination of long-term growth. For example, Lucas (1988) stresses the impact of education by pointing out the importance of learning externalities. Growth theories by Barro (1991), Barro and Sala-i-Martin (1995) and many others following them show that education has a positive effect on economic growth; and Webber (2002) verifies this positive effect by estimating the impact on three different levels of education: primary, secondary and tertiary. Recently, Caselli (2005) finds that differences in human capital can explain at most 40% of the differences in output per worker across countries, which claims that education has a strong indirect effect on economic growth in addition to the direct human capital effect, for the reason that educated workers are required for industrialization and mechanization.

One of the most widely accepted theoretical explanations illustrating the causal effect of education on economic growth is the human capital theory (see e.g. Becker 1964), which interprets that educated workers have higher human capital and thus possess higher productivity; therefore if a country has more educated workers, then it has higher productivity.

2.1.2 Education and Poverty Reduction

Education has been recognized by development organizations and policy makers as a powerful instrument to break the vicious cycle of poverty. World Bank (1995), for example, summarizes their human capital enhancement strategies for poverty reduction by investing in education and promoting the productivity of labour in indigent and developing areas. The

Bank stresses the importance and effectiveness of basic education and clarifies the key role of education in poverty alleviation as:

> "Education—especially basic (primary and lower-secondary) education—helps reduce poverty by increasing the productivity of the poor, by reducing fertility and improving health, and by equipping people with the skills they need to participate fully in the economy and in society." (World Bank 1995, p.1)

Besides, empirical research by e.g. Gundlach *et al.* (2004) finds that more quality-adjusted education contributes to increase the income of the economically disadvantaged as well as the average income.

In addition to the work of development organizations, many governments in developing countries around the world have launched a series of conditional cash transfer intervention programs towards education promotion for the people in social deprivation conditions. Evidence can be found as *Oportunidades* in Mexico, *Bolsa Escola* in Brazil, *Chile Solidario* in Chile and some others in South America, Africa and Asia. Evaluation research towards the schooling intervention of these anti-poverty programs has presented positive results of enriched and enhanced educational attainment to the objective of poverty reduction.

One of the pilot demonstrations is the study of Duflo (2001) on the effect of a school construction program (the Sekolah Dasar INPRES program) in Indonesia on schooling attainment. She applies a difference-in-differences technique to evaluate the impact of schooling infrastructure on education and earnings. The results suggest a positive outcome that children in this program received 0.12 to 0.19 more years of schooling as a result of each new primary school constructed per 1000 children, which contributed towards a 1.5 to 2.7 percent increase in wages.

These previous research and studies throw light on the critical relationship between the development of education and pro-poorness of growth, exemplifying for further studies in the field of micro-development research applying various evidence and methods.

2.2 Defining Pro-poor Growth

Pro-poor growth (PPG), as a term usually mentioned by development organizations, is a concept which captures both the objectives of poverty reduction and equity improvement. Generally, pro-poorness of growth is the growth that is beneficial to the poor, and provides development opportunities for improving their social deprivation conditions. Specifically, there have been two major definitions of pro-poor growth (Ravallion 2004). One is defined by Kakwani and Pernia (2000), specifying that pro-poor growth occurs when incomes of the poor increase at a higher rate than those of the non-poor. Another definition is made by Ravallion and Chen (2003), stating that pro-poor growth is the growth that has an effect on poverty reduction.

In practice, however, there are no fundamental dissimilarities between the two definitions. In this paper, as the meaning of pro-poor growth is primarily employed conceptually rather than measuring the specific PPG rate, there is no necessity to draw a distinct line between the two definitions. Pro-poor growth is hence defined as the growth that reduces poverty and provides development chances for the economically disadvantaged.

2.3 The *Oportunidades* Program in Mexico

2.3.1 Program Description

The program *Oportunidades* (formerly known as PROGRESA before 2002) is a conditional cash transfer program operated by the Mexican government, aiming at poverty reduction and human capital development for a better future. First launched in 1997 in rural communities, the program has progressively extended its influence into urban areas in Mexico since 2002, which has helped more than five million households covering one quarter of the overall population in Mexico to overcome poverty and inequity for better living and future. The program provides benefits to families in extreme poverty conditions, investing especially to their young generation in education, healthcare and nutrition.

One of the most pivotal implementations of *Oportunidades* is the investment in education for children and youth from high social deprivation backgrounds mainly through the way of providing conditional monetary educational grants (as well as monetary and in kind support for school materials). The conditions for the educational grants include that the school attendance rate of beneficiaries must be at least 85 percent monthly and annually, and the subsidy for a same grade cannot be received more than twice. Grants are provided from grade 3 in primary school up to grade 12 of high school level, and girls are expected to gain more than boys from the secondary school for overcoming the higher dropout rate and gender inequality. Monetary transfers are typically paid to mothers from the eligible households if their children are enrolled and attend to school accordingly; while new design now facilities that if authorized by the mother, subsidies for upper secondary school can be received by the youth themselves[3], in such way to promote more incentives for the youth to go to school voluntarily and to offset higher opportunity costs for older students. Different subsidy amounts for each grade are presented in Table 2.1. as follows:

Table 2.1. Educational grants per month for school attendance (nominal pesos)

Grade	Boys			Girls		
	2002	*2003*	*2004*	*2002*	*2003*	*2004*
Primary school						
3rd grade	100	105	110	100	105	110
4th grade	115	120	130	115	120	130
5th grade	150	155	165	150	155	165
6th grade	200	210	220	200	210	220
Secondary school						
7th grade	290	305	320	310	320	340
8th grade	310	320	340	340	355	375
9th grade	325	335	360	375	390	415
High school						
10th grade	490	510	540	565	585	620
11th grade	525	545	580	600	625	660
12th grade	555	580	615	635	660	700

Source: Behrman, Gallardo-García, Parker, Todd and Vélez-Grajales (2010, Table1)

2.3.2 Evaluated Educational Impacts and Applied Methods

Since its launch in 1997, *Oportunidades* has been evaluated and proved to have positive and evident schooling impacts on children and youth. In the more concentrated research focusing on the evidence from rural areas, Schultz (2004), for example, indicates

[3] Information from The World Bank, Children & Youth Development Notes (CYDNs), Volume II, Number 4, March 2007.

that an overall increase in educational attainment is approximately 10 percent and estimates an internal rate of return for the program's educational benefits, which is as strong as eight percent per year. Behrman, Parker and Todd (2011) conduct a five-year following investigation of the program's schooling impact by inspecting the evidence of youth who were 9-15 years old in 1997 and turned to 15-21 in 2003, showing that children from intervention households gain additional grades of schooling from 0.7 years to 1.0 years, which depends on the student's age and gender. In the study of *Oportunidades* in urban settings, although there are less research, Behrman *et al*. (2010) make a short-term evaluation of the program's schooling impact and find significantly positive results for children and youth in educational attainment, school enrolment and time devotion on homework study.

Most of the evaluation research on the impact of *Oportunidades* uses the method of difference-in-differences estimator or difference-in-differences matching technique[4], for these approaches grant the advantage of controlling for the observable characteristics and unobservable time-invariant heterogeneity of observations. Difference-in-differences matching appears especially effective for the study of the program's impact on urban areas, for its effectiveness on correcting the problem of selection bias. Unlike the strategy in rural areas, the program implemented in urban areas is non-experimental, i.e. households who considered they met the eligibility criteria had to go to the central-located office to sign up and apply for enrolment in the two months open-window period. As a result, some of the eligible families did not even be aware of the application during that period; and more motivated families could be more willing to get into intervention, thus the problems of self-selection bias and administrative selection bias exist. Therefore, research depends on the approaches of difference-in-differences and matching to deal with this problem.

Besides the strategies of double difference and matching, the method of instrumental variable (IV) is also commonly applied for causal inference for its capability of eliminating the time-variant unobservable bias. The key of the IV estimation is to implement a variable that is in correlation with the determination of program participation or assignment, but is exogenous to the unobservable characteristics relating to the outcome.

