The effect of child labour and low education on adult's labour market experience. The case of Guatemala

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Preliminary version. Please do not quote

Abstract

The aim of this paper is to analyze the causal effect of a low investment in education and the early entry into the labour market on labour market experience during adulthood. Following a quasi-experimental approach we establish the conditions of an experimental study applying a matching method that assures for the comparability between control and treatment groups. We identify different types of treatment depending on age at first entry into the labour market and on the level of education achieved. Then we estimate the effect of the treatment on adult's employment status and labour earnings. We focus on males and draw our data from the Guatemala Living Standard Measurement Survey (ENCOVI, 2000). We find that accumulated education assures a higher level of earnings in adulthood. Males that performed child work obtain a lower remuneration in the labour market, but have a higher probability of finding a job in adulthood. Experience matters among those who performed child labour since work experience has a positive effect on earnings, especially for older cohorts.

JEL Classification: C21, J13, J21, J24, O15, O54

KEYWORDS: Child Labour, Education, Returns to Education, Wellbeing, Longitudinal data, Matching Estimators, Average Treatment Effects, Unconfoundedness, Guatemala.

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1 Introduction

In the poorest countries the decision to invest in education is often subject to the necessity to send children to work. The impact of child labour on future adults' earnings is strictly related to the choice of investment in education and to the returns on the investment in human capital in the labour market (see for example Checchi, 2005).
While returns to education, i.e. causal effects of education on earnings, have been widely studied with reference to developed countries, this issue has been poorly investigated in the context of developing countries.

The literature of returns to education focuses on the impact of different levels of education on earnings with the assumption that children start to work immediately after school age (see for example the pioneering research of Becker, 1964, 1967 and Becker-Chiswick, 1966). This is a strong assumption in general but becomes unrealistic in developing countries where households are so poor that children are often forced to work during school age. At the same time, it is also not possible, as often done, to summarize the individual experience with the years devoted to an activity, since in some unskilled works, the period of "experience" can be restricted to a very small initial period at work. However, in developing countries the returns to education can be different than those in developed countries and the specific knowledge acquired in a job may play a part in the trade off between human capital and experience (see Cigno, 2004, Cigno and Rosati, 2005). This paper gives a contribution to this literature applying the framework of causal inference to measure the impact of child labour on adults' employment and earnings. The effect of child work on earnings and employment can not be interpreted as the full complement (with opposite sign) of the effect of education on the same output variables. This is firstly because work and study are not mutually exclusive for children since in the majority of the cases children combine work and study. Secondly, because the specific effect of work and study will be different. This study aims to compute the effect of education and child work on employment and earnings in Guatemala. In principle, it is possible to estimate the effect of education, the effect of child labour and the effect of combining child labour with schooling. However, we prefer to study the first two effects separately and compute them with respect to some subgroups of the population in order to capture a specific effect. For example, restricting the computation of the causal effect of education on earnings for those individuals that experimented child labour allows us to study the causal effect of education for individuals that combined child work and schooling during childhood.

The paper is organized as follow: section 2 describes the Guatemala LSMS survey and gives some descriptive analysis of the dimension of employment and earnings by education levels and child work definitions, section 3 describes the econometric methodology applied to compute causal effect with two treatments, section 4 reports the causal effect of education and child work on employment and earnings, section 5 concludes.

2 Data set and variable definition

This study aims to answer to the following research questions: (i)May the level of education a children achieve during childhood *causes* his/her employment opportunities and earning capacity in adulthood? (ii) May work during childhood *causes* different employment opportunities and earning capacity in adult life?

To answer these two questions we rely on a causal inference approach. The causal statement is intrinsically related to time and require to compare outcome at least in two points in time. In fact there is a time ordering between causes and effects since the causes must precede the effect in time.

The importance of time in causal study impose the use of panel data or event history data. The use of both type of data present advantages and disadvantages. In panel studies the same persons or units are re-interviewed or observed at a series of discrete points in time. This means that there is information about the events at each pre-determined survey point. The weakness of this type of data is that the repetition of interviews and the inevitable attrition of the sample make them very expensive and seldom available for developing countries[1].

The use of retrospective studies represent a valid alternative to the use of panel studies since they collect information on previous points in time during the same interview and have the advantage of normally being cheaper than the collection of data with a long-term panel study. However, they also suffer from the limitation that respondents can hardly remember the timing of changes. Particularly problematic may be retrospective questions concerning motivational, attitudinal, cognitive or affective states. For these non-factual data, panel studies have the advantage of recording current states of the same individual over time. Another limit of retrospective data is that, since are necessarily based only on survivors, they may result in a misrepresentation of a specific population. Thus, subjects who have died or migrated during the study will necessarily be omitted[2].

In this study we rely on the Guatemala Living Standard Measurement Survey (ENCOVI, 2000) that includes some retrospective questions with particular regards on individual labour and educational history whereas some questions on parent's history, for parents dead or absent, are addressed to children in the households.

The ENCOVI is a multi-purpose, nationally representative sample survey, comprising 7276 households for almost 38000 individuals. The survey is representative at the national and regional level as well as in urban and rural areas. The ENCOVI is a particularly rich survey: it includes not only the standard modules present in the LSM survey such as characteristics of the household, dwelling, health, education, migration, economic activities, fertility, expenditure and so on; but also includes modules on social capital, exclusion, adverse situation, citizen security, participation in organization, citizenship participation,

[1] In panel studies the composition of the sample normally diminishes selectively over time with a particularly strong reduction during the first panel waves (Blossfeld and Rohwer, 2002)

[2] With regard to this limitation and in the logic of the study of the causal effect of child work on well-being; by using retrospective data we may not study the effect of child work on mortality since we do not have information on child labour for deceased individuals.

participation and benefits from social assistance programs, training for work and time use. The richness of the information and the good quality of the data-set allows us to investigate many different issues. For our purpose we focus on modules on education and economic activities. The module on education is addressed to children less than seven years old for preschool education and to all individuals seven years and older for questions on schooling. Questions on economic activities are addressed to all household members 5 years of age and older. Direct informants are father or mother for children under 12 years of age. Questions on the characteristics and composition of the household" such as age of household components, highest education level, and the principal occupation of parents, are also included in the questionnaire.

Of particular interest for address our research questions in a causal assessment framework are some retrospective questions included in the survey. For example the questions "how old was ... when s/he registered the first time in first grade of primary school?" and "how old was ... when s/he registered the first time in first grade of secondary school?" are used to establish a variable that control for the education level of an individual when s/he enter the labour market for the first time. Another crucial retrospective question is "How old were you when you had your first paying job or your first job helping without pay on the family farm or business?". This variable allows us to define the child work variables. Turning to the weakness of the retrospective data, the question we use for this study have the advantage of be related to factual data that for their nature make easer to remember the data in which the event occurred. On the other hand, since this questions only inform on the starting point of an event, they are unable to provide information on the events occurred between the starting point and the time of interview[3]. This implies, for example, that we may observe at which age a child start to work for the first time but we may not observe if afterward s/he exit the labour market or how many times s/he exit and entered in the labour market. The same considerations are also valid for variables on schooling. This implies that we are able to evaluate the causal effect of start to work and/or study at a certain age without be able to differentiate among children with different path on job and school history between the starting point and the interview time.

2.1 Extent of children's work and school attendance

Guatemala legislation contains some rules for the protection of children. The National Labour Code (Codigo de Trabajo) set the basic minimum age to work at 14 year old. Children under 16 are prohibited from engaging in "unhealthy and dangerous" conditions and all minors are prohibited from engaging in night work. However, the Inspector General of Labor (IGT) has authority to grant a work permit to an underage child if that child is an apprentice, "extreme poverty" warrants the child's contribution to the family income, or if he or she is engaged in work that is light in "duration and intensity".The Guatemalan labor code's provisions concerning the work of children have not effectively limited the

[3]Panel data are not necessarily more appropriate on this since they also collect information in stated points in time. On the other hand, retrospective questions that investigate on the duration of states, could overcame this problem.

number of children working and the number of children under 14 who work is definitely higher the the number of authorization granted by the IGT.

According to the international legislation on child labour the minimum age to be engaged in economic activities should not prevent the child from the completion of compulsory schooling, and in any case shall not be less than 15 years (ILO convention No. 138). In Guatemala school starts at 7 and the compulsory education (ciclo basico) requires 9 years of study to be completed. Making schooling compulsory up to the age of 15 and establishing as minimum age to work the age of 14 years the national legislation, currently, appear inconsistent with the international legislation. This arise in spite of the fact that in 1990 Guatemala ratified ILO Convention No. 138 on the Minimum Age and the UN Convention on the Right of the Child. More recently, in 2001, the country also ratified the ILO Convention No. 182 on the Worst Form of child labour.

However, because of the absence of effective mechanisms for the enforcement of legal regulations children's work is very common in Guatemala. The country ranks third highest in prevalence of children's work of the 14 Latin American and Caribbean (LAC) countries where data are available, behind Bolivia and Ecuador. In terms of GDP per capita, Guatemala ranks fifth lowest of the 14 LAC countries.

Coherently with international legislation and in order to have comparable information among international statistics we focus on children aged 7-14. Table 1 shows that one-fifth of children in this age group are engaged in work (about 507,000 in absolute terms). It also shows that a significant proportion of children are reported as neither working nor attending school (about 18 percent).

This category often includes children, mainly girls, that contribute to household welfare, i.e. performing household chores. Children of this group particulary merit policy attention. They neither benefit from schooling nor from the learning-by-doing as children that work in light work and accumulate specific experience. Moreover some studies suggest that this group of children is more at risk of entering in work when households are faced with sudden loss of income or other types of shock (Guarcello, Mealli and Rosati, 2003). Finally this category may include the worst form of child labour that for their characteristics may be misreported during a survey interview.

Table 1 also shows that gender differences in child activity status exists. Boys are more likely to work, but girls are more likely to be neither working nor attending school. Important geographical differences are also present. Children are more likely to work and less likely to study if they live in a rural area.

In a view of long period, the persistent high proportion of children that work and do not attend school in Guatemala impose to understand the *causal* effects that perform child labour during childhood may have on children well-being once adults. Individuals who enter in the labour market very young may find difficult attend school and probably will be the low educated and low skilled worker of the future. In turn, a country with an unskilled and low educated labour force will hardly be able to deal the challenge for growth.

