Three Essays on Child Development

DISSERTATION

Presented in Partial Fulfillment of the Requirements for

the Degree Doctor of Philosophy in the

Graduate School of The Ohio State University

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Graduate Program in Economics

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2016

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ABSTRACT

Economics literature is interested in how child cognitive and socio-emotional skills develop during childhood. Evolution of skills is crucial to determine productivity, criminality among other social and economic outcomes. The government has a role in shaping abilities improving conditions at home or school. Thus, initial deficiencies of children in disadvantageous households can be compensated by increasing resources or material investments. These essays investigate how computers and income affect traditional measures of academic success. Also, how parental conflict is involved in a dynamic framework is investigated.

The first chapter analyzes whether access to computers in schools improves performance in math and language standardized tests. Computers and in general technology are part of current living conditions, therefore, there has been a lot of debate whether they contribute to learning. Computers can affect tests because they can substitute or complement teachers and material inputs at school. The analysis is carried out using "Computadores para Educar" a nationwide program in Colombia that allocates computers in public schools. The program started in 2000 as a presidential initiative to improve access and use of information technologies. Results indicate that there is no gain on language and mathematics achievement tests.

In the second paper, we focus on the analysis of how cash transfers that affect the budget constraint may have a different effect on child outcomes over the income distribution. Using the National Longitudinal Survey of Youth 1979, we analyze the impact of support assistance on children from households with low to moderate income in the United States. The data is consistent with two specifications for the relationship between child outcomes and income: a linear and linear in the logarithm. This finding implies that public programs aiming to improve math and reading achievement tests may increase transfers to children from households at the low end of the income distribution.

The final chapter includes the effect of parental conflict into skill development during childhood. Parental conflict is a non-tangible input related with psychological well-being of the parents. There is evidence that conflict adversely affects cognitive and non-cognitive skill development, but this is the first study that jointly analyzes the impact on both skills. Estimates suggest that reductions in conflict benefits skills and adult outcomes. Cognitive development is more affected during early childhood and non-cognitive development for later ages. The effect of reducing parental conflict on years of education completed is similar to the effect of increasing parental time but lower than the effect of increasing material investments.

This is dedicated to my north star

ACKNOWLEDGMENTS

During these years I have received encouragement and great contributions from a great number of individuals. Dr. David M. Blau who has been a mentor, and excellent advisor. His availability, guidance and clarity has made this a fulfilling journey. Drs. Daeho Kim and Kurt Lavetti who provided his ideas, support, and teach me a lot as instructors too. I have learned a great deal from her classes, and from watching her teach.

In addition, thanks to Deicy Cristiano, who patiently went over drafts of this manuscript and provided valuable comments, and to Liliana Cristiano who carefully explained psychology topics involved in this research.

I also acknowledge the support from the Colombian Institute for the Evaluation of Higher Education ICFES, and the NLSY79 which provided the data for this research.

I express my deepest gratitude to my fellow classmates from whom I not only learned so much, but also, who have made being away from my country, my family, much more bearable. Finally, thanks to my mom, daughter and my girlfriend who cared for me at every step, and stood by me in the darkest hours.

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PUBLICATIONS

Research Publications

L. Melo, F. Nieto, M. Ramos "A Leading Index for the Colombian Economic Activity". *Borradores de economía*, 243, May 2003.

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FIELDS OF STUDY

Major Field: Economics

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CHAPTER 1

DO COMPUTERS IN SCHOOLS HELP STUDENTS TO LEARN?

ABSTRACT

During last decades, Information Technology has been changing productivity at work, home, and school. In recent years, worldwide programs that incorporate computers at schools were implemented with small or no impact on academic outcomes. This paper analyzes the impact on mathematics and language test scores of "Computadores para Educar", a national program in Colombia designed to reduce the digital gap in public schools. Estimates using a difference in difference approach shows no gain on language and mathematics cognitive achievement tests. While there is a higher impact of the program in rural schools, not all estimates are significant. Also, any potential benefit of the program during the first two years disappears in the third.

1.1 Introduction

The development of information technology has altered daily life activities like shopping, banking and communicating. Productivity at home and work also has increased since the involvement of technology. Thus, information technology has been incorporated in all activities including learning. Economics has focused on analyzing the effects of computer use on cognitive development (eg [2, 57, 6, 7, 50]). Computers may substitute or complement other educational inputs, offering alternative strategies to teach topics to students.

Worldwide public programs have been implemented to improve access and exposure of students to information technologies, giving researchers an opportunity to investigate the effect of computers on different educational outcomes. Evaluating the impact of information technologies is of interest for public policy not only to guarantee that resources improve educational outcomes but also because society itself will be more productive with more skilled, competitive, and able individuals.