4 See, e.g. Schultz (2004), Skoufias (2005), Behrman, Parker and Todd (2011), Behrman, Gallardo-García, Parker, Todd and Vélez-Grajales (2010).

However, in the context of evaluation of *Oportunidades*, if assuming that the treatment assignment (T) is endogenously biased, then finding the appropriate instrument Z, which $\mathrm{cov}(T, Z) \neq 0$ and $\mathrm{cov}(Z, \varepsilon) = 0$, where ε denotes to the unobserved heterogeneity, is very difficult due to the complexity and dynamic of the program's arrangement. In the previous research concerning the evaluation of *Oportunidades*, Angelucci and Attanasio (2006) implement the area type of households' residence as an instrument for treatment assignment. However, this might not be precisely valid. For one thing is this application is based on one of the assumptions that the participation decision and outcomes of interest of the eligible are not affected by those of the others. Nevertheless, other research indicates that peer-group and social interaction impact is evident in the program's outcomes (see e.g. Lalive and Cattaneo 2009). Besides, as the *Oportunidades* program is a comprehensive and dynamic human capital investment project, which is increasing its coverage to economically disadvantaged households across the country progressively, the area of residence may not be completely exogenous to the treatment participation. Taking account of the complexity of the application of IV, this paper takes the methods of standard difference-in-differences and difference-in-differences propensity score matching as the approaches for estimation.

3. Theoretical Study

3.1 Causal Effect of Education on Earnings

3.1.1 Human Capital Theory of Education and Earnings

Human capital theory provides economic theoretical explanations for the major determination and variation of individuals' education and earnings, fundamental contributions are made by Mincer (1957, 1958, 1962 cited Berndt 1991), Schultz (1960, 1961 cited Berndt 1991), and Becker (1962, 1964 cited Berndt 1991).

The theory gives explanations of the causal relationship between education and earnings from two wings of reasoning in labour economics. From the labour supply side, workers with longer years of schooling demand for sufficiently higher level of earnings for the sake of compensating the opportunity costs and school payment costs which they have paid for higher education. From the labour demand side, with the intention of demanding higher earnings, the more educated workers must possess higher productivity than less educated workers, which can be accomplished in turn by gaining more accumulated human capital through longer years of education.

The human capital theory implies that costs and benefits of schooling, which include current school payment costs, opportunity costs for taking schools instead of working, and the presumable future wage premium, must be taken into account for individuals when determining their education levels in order to maximize the present value of their wealth.

3.1.2 Human Capital Earnings Function

The human capital earning function of Mincer (1974) has been an essential framework for the study of education return and earnings determination. The Mincerian function illustrates the determination of individuals' earnings with the effect of educational attainment and human capital stock of experience, which takes the form as:

$$\ln W_i = \beta_0 + \beta_1 S_i + \beta_2 X_i + \beta_3 X_i^2 + \epsilon_i \; , \qquad (3.1)$$

where $\ln W_i$ is the natural logarithm of the wage for individual *i*, which is approximately normally distributed; S_i is the years of schooling for individual *i*; X_i and X_i^2 denote experience and experience squared respectively; and ϵ_i is an error term.

The human capital earnings function has been widely employed in estimating the rate of return to education. With the application of this model, worldwide evidence verifies that workers with higher level of schooling have higher average wages (e.g. Psacharopoulos 1994).

3.1.3 Causal Modelling of Education and Earnings

Based on the human capital theory and the human capital earnings function, Card (1995) develops a static model which is built on the classic model of Becker (1967 cited Card 1995). The model assumes that a person determines his/her schooling years S by maximizing a utility function $U[S, W(S)]$, where

$$U[S, W(S)] = \ln W(S) - F(S) \; , \qquad (3.2)$$

W(S) denotes the average annual wage this person earns given his/her schooling level of S years; F(S) represents an increasing convex function whose first order derivative $F'(S)$ represents the marginal costs of S years of schooling. Generally, $F(S)$ should be a strictly convex function and $F'(S)$ is strictly increasing, for the reason that the marginal costs of education are increasing with years mainly because of the opportunity costs rising with the growing ages of individuals and the actual schooling fees and payments escalating with higher levels of education.

Maximizing the utility function $U[S, W(S)]$ to get the optimal schooling choice takes the first-order condition of model (3.2), i.e. $\frac{\partial U}{\partial S} = \frac{W'(S)}{W(S)} - F'(S) = 0$,

$$\frac{W'(S)}{W(S)} = F'(S), \qquad (3.3)$$

where $\frac{W'(S)}{W(S)}$ is the marginal return to schooling which can be considered as marginal benefits of education. The equation (3.3) implies that the optimal schooling choice satisfies the condition that the marginal benefits of education equals the marginal costs of that.

The model of Card (1995) makes more assumptions to decompose the equation (3.3) further with the consideration of individual heterogeneity concerning marginal benefits and marginal costs of education. That is both sides of (3.3) are assumed to have linear functions with individual-specific intercept and schooling-specific slope:

$$\frac{W'(S)}{W(S)} = b_i - k_1 S\ , \qquad (3.4)$$

$$F'(S) = r_i + k_2 S\ , \qquad (3.5)$$

where b_i, r_i are random variables capturing inherent characteristics of individuals and have some joint distribution across the population $i = 1,2, \ldots$; $k_1, k_2\ \geq 0$, capturing the costs rates for adding one more year of schooling. Applying equations (3.4) and (3.5) into (3.3) to get the result of optimal schooling determination, i.e. $b_i - k_1 S = r_i + k_2 S$,

$$S^* = \frac{(b_i - r_i)}{k}, \qquad (3.6)$$

where S^* is the optimal level of schooling, and $k = k_1 + k_2$ generalizes the overall costs rate of education including actual schooling payments and opportunity costs.

The equation (3.6) indicates that the choice of optimal schooling years is inversely proportional to the overall costs rate of schooling — in other words, the determination of education level for an individual is negatively affected by the total costs of education one has to take.

3.2 Economic Incentives of Conditional Cash Transfer to Education

As introduced in the previous chapter, *Oportunidades* is a conditional cash transfer program founded on the purpose of increasing human capital investment for children and youth who are from the economically disadvantaged families. One of the most notable characteristics of cash transfers in this program is to provide educational grants and school material monetary support to the children and youth in participating families from grades 3 to 12 on the conditions that they attend school regularly and reach at least 85 percent rate of school attendance, etc.

In this way of designing, the conditional cash transfers strategy provides effective economic incentive for children and youth under intervention to increase their education investment. More specifically, the most significant incentive is to decrease the overall costs of schooling by reducing both the opportunity costs and the actual school payment costs.

The effect of conditional cash transfer scheme can be illustrated in the following figure[5]:

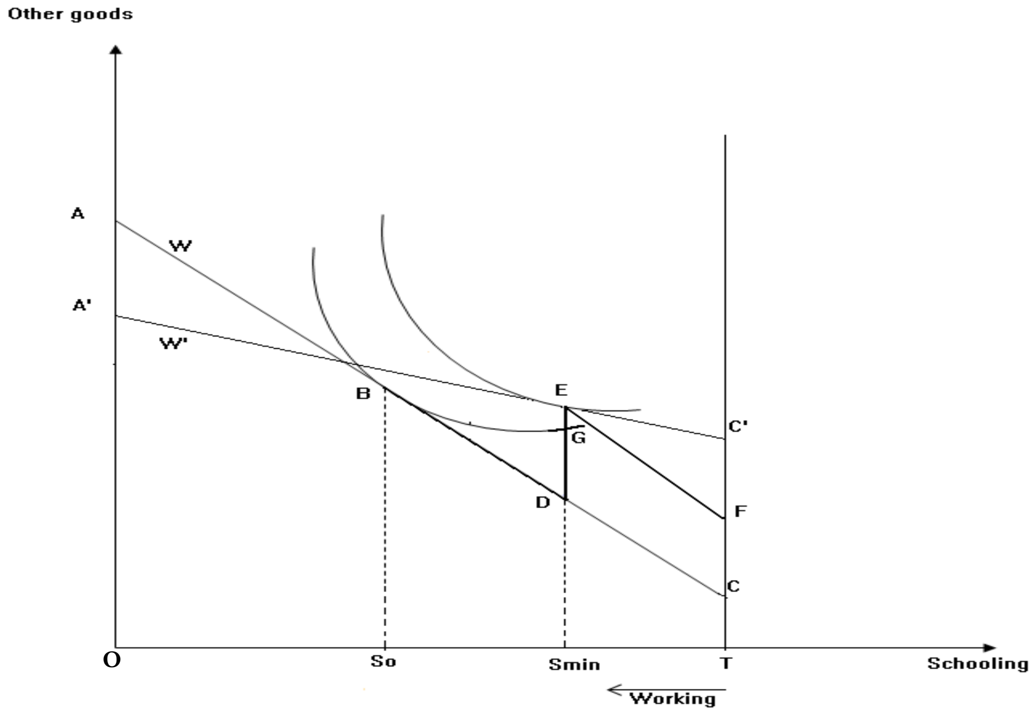

Figure 3.1 Economic Incentives of Conditional Cash Transfers

Suppose schooling is a “normal goods” for individuals, household budgets are divided between consumption on education and other goods. Let T denote the total amount of time for a youth that can be spent either on schooling or on working. Therefore, if S=0, which means the youth spends all the available time in working, then OA denotes the maximum amount of other goods the household can consume; if the time spent on schooling S equals to

[5] The figure and regarding analysis are based on Skoufias (2005), p.18-21, Figure 2.1, and Daz, Do, and Özler (2004, Figure 2).

T, which means the youth devotes all the available time in education, then CT represents the consumption of other goods when the youth does not work at all. The line AC is a budget constraint of the youth's household, which describes the current opportunity set, whose slope indicates the present real market wage W if the youth works, representing the opportunity cost of education.

Suppose that at the beginning, the youth spends the time of S_0 on education, and after the intervention of the conditional cash transfer program, he/she spends more time on schooling and reaches the minimum requirement of 85 percent of school attendance $S_{\min}$. At the same time, the household gets the educational cash transfer CF, which is a non-labour income increase for the household benefiting from the CCT program, so the budget line between $S_{\min}$ and T shifts up without changing the slope. The new budget constraint of the family is ABDEF, and the indifference curve rises up because of the cash transfer. Notice that G is the intersection point of the original indifference curve and the vertical line of $S_{\min}$, therefore the minimum cash transfer that makes the household just indifferent between taking S_0 and $S_{\min}$ is the amount of DG. Apparently, the amount of CF is greater than that of DG; for this reason, the cash transfer provides sufficient economic incentives to induce the household to let the youth spend more time on education. Besides, the increased non-labour income provides indemnity for the household to offset the possible increased school payment costs for the family member taking more education.

Furthermore, taking account of the "distorted" budget constraint ABDEF when the new equilibrium point E is not a tangency point, Skoufias (2005) applies the approach of "linearizing the budget line" by introducing a line $A'C'$ which is tangent to the new indifference curve at E. The "linearized" budget line $A'C'$ intersects with the vertical line of T at C', which gives a level of non-earned shadow income, corresponding to the shadow wage W' that is lower than W. This indicates that the conditional cash transfer has an effect of lowering the opportunity cost of education. Overall, the total benefits that the CCT program provides to the household are the explicit cash transfer CF as well as the implicit additional income $C'F$ earned from lowered opportunity cost of schooling.

Summarily, the conditional cash transfers provide the household with salient economic incentives to increase the young's education, for the reason that the strategy can decrease both the actual school payment by offering non-labour income (CF) and monetary support for school materials (as a way of educational benefits designed in the program) and the opportunity cost of education by reducing the price of schooling (lower shadow wage). That is, the program strategy supplies an effective mechanism to significantly decrease the denominator of equation (3.6), thus, *ceteris paribus,* the schooling years of S should increase. Therefore, with the economic incentives from schooling intervention of this CCT program, the enhancement in education of participants can be reasonably expected.

3.3 Econometric Methodology for Treatment Effects Analysis

3.3.1 Treatment Effects Framework

With the purpose to investigate the educational impact on earnings of youth from economically disadvantaged backgrounds, short-term evidence from the *Oportunidades* program is taken for empirical analysis, for the program's schooling intervention to the participated urban youth from impoverished families. The critical concern with this research is to identify and evaluate the program's treatment effects of interest.

Because only individuals who actually participate in the program and receive the corresponding intervention could reflect the treatment effect, the core parameter of interest concerning impact evaluation is the "average treatment effect on the treated" (ATT). Suppose for a program under evaluation, the participated individuals constitute a treatment group (T), and a control group (C) consists of non-participated individuals. Denote Y as the outcome under research, more specifically, Y_1 is the outcome under the intervention of the treatment, Y_0 is the outcome without the intervention of the treatment. Then the average treatment effect (ATE) is:

$$\mathrm{ATE} = \mathrm{E}(Y_1 - Y_0). \tag{3.7}$$

The average treatment effect on the treated is:

$$\mathrm{ATT} = \mathrm{E}(Y_1 - Y_0|\mathrm{T}) = \mathrm{E}(Y_1|\mathrm{T}) - \mathrm{E}(Y_0|\mathrm{T}). \tag{3.8}$$

Apparently, $\mathrm{E}(Y_1|\mathrm{T})$ is the observable outcome of the treatment group under the intervention; while $\mathrm{E}(Y_0|\mathrm{T})$ the potential outcome of the treated when absent from the intervention, is an unobservable counterfactual outcome. Thus there exists the so-called "Fundamental Problem of Causal Inference" (Holland 1986) that is the impossibility of observing the outcome that the treated group would have gained without the treatment. The only non-treatment outcome that can be observed is $\mathrm{E}(\mathrm{Y}_0|\mathrm{C})$, which is the parallel result of the control group. In practice, when taking $\mathrm{E}(\mathrm{Y}_0|\mathrm{C})$ as the counterfactual in replace of $\mathrm{E}(\mathrm{Y}_0|\mathrm{T})$, the estimated ATT is:

$$\widehat{\mathrm{ATT}} = \mathrm{E}(\mathrm{Y}_1|\mathrm{T}) - \mathrm{E}(\mathrm{Y}_0|\mathrm{C}). \qquad (3.9)$$

Consequently, there generates a difference between the estimated and real ATT:

$$\widehat{\mathrm{ATT}} - \mathrm{ATT} = \mathrm{E}(\mathrm{Y}_0|\mathrm{T}) - \mathrm{E}(\mathrm{Y}_0|\mathrm{C}) = \mathrm{SB}. \qquad (3.10)$$

This difference is mainly attributable to selection bias (SB) which generally caused by voluntary and self-selected character of participation in non-random intervention when treatment and control group are not randomly assigned. For most quasi-or-non-experimental program e.g. *Oportunidades*, the problem of selection bias should be taken into consideration when identifying and evaluating the treatment effect. With regard to employ quasi-experimental or non-experimental micro-data for inference of causal relationships, strategies of standard difference-in-differences and propensity score matching combined with difference-in-differences are commonly applied econometric methods, for their functions of pinpointing the treatment effects and correcting the problem of selection bias.

3.3.2 Difference-in-Differences

Difference-in-Differences (DiD) estimation evaluates treatment effect by comparing the outcome differences of treated and control group before and after the intervention. Suppose a program intervention takes effect from a baseline period (t_0) to a follow-up period (t_1), then DiD estimator captures the treatment effect as:

$$\mathrm{ATT} = \mathrm{E}\left(\mathrm{Y}_\mathrm{T}^{\mathrm{t}_1} - \mathrm{Y}_\mathrm{T}^{\mathrm{t}_0}\right) - \mathrm{E}(\mathrm{Y}_\mathrm{C}^{\mathrm{t}_1} - \mathrm{Y}_\mathrm{C}^{\mathrm{t}_0}). \qquad (3.11)$$

Hence the counterfactual outcome difference of the treated before and after intervention is represented by the outcome difference of the control group during the same period.