Table 1: **Children aged 7-14, by sex, type of activity and residence**

Sex	Activity	Urban		Rural		Total	
		%	No.*	%	No.*	%	No.*
Male	Work only	4.3	19	12.3	104	9.5	123
	Study only	73.9	334	53.9	456	60.9	790
	Work and study	10.1	45	19.7	167	16.4	212
	Total work**	14.4	64	32.0	271	25.9	335
	Total study***	78.2	379	73.6	623	67.3	1002
	Neither	11.8	53	14.1	119	13.3	172
Female	Work only	4.1	18	6.8	54	5.9	72
	Study only	74.6	323	58.4	464	64.1	787
	Work and study	7.6	32	8.3	66	8.1	99
	Total work**	11.7	50	15.1	121	14.0	172
	Total study***	82.2	356	66.7	530	72.2	887
	Neither	13.8	60	26.5	210	22	270
Total	Work only	4.2	37	9.7	158	7.7	195
	Study only	74.2	657	56.1	920	62.4	1577
	Work and study	8.8	78	14.2	233	12.3	311
	Total work**	13.0	115	23.9	392	20.0	507
	Total study***	83.0	736	70.3	1153	74.7	1889
	Neither	12.8	113	20.1	330	17.5	442

* Numbers expressed in thousands

** 'Total work' refers to children that work only and children that work and study.

*** 'Total study' refers to children that study only and children that work and study.

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by UCW project team.

2.2 Definition of key variables

As specified, we are interested in the study of the effect of a change in the level of education on an adult's employment status and earnings. Since employment and earnings are intrinsically less stable in the first and in the last phase of working life, we concentrate our attention on adults in the age-class 25-49. In addition, earnings for individuals in old age may not be representative of the real returns to education and work experience. This is for two reasons. The former is an economic reason and rely on the fact that because of the deterioration of human capital the earnings of an old man can be lower than that of a young one. In addition, the estimation of labour productivity for retired can result complex since it is not evaluated by the labour market. The latter is due to the use of retrospective data that makes makes the information given by older individuals less reliable.
We study the effect of two different types of policies. The first aims to study the causal

effect of an increasing in educational level (considering three level of education), the second aims to evaluate the causal effect of a increasing in the age in which children enter in the labour market for the first time(considering three age). For both policies three binary variables are created. The variables created to study the causal effect of the policy on school attendance are the following:

$$Primary \begin{cases} 1 \text{ if individual has at least a primary degree} \\ 0 \text{ otherwise} \end{cases}$$

$$Compulsory \begin{cases} 1 \text{ if individual has at least a compulsory degree} \\ 0 \text{ otherwise} \end{cases}$$

$$Secondary \begin{cases} 1 \text{ if individual has at least a secondary degree} \\ 0 \text{ otherwise} \end{cases}$$

The variables created to study the policy on the reduction of child labour are the following.

$$child\ work14 \begin{cases} 1 \text{ if individual started to work under 14 years of age} \\ 0 \text{ otherwise,} \end{cases}$$

$$child\ work12 \begin{cases} 1 \text{ if individual started to work under 12 years of age} \\ 0 \text{ otherwise,} \end{cases}$$

$$child\ work10 \begin{cases} 1 \text{ if individual start to work under 10 years of age} \\ 0 \text{ otherwise.} \end{cases}$$

Looking at the output variables we define *employed* equal to one if an individual in the last week worked for a salary or wages, for himself, or providing paid work to other persons. Individuals that did not work in the last week but (i) worked at least one hour in the last week, (ii) helping in a family business, in construction or on a farm, (iii) selling lottery tickets, food, magazines or other products, washing, ironing or sewing clothing for other persons, (iiii) cleaning cars, shining shoes or another similar activity, also are defined as employed. In addition, we treated as employed individuals that, despite not working last week, have some job or business from which they were absent for leave, illness, vacation, maternity leave or other motives. Finally, individuals that in the last 12 months worked for a salary or wage or helped with a family business or for other persons are considered employed.
The second output variable is *earnings*. It represents total annual labour earnings for each individual. It is constructed as the sum of the following components: the annual income or earning for individuals that work as independent workers[4], the annual gross salary before deduction including commissions, overtime, representation costs, per diems, and other

[4]Independent workers are those that work on their occupation: (i)as boss or owner of the company or work in their own farm or as an active member (ii) as worker for himself or his family.

required contributions for dependent worker[5]. It also includes payment for bono 14, tips in cash, the equivalent value of annual free food or subsidized supplies, the equivalent value of annual housing received as part of the pay, the equivalent value of annual clothes or uniforms received without cost, the equivalent value of free transportation or additional payment for transportation received, Christmas bonus, the equivalent value of the right to vacations. Obviously, earnings variables is defined only for employed individuals. The earnings for unemployed, inactive or unpaid workers are reported equal to zero, whereas missing values are left for individuals that work but do not respond to questions on their earnings.

2.3 Descriptive analysis

Before analysing the causal effect of education and child work we describe the observed relationship between the treatment variables (education and child work) and the output variables (employment and earnings).

Table 2: **Number and percentage of individuals by educational levels and age class**

Age class	Primary		Compuls.		Second		Total
	No.	%	No.	%	No.	%	
25-30	1147	45.66	623	24.8	415	16.52	2512
35-40	1531	39.00	848	21.83	567	14.60	3884
40-45	530	33.00	318	19.64	240	14.82	1619
45-50	433	30.51	234	16.49	175	12.33	1419
Total	3641	38.59	2023	21.44	1397	14.81	9434

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000.
Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

In table 2 we report the individual's distribution by age class and level of education achieved. The first number reported for each category (cell) is the number of individuals and the second number is the percentage of individual for the reported level of education in each age class. The table shows that, for all levels of education, the percentage of educated individuals increases going from the older to the younger class. This suggests an increasing trend in the level of education.

In table 3 we report the individual distribution by age class and child work definitions. As in tab 2 for each cell we report the number of individuals and the percentage by age class. The table shows a decreasing percentage of child workers passing from the older age class to the younger. However this trend is less evident than that described in table 2 for

[5]Dependent workers are those that work in their occupation as: (i) a government employee, (ii) an employee or worker in a private company, (iii) a day worker or unskilled worker, (iv) domestic employee.

Table 3: **Number and percentage of individuals by child work definitions and age class**

Age class	Child work14		Child work12		Child work10		Total
	No.	%	No.	%	No.	%	
25-30	1382	54.93	910	36.17	436	17.00	2516
35-40	2307	59.06	1532	39.22	754	19.30	3906
40-45	929	57.03	601	36.89	309	18.97	1629
45-50	833	58.00	554	38.71	284	19.85	1431
Total	5451	57.49	3597	37.94	1783	18.80	9482

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

education. More in detail, a peak in the percentage of child workers is reported in the age class 35-40 for all the definitions of child work. Since data were collected in 2000 the first definition of child work refers to children that started to work before the period 1974-1979 (the second definition refers to the period before 1972-1977 and the third definition refers to the period before 1970-1975). Finding an explanation for this regularity in observed data could be very complex, however it seems that child work follows the volatility of some economic parameters (see for instance Portes, 1989; Franks, 1994; Pradhan and van Soest, 1995; Galli and Kucera, 2003).

Figure 1 shows the percentage of employed by age class and educational levels whereas figure 2 shows the percentage of employed by age class and child work definitions. In figure 1 we note that individuals with a higher level of education are more likely to be employed when adult. This is verified for all the educational levels. The graph also shows that the percentage of employed increases only slightly as the level of education increases suggesting a small marginal effect of higher levels of education on employment. In figure 2 the percentage of employed in adulthood is higher for individuals that worked during childhood. However, if we left out the youngest class, we note that for children that started to work very young (before 12 years or before 10 years of age) the employment rate in adulthood is lower than that of those who started to work before 14. Empirical results seem to suggest that child work has a positive effect on the probability of being employed in adult life. This effect is especially evident in the first phases of work life where the difference in the percentage of employment between individuals that experimented child work (following the three definitions) and those that did not experiment child work is higher. This positive effect seems stronger if individuals started to work during adolescence and tend to decrease if children started to work younger.

In figures 3 and 4 we report earnings by age class and levels of education in urban and rural areas. Figure 3 shows that in both urban and rural areas an adult's earnings is higher for a higher levels of education. Earnings follow the same trend for all the

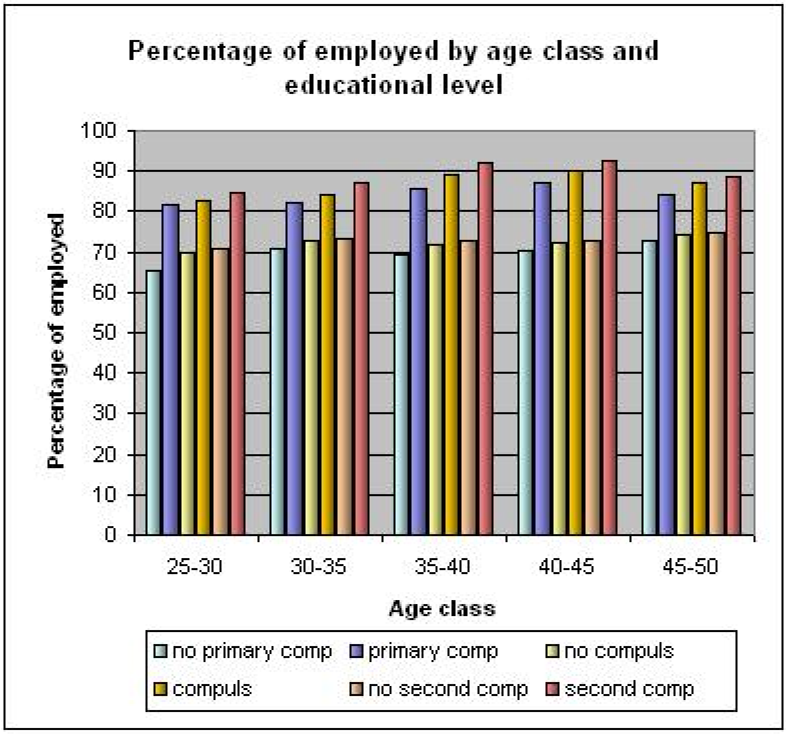

Figure 1: **Percentage of employed by age class and educational levels**

levels of education both in urban and rural areas. However, while in urban areas the distance between the different levels of education is constant, in urban areas the difference in earnings tend to increase in periods in which earnings increase and tend to decrease in periods in which earnings are lower. More precisely, earnings for individuals with a primary level of education tend to be constant by age class and the difference in remuneration among education levels is essentially due to the higher level of earnings of individuals with compulsory or secondary education in periods in which earnings increase. We note that for both urban and rural areas the earnings trend is not monotonic but appears cyclic. Moreover, when comparing the results in the two areas we may observe a countercyclical pattern of urban and rural earnings. In a more detailed graph in which we report earnings for individuals from 25 to 49 years of age and educational level we find a cyclical pattern with an increasing trend of earnings (see figure 3 in Appendix). The cyclical pattern of earnings could be due to the use of a measure of earnings that includes all labour earnings and not only wages (that are in general more stable) and to the volatility of the economy in Guatemala.
Drawing in the same graph for individuals with and without a certain level of education (primary-compulsory-secondary) we find that in urban areas, earnings are always higher