Research has focused on two channels through which computers affect learning. The first channel is the computer aided instruction and describe how cognitive skills are affected by the use of specific software. The computer literacy is the second channel and describes how computers improve academic outcomes because of the knowledge of using a computer. Research has found no significant effect on mathematics and language test scores in the majority of industrialized countries. On the other hand, evidence in developing countries is mixed, suggesting both positive and negative impact.

This paper analyzes the impact on elementary, middle, and high school cognitive achievement tests of Computadores Para Educar (CPE). This is an ongoing program aimed to guarantee students in public schools access to information technologies. During the initial years of the program, the allocation focuses on schools with constraints to access to computers while later the focus was set on allocating computers to schools with higher enrollment. Two studies investigated CPE program's effect, with opposite conclusions. Using a random assignment experiment, [7] found a small effect of the program on achievement tests for elementary and middle school. However, [50] found an increasing impact with the time of exposure from -0.01 (1-year exposure) to 0.15 (8 years in the program) standard deviations on high school test performance.

The main contribution is to investigate the effect of computers on mathematics and language tests scores at different stages of education. In spite of the existence of a lot of research in the world about this topic, the CPE program allows studying some distinctive facts. Because of its dynamic structure and national coverage, the better estimate of the program's effect is obtained comparing schools treated between 2002 and 2005 and schools that receive computers after 2005. Given the similarity of observable characteristics, recipients after 2005 provide a natural counterfactual for benefited schools during the initial years of the program. The dynamic allocation allows evaluating the effect by the length of exposure. Additionally, it is possible to compare the effect by school location (urban and rural) and by school size (small and big).

This study overcomes difficulties faced by previous studies. First, it includes a dynamic structure that will account for the training phase for teachers of the program. Second, a proxy for a teacher promotion reform is included to avoid bias. The reform aimed to increase the productivity of professors hired after 2002 and may affect public schools differentially. Finally, analyzing the effect of computers on schools instead of home isolate factors not related to the impact on children, that can act through other channels like parents job search or labor outcomes.

Estimates using a difference in difference approach suggest no gain on mathematics and language test scores. Although the estimated effect is higher in rural than in urban schools, most of the estimates are not statistically different. Moreover, there is evidence of a non-constant effect by the length of exposure. Any effect during the first two years vanishes in the third year. Thus, the score of non-recipient schools is similar to the score of schools with three o more years into the program.

The remainder of this paper is structured as follows. Section 2 outlines the main findings in the literature about the effect of computers on academic outcomes. Section 3 describes the main characteristics of the CPE program. Section 4 presents the conceptual framework for a school facing the CPE program. Section 5 describes the data on test scores and the CPE program used in the estimation. Section 6 presents the program's impact on language and mathematics standardized test scores considering three approaches. First, we assume that the program has a constant impact, independent of the length of exposure. Second, we allow heterogeneity of the program's impact by school location and school size. Finally, we allow the treatment effect to differ by the length of exposure to the program. Section 7 presents a discussion of the results and concludes.

1.2 Literature Review

The economics literature has studied the benefits of computers on the labor market and educational outcomes. Research has focused on measuring the effect of using computers on wages, academic test performance, school retention among others.

[46] shows that users of computers have earnings significantly greater than nonusers. [25] demonstrate that this finding was misleading, given that returns to the use of pencils are similar to the previously estimated return to computer use. They conclude that unobservable characteristics explain the wage differential between computer users and nonusers. [13] found that the ability to use a computer does not yield a significant return. They control for the level of sophistication of using computers, required math and writing skills, and for each worker computer use. Their main conclusion is that computer use does not increase worker's productivity.

In estimating the effect of computers on academic outcomes literature has identified two channels. The first is the computer literacy channel, which describes how academic outcomes improve as a consequence of students having a basic knowledge of computer software like word processing and spreadsheet programs. The second channel is the computer aided instruction, that is the effect of using specific software in the learning process. This section presents evidence of the effect of computer-aided instruction from [2, 57, 6] and about the effect of computer literacy from [33, 47].

In Israel [2] found a negative relationship between computer aided instruction and Hebrew and mathematics tests for fourth and eighth grades. However, those results are only precisely estimated for the fourth-grade students. The authors control for the intensity in which each professor use computers. Estimates of the program effect are obtained using "Tomorrow 98" recipient as an instrument for computer intensity.

Also, a regression discontinuity specification using the applicant's rank is estimated.[1]

[57] evaluate the impact on reading ability of the Fast forWord software using a random assignment experiment.[2] The experiment was run in four urban schools for students in the 20% bottom or with a significantly lower score than the state's standardized test in 2001 and 2002. Estimates indicate a small effect of the program. Although there is improvement in some language skills, those gains do not translate into the reading skills measured by standardized tests.