Under this approach, the two "within parentheses" differences eliminate the systematic effect of individuals, and the "outside parentheses" difference removes the common time trend effect for the two groups, thus both group-specific and time-specific effects are allowed for. Therefore, DiD approach eliminates bias caused by observable and unobservable time-invariant effects, i.e. the time-constant linear selection bias and the time effect of common trend across the two groups can get controlled.

However, the validity of DiD estimation relies on the assumption of common trend, which largely depends on the appropriateness of the construction of the control group. Hence if there are observable characteristics resulting in inconsistent trend between the treatment group and the control group, the estimates of DiD approach would be biased.

3.3.3 Difference-in-Differences Propensity Score Matching

Propensity score matching (Rosenbaum and Rubin 1983) technique enables the correction for selection bias basing on observable characteristics that may affect intervention participation or assignment. Selection bias can be reduced in this way by matching individuals in the control group who have similar pre-treatment characteristics (thus in the analogous selective ways) as those in the treatment group; that is to "reconstruct" the control group by matching the statistical equivalent individuals concerning the time-variant characteristics to the treatment group.

Propensity score matching (PSM) is based on two basic assumptions (see e.g. Rosenbaum and Rubin 1983). The most fundamental one is the Conditional Independence Assumption (CIA), which states that conditional on observable characteristics Z, the outcomes are independent of treatment, i.e. $\mathrm{Y}_0, \mathrm{Y}_1 \perp \mathrm{T} \mid \mathrm{Z}$. The second one is the Matching Assumption, stating that for each value of Z, there are both treated (T) and untreated (C) possibilities, i.e. $0 < \Pr(\mathrm{T} \mid \mathrm{Z}) < 1$.

Defining p(z) = $\Pr(\mathrm{T} \mid \mathrm{Z} = \mathrm{z})$ as the propensity score, which means the probability for an individual getting the treatment intervention given z, a combination of the two assumptions implies that the outcomes are independent of treatment conditional on the propensity scores, i.e. $\mathrm{Y}_0, \mathrm{Y}_1 \perp \mathrm{T} \mid$ P(Z). Thus, the "counterfactual problem" can be solved as

$$E(Y_0|T,P(Z)) = E(Y_0|C,P(Z)). \qquad (3.12)$$

Therefore, the average treatment effect on the treated conditional on the observable characteristics estimated by the matching is

$$ATT = \frac{1}{N}\sum_{u\epsilon\{T\}}\left(Y_{1,u} - \sum_{v\epsilon\{C\}} w(u,v)Y_{0,v}\right), \qquad (3.13)$$

where u denotes individuals in the treatment group, and v denotes individuals from the control group; N is the total population size; $Y_{1,u}$ is the outcome of the treated, while $Y_{0,v}$ is the outcome of the untreated; $w(u,v)\epsilon(0,1]$ denotes the weight given to the v from the control group in matching with the u from the treatment group, and $\sum_v w(u,v) = 1$.

In this way, the propensity score matching approach eliminates bias caused by observable pre-treatment disparities between the treated and the untreated. However, when taking account of unobserved heterogeneity, the propensity score matching should be combined with difference-in-differences to deal with that problem.

Difference-in-differences propensity score matching (DiD-PSM) method first applied by Heckman, Ichimura and Todd (1997) is implemented in handling the bias from unobserved individual characteristics. As analyzed in the previous part, in the case of *Oportunidades* program, more motivated households tend to self-select into the treatment intervention. The motivation effect partially attributes to unobservable characteristics which cannot be isolate from the impact of treatment merely by the matching estimator, thus generates bias and the Conditional Independent Assumption (CIA) is violated.

However, if the unobserved characteristics are time-invariant, the effect can be removed with the combination of propensity score matching and difference-in-differences. Difference-in-differences propensity score matching relaxes the CIA to the extent that inasmuch as sharing the common trend, the counterfactual outcome of the treated can be different from the observed outcome of the untreated (see e.g. Heckman *et al.* 1998), i.e.

$$E\left(Y_0^{t_1} - Y_0^{t_0}\middle|T,P(Z)\right) = E\left(Y_0^{t_1} - Y_0^{t_0}\middle|C,P(Z)\right), \qquad (3.14)$$

where t_0 is the baseline of the intervention, t_1 is the follow-up period. Conjointly with the Matching Assumption, the average treatment effect on the treated can be estimated by the difference-in-differences in means between the treatment and control groups:

$$\mathrm{ATT} = \frac{1}{N}\sum_{u\epsilon\{T\}}\left((Y_{1,u}^{t_1} - Y_{0,u}^{t_0}) - \sum_{v\epsilon\{C\}} w(u,v)(Y_{0,v}^{t_1} - Y_{0,v}^{t_0})\right), \quad (3.15)$$

where $w(u, v)$ is the same weight using the PSM approach, given to the v from the control group in matching with the u from the treatment group.

In a word, PSM method deals with observable characteristics and then reduces the time-variant factors of heterogeneity, thus increasing the credibility of the parallel trend assumption of the DiD estimator; and DiD enhances the PSM approach by eliminating the time-invariant unobserved heterogeneity. Therefore, difference-in-differences propensity score matching estimator works further to control of heterogeneity and to handle the problem of selection bias.

4. Empirical Analysis

4.1 Data Description

4.1.1 Data Sources

Aiming at studying the causal effect of education on earnings for pro-poorness, short-term evidence of Mexican *Oportunidades* program is taken for causal inference. The data used in this empirical analysis are from the official database of *Oportunidades* program — Urban Household Evaluation (ENCELURB) Surveys [6], which contain socioeconomic information of households and their members in urban areas of Mexico. Covering the information from both households who are participating in the program and those who are out of the program's intervention, the surveys keep track of the records from pre-program baseline year 2002 to the follow-up year 2004. The baseline survey ENCELURB 2002 collects the socioeconomic facts of households and individuals prior to the launch of the program, and the follow-up surveys ENCELURB 2003 and 2004 include the corresponding information after the program's implementation for one year and two years respectively. Households' data are collected by gathering socioeconomic characteristics information through the form of questionnaires from the baseline year 2002. Although there is a certain proportion of attrition and new addition from 2002 to 2004, a considerable amount of households and individuals are kept track of information for all the years, therefore a panel data analysis is feasible.

The database distributes the households sample into two groups — intervention group and comparison group. Intervention group contains the eligible households from the program's intervention zones; while the comparison group consists of eligible households from the intervention but not participate in the program, eligible households in the non-intervention zones, almost eligible households in the intervention zones, and a small fraction of non-eligible households in the intervention zones. This is illustrating that even for members from the comparison group most of them are in equivalent poverty situations nevertheless in absence of the *Oportunidades*' invention. The eligibility status is determined

[6] The datasets is available from: http://evaluacion.oportunidades.gob.mx:8010/en/index.php.
The methodology behind the datasets are explained in the official urban technical note, available from: http://evaluacion.oportunidades.gob.mx:8010/b34e550cd0d8b7c93e609ccff4ea5593/notas/general_urban_methodology_note.pdf

according to the social deprivation score[7] of each family based on their socioeconomic situation.

4.1.2 Estimation Strategy and Data Subsample

The strategy of this study is to make use of the identified schooling impact of the program on the economically disadvantaged youths to investigate this educational effect upon their earnings in short-run (two years) with the comparison of their non-intervention peers. To facilitate this research objective, the subsample for estimations is composed of the youths who have complete and consistent information from the databases of 2002 to 2004, aged 14[8]-20 in 2002 and 16-22 years old in 2004 with a record of working income. The comparative analysis is conducted between a treatment group and a control group: the treatment group consists of eligible young people from the households under the program's intervention who showed attendance to school in 2002 and whose school grades have been within the subsidy-eligible grade levels (grades 3-12) across the three years[9], thus to ensure that the individuals of treatment group are those who actually received the *Oportunidades*' educational intervention from the baseline; the control group contains young people from the non-participant households for the three years, implying that those individuals are out of the program's impact in the whole research period. Totally, the treatment group contains 216 eligible individuals from intervention households; the control group includes 480 same-aged young people from non-intervention households (see Table 4.1).