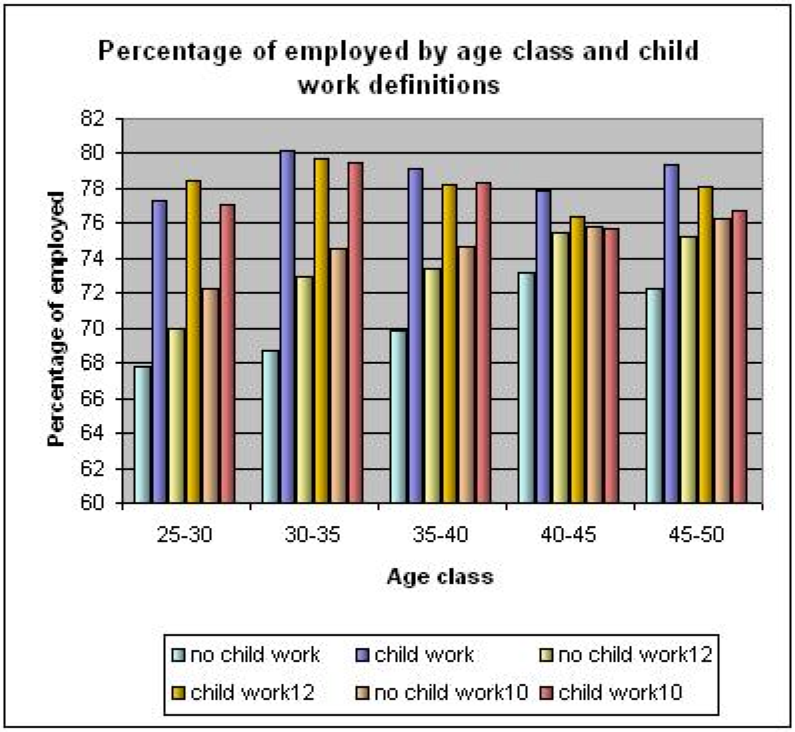

Figure 2: **Percentage of employed by age class and child work definitions**

for individuals with a diploma than those without it.

Figure 5 shows earnings by age class and definitions of child work in urban areas. We observe an increase in earnings through age class for individuals that worked before 14 years of age. Comparing earnings of individuals that started to work before 12 years of age with those of individuals that started to work before 14 years of age we note that the first are also increasing and almost of the same magnitude than the latter but seems to be more volatile. Finally, earnings of individuals that worked before 10 years of age are very volatile through life work. Figure 6 shows that the situation in rural areas is rather different. Earnings of individuals that start to work before 14 are more or less stable through work life whereas earnings for individuals that work before seem to have a concave patten through work life with low earnings in the first and last phases of work and high earnings in the central phases. If we report earnings by age for individuals from 25 to 49 years of age and child work definition, we find, for all the definitions of child work, a slightly increasing pattern with a strong volatility. The variability in earnings seams to be higher for individuals that start to work younger (see figure 4 in Appendix). Drawing in the same graph earnings for individuals that experimented or did not experiment child work for all the definitions of child work (child work14, child work12, and child work10), we find that generally, both in urban and rural areas, the first have lower earnings than

the latter. Some irregularities are found for the last definition of child work (See figure 6 in Appendix).
It should be noted that those described above are only correlated between observed variables and that we cannot interpret them as causal relationships. For instance, we are not saying that education and child work causes occupation but only that we observe a higher percentage of employed among educated children and among children that experimented child work. This empirical relationship could be the result of numerous effects that we are not observing. For example the individual in the group of "child work" and those in the group of "no child work" could be completely different in their individual and household characteristics. In the next sections we describe the causal inference approach and we attempt to compute the causal effect of education and child work.

3 Econometric methodology

Causal inference is an important tool in the programme evaluation since it considers "what if" questions. The achievement of a certain level of education and the increasing of the age in which a child enter in the labour market may be considered as two different programmes. Each child may be assigned to a programme that promotes school attendance or to a programme that aims to reduces child work enrolment. In the case of the schooling programme we may suppose that the child assigned to the programme is supported to achieve a certain level of education (e.g. compulsory education level). In the case of the programme on the reduction of child labour the child assigned to the program is, for example, be helped to start work after the minimum age imposed by law (e.g. 14, as declared by ILO). In both cases the child involved in the programme are considered as treated; e.g. subject to a treatment. The children that will not follow the programme can be considered as belonging to a control group. The criterium used for the assignment to the programme assumes particular importance to estimate the causal effect of the treatment.

In our study children are not really assigned to a programme according to a an experimental design and so a "selection problem may arise.

However, even in the absence of a specific programme we may still try to identify the causal effect of going to school or work during childhood. In this case, children decide by themselves, or their parents decide for them, if to be treated, i.e. to obtain the compulsory educational degree or go to work before 14.

In the absence of a specific programme, the main econometric problem is to estimate the effect of child labour or a school degree is that these variables can be endogenous. The parents' decision on investment in education and/or on send their child to work can dependent on the expectations on future employment and earnings, that is, some variables are related both to the treatment and to the output. Thus, if treatment variables are endogenous no causal interpretation could be given because treatment and control groups are different not only in their treatment status. The applied economic literature has studied causal effects even in non experimental settings using the framework of *randomized experiments* and the *potential outcomes approach* (Holland 1986, Rubin 1974). This approach defines the causal effect as the comparison of the potential outcome variables on the same unit measured at the same time. It is applicable both at two treatments program and multiple treatments program.

3.1 Two treatments

Let us assume that for each unit there exists only two levels of treatment, to be treated or non-treated. In this case, following the potential outcome approach, the casual effect is obtained by the comparison between the outcome of an individual if treated and the outcome of the same individual if not treated at the same time. Let $Y(0)$ be the value of the outcome if a unit is exposed to treatment $T = 0$ and $Y(1)$ the value of the outcome if a unit is exposed to treatment $T = 1$; the individual causal effect is defined as $Y(1) - Y(0)$. The difficulty to compute the causal effect of a single unit (e.g., an individual) is related to the impossibility to observe the *contrafactual*. For the same individual at the same time we cannot observe both $Y(0)$ and $Y(1)$. As stressed in Holland (1986), it is impossible to observe the value $Y(1)$ and the value $Y(0)$ for the same unit and, therefore it is impossible to observe the effect of T on one unit. A possible solution for this problem, known as *the fundamental problem of causality*, is to use a statistical approach that focuses on the computation of an average causal effect in the population or in a subgroup of the population. The average causal effect is defined as $E[Y(1) - Y(0)]$. It could be computed with regard to different subgroups of the population. A parameter of interest is the *Average Treatment Effect* defined as $E[Y(1) - Y(0)]$ which is the difference between the outcome if treated and the outcome if untreated for a person randomly drawn from the population. A more informative measure is the *Average treatment effect on the treated* defined as $ATT = E[Y(1) - Y(0)|T = 1]$, which is the expected outcome difference for a person randomly drawn from the subpopulation of participants in the program.

As said before, the treatment assignment can depend on the outcome variables, $Y(0)$ and $Y(1)$, but may also depend on other measurements, X. Thus, we can write that $P(T = 1 \mid Y(0), Y(1), X)$. In the computation of the causal effect we deal with a selection bias problem. Selection bias arises first because individuals select (or are assigned to) a programme on the bases of some known characteristics and assumption on the expected outcome value. Secondly because unobserved characteristics are correlated with the programme participation decisions and the potential outcomes. The ideal solution to avoid selection bias is to assign individuals randomly to the programme. Randomization ensures that the probability to be assigned to a programme is independent from the potential outcomes and that the differences between treatment and control group are not systematic. However a random assignment to a program, i.e. medical or social program, is often not practicable for ethical reasons. An alternative is given by the *quasi-experimental approach*. The idea is to mimic a random experiment creating a comparison group which is as similar as possible to the treated group. The “Selection on observable assumption” states that the value of the treatment of interest is independent of potential outcomes after accounting for a set of observable characteristics, X. This assumption, also known as exogeneity of treatment assignment, is equivalent to unconfoundedness. Unconfoundedness holds when

$P(T = 1 \mid Y(0), Y(1), X) = P(T = 1 \mid X)$ and X is fully observable. Following Rosenbaum and Rubin (1983) we have unconfoundedness when

$$Y(1), Y(0) \perp T \mid X \tag{3.1}$$

It is important to note that the unconfoundedness assumption cannot be tested but can be a useful staring point. The implicit assumption is that, if we are able to control for the distribution of all the relevant observable covariates, we potentially are controlling also for unobservable characteristics as long as those are associated with observables[6]. Under unconfoundedness the average treatment effect can be identified within subgroups of the population that have the nearest possible value of X. The ATT can be defined as follows:

$$\begin{aligned} E[Y(1) - Y(0) \mid T = 1] = E\{E[Y(1) - Y(0) \mid T = 1, X = x]\} = \\ E\{E[Y(1) \mid T = 1, X = x] - E[Y(0) \mid T = 1, X = x]\} = \\ E\{E[Y(1) \mid T = 1, X = x] - E[Y(0) \mid T = 0, X = x]\}. \end{aligned} \tag{3.2}$$

The ATT effect in the population can be obtained as a mean of the ATT in the subgroups of the population, so that

$$E[Y(1) - Y(0) \mid T = 1] = E\{E[Y(1) - Y(0) \mid T = 1, X = x]\}. \tag{3.3}$$

In principle, one would like to compare the potential outcomes of individuals that have the same values for all the covariates in order to obtain an estimate of the causal effect. If the covariates, X, are continuous, controlling for them may require some smoothing techniques. Under unconfoundedness a regression model may be used that adjusts for pre-treatment covariates. In the presence of a large number of covariates it can be difficult to find an appropriate specification of the model. In addition, using the regression model could be difficult to check for the extent overlapping of the distributions of the treated and control group. The conditional independence assumption 1 requires the identification of a "region of common support". The region of common support is given by the $X = x$ which are in common between treated and control units. Let R^1 be the support of X among the participants in the program and let R denote the support of X in the population. R will be the union of the two treatment group supports: $R = R^1 \cup R^0$. The average treatment effect on the treated $E[Y(1) - Y(0) \mid T = 1]$ is only defined if $R^1 \subseteq R^0$, i.e. if any x among the participants in treatment also belongs to the support of the control subpopulation. Analogously, the identification of the average treatment effect $E[Y(1) - Y(0)]$ requires that $R^1 = R^0 = R$. This condition is automatically satisfied in the case of randomized experiments since each unit has a positive and equal probability to be treated or not treated.