[6] studied the impact of a 2-year computer aided instruction program as a remedy to the shortage of teachers in Vadodara India. The program was randomly assigned to schools, using three variables to stratify: gender, the language of instruction, and the average math scores in the previous year. They found increases in math scores of 0.35 and 0.47 standard deviations in the first and second year, and a small effect of 0.1, one year after leaving the program. The authors associate this positive evidence to the fact that the program adapts to the children's achievement level.

[33] analyzed the effect of availability of computers at home and school on student test scores using the Programme for International Student Assessment (PISA). After controlling for household and school characteristics they found a negative impact of computers at home, because they seem to distract students from learning. The impact is positive if computer use is oriented to education and communication. Estimates

[1] Tomorrow 98 is a project sponsored by Israeli state lottery to computerize educational activities in each school. It includes financial resources to improve hardware, software and teacher's training.

[2] FFW is a computer game software intended to improve the reading ability of kids by focusing on improving phonetic skills, slowing and magnifying the correct pronunciation of some words.

of the availability of computers at school indicate no effect on achievement tests, but this relationship has an inverted u pattern. [47] study the effect of computers and software using a program that benefits schools with an enrollment of disadvantaged students higher than 70%. The design of the subsidy allows estimating a regression discontinuity within a difference in difference specification. There is a negative impact of the program on test scores for language, arithmetic, information processing and world orientation, with some estimates precisely estimated.

Another set of studies has focused on the use of computers at home. The main challenge of this literature is to separate the effect due to computer use from the effect due to parental labor outcomes. For instance [31] analyzed the impact of computers on a broad set of educational outcomes. The authors run a 1-year field experiment in California allocating home desktop computers to students from public schools, without additional assistance or training. The increase in computer time is associated with increments in usage for schoolwork, social networks, and games. However, the increase in use does not translate into gains on attendance, grades, standardized test scores, or disciplinary behavior problems. The authors claim that their design allows ruling out even small or modest outcomes.

In Colombia, the impact of the CPE program has been analyzed in two papers. First, [7] analyzed a random assignment experiment on the north-western region of Colombia, where 50 out of 100 potential beneficiaries get computers. The randomization was stratified using the department and type of school {elementary, middle, high school}. In 2006, a baseline survey was made collecting data about schools, teachers, and students. In order to check the effect of the program, a second survey was conducted 18 months later. Due to a high migration rate, a 37% attrition rate was found. On average attritors in control and treatment groups are similar, which supports the internal validity of the exercise. [3] However, attritors and non-attritors characteristics differ in 8 variables. To address any potential bias coming from these differences a dummy variable for the attritors and the interaction with the treatment is included in the specification.

Overall the estimates indicate a small effect of the program on test scores and other outcomes. The authors mainly attribute this result to the fact that computers improve computer literacy instead of being incorporated into aid instruction. The follow-up survey revealed that computer use in class activities was similar for control and treatment groups, only in the computer science class there was a clear difference. There are two drawbacks of the analysis. First, the analysis estimates the short-run impact of the program. Given the 1-year training phase and the 18-month span between the surveys, the estimates capture the effect of being 6 months in the program. The second drawback of the analysis is the high attrition rate that may invalidate results.

[50] found a positive impact of the program on academic performance for 11^th grade students. The authors estimate an increasing effect of the program with the time of exposure from -0.01 (1 year of exposure) to 0.15 (8 years in the program)

[3] On 15 out of 18 variables, there was no statistical difference in the mean. The three variables in which both groups differs are: receiving allowance, talk to teacher outside the class, and number of hours studied outside the regular classes.

standard deviations using OLS, and from 0.26 to 0.49 using IV to control for selection bias due to nonobservable characteristics. The specification is very flexible for exposure to the program, with two instruments for each indicator of duration. The first instrument is the percentage of schools in the same municipality benefited for at least as many years as the indicator. The second instrument is the percentage of students in the same town benefited for at least as many years as the indicator. Instruments are relevant, a high percentage of beneficiaries indicate an adequate town infrastructure, thus a higher probability of being treated. However, the instruments fail the exclusion restriction. Town infrastructure is also correlated with the existence in the town of other key educational inputs. Finally, the analysis ignores a teacher's promotion regime implemented in 2002, that can affect differentially schools.