Table 4.1. Number of observations in treatment and control groups.

Year	**Treatment**	**Control**	**Total**
2002	216	480	696
2004	216	480	696
Total	432	960	1392

[7] The deprivation score is used as one of the conditioning variable in the application of propensity score matching to remove the possible corresponding bias.
[8] The minimum legal age for work is 14 in Mexico according to the Mexican Constitution.
[9] Even if an individual was not in grade 3-12 in 2002, e.g. he/she was in grade one in 2002 but as long as he/she continued his/her education throughout the years and turned to grade 3 in 2004 and became subsidy eligible, it is still reasonable to infer that he/she has been affected by the *Oportunidades*' (incentive) schooling impact, thus this kind of observations are included in the treatment group.

4.1.3 Descriptive Statistics

As the framework of this empirical analysis is firstly to identify the educational impact of the program on the youths of treatment group and then to test whether the two groups with a difference in schooling exhibit a disparity in their change of earnings in the two-year research period, the focuses of analysis are the individuals' schooling years as a measure of education achievement on the first stage, and their incomes, applied in the form of logarithmic weekly earnings in the estimation on the second stage.

Summary statistics of the basic information on the observations of treatment group and control group in the baseline year and the follow-up year are presented in Table 4.2.a. and Table 4.2.b.

Table 4.2.a. Descriptive statistics on basic information of the observations.

	Obs	Mean	St. Dev.	Min	Max
2002					
Schooling years	696	7.379	2.372	1	12
Weekly earnings(pesos)	696	395.0	323.3	20	5000
Age	696	17.18	1.861	14	20
Male*	696	0.730	0.444	0	1
2004					
Schooling years	696	7.843	2.545	1	14
Weekly earnings(pesos)	696	488.7	249.1	10	2450
Age	696	19.18	1.860	16	22
Male*	696	0.730	0.444	0	1

*Dummy variable: =1 if male; =0 if female.
Source: Author's calculations with ENCELURB 2002, 2003, 2004 data.

Table 4.2.b. Descriptive statistics on basic information of the observations by treatment and control group.

	Obs	Mean	St. Dev.	Min	Max
2002					
Treatment Group					
Schooling years	216	8.204	2.306	1	12
Weekly earnings(pesos)	216	315.3	248.5	20	1750
Age	216	16.53	1.749	14	20
Male	216	0.630	0.484	0	1
Control Group					
Schooling years	480	7.008	2.310	1	12
Weekly earnings(pesos)	480	430.8	346.1	20	5000
Age	480	17.48	1.837	14	20
Male	480	0.775	0.418	0	1
2004					
Treatment Group					
Schooling years	216	9.176	2.542	3	14
Weekly earnings(pesos)	216	458.9	273.8	10	1650
Age	216	18.53	1.749	16	22
Male	216	0.630	0.484	0	1
Control Group					
Schooling years	480	7.244	2.310	1	13
Weekly earnings(pesos)	480	502.1	236.2	10	2450
Age	480	19.48	1.835	16	22
Male*	480	0.775	0.418	0	1

Source: Author's calculations with ENCELURB 2002, 2003, 2004 data.

The school attendance information of observations in treatment and control groups in the baseline year and the follow-up year are presented in Table 4.3.

Table 4.3. School attendance and full-time work situations of observations.

Year	**Treatment Group**		**Control Group**	
	2002	*2004*	*2002*	*2004*
Total number of Obs.	216	216	480	480
Age	14-20	16-22	14-20	16-22
Number of school attendance	216	70	55	40
Percentage of schooling	100%	32.41%	11.46%	8.33%
Number of out-of-school (Full-time work)	0	146	425	440
Percentage of full-time work	0	67.59%	88.54%	91.67%

Source: Author's calculations with ENCELURB 2002, 2004 data.

The descriptive statistics on the basic information of the observations indicate that as the objects in this research are youth from impoverished families, there is obvious evidence showing that on the whole the economically disadvantaged youths spend relatively limited time on education compared to the general situation in developed areas around the world. The treatment group, as those young students who were attending school in the baseline year receiving the educational impact of *Oportunidades*, presents comparatively longer average years of schooling than the control group members who are from non-invention households of approximately equivalent socioeconomic situation[10]. It is noticed that these young people under study attending school and participating in work simultaneously or joining the full-time workforce relatively earlier, a common practice for children from poor families in Mexico especially when they reach the legal working age, for the sake of sharing the economic burden of their families. This "bitter reality" reemphasizes the research necessity and reason why this paper is interested in investigating whether an enhancement in education could have a beneficial impact on the economically disadvantaged young for their earnings and thus to infer a contribution to pro-poor growth, although with the limitation of the research period due to the availability of data, short-term impact is under the focus of exploration.

4.2 Econometric Specification

The estimation approaches applied in this study are difference-in-differences (DiD) estimation and difference-in-differences propensity score matching (DiD-PSM) method, with an analysis strategy of first identifying the educational impact of *Oportunidades* on treated youths compared with their untreated peers, and then testing the disparity in earnings changes of the two "educational non-identical" groups in the two years, controlling for observable and unobservable bias within the capability of methods.

4.2.1 Difference-in-Differences Estimator

The difference-in-differences specification compares the change in the average outcome of interest for the treatment group with the change for the control group before and after the program's intervention. To identify the schooling impact of the program, the basic estimating equation employing difference-in-differences is:

[10] More precise analysis of identifying the educational differences between the two groups is conducted in the latter estimation part.

$$S_{it} = \beta_0 + \beta_1 Tr_i + \delta_0 Yr_{i2004} + \delta_1 Tr_i \cdot Yr_{i2004} + \varepsilon_{it}, \tag{4.1}$$

where S_{it} is the schooling years that an individual i completed in period t (2002 or 2004); Tr_i is a dummy variable, equals one if the individual is under the program's intervention, equals zero if the individual is in the control group; Yr_{i2004} is a time period dummy, equals one if the observation is in year 2004, equals zero if in year 2002; the interaction term $Tr_i \cdot Yr_{i2004}$ works as a dummy variable, equal to one for those observations in the treatment group in year 2004; and ε_{it} is an error term.

The estimated coefficient $\hat{\delta}_1$ is the difference-in-differences estimator, capturing the causal effect of the program's educational intervention on schooling years:

$$\begin{aligned} \hat{\delta}_1 = \quad & [E(S|Tr = 1, Yr_{2004} = 1) - E(S|Tr = 1, Yr_{2004} = 0)] \\ & -[E(S|Tr = 0, Yr_{2004} = 1) - E(S|Tr = 0, Yr_{2004} = 0)]. \end{aligned} \tag{4.2}$$

The DiD specification for examining the earnings differences between the treatment and control group is with the same reasoning, apart from controlling for covariates based on Mincerin wage function (Equation (3.1)), i.e.:

$$\ln W_{it} = \gamma_0 + \gamma_1 Tr_i + \theta_0 Yr_{i2004} + \theta_1 Tr_i \cdot Yr_{i2004} + \alpha_1 S_{it} + \alpha_2 X_{it} + \alpha_3 X_{it}^2 + \mu_{it}, \tag{4.3}$$

where $\ln W_{it}$ is the logarithmic weekly earnings an individual i earned in period t (2002 or 2004); Tr_i, Yr_{i2004}, $Tr_i \cdot Yr_{i2004}$ and S_{it} denote the same meanings as in equation (4.1); X_{it} is the potential experience for observations representing as $X_{it} = A_{it} - S_{it} - 5$[11], where A_{it} is the age of the individual i in period t, and X_{it}^2 is a quadric term; μ_{it} is an error term.