[6] The analyses involving adjustment for unobservable covariates tend to be very sensitive to distributional and functional specification (see Heckman and Hotz, 1989 for theoretical discussion and Lalonde, 1986; Dehejia and Wahba, 1999; Copas and Li, 1997 for theoretical and applied papers).

In order to limit these difficulties the estimation can be reduced into a one dimensional problem using the propensity score technique. The propensity score is defined as the conditional probability of receiving a treatment given pre-treatment characteristics (Rosenbaum and Rubin, 1983):

$$p(X) \equiv Pr\{T = 1 \mid X\} = E\{T \mid X\}. \tag{3.4}$$

where $T = \{1, 0\}$ indicates the exposure to treatment and X is the vector of pre-treatment covariates.
The "balancing of pre-treatment variables given the propensity score" says that units (e.g., individuals) with the same value of the propensity score have the same distribution of observable characteristics independently of the treatment status. In other words, *balancing property ensures that* T *is independent of* X *given the propensity score,* $p(x)$. More formally we can say that

$$T \perp X \mid p(x) \tag{3.5}$$

The "unconfoundedness given the propensity score" says that the exposure to treatment and control is random for a given value of the propensity score. This assumption requires that the assumption of unconfoundedness (1) and the balancing property (5) are verified. Given 1 and 5 we get that

$$Y(1), Y(0) \perp T \mid p(X) \tag{3.6}$$

if the propensity scores, $p(x)$ is known the Average Treatment Effect on Treated (ATT) can be estimated as follows:

$$\begin{gathered} E[Y(1) - Y(0) \mid T = 1] = EE[Y(1) - Y(0) \mid T = 1, p(X)] = \\ E\{E[Y(1) \mid T = 1, p(X)] - E[Y(0) \mid T = 1, p(X)]\} \\ E\{E[Y(1) \mid T = 1, p(X)] - E[Y(0) \mid T = 0, p(X)]\}. \end{gathered} \tag{3.7}$$

and the ATT effect in the population can be obtained as a mean of the ATT in the subgroup of the population

$$E[Y(1) - Y(0) \mid T = 1] = E\{E[Y(1) - Y(0) \mid T = 1, p(X)]\}. \tag{3.8}$$

Rosenbaum and Rubin (1983) showed that when the balancing property and the unconfoundedness assumption are verified, then the propensity score can replace the use of the vector of covariates in the computation of the treatment effect.

3.2 Propensity score and ATT

As discussed in previous sections, we are interested in the effect of education and child work on employment and earnings. We study these effects following the causal inference approach in a *non experimental study* in which random selection in the treatment and control group is not available. Using a matching method we re-establish the conditions of an experiment study and assure for the comparability between control and treatment group. In this section we discuss how the propensity score will be used for the analysis of the effect of education and child work on adult's employment and earnings using a matching approach. For both education and child work treatments we compute the ATT on employment and earnings using different specifications of the treatments. The propensity score is estimated using the following model

$$Pr\{T = 1 \mid X\} = F(h(X)) \tag{3.9}$$

where T is a two level treatment, $F(\cdot)$ is the logistic cumulative distribution and $h(X)$ is a function of the covariates described in table 4. The first step is to compute the propensity score. We compute a propensity score for the two types of treatment respectively and for each of them for the three specifications reported in subsection 3.2.
In the second step the conditional expectations $E[Y(1) \mid T = 1]$ and $[Y(0) \mid T = 1]$ are estimated. We split the sample in to intervals until in all intervals the average propensity score of treated and control units do not differ. Within each interval, we test that the means of the propensity score do not differ between treated and controls units. If this condition is not verified in one interval we split off the interval and test it again. The tests continue until in all intervals the mean of propensity score does not differ between control and treated individuals. This condition assures for the Balancing Hypothesis reported in 5.
Since the propensity score is a continuous variable the probability of observing two units with the same propensity score is practically impossible. In literature there are various methods to overcome this problem, for a description of the most widely used see Becker and Ichino, 2002. In this study we use the *Nearest Neighbor Method*. The method used takes each treated unit $N_i(T)$ and searches for the control unit with the closest propensity score. It is applied with replacement in the sense that the same control units could be used for more than one treated unit. In the third step, the average of the difference between the outcome of the treated units and the outcome of the matched control units gives the Average Treatment Effect on the treated (ATT).
Let $C(i)$ be the set of control units that match with the treated unit i with a propensity score of value p_i. The nearest neighbour matching sets in the group of control is defined as [9]

$$C(i) = \min \parallel p_i - p_j \parallel \tag{3.10}$$

Let us define the weights

$$w_{ij} \begin{cases} \frac{1}{N(C)_i} \text{ if } j \in C(i) \\ 0 \text{ otherwise.} \end{cases}$$

where $N_i(C)$ is the number of controls matched with observation $i \in T$. The matching estimator of ATT can be written as

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$$A\hat{T}T = \frac{1}{N(T)} \sum_{i \in T} [Y(T)_i - \sum_{i \in C(i)} w_{ij} Y(C)_j] \tag{3.11}$$

Like the binary treatment propensity score method, the generalized propensity score method requires three steps. In the first step the score $p^{r/rs}(x)$ is estimated. In this phase we may distinguish two cases. If the values of the treatment are qualitatively distinct and without a logical ordering it is possible to use discrete response methods such as multinomial or nested logit. On the contrary, if the treatments correspond to ordered levels of a treatment we may impose smoothness of the score in t. In the second step the conditional expectation is estimated. And finally, in the third step, the average response at treatment level t is estimated as the average of the estimated conditional expectation obtained from step two, averaged over the distribution of the pre-treatment variables.

4 Results

Table 4: **Pretreatment characteristics**

Variable name	Description
male	1 if male, 0 if female
fgprimary	1 if individual has first grade primary before starting work, 0 otherwise
fathpres	1 if father present in the household, 0 otherwise
agefathpres	age of father present
mothpres	1 if mother present in the household, 0 otherwise
agemothpres	age of mother present
urban	1 if urban area, 0 if rural area
matlangdummy	1 if Spanish, 0 otherwise
fathocc1	1 if father is salaried or domestic employee, 0 otherwise
fathocc2	1 if father is day worker, 0 otherwise
fathocc3	1 if father is independent worker or worker on his own farm, 0 otherwise
fathocc4	1 if father owner, boss or landlord, 0 otherwise
fathocc5	1 if father retiree, pensioner, or hh chores, 0 otherwise
fathliterate	1 if father literate, 0 otherwise
mothliterate	1 if mother literate, 0 otherwise

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

In this study propensity score is defined as the probability that a child, with the pre-treatment characteristics X described in table 4, achieves a certain level of education (primary, compulsory or secondary) or experiment child work at a certain age (at 10, 12 or 14 years of age). We study the effect of education and child work experience on employment and earnings focusing on individuals from 25 to 49 years of age in order to concentrate our attention on the more stable period of work life. Individuals are classified in 5 cohorts of 5 years to capture cohort effects and changes in time. Since a large percentage of adult females is employed in unpaid work or as housewives, we focus on the effect of education and child work on males' employment and earnings.

4.1 The effect of education and child work on employment

Table 5: **Average Treatment Effect on employment for education levels**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT (* 100)	ST.ER. (* 100)	t
Primary	25-29	1145	894	4.00	4.40	0.90
	30-34	807	789	1.00	5.60	0.19
	35-39	724	798	-0.50	4.70	-0.11
	40-44	529	641	4.30	4.70	0.91
	45-49	433	609	3.10	5.90	-0.52
Compulsory	25-29	623	854	4.40	3.70	1.19
	30-34	442	683	2.70	3.80	0.70
	35-39	406	532	9.00	3.50	2.56
	40-44	317	477	3.00	4.40	0.68
	45-49	234	408	-3.40	4.00	-0.85
Secondary	25-29	415	760	8.40	3.50	2.42
	30-34	283	510	6.20	3.70	1.68
	35-39	284	459	10.70	3.30	3.28
	40-44	239	427	6.20	3.90	1.59
	45-49	175	367	-1.90	4.10	-0.48

Results from Matching Procedure using "Primary", "Compulsory" and "Secondary" as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

The specification of propensity score is achieved by checking if the balancing propriety described in 5 is satisfied. The computation of ATT is obtained using the nearest neighbour matching method. We restrict the computation of the ATT to the region of common support checking the extent of the overlapping between the distributions of treated and control groups. The comparison of the distribution of propensity score for treated and control groups of the child work treatments is shown in Appendix in figure 7.

Table 6: **Average Treatment Effect on employment for child work definitions**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT (* 100)	ST.ER. (* 100)	t
Child work	25-29	1382	840	7.30	2.60	2.82
	30-34	1161	677	9.80	2.70	3.67
	35-39	1146	688	8.30	3.10	2.67
	40-44	929	586	0.30	3.60	0.07
	45-49	833	534	9.80	3.40	2.88
Child work12	25-29	910	1193	18.70	2.40	7.78
	30-34	753	938	14.20	2.70	5.35
	35-39	779	943	5.70	2.70	2.15
	40-44	601	829	2.80	2.80	0.98
	45-49	554	731	4.10	2.90	1.38
Child work10	25-29	436	1399	2.90	2.60	1.11
	30-34	381	1086	10.80	3.00	3.60
	35-39	373	1117	6.00	3.00	1.97
	40-44	309	932	3.10	3.30	0.92
	45-49	284	768	4.60	3.40	1.38

Results from Matching Procedure using “Child work”, “Child work12” and “Child work10” as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

Using the covariates described in tab 4, only in very few cases the balancing propriety is not satisfied.