In summary evidence of information technologies effect on academic outcomes, it is not clear whether there is a benefit. Estimated benefit ranges from -0.15 to 0.52 standard deviations, differences in estimates do not depend on the schooling level or subject tested. Moreover, any positive benefit in the short run is nor permanent. Evidence for the CPE program is mixed, but comparing baseline models the effect of the program seems to be small.

1.3 Description of the program

In 2001 the minister of education of Colombia started "Computadores para educar" (CPE) a program that intends to close the gap in access to information technologies in public schools. Refurbished computers donated by the private sector are distributed to public schools, libraries, and cultural houses that satisfy these criteria: apply to the program, are powered, and have an exclusive physical space to install the computers. During the application process schools fill a form that allows CPE staff to rank them, and computers are allocated to those with a higher score.[4] Between 2001 and 2010, there were two allocation rules of computers, both use the same variables to determine allocation but with different weights.

In 2001, the minister of education of Colombia started "Computadores para educar" (CPE) a program to close the gap in access to information technologies in public schools. The private sector grant refurbished computers to powered public schools, libraries, and cultural houses that apply to the program and dedicate a classroom to the computers. First schools are ranked using their essential characteristics. Higher ranked schools receive the computers.[5] Two allocation rules were used between 2001 and 2010, both use the same variables but with different weights.

First, between 2001 and 2006 computers were allocated in a ratio of 20 kids per computer. Assignation focuses in schools located in the countryside, with a high percentage of minorities like African-Colombian or Indigenous, and that can share computers with the community. This selection maximizes impact by focusing on schools with higher limitations in access to computers, or in more disadvantaged communities that are expected to have the highest rates of return. Beginning 2006 the program focuses on satisfying the national goal of 12 students per computer. Thus, the central

[4]Information collected include the following variables: if school have students from a specific ethnicity, students with disabilities, sources of resources, total enrollment and per grade and information about computers stock and preventive maintenance.

[5]Information about student ethnicity and disability, which is the origin of the resources, enrollment, and computers stock and preventive maintenance.

objective was to increase coverage. Between 2001 and 2008 the program benefited 14,939 institutions by distributing 167,161 computers and training 161,214 teachers. Computers were allocated to 23.5% of public schools and had covered 43.3% of the students at public institutions. The program has extended to 96% of Colombian towns.

The program is divided into three phases. First, computers are allocated, installed, and corrective and preventive maintenance are provided. The second phase is 1-year teacher training run by universities in the region of the benefited school. This stage seeks to develop technical, technological, educational, and communicative abilities in teachers to boost teacher use of computers. Finally, teachers by themselves introduce technology into their education practices.

Beneficiaries of the program are classified into three groups: schools without computers, schools with a ratio of students to computers higher than the benchmark (12 kids per computer), and previous recipients of the program whose computers are now obsolete. Figure **??** shows computers granted by the program for each category. Between 2001 and 2009, the target were schools without access to information technology.[6] Starting 2010, allocation re-orientates to replace outdated computers and to institutions with a higher student-computer ratio than the national goal (50.3% and 28.8% respectively).

[6]Between 2001 and 2007 CPE was the only program that provides computers. In 2008 local and national programs started.

The CPE program has improved access to computers in public schools as suggested by the reduction of students-computers ratio shown in figure **??**. In 2002, there were more than 700 students per computer granted by the program, computers allocated up to 2012 have decreased this ratio up to 20. This figure constitutes an upper bound of the student-computer ratio given that it considers total enrollment in public schools, instead of enrollment at benefited schools.

Between 2001 and 2009, the program only distributed desktop computers. Laptops and tablets introduced in 2011 and 2012 and they represent over 66% and 8% of the devices granted. Laptops were mainly oriented to schools with out of date computers (53.2%), and to schools with high students to computer ratio (22.3%). Tablets were almost exclusively allocated to schools with a high computer ratio.

1.4 Conceptual framework

The economic problem faced by public schools in Colombia is the following. Before the program, each school chose the quantities of computers and other educational inputs to maximize its education production function subject to its budget constraint. Optimal decisions in this environment depend on marginal costs and benefits of computers, given preferences, and productivity of computers in each school.

The program increases the budget available to get computers and restricts computers to be at least the quantity granted by the program. Moreover, applying to the program crowds out resources from other educational inputs. Schools incur some cost while some schools need a new room for computers other schools need to acquire small safety materials. If the application cost is higher than the benefit, schools are worse off by entering into the program. Thus, only schools with a positive benefit will apply satisfying the constraint on computers. The number of computers depends on its productivity and the other inputs productivity. Finally, the problem for a school that does not apply remains as described in the previous paragraph.