Similarly, the difference-in-differences estimator in equation (4.3) is the estimated coefficient $\hat{\theta}_1$, where

$$\begin{aligned} \hat{\theta}_1 = \quad & [E(\ln W|Tr = 1, Yr_{2004} = 1) - E(\ln W|Tr = 1, Yr_{2004} = 0)] \\ & -[E(\ln W|Tr = 0, Yr_{2004} = 1) - E(\ln W|Tr = 0, Yr_{2004} = 0)], \end{aligned} \tag{4.4}$$

interpreting the differences between the change of earnings for the treatment group from 2002 to 2004 and the change of earnings for the control group over the same period.

[11] I use 5 instead of 6 because of the data from the database showing the evidence that some individuals start grade one at an earlier age. Same way of process can be found in Behrman *et al.*, 2010.

4.2.2 Difference-in-Differences Propensity Score Matching Estimator

In order to take the difference in the pre-treatment characteristics between the treatment and the control group into account, and thus help to diminish the associated bias (e.g. self-selection bias), the estimation of propensity score matching (PSM) combined with difference-in-differences (DiD) is also implemented. Difference-in-differences matching is analogous to the standard DiD estimation, but reweights the observations from the control group by calculating their propensity scores to match them with the observations in the treatment group, so as to enable the two groups statistically equivalent.

The difference-in-differences propensity score matching estimator is estimated in three steps. The first step is to estimate the propensity scores basing on the pre-treatment characteristics variables, i.e. estimating

$$\mathrm{Pr}(\mathrm{Tr} = 1|\mathrm{Z}), \qquad (4.5)$$

where Z denotes the conditioning variables for matching, which include geographic location and poverty status of the family, basic socioeconomic characteristics and demographic features of the household in 2002, the education levels and employment status of the head of household and spouse, and some indications of consumption habits of the family members, as well as the involvement with other anti-poverty programs of the household[12]. All of these variables are measured before the launch of the program, which are exogenous and invariant to the program's intervention and affect simultaneously both the decision of participation and the outcomes of interest. The propensity score model is estimated using logistic regression.

The second step is to match each individual from the treatment group to one or more untreated individuals on propensity scores. In this paper, the Gaussian kernel matching estimators with local linear regression[13] is applied as matching algorithm, i.e. the weight function is (Cameron and Trivedi 2009, p.875, 300):

$$\mathrm{w(u, v)} = \frac{\mathrm{K}(\mathrm{z_v} - \mathrm{z_u})}{\sum_{\mathrm{v}\epsilon\{\mathrm{Tr}=0\}} \mathrm{K}(\mathrm{z_v} - \mathrm{z_u})}\,, \qquad (4.6)$$

[12] A complete list of all the conditioning variables used in the propensity score model with specific explanation is presented in Appendix.
[13] As one of the most popular matching estimators of causal effect with wide application, see e.g. Buscha *et al.* (2010), Bergemann *et al.* (2009). Research by e.g. Galdo *et al.* (2007) shows that Gaussian kernel possesses the advantage of smaller MSEs (mean square errors) for the local linear estimator.

where u denotes treated individuals and v denotes untreated individuals; K is a Gaussian kernel, $K(z) = (2\pi)^{-1/2}\exp(-z^2/2)$, using all the untreated observations. And the final step is to compute the impacts with difference-in-differences before and after the treatment, analogous to the standard DiD.

4.3 Results

The results are presented in two stages, first is the identification of differences in schooling attainment between the treatment group and the control group, followed by the causal inference part reasoning from the discrepancy in education to the disparity in increase of earnings.

4.3.1 Education Attainment

The estimated result of equation (4.1), which is showing the estimated program impact on schooling years for youths from the treatment and control groups applying difference-in-differences estimation, is presented in Table 4.4.a. and Table 4.4.b.:

Table 4.4.a. Difference-in-differences estimation on schooling attainment (Estimation on Regression (4.1))

	(4.1)
VARIABLES	**Schooling years**
Treat·Year2004	0.737***
	(0.277)
Treat	1.195***
	(0.189)
Year2004	0.235
	(0.149)
Constant	7.008***
	(0.105)
Observations	1392
R-squared	0.099

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.4.b. Difference-in-differences estimation on schooling attainment

Outcome Variable(s)	2002 (Base Line)			2004 (Follow Up)			DIFF-IN-DIFF
	Control	Treated	Diff(BL)	Control	Treated	Diff(FU)	
Schooling years	7.008***	8.204***	1.195***	7.244***	9.176***	1.932***	0.737***
Std. Error	0.107	0.160	0.192	0.107	0.160	0.192	0.272
t	65.43	14.49	6.22	9.21	13.05	5.03	2.71
P > |t|	0.000	0.000	0.000	0.000	0.000	0.000	0.007
Observations	480	216	696	480	216	696	1392

a. Means and Standard Errors are estimated by linear regression.
b. Inference: *** p<0.01; ** p<0.05; * p<0.1

Table 4.4.a. presents the regression version of the difference-in-differences estimates, while Table 4.4.b. displays a detailed difference-in-differences analysis of the treatment group and the control group from the baseline year to the follow-up year.

The estimated coefficient on “Treat” is 1.195 (see Table 4.4.a), means that even in the absence of the treatment intervention, the youths in the treatment group have on average 1.195 longer years of schooling than their peers in the control group, which is also the difference between schooling years of the two groups in the baseline year (see Table 4.4.b). This is in accordance with the evidence from the descriptive statistics, which is reasonable because the treatment group members are those who were attending schools (so could get the program’s educational intervention) during the baseline year, while the control group’s young people are not necessary the case. The difference-in-differences estimate in the results is 0.737, which means the youths in the treatment group tend to increase on average 0.737 more schooling years than their peers in the control group during 2002 to 2004 due to the program’s intervention, and this discrepancy in the boost of schooling years between the two groups is showed statistically significant at the one percent level.

The difference-in-differences propensity score matching estimator applying Gaussian kernel function gives the result in Table 4.5.

Table 4.5. Difference-in-differences matching estimation on schooling attainment

Outcome Variable(s)	2002 (Base Line)			2004 (Follow Up)			DIFF-IN-DIFF
	Control	Treated	Diff(BL)	Control	Treated	Diff(FU)	
Schooling years	7.012***	8.204***	1.192***	7.225***	9.176***	1.951***	0.759*
Std. Error	0.101	0.260	0.279	0.101	0.260	0.279	0.395
t	69.64	11.59	4.27	9.13	11.33	3.91	1.92
P > |t|	0.000	0.000	0.000	0.000	0.000	0.000	0.055
Observations	480	216	696	480	216	696	1392

a. Means and Standard Errors are estimated by linear regression.
b. Inference: *** p<0.01; ** p<0.05; * p<0.1

The difference-in-differences propensity score matching estimate is 0.759, statistically significant at the level of 10%. The result indicates that the increase in schooling years over the two years of the youths in the treatment group is on average 0.759 years more than that of their peers in the control group. Notice that the DiD-PSM estimate is quite similar with that of the standard DiD, although the former is less significant than the latter.

Overall, the two approaches of estimation confirm that comparing with their peers in the control group, the youths in the treatment group on average have an evident advantage in education.

4.3.2 Earnings Enhancement

After identifying the schooling differences between the youths from the two groups, the next stage is to examine whether the young people from economically disadvantaged background with a discrepancy in education attainment result in a distinguishable difference in their change of earnings during the short-term period.

Since the identification tests in the first step have confirmed that the treatment group is education advantaged, while the control group is education disadvantaged, in this step the treatment group is denoted as “Edu-adv”, and the control group is denoted as “Edu-disadv”.

Table 4.6.a. and Table 4.6.b. present the estimated result of equation (4.3), which is showing the estimated difference between the increases of earnings of the education advantaged group and the education disadvantaged group using difference-in-differences estimation.