Because of the large number of treatments studied we report only the graphics of compulsory and child work14 treatment for each cohort as example.

Tables 5 and 6 show the average treatment effect on employment respectively for education levels and child work definitions.

In table 5 we observe a positive effect of education on occupation. Individuals who receive at least primary education seems to have a higher probability of being employed in adult life than illiterate individuals. The positive effect of education seems to increase as the investment in education rises. The effect of obtaining at least compulsory education is in general higher than the effect of obtaining at least primary education. In the same way, the effect of obtaining at least secondary education is higher than the effect of obtaining at least compulsory or at least primary education. These results suggest that higher investments in education during childhood increases the probability of being employed in adult life.

Considering any of the three definitions, child work has a positive effect on the prob-

ability of being employed (see table 6). Individuals that experienced child work have a higher probability of being employed in adulthood. These results suggest a positive effect of work experience even when individuals start working very young. Estimations show that the positive effect of experience on employment is positive even when we study the causal effect of child work for individuals that entered the labour force before 12 or 10 year old. Estimations appear highly significative in about all cohorts for the first definition of treatment (child work before 14 years) and slightly less significative in the last cohorts of the second and the third definitions of treatment. The magnitude of the effect changes among cohorts even for the same treatment. This is probably due to a cohort effect.
For both type of treatments (e.g. schooling and child work) the effect on employment seems to diminish as the distance from the moment of the treatment increases.

4.2 Focusing on males: The effect of education and child work on employment and earnings

Average Treatment Effect on male's employment for education levels

Table 7: **Average Treatment Effect on Male's employment for education levels**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT (* 100)	ST.ER. (* 100)	t
Primary	25-29	613	369	-1.90	1.70	-1.12
	30-34	433	332	-1.10	2.40	-0.45
	35-39	395	379	-1.20	0.90	-1.29
	40-44	292	335	-2.40	1.20	-1.95
	45-49	242	318	-1.50	3.20	-0.46
Compulsory	25-29	316	406	0.10	1.80	0.06
	30-34	229	365	-1.50	1.70	-0.89
	35-39	214	301	-1.60	1.30	-1.19
	40-44	176	231	-1.60	2.00	-0.80
	45-49	132	234	-2.00	2.30	-0.89
Secondary	25-29	205	338	0.30	1.70	0.16
	30-34	146	266	-0.40	2.10	-0.18
	35-39	151	262	1.00	1.30	0.80
	40-44	113	193	-0.90	2.00	-0.46
	45-49	101	231	-0.20	2.00	-0.09

Results from Matching Procedure using "Primary", "Compulsory" and "Secondary" as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

Average Treatment Effect on male's employment for child work definitions

Table 8: **Average Treatment Effect on Male's employment for child work definitions**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT (* 100)	ST.ER. (* 100)	t
Child work14	25-29	711	335	2.30	1.60	1.47
	30-34	588	270	2.80	1.60	1.72
	35-39	583	270	-0.40	1.00	-0.42
	40-44	497	239	1.20	1.70	0.72
	45-49	441	231	7.20	2.20	3.26
Child work12	25-29	465	492	3.00	1.20	2.57
	30-34	370	412	2.60	1.20	2.09
	35-39	393	416	-0.20	0.80	-0.26
	40-44	318	362	-0.20	0.10	-0.16
	45-49	286	356	1.50	1.60	0.89
Child work10	25-29	216	571	3.80	1.20	3.11
	30-34	187	492	0.60	1.10	0.54
	35-39	184	514	0.40	0.90	0.44
	40-44	152	435	0.20	1.30	0.13
	45-49	136	397	0.10	1.90	7.10

Results from Matching Procedure using “Child work14”, “Child work12” and “Child work10” as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

According to ENCOVI (2000), in Guatemala about 40 percent of the population older than 14 is employed; however, a strong difference exists in gender participation in the labour market. In 2000 less than 28 percent of females was employed compared to more than 54 percent of males. If we restrict the sample to individuals aged from 25 to 49 (as we did in our study of causal effect of education and child work), gender difference appears more clearly. Nearly 96 percent of males in the age class 25-49 are employed whereas only half of the females in the same age group results as employed. Focusing on males we find that the effect of education on employment seems to be less evident than what we observe in the entire population (see table 7). This suggests that education has a stronger impact on employment for females than for males. The higher percentage of employed males in the range $25-49$ means that during the central period of work life, men are employed even if not educated. This suggests that there is not a positive effect of investment in education on employment for males from 25 to 49 years. The higher impact of education on female employment is consistent with results observed in the overall estimation of returns to education.The profitability of investment in women's education is greater than that of men's and the rate of return of women may result higher if we consider that for more educated women it is easier to find a job.

The effect of child work on employment is still positive when we compute the causal effect only for males but lower than the effect observed without distinguishing by gender (see table 8) suggesting that the experience of child work has a strong impact on female employment.

Table 9: **Average Treatment Effect on Men's earnings for education levels**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT	STD. ERR	t	ATT%
Primary	25-29	583	357	10836	3552	3.05	73.30
	30-34	420	321	20860	3606	5.78	154.50
	35-39	384	386	17734	4942	3.59	82.74
	40-45	287	324	15267	4728	3.23	53.32
	45-49	238	312	23824	6077	3.92	97.27
Compulsory	25-29	299	394	16581	2976	5.58	97.32
	30-34	225	358	24571	5271	4.66	111.14
	35-39	207	294	25599	4545	5.63	101.33
	40-44	172	200	32758	6138	5.33	119.60
	45-49	129	222	44145	7566	5.83	174.56
Secondary	25-29	190	317	18732	3763	4.98	94.64
	30-34	143	258	31441	5693	5.52	136.77
	35-39	145	262	36764	5477	6.71	145.28
	40-44	130	187	39006	7319	5.33	123.20
	45-49	98	224	50359	9114	5.53	181.87

Results from Matching Procedure using "Primary", "Compulsory" and "Secondary" as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

In tables from 9 to 13 we study the causal effect of education and child work on earnings. Since ATT is defined as $ATT = E(Y(1) - Y(0) \mid T = 1)$ and the output variables are given by different potential level of earnings, the ATT is expressed in terms of variation of earnings due to the treatment. This result is not easily interpretable and it is difficult to compare it with other applications in other countries and times. In order to obtain a more comparable result in the last column of the following tables we report the percentage variation of earnings due to the treatment with respect to the average earning of the treated in the absence of treatment (that is to say $\sum_{i \in T} Y(0)_i / N_T$).

Table 9 shows that education has a positive effect on earnings for any level of education. The effect of education seems rather volatile during an individuals work life and the analysis does not suggest a clear trend in the effect on earnings. However, the effect of education

Table 10: **Average Treatment Effect of secondary education on Male's earnings for men with compulsory education**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT	STD. ERR	t	ATT%
Secondary	25-29	190	90	12943	4186	3.09	50.60
	30-34	143	58	27008	6656	4.06	98.49
	35-39	145	47	39533	6995	5.65	175.41
	40-44	130	29	46075	14332	3.21	187.37
	45-49	98	30	26802	13661	1.96	52.30

Results from Matching Procedure using "Primary", "Compulsory" and "Secondary" as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

Table 11: **Average Treatment Effect on Men's earnings for educational level and individual that experimented child work14**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT	STD. ERR	t	ATT%
Primary	25-29	281	268	11442	1940	5.90	101.25
	30-34	204	227	10234	2183	4.69	73.71
	35-39	192	296	19213	5639	3.41	115.80
	40-44	134	220	18471	5019	3.68	106.48
	45-49	100	226	19012	6681	2.85	94.35
Compulsory	25-29	122	195	17049	2710	6.29	121.74
	30-34	87	270	13609	3307	4.12	79.67
	35-39	79	316	30589	9488	3.22	147.77
	40-44	64	87	37129	8343	4.45	200.20
	45-49	47	117	33160	10470	3.17	156.78
Secondary	25-29	73	127	11506	4148	2.77	54.92
	30-34	45	144	21742	5046	4.31	117.70
	35-39	52	129	48620	10196	4.77	232.03
	40-44	41	74	52090	11854	4.39	240.16
	45-49	35	114	42626	12569	3.39	185.57

Results from Matching Procedure using "Primary", "Compulsory" and "Secondary" as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

is always positive and in general very high with a peak of almost 200 percent for the last cohorts of compulsory and secondary education.
Primary education has a lower effect for each age class than the other levels of education whereas the impact of compulsory education on earnings is slightly lower than that of secondary education.

This weak difference between compulsory and secondary education effect let us suppose that the marginal effect of secondary education on the increasing of earning is low and that the higher earnings of an individual with secondary education with respect to the illiterate one is maines due to compulsory education.

In order to focus on the effect of a higher level of education in table 10 we report the increase in male's earnings due to secondary education for men with compulsory education. The causal effect reported in this table is in general lower than those reported in table 9. In this case we are estimating the effect on males' earnings due to the achievement of a secondary education level versus a compulsory one. Thus, this effect may be interpreted as a marginal effect, e.g. the variation of earnings due to the last level of education achieved. We note that the advantage of passing from compulsory to secondary is still very high. It is worth investing in schooling even for a level of education higher than compulsory.

In table 11 we study the causal effect of education on children that experimented child work before 14 years of age. In other words, in this table we are investigating the effect of education for children that during childhood combined work and study.
Comparing results obtained in table 9 and 11, e.g. comparing results of males that worked full time with those of males that studied and worked part time during childhood, we note that the effect of education on earnings is often higher for individuals that combined child work and schooling. This is verified for all levels of education. These results suggest that work experience has a positive effect if combined with a certain level of education. Individuals that have combined child work and schooling during childhood are able to obtain returns to education as high as those of individuals that did not experience child work, and for some cohorts, even higher[7]. Table 12 shows the average treatment effect of secondary education on male's earnings for males with compulsory education that experimented child work. Comparing results in table 12 and 10 we note that the marginal effect of secondary education is higher for individuals that experimented child work.