In Colombia, each school define its short and long run objectives and summarizes them into a document called "institutional educational program (PEI)". This document is constructed considering preferences of principals, staff, and community. Some schools focus their planning on more applied fields like environmental or farming, to train students to be productive in their towns. While another group of schools, can define their objectives in a more traditional way, focusing exclusively on academic achievement. The differences in the definition of the PEI creates that inputs, input productivity, and optimal allocation are not the same across schools. Thus, the program effect is not constant making that some schools rationally do not to apply. The existence of the PEI may bias the estimate of the program effect. For instance, schools aiming high-quality of education will use test scores as indicators of quality. Therefore, those schools increase use of other educational inputs, independently of being in the program. In consequence, test scores will rise by other factors than computers, creating an upward bias in the OLS estimator. A school fixed effect will account for those unobserved idiosyncratic factors that are constant over the time of analysis. [7]

1.5 Data

The potential benefits of the CPE program on standardized test scores. In Colombia, there are three stages of education at which paper-based achievement tests are administered: elementary (5^{th} grade), middle school (9^{th} grade), and high school (11^{th} grade).[8] These tests are also known as SABER 5, 9, and 11 and are administered by the ICFES.[9] The First two tests are a reference of the quality at initial stages. They test cognitive skills in language (Spanish) and mathematics and have been applied in three waves: 2002-2003, 2005-2006, and 2009.

Test for the 11^{th} grade is a benchmark for quality of the schools and by most universities as a measure of academic knowledge. This test evaluates biology, philosophy, physics, language, math, chemistry, geography, and social sciences. Also, a foreign language component was mandatory after the second semester of 2006. The second piece of information is the list of recipients between 2001 and 2009, the kind of computer allocated (desktop, laptop, tablet), the number of elements delivered, and the specific date.

[7] A Hausman test indicates differences between the parameters from a fixed and a random effect panel data, providing evidence that idiosyncratic components must be accounted for in the specification.

[8] There is no advantage for students with a higher computer literacy, given that these are paper-based tests.

[9] ICFES is a national institute in Colombia that provides an assessment of the quality of education.

1.5.1 Descriptive statistics

Recipients are divided into two groups using the SABER 5 and 9 test dates to ease comparison of the treatment effect. Thus the first, *"treatment 1"* consists of schools that receive computers between 2001 and 2005 and the second group *"treatment 2"* includes recipients between 2006 and 2009.[10] Finally, all other public schools are classified as non-recipients.

Table 1.1 presents descriptive statistics for school location, gender, age, grade, and school enrollment. Statistics for 5^{th} grade for treatments one and two are similar: about 60% of recipient schools are located in rural zones, with an average enrollment of 400 students. But recipients and non-recipients are different. Among non-recipients, 76% are in the countryside, and average enrollment is half of the registered in treated schools. At standard levels, it is not possible to reject that observable characteristics between the two treatment groups are the same. Consequently, it may be reasonable to assume that unobservable characteristics in treated schools are similar. However, this conclusion is less plausible and rejected by the data for non-recipient schools. The change in the allocation rule seems not to have an effect on comparability across treatments, this is due to the homogeneity across elementary schools.

On the other hand, characteristics of the middle and high school differ among treatments. The similarity between the middle and lower panel of table 1.1 is not

[10] Therefore, the group defined as treatment 2 will reflect a weighted average of the two allocation rules. As a robustness check estimations were performed using schools in treatment 2 with the same allocation rule than schools in treatment 1, estimates of the program effect do not change considerably.

surprising given that in Colombia middle and high school education are provided in the same institution. The percentage of rural recipients in treatment 2 is between 12 and 15% lower than in treatment 1 and school enrollment is around 30% higher in treatment 2 than in 1. These facts are consistent with the change in the allocation rule. Moreover, about 25% of non-recipient schools are in rural areas; this is about half of the percentage of treated schools located in the countryside. Average enrollment is almost the double in the non-recipients than in schools in treatment 1.

1.6 Empirical results

This section presents evidence of the impact of the program. First, a homogeneous effect is assumed, then heterogeneity of the treatment effect by school size, location, and exposure is inspected. Subsection 1.6.1 discusses the most reliable specification considering school characteristics and a concurrent teachers' promotion reform, to improve teacher's quality. Following subsections allow heterogeneity under three alternative approaches. Subsection 1.6.2 presents estimates considering a non-homogeneous impact for each treatment. In subsection 1.6.3 the effect of the program is allowed to vary by school size and location. Then, in subsection 1.6.4 the measure of the program is changed to intensity given by the length of exposure, imposing a polynomial relation for duration effect (linear or quadratic) and a non-parametric estimation. This analysis determines whether the effect is persistent over time.