Table 4.6.a. Difference-in-differences estimation on earnings
(Estimation on Regression (4.3))

VARIABLES	(4.3) **lnearnings**
Treat·Year2004	0.194***
	(0.0750)
Treat	-0.205***
	(0.0597)
Year2004	0.0779*
	(0.0420)
schooling years	0.0725***
	(0.0115)
male	0.232***
	(0.0381)
exp	0.174***
	(0.0219)
exp2	-0.00688***
	(0.00151)
Constant	4.474***
	(0.140)
Observations	1392
R-squared	0.183

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6.b. Difference-in-differences estimation on earnings

Outcome Variable(s)	**2002 (Base Line)**			**2004 (Follow Up)**			**DIFF-IN-DIFF**
	Edu -disadv	Edu -adv	Diff(BL)	Edu -disadv	Edu -adv	Diff(FU)	
lnearnings	4.474***	4.269***	-0.205***	4.552***	4.541***	-0.011	0.194***
Std. Error	0.131	0.126	0.053	0.146	0.143	0.054	0.071
t	34.19	2.84	-3.87	5.01	5.70	3.42	2.72
P > |t|	0.000	0.000	0.000	0.000	0.000	0.837	0.007
Observations	480	216	696	480	216	696	1392

a. Controlling for covariates of schooling years, male, experience and experience square.
b. Means and Standard Errors are estimated by linear regression.
c. Inference: *** p<0.01; ** p<0.05; * p<0.1

Table 4.6.a. displays the estimated result of the difference-in-differences regression (4.3), and Table 4.6.b. displays a detailed difference-in-differences analysis of the education

advantaged group and the education disadvantage group from the baseline year to the follow-up year.

As analyzed in the part of descriptive statistics (Table 4.3), during the baseline year, all of the members in the education advantaged group were attending school, while only 11.46% of the members in the education disadvantaged group were going to school, 88.54% of them had already become full-time workers; therefore it is logical to argue that because the youths in the education disadvantaged group devote more time in work and participate in jobs early than their education advantaged peers, their incomes level should be higher at that time. That explains the reasons why on average earnings of the education disadvantaged group is approximately 20.5% higher than the earnings of the education advantaged group prior to the intervention during the baseline, which is given by the estimated coefficient of "Treat" (Table 4.6.a) and the estimated coefficient of "Diff(BL)" (Table 4.6.b), both indicating this situation.

However, the difference-in-differences estimate showed in the two tables is 0.194 and statistically significant at the one percent level. This result implies that over the two years the increase in earnings of the education advantaged group is on average about 19.4% higher than the increase in earnings of the education disadvantaged group, despite the fact that till 2004 over 91% of the education disadvantaged group members have been full-time workers, while comparatively less than 68% of the education advantaged group are working full-time (see Table 4.3).

The difference-in-differences propensity score matching estimator applying Gaussian kernel function gives the result in Table 4.7.

Table 4.7. Difference-in-differences matching estimation on earnings

	2002 (Base Line)			**2004 (Follow Up)**			**DIFF-IN-DIFF**
Outcome Variable(s)	Edu -disadv	Edu -adv	Diff(BL)	Edu -disadv	Edu -adv	Diff(FU)	
lnearnings	5.925***	5.477***	-0.448***	6.146***	5.933***	-0.213***	0.235**
Std. Error	0.026	0.068	0.073	0.026	0.068	0.073	0.103
t	225.38	-0.66	-6.14	14.33	9.15	2.77	2.27
P > |t|	0.000	0.000	0.000	0.000	0.000	0.004	0.023
Observations	480	216	696	480	216	696	1392

a. Means and Standard Errors are estimated by linear regression.
b. Inference: *** p<0.01; ** p<0.05; * p<0.1

The difference-in-differences propensity score matching result shows a more distinguishable gap between the earnings of the two groups in the baseline year. This might be explained as a result that the matching approach matches observations from the two groups with their family poverty situations. As stated before, the education disadvantaged members from the non-intervention households containing not only the eligible (poor) while untreated households but also the almost-eligible and non-eligible families, then after matching, youths in the control group have comparatively equivalent poverty status with the treatment group. Since the control group members are education disadvantaged youths who have evolved in workforce for a relatively longer time (especially so when they are from poor families), consequently they have higher incomes in the baseline period.

However, the difference-in-differences propensity score matching estimate is 0.235, statistically significant at the level of 5%, indicating that over the two years the increase in earnings of the education advantaged group is on average about 23.5% higher than the increase in earnings of the education disadvantaged group. Taking into account the earnings gap from the baseline year, this evident enhancement in the increase of earnings of the education advantaged group comparing to that of the education disadvantaged group, especially infers the positive effect of education on the increase of earnings in respect of pro-poorness.

Overall, the two approaches of estimation prove that the earnings of the education advantaged youths show a salient tendency toward more progressive enhancement than that of their education disadvantaged peers.

5. Discussion and Conclusions

5.1 Discussion

The empirical analysis taking evidence from the human capital development program *Oportunidades* proves the theoretical indication that with the economic incentives provided by the conditional cash transfer to overcome costs of schooling for the poor, the education attainment of the economically disadvantaged youth who participated in the educational intervention has been significantly enhanced. With the identified education advantage, the earnings of this group of young people has been shown to increase at a higher rate than those of their education disadvantaged peers, most of whom are also from impoverished backgrounds but with less attainment in education. This is a confirmation of the belief that education can make a fundamental contribution to the well-being of the poor and to the pro-poorness of growth. As the research subject is the youth of poor, it is also logical to infer that education provides pivotal opportunities for better development and promising future of the economically disadvantaged young people. This outcome is in accordance with the human capital theory that more educated workers possess higher productivity and deserves better payoff.

The empirical research of *Oportunidades* for causal inference takes short-term evidence from 2002 to 2004 for only two years. Large-scale intervention like *Oportunidades*, as analyzed by Bettinger (2006), is generally slow to develop, which is supposed to expect relatively smaller short-run effect and greater long-run impact, especially for the intervention in urban areas, which is lately launched and still expanding its influence progressively towards more households of social deprivation conditions. Therefore, it is reasoned to expect more significant results of the schooling impact on economically disadvantaged youth for enhancement of their future incomes and well-being in the long run.

5.2 Conclusions

In this paper, the impact of the accumulation of education on the enhancement of earnings for the economically disadvantaged youth is under research, with the aim of inferring the causal effect of education on earnings for poverty reduction and pro-poor growth. To facilitate this objective of study, significant evidence from a well-acknowledged conditional cash transfer program — *Oportunidades* in Mexico is exploited for empirical analysis, using data from the program concerned urban areas in Mexico during a research period from 2002 to 2004.

With the support of the causal model of return to education (Card 1995) , theoretical analysis shows that the scheme of conditional cash transfer in educational intervention provides sufficient economic incentive for impoverished households by reducing the schooling costs so that enabling the economically disadvantaged youth to increase their education accumulation. Empirical evidence confirms this theoretical analysis by showing that the treatment group who receives the schooling impact of the program is education advantaged comparing with the non-intervention group. With this educational discrepancy as a prerequisite, the following comparison research on the earnings of the education advantaged group and the education disadvantaged group shows that — earnings of youth with advantaged schooling attainment increase at an evident higher rate over the two-year research period. This empirical result infers a salient effect of education accumulation on the achievement of poverty reduction and pro-poor growth. Estimations are applied with the methods of difference-in-differences and difference-in-differences propensity score matching respectively to control for the observable and unobserved heterogeneity which causes selection bias. As a result, the two approaches give analogous findings, both indicating positive impact of education on earnings for pro-poorness of growth.

In conclusion, a short-term empirical analysis in this paper using micro-data from the Mexican human capital development program — *Oportunidades*, shows that education accumulation plays a critical role in the enhancement of earnings for economically disadvantaged youth and therefore promotes the progress of poverty reduction and pro-poor growth. With this plot in mind, one can expect that increasing investment in education for children and youth in impoverished situations could expect promising effect on breaking the vicious circle of poverty; on providing them with more opportunities for future development and better well-being; and on the achievement of pro-poorness of growth as a whole. Further research could focus on the long-term effect of education on earnings for poverty reduction and pro-poor growth, as well as investigating the evidence from other parts of economically disadvantaged and developing areas around the world.