In table 13 we study the casual effect of experienced child work during childhood on adult male's earnings. It shows a negative effect of child work in the first period of work life and a positive effect in the last period. This result is confirmed for any definition of child work with a stronger evidence for children that start to work early, e.g. before 10 years of age. The causal effect of child work on earnings could be interpreted as the consequence of a change in the remuneration of child work in the labour market over time. Older workers are those that enter the labour market in an early time in which the required skills were lower and child work was an instrument to obtain some work experience. Young people

[7]We are focusing on the effects of combining child work and schooling on adult earnings, ignoring the potential negative effect of child work on children's attendance and ability at school. Some studies show that child work has a negative impact on child performance at school. See Heady, 2000 and Ridao-Cano, 2001.

Table 12: **Average Treatment Effect of secondary education on Male's earnings for men with compulsory education that experimented child work14**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT	STD. ERR	t	ATT%
Secondary	25-29	73	30	-3225	8461	-0.38	-9.04
	30-34	45	29	22332	5662	3.94	124.88
	35-39	52	18	48936	12281	4.31	237.12
	40-44	41	15	49222	13195	3.73	200.43
	45-49	35	11	39300	14938	2.63	149.45

Results from Matching Procedure using “Primary”, “Compulsory” and “Secondary” as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

Table 13: **Average Treatment Effect on Men's earnings for child work definitions**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT	STD. ERR	t	ATT%
Child work14	25-29	676	325	-1446	2970	-0.49	-8.39
	30-34	567	262	13100	7548	-1.73	-40.50
	35-39	570	263	-1727	5589	-0.31	-7.80
	40-44	481	227	-103	6603	-0.2	-0.54
	45-49	430	227	511	7403	0.07	2.87
Child work12	25-29	435	481	-2967	1982	-1.50	-17.35
	30-34	355	405	-7338	4609	-1.59	-31.90
	35-39	382	408	3233	4147	0.78	17.98
	40-44	306	358	1475	4497	0.33	8.84
	45-49	277	348	4147	4904	0.85	26.97
Child work10	25-29	205	536	-2645	1927	-1.37	-15.65
	30-34	181	473	-2130	4130	-0.52	-10.80
	35-39	177	478	9042	6226	1.45	48.59
	40-44	147	413	3440	4414	0.78	22.50
	45-49	132	402	6234	5427	1.15	39.60

Results from Matching Procedure using “Child work14”, “Child work12” and “Child work10” as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. INE Guatemala. Elaborated by author Estadisticas (INE) Guatemala. Elaborated by author.

that enter the labour market in a more recent period need higher skills and the experience accumulated during child work can not assure a higher productivity.

Table 14: **Average Treatment Effect on Men's earnings for child work definitions and individuals that experimented child work14**

TREATMENT	AGE CLASS	N. TREAT.	N. CONTR.	ATT	STD. ERR	t	ATT%
Child work12	25-29	435	200	-1342	2185	-0.61	-8.67
	30-34	355	182	3591	2339	1.54	29.74
	35-39	382	160	3637	3596	1.01	20.69
	40-44	306	151	3301	4881	0.68	22.20
	45-49	277	136	6313	3701	1.71	47.78
Child work10	25-29	205	304	-598	1919	-0.31	-4.03
	30-34	181	275	3353	2158	1.55	23.56
	35-39	177	274	9698	5943	1.63	54.02
	40-44	147	253	3163	3766	0.84	20.32
	45-49	132	227	8931	4773	1.87	68.47

Results from Matching Procedure using "Child work12" and "Child work10" as treatment variables

Source: Encuesta de Condiciones de Vida (ENCOVI) 2000. Instituto Nacional de Estadisticas (INE) Guatemala. Elaborated by author.

On one hand, we may define a treatment variable as the combination of the two treatments. As we said before, school attendance and child work are not two activities mutually exclusive. Often, in developing countries, children combine work and study. The impact on employment and earnings of combining work and study could be different respect to the sum of the two effects analyzed separately. On the other hand, we may treat each type of treatment as a multilevel treatment. In other words, we may treated education as a three levels of the same treatment: primary, compulsory, and secondary and, in the same way, we may treated child work as a three (ordered) levels of treatment: work at 10 years of age, work at 12 years of age and work at 14 years of age. We opted to analyze the propensity scores for each variable separately and decided to treat the different levels of each type of treatment as a single separate treatment. Since in literature there are very few study on the causal effect of child work this application could be interpreted as the first necessary step in the investigation of the causal relation between child work and future work conditions in developing countries. The considerations done leave space for farther application on this issue.

In table 14 we study the effect of starting work very young versus entering the labour market after 14 years of age. Comparing the results in table 13 and in table 14 we observe that individuals that in recent years have performed child work starting to very young e.g before 10 years or before 12 years have an average earning lower than individuals that start to work before 14 years of age. This means that for men in the first cohort entering the labour market too early has a negative causal effect on earnings even if compared to individuals that start working before 14. However, the effect of a very early entry in the labour market seems to have a positive effect for men in the older cohorts even when the control group is given by men that performed child work. A possible interpretation of these results could be that for individuals that performed child work the accumulated experience matters in the determination of earnings returns. Among individuals that performed child work, having a longer experience ensures a higher return in earnings. However, this is not true for early generations that report negative effects of child work on earnings.

The analysis developed in this study may be extended in two ways. First we may define a treatment variable as a combination of the two treatments (schooling and working). Since school attendance and work are not mutually exclusive, in principle one may define four different treatments: study full time, work full time, combine work and study, and no activities. A second extension may treat this issue using the framework of the multiple treatment models. One may define the diploma achieved or the age in which an individual enters the labour market as different levels of the same treatment. For each type of treatment and for each level the estimate of ATTs could be computed. However, computing the average treatment effect by subgroup of the population, e.g. the casual effect of secondary for those that have achieved compulsory education or the causal effect of education for those that experienced child work, we were able to find the same information that we would obtain with the two extensions suggested before.

5 Conclusions

In this paper we studied the causal effect of education and child work on employment and earnings. The survey used (ENCOVI 2000) reports some retrospective questions on education and work activities that allows us to obtain information on the entire work life of individuals without using panel data. After a descriptive analysis we describe the econometric methodology of causal inference adopted for the analysis. We first discuss the case of a two treatments model and then the extension of the multiple treatments model. For the econometric analysis we identified two types of treatment. The first is defined by the level of education achieved, and the second by the age of entry in the labour market. The effect of education is studied using three definitions of treatment versus no treatment: at least primary education versus non education, at least compulsory versus non education, and at least secondary versus non education. In the same way we define three different specifications of child work treatment versus non treatment: work before 14 years versus work later, work before 12 years versus work later, and work before 10 years versus work later. We restrict our sample to individuals from 25 to 49 years in order to concentrate our attention on the more stable period of work life. We first study the effect of the two treatments on employment without distinguishing by gender and then we study the effect of the two treatments on employment and earnings focusing on men. We find a positive effect of education on employment especially evident for a higher level of education. Since in the sub-sample used in the analysis men are nearly fully employed, we did not find a positive effect of education on male's employment suggesting that education has a strong impact for female employment. Child work has a positive casual effect on employment. This effect is more evident in the first cohorts and is very high also for children that entered the labour market very young. It is still positive when we compute the causal effect only for males but lower than the effect observed without distinguishing by gender suggesting that experiencing child work has a strong impact on female employment. Studying the causal effect of the two treatments on earnings for Guatemala seems particularly complex given the high volatility of the economy in this country. Thus, for the same treatment and output we may find very different results moving through age groups. In spite of this difficulty, it is possible to find some common aspects. Focusing on males, we find that education has a positive effect on earning for all the age classes. This effect seems to increase with the rise of the level of education. The estimation suggests that it is worth investing in schooling even for education higher than compulsory. Individuals that during childhood combined work and schooling have higher levels of returns to education than those that have only studied. Child work seems to have a negative effect on earnings for the first cohorts and a positive effect for older individuals. This may be the result of a different remuneration of child work experience in the labour market over time. Finally, children who enter the labour market very young have a negative causal effect in the first cohorts even when the control group is given by children that experimented child work at an older age. This means that for the new generations performing child work very young has a higher negative effect than experimenting child labour after 14 years. However, the effect of a very early entry in the labour market seems to have a positive effect for men in the older cohorts even when the control group is given by men that performed child work. For older generations the accumulated experience matters in the determination of earnings returns. Among men that performed child work and had a longer experience is ensured a higher returns in earning. The results of this study show that accumulated education assures a higher level of earnings in adulthood whereas individuals that performed child work obtain lower remuneration in the labour market. However it is important to note that child work has a positive effect on the probability of finding a job in adulthood. Among individuals that performed child work those who had more work experience registered a positive effect on earnings, especially for older generations. Policies that aim to ensure a higher well-being have to take into account both the effect on employment and on earnings of the two types of treatments. The decision to perform child work could be interpreted as a rational household choice not only for the short term but also in the long term if an individual took in account the positive effect of them on the opportunity of finding a job. An important extension of this study should be to investigate on the quality of work performed by individuals with different levels of education and different work experience.