1.6.1 Model specification

This section presents the basic specification used to analyze the effect of the CPE program on academic test scores. First, we show estimates using a difference in difference approach including school and time fixed effects; then we include department trends as proxy of the teacher's promotion reform. As a result of idiosyncratic differences across schools we include school fixed effects. Also, there might be differences the cohorts of students or in the test difficulty, to address for them and other time-related differences in the specification time effects are included. Thus, common factors across recipients and non-recipients that differ by the year of analysis will not bias our estimates. The initial specification is a traditional difference in difference approach for multiple periods:

$$y_{i,t} = \alpha T_{i,t} + \sum_i \delta_i + \sum_t \tau_t \tag{1.1}$$

where $y_{i,t}$ denotes the standardized test score for school i in t, $T_{i,t}$ is 1 if school i is treated before period t by the CPE program, δ_i is a school fixed effect and τ_t is the time effect. There are three assumptions implicit in equation 1.1: *(i)* The program effect α is the same for all schools independent of year of treatment; *(ii)* the effect is independent of exposure; *(iii)* the trend in unobservable characteristics is the same for recipients and non-recipients between the first and second waves. The identification of the impact of the CPE program the difference in difference estimator requires that the change of the outcome for treated schools can be decomposed into two components: the change in test scores due to the program and the trend, which is the score for recipients in the absence of the program. That is, a reference group is required to account for the unobserved counterfactual.

Estimates from equation 1.1 do not consider a reform in 2002 that toughened requirements on teacher promotion. In the old regime, promotion depends on completion of training-courses or years of experience while in the new regime teaching, and cognitive skills of the teachers are tested. This reform creates incentives for teachers to become more skilled and productive. Already employed teachers decide whether to stay in the old regime or to change, while instructors hired after 2001 must start in the new regime.[11]

Incentives for young teachers create a differential in the quality of professors, such that instructors in the new regime have higher productivity. If this reform differentially affects schools and it is not accounted into the specification, the estimated treatment effect will be biased. For instance, if schools that hire younger teachers also are CPE recipients improvements in test performance would be explained by better instructors and the CPE program. Additionally, more productive individuals live in towns with better economic conditions. If computers are allocated to schools in cities with better access to utilities, infrastructure, and also with more productive teachers, the estimate will also reflect those economic conditions.

Data for this reform is hard to obtain because in Colombia decentralized secretaries of education are responsible for managing resources and keeping records of

[11] [54] analyzes how this reform affects educational outcomes like dropout rate and test performance at 5^{th} and 9^{th} grades. Results indicate that increases in the proportion of teachers under the new regime are negatively related to school desertion and improve performance at 9^{th} math and language tests up to a quarter of standard deviation.

public schools.[12] Moreover, until 2010 there was no requirement for each secretary to report information about school teachers and staff. Thus, not all schools keep records. Therefore, to address the bias due to this reform and given restrictions to obtain information, two set of variables are used.

First, school fixed effects control both school hiring and non-observed differences in city's economic conditions constant over time. Second, department trends are included to capture changes in demographic and economic characteristics common to recipients and non-recipients. Although secretaries, distribute resources and establish educational policies they follow national and departmental guidelines. Moreover, traditions, culture, and economic and demographic conditions are shared by departments.[13] Given that new teachers begin in the new regime, this reform is linked to changes in demographic conditionsthose department linear time trends will control for differences in unobserved demographic, economic and educational conditions across departments.[14] These trends account for the effect of the reform if the change is approximately constant over time, and if the impact of the reform is homogeneous inside each department by location and school size.

Table 1.2 presents estimates of the treatment effect for language and mathematics of two specifications of equation 1.1. [15] First column presents estimates without

[12]In 2013, there were 94 secretaries distributed across the 32 departments

[13]For instance, in 2006 and 2008 new laws for retention of students were promulgated, lowering dropout rate.

[14]To check the robustness of this selection, baseline estimations were performed using direct measures of demographic and economic conditions such as department GDP, population, and average age. Estimates were similar.

[15]For comparability estimates for the 11^{th} grade are restricted to years 2002, 2005 and 2009.

the department trends and the second column presents those estimates controlling for the teacher promotion regime. If there is no "substantial" difference in estimates between columns, it is arguable that the new promotion regime is unrelated to the CPE program.

Estimation is performed using a balanced panel. For language there are 25281, 6699, and 10773 observations for the 5^{th}, 9^{th}, and 11^{th} grade test scores. For mathematics there are 25455, 6702, and 10773 observations.[16] Without adding department trends, estimates of the treatment effect indicate a reduction in score of 0.04 and 0.06 standard deviations in language for the elementary and middle school, while for the 11^{th} grade score of treated schools increases by 0.07.