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Appendix

The Complete List of Conditioning Variables[14] Used in Generating Propensity Scores in DiD-PSM[15]

Categories and Variables	Description
Geographic locations	
Entity6_25_26_28	=1 if the household locates in Coahuila, or Sinaloa, or Sonora, or Tamaulipas; =0 if otherwise
Entity11_16_24	=1 if the household locates in Guanajuato, or Michoacan, or San Luis Potosi; =0 if otherwise
Entity13_15_21_29	=1if the household locates in Hidalgo, or Estado de Mexico, or Puebla, or Tlaxcala; =0 if otherwise
Entity4	=1 if the household locates in Campeche; =0 if otherwise
Entity7	=1 if the household locates in Chiapas; =0 if otherwise
Entity12	=1 if the household locates in Guerrero; =0 if otherwise
Entity17	=1 if the household locates in Morelos; =0 if otherwise
Entity27	=1 if the household locates in Tabasco; =0 if otherwise
Poverty status of the household	
Cal_soc	Socioeconomic poverty score of the family
Cal_soc2	Square of the socioeconomics poverty score
Poor1	=1 if the household's socioeconomic poverty's classification =1 "poor"; =0 if otherwise
Alpoor1	=1 if the household's socioeconomic poverty's classification =2 "almost poor"; =0 if otherwise
Cal_tam	Tamizaja poverty score of the family

[14] Source and reference: ENCELURB 2002; Behrman *et al*. (2010, Table B.1).
[15] The DiD-PSM estimation in this paper is applied with the STATA module "diff" which authored by Villa, J.M., Nov, 2011.

Cal_tam2	Square of the Tamizaja poverty score
Poor2	=1 if the household's Tamizaja poverty's classification =1 "poor"; =0 if otherwise
Alpoor2	=1 if the household's Tamizaja poverty's classification =2 "almost poor"; =0 if otherwise
Soc_miss	=1 if the poverty classification information is missing; =0 if otherwise
Socioeconomic characteristics of the household	
dirtfloor	=1 if the household has dirt floor; =0 if otherwise
floormiss	=1 if the floor material information is missing; =0 if otherwise
provceil	=1 if the ceilings of the household is made of provisional materials; =0 if otherwise
ceilmiss	=1 if the ceilings material information is missing; =0 if otherwise
provwall	=1 if the walls of the household is made of provisional materials; =0 if otherwise
wallmiss	=1 if the walls material information is missing; =0 if otherwise
rooms	Total number of rooms in the house
rmiss	=1 if the information of the number of rooms is missing; =0 if otherwise
hwater	=1 if the house has inside water system; =0 if otherwise
hwmiss	=1 if the water information is missing; =0 if otherwise
hwc	=1 if the house has a toilet or latrine inside; =0 if otherwise
wcmiss	=1 if the WC information is missing; =0 if otherwise
ownhs	=1 if the house is owned by a member of the family; =0 if otherwise
ownhsmiss	=1 if the house ownership information is missing; =0 if otherwise
renths	=1 if the house is rented; =0 if otherwise
atebeef	=1 if last week beef was eaten in the household; =0 if otherwise
beefmiss	=1 if beef information is missing; =0 if otherwise
atechicken	=1 if last week chicken was eaten in the household; =0 if otherwise

chkmiss	=1 if chicken information is missing; =0 if otherwise
atepork	=1 if last week pork was eaten in the household; =0 if otherwise
porkmiss	=1 if pork information is missing; =0 if otherwise
atefish	=1 if last week fish was eaten in the household; =0 if otherwise
fishmiss	=1 if fish information is missing; =0 if otherwise
ateegg	=1 if last week eggs were eaten in the household; =0 if otherwise
eggmiss	=1 if egg information is missing; =0 if otherwise
atemilk	=1 if last week milk was consumed in the household; =0 if otherwise
milkmiss	=1 if milk information is missing; =0 if otherwise
newspaper	=1 if last week the household spent money on newspaper; =0 if otherwise
nwspmiss	=1 if newspaper information is missing; =0 if otherwise
hcar	=1 if the household has a car; =0 if otherwise
htruck	=1 if the household has a truck; =0 if otherwise
htv	=1 if the household has a set of television; =0 if otherwise
hrefrg	=1 if the household has a refrigerator; =0 if otherwise
hstove	=1 if the household has a stove; =0 if otherwise
hwshm	=1 if the household has a washing machine; =0 if otherwise
hanimal	=1 if the household has working or consumption animals; =0 if otherwise
business	=1 if the household has a business; =0 if otherwise
Education and employment situation of the head of the household	
headfe	=1 if the head of the household is a female; =0 if otherwise
Edu0	=1 if the education of the head of household is less than or equal to 5 years; =0 if otherwise
Edu1	=1 if the education of the head of household is equal to 6 years; =0 if otherwise

Edu2	=1 if the education of the head of household is longer than 6 years but less than or equal to 9 years; =0 if otherwise
Edu3	=1 if the education of the head of household is longer than 9 years but less than or equal to 12 years; =0 if otherwise
Edu4	=1 if the education of the head of household is longer than 12 years; =0 if otherwise
edumiss	=1 if the education information of the head of household is missing; =0 if otherwise
fhdw	=1 if the head of household is employed; =0 if otherwise
fhdwmiss	=1 if the employment information of the head of household is missing; =0 if otherwise
phdw	=1 if the partner of the head of household is employed; =0 if otherwise
phdwmiss	=1 if the employment information of partner of the head of household is missing; =0 if otherwise
<u>Demographic features of the household</u>	
Tothm1	=1 if the total number of the household members is equal to 1; =0 if otherwise
Tothm2	=1 if the total number of the household members is equal to 2; =0 if otherwise
Tothm3	=1 if the total number of the household members is equal to 3; =0 if otherwise
Tothm4	=1 if the total number of the household members is equal to 4; =0 if otherwise
Tothm5	=1 if the total number of the household members is equal to 5; =0 if otherwise
Tothm6	=1 if the total number of the household members is equal to 6; =0 if otherwise
Chidy6	Number of children younger than 6 years in the household
Childy6miss	=1 if the information of number of children younger than 6 years in the household is missing; =0 if otherwise
age	The age of the youth under research
male	=1 if the gender of the youth under research is male; =0 if female
<u>Indications of consumption habits of the household</u>	
hspf	=1 if extra income for the husband is spent on food; =0 if otherwise

hspsc	=1 if extra income for the husband is spent on shoes and clothes; =0 if otherwise
hsph	=1 if extra income for the husband is spent on things for house; =0 if otherwise
hspmiss	=1 if the information of the husband's expenditure for extra income is missing; =0 if otherwise
wspf	=1 if extra income for the wife is spent on food; =0 if otherwise
wspsc	=1 if extra income for the wife is spent on shoes and clothes; =0 if otherwise
wsph	=1 if extra income for the wife is spent on things for house; =0 if otherwise
wspmiss	=1 if the information of the wife's expenditure for extra income is missing; =0 if otherwise
Participation in other anti-poverty program	
ptortilla	=1 if the household participates in the free tortilla program; =0 if otherwise
pmilk	=1 if the household participates in the free milk program; =0 if otherwise
pmoney	=1 if the household participates in the DIF program; =0 if otherwise
pbrkfst	=1 if the household participates in the free breakfast for school kids program; =0 if otherwise
pschlor	=1 if the household participates in scholarship program other than Oportunidades; =0 if otherwise
pint	=1 if the household participates in the INI program; =0 if otherwise
phouse	=1 if the household participates in the housing subsidies program; =0 if otherwise
pprocampo	=1 if the household participates in the PROCAMPO program; =0 if otherwise
pfonaes	=1 if the household participates in the FONAES program; =0 if otherwise
ppet	=1 if the household participates in the PET program; =0 if otherwise