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Appendix

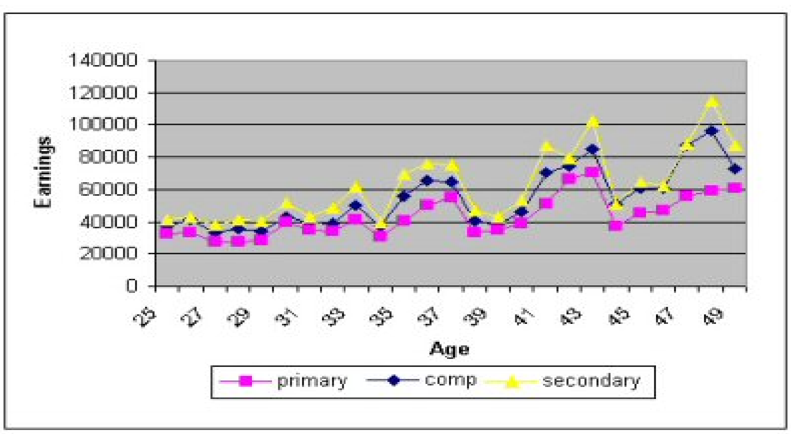

Figure 3: **EARNINGS BY AGE AND EDUCATIONAL LEVEL**

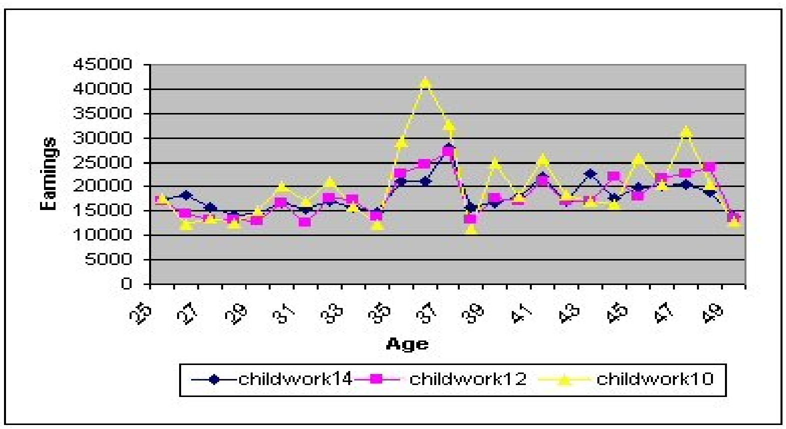

Figure 4: **EARNINGS BY AGE AND CHILD WORK DEFINITIONS**

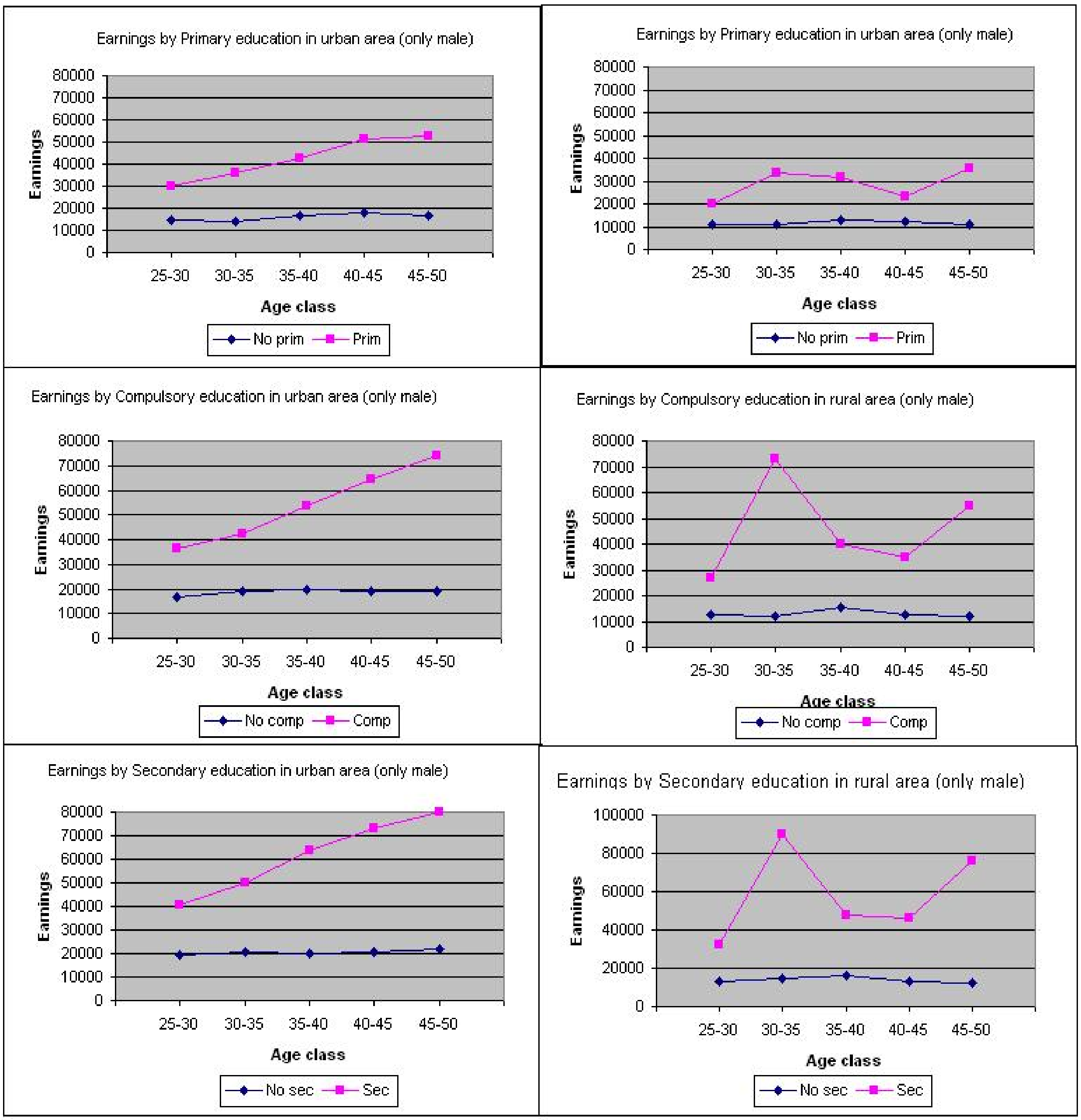

Figure 5: **EARNINGS BY EDUCATION**

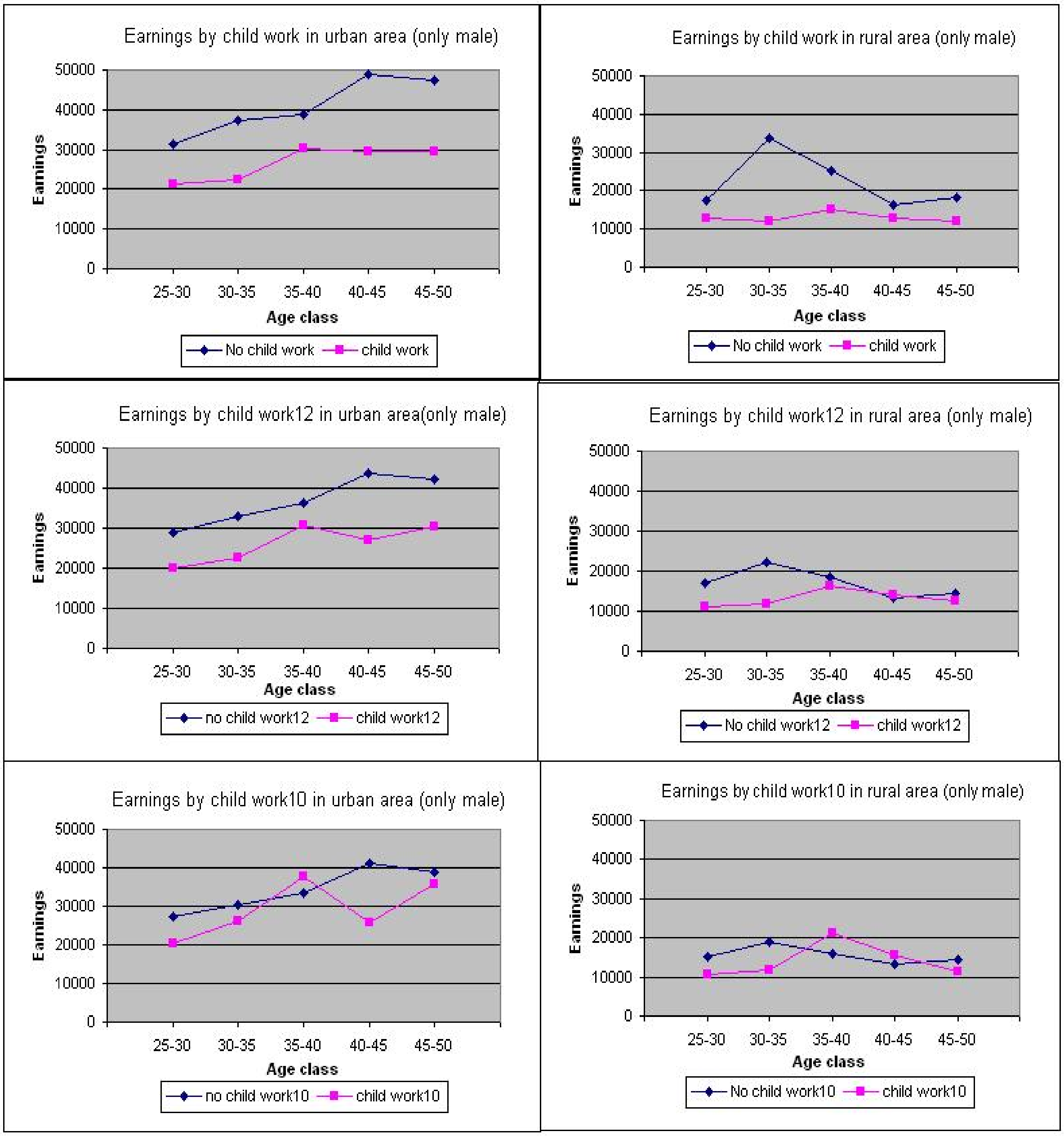

Figure 6: **EARNINGS BY CHILD WORK**

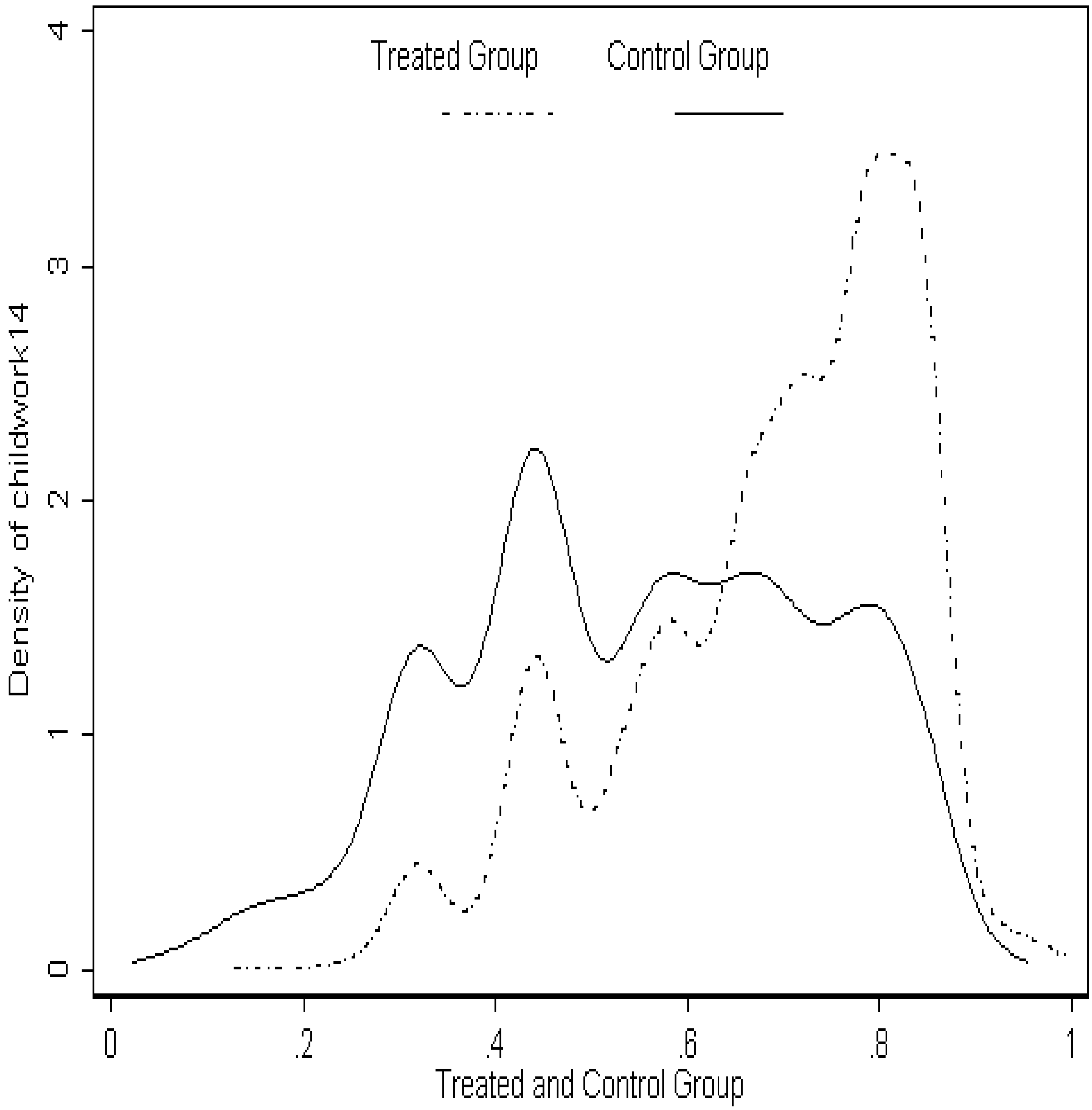