In mathematics, estimates of the treatment effect are negative for elementary and middle school tests, and positive for SABER 11 test. Adding department trends, the predicted impact on the 5^{th} and 9^{th} grade test score increase, being higher the increment for the middle school. If the only effect captured by the department trends is the new promotion regime, the higher estimates in the second column indicate a lower quality of teachers in recipient schools. This low-quality finding is consistent with the allocation rule until 2006 where computers were allocated to more disadvantaged schools. On the other hand, estimated impact for the 11^{th} grade reduces between column 1 and 2, indicating an upward bias without controlling for department trends. In this case, time-varying unobserved factors are positively correlated with the program. This correlation can be due to the focus of educational policies on

[16]Estimates using all available sample do not differ with respect to the results presented in this paper.

these outcomes as reference of quality of education at each institution.

In summary, initial estimates of the treatment effect that address the promotion regime indicate that there is no gain from the program on academic test scores for any of the schooling levels studied. Benefit for language test score ranges from -0.01 to 0.01; in mathematics, it ranges from -0.006 to 0.021. However, this no effect estimate could mask heterogeneity of the benefit across schools. For instance, there could be heterogeneity caused by the change in the allocation rule although this was an exogenous change and it must not bias estimates. If the effect differs under each allocation rule, the estimated impact is an average of the effects for each group. Also, the non-significant estimate may hide differences in the program effect by location, size, or exposure.

1.6.2 Alternative measures of benefits of being in the program

In this section, alternative measures of the program's impact are estimated relaxing assumptions from equation 1.1 to allow for heterogeneity on the benefit. A first way to include heterogeneity is allowing the treatment effect to vary depending on the timing of the allocation, as defined in section 1.5.1.

$$y_{i,t} = \alpha_1 T_{1i,t} + \alpha_2 T_{2i,t} + \sum_i \delta_i + \sum_t \tau_t \tag{1.2}$$

where T_{1it} and T_{2it} are indicator variables for schools in treatment 1 or 2 being benefited at period t.[17] For comparability, column 1 in table 1.3 reproduces estimates from the second column of table 1.2. This column is an average of the impact for both treated groups presented in columns 2 and 3. Thus, program's impact of -0.01 for language test scores at elementary school is decomposed into -0.04 and 0.014 for schools in treatments 1 and 2.

For middle school, benefited institutions during the first part reduce their score by 0.025 standard deviations while schools treated after 2005 increase their score by 0.03. At both schooling levels, the impact during the second part of the treatment is higher. In contrast, the effect on high school test scores is greater for schools treated before 2006 (0.015) than the estimated impact for schools in the second part (-0.011). Therefore, the evidence is inconclusive about what treatment is "better" for language test scores. As equation 1.1 is nested into equation 1.2, an F-test on the latter, restricting estimates from both treatments to be equal will select which specification fits the data better. Results in column 4 reveal a heterogeneous impact, rejecting null hypothesis at 0.16%, 3.04%, and 8.99% significance levels for $5^{th}, 9^{th}$, and 11^{th} grades, respectively.

In mathematics, the evidence does not support that a particular treatment has a higher benefit. For the 5^{th} grade, schools in the first part of the treatment increase

[17] This specification is equivalent to: $y_{i,t} = \alpha_{11} T_1 \times post1_t + \alpha_{12} T_2 \times post2_t + \delta_i + \tau_t$ where T_i denotes a school in treatment i and $posti_t$ is a dummy variable indicating whether schools got computer at time t.

their score by 0.03 standard deviations while the average score for schools in the second part is not affected by the program. For the 9^{th} grade, there is a higher impact of the treatment for schools in treatment 2 (0.05), compared with a reduction for treatment 1 schools (0.03). Finally, first-treated schools increase their 11^{th} grade test score by of 0.046 and schools in treatment 2 have a reduction of 0.023. The homogeneity of the program's impact (column 4) is rejected at 8.44%, 1.33%, and 0.0% for elementary, middle, and high school test scores.