Figure 7: **DISTRIBUTION OF PROPENSITY SCORE FOR TREATED AND CONTROL GROUP. TREATMENT: CHILD WORK14, AGE GROUP 25-49.**

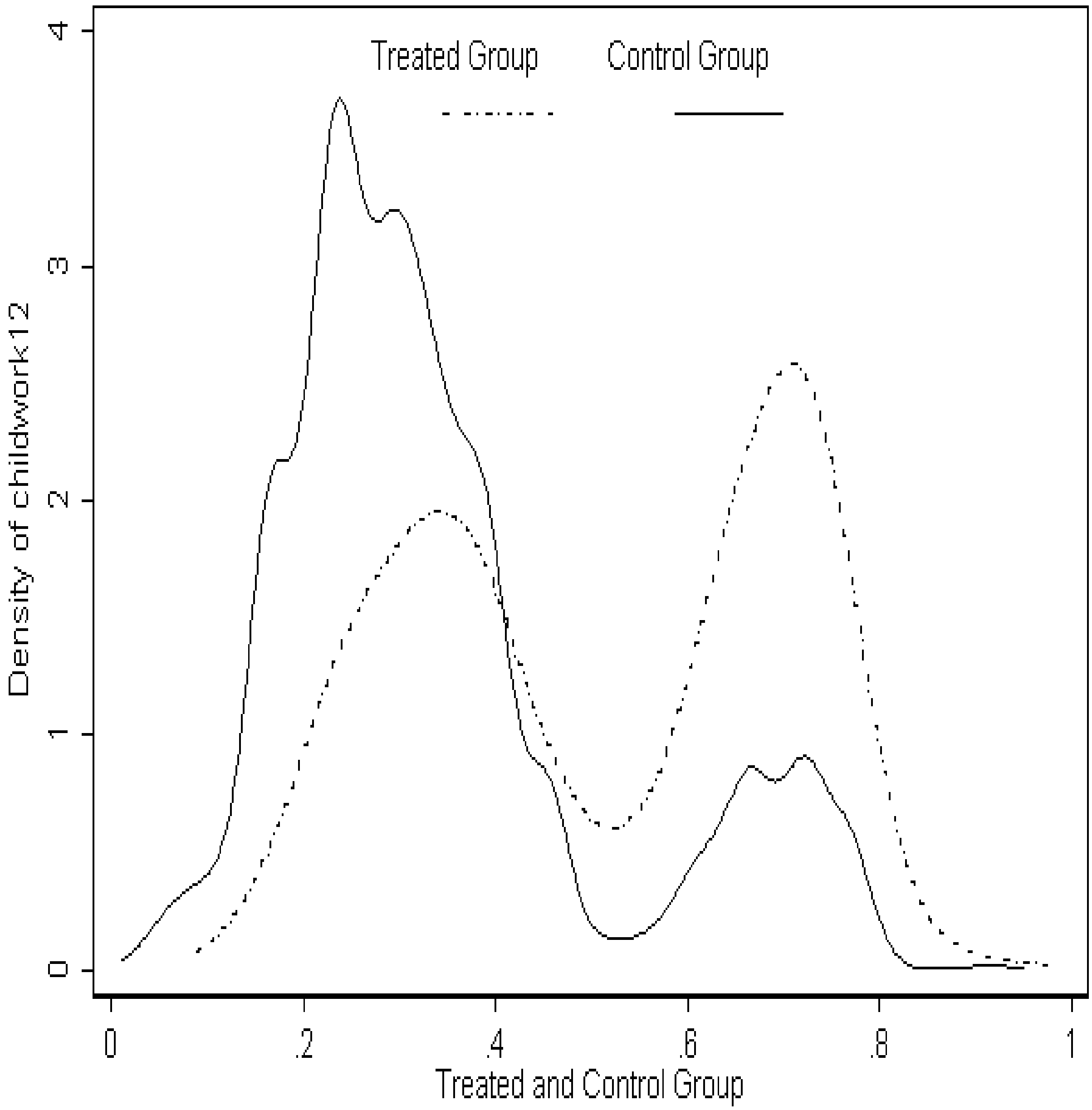

Figure 8: **DISTRIBUTION OF PROPENSITY SCORE FOR TREATED AND CONTROL GROUP. TREATMENT: CHILD WORK12, AGE GROUP 25-49.**

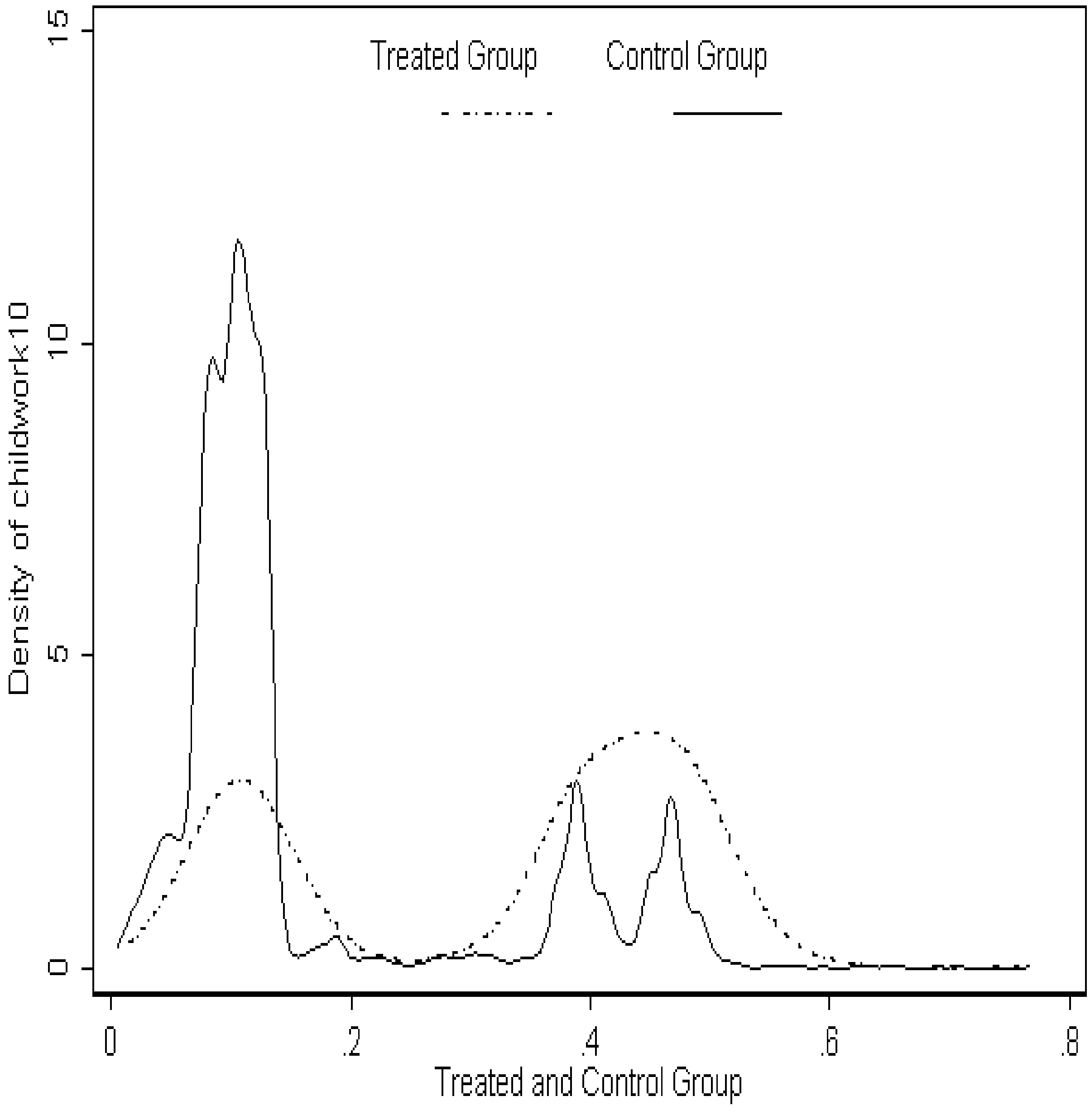

Figure 9: **DISTRIBUTION OF PROPENSITY SCORE FOR TREATED AND CONTROL GROUP. TREATMENT: CHILD WORK10, AGE GROUP 25-49.**