Taking advantage of the nature of the data is possible to use a more flexible specification, which nests previous equations. A multi-period and multi-treatment specification that allows treatment 2 and non-recipient schools to have a different trend between the first and second wave, and the effect of the program for schools in treatment 1 to differ by wave, is:

$$y_{i,t} = \beta_0 + \beta_1 T_{1i}\tau_1 + \beta_2 T_{1i}\tau_2 + \beta_3 T_{2i}\tau_1 + \beta_4 T_{2i}\tau_2 + \tau_1 + \tau_2 + \delta_i + \epsilon_{i,t} \tag{1.3}$$

T_{1i} and T_{2i} are dummy variables for the school being a treatment 1 or 2 recipients respectively, and non-recipients schools are the omitted category. τ_1, τ_2 are time dummies for the second and third waves tests scores. This specification follows three groups between 2002 and 2009, where some schools never got treated, and other were treated with different timing, exposure, and allocation rule.[18] Two restrictions are imposed in 1.2 relative to equation 1.3. First, β_3 is restricted to be 0, i.e. schools

[18]Table A.1 of appendix A presents the complete estimation of equation 1.3 for language at the 5^{th} grade.

treated after 2006 have the same behavior before treatment as non-recipients and $\beta_1 = \beta_2$ i.e. the treatment effect is constant independent of exposure for benefited schools prior 2006.

In this framework, we also can consider non-recipients as the comparison group. For identification, it is assumed that the trend in unobservable for non-benefited schools is the same that the trend of benefited schools after treatment. The difference in difference estimator of the treatment effect is β_1 for schools treated before 2006 and $\beta_4 - \beta_3$ for schools treated between 2006 and 2009. These estimates are presented in columns 3 and 4 of table 1.4, and are directly comparable to columns 1 and 2 that are reproduced from Table 1.3. In language, estimates for elementary and middle school test scores of equations 1.2 and 1.3 keep the trend described. For the 11^{th} grade the estimated impact of the program is lower for treatment 1 and higher for treatment 2 than the estimates of equation 1.2. In mathematics, only the 9^{th} grade estimates are similar to those presented in columns 1 and 2. Schools in treatment 1 have a significant increase of about 0.1 standard deviations in elementary and high school test scores, but schools treated after 2005 have a reduction of 0.05 standard deviations.

In summary, using non-recipients as the comparison group, there is evidence of a small effect of the program that can differ across treatments. In language for elementary schools, first treated have a reduction of the score, and second treated have a positive impact. For the middle school the effect is similar, independent of the treatment; for the 11^{th} grade, there is a benefit of the program on achievement tests for schools in treatment 2 while the score reduces for schools in treatment 1. For mathematics, trends in estimates differ between specifications, so it is better to focus on the most flexible specification, where there are benefits for schools in treatment 1 in elementary and high school tests, but a reduction of the score for schools in treatment 2. For scores of the middle school, there is no gain of the CPE program on any subject.

The validity of previous results hinges on the common trends assumption that is not possible to test without pre-treatment data. Equation 1.3 yields a direct test for schools in treatment 2, if $\beta_3 = 0$ it is arguable that non-recipients share trends in unobservables with schools in treatment 2. Results for this test are presented in column 1 of table 1.5. In language, p-values for this hypothesis are: 0.80, 0.35, and 0 for elementary, middle, and high school; therefore, the common trends assumption holds for elementary and middle school and estimates of the impact are valid. On the other hand, in mathematics, p-values are: 0, 0.68, and 0 for 5^{th}, 9^{th}, and 11^{th} grades, so the common trends assumption only holds for the middle school. With respect to the estimates for schools in treatment 1, differences in observable characteristics presented in section 1.5.1 suggest that the common trends assumption is not reasonable. Thus, the comparison between those two groups may include confounding idiosyncratic factors to either group. Thus, a better counterfactual is required.

As recipient schools are similar in their observable characteristics independent of the date of treatment, schools in treatment 2 are a better counterfactual for schools in treatment 1. Neither first nor second treated schools have computers in 2002 and only schools in treatment 1 got by computers by 2005. Thus, program's impact is computed as $\beta_1 - \beta_3$ in 1.3. That corresponds to the difference between scores in the first and second wave for schools under treatment 1 and the change in score for the same waves for schools in the treatment 2.[19] Column 5 of table 1.4 reports these estimates, that are comparable with those from columns 1 and 3, using a different counterfactual.

For language at elementary school, the average test score for recipients decreases by 0.06 standard deviations, the impact at middle and high school is nonsignificant and around zero; for mathematics in elementary school, there is a reduction of 0.01 standard deviations while this effect increases for middle school to 0.034. However, both estimates are not precisely estimated; meanwhile, high school test scores for schools in the first part of the treatment increase by 0.05 standard deviation. In summary, estimates indicate a small impact of the program, not precisely estimated for the majority of specifications, except for language in elementary (-0.05) and mathematics in high school (0.05).

Before concluding this section, results for the other 2 restrictions imposed on specification 1.3 to be consistent with equations 1.1 and 1.2 are presented. The test for a constant effect independent of the length of exposure is presented in column 2 of table 1.5. In language and mathematics, the F-tests are rejected at the 5% and indicate that staying three additional years effect is different. Finally, column 3 presents

[19]An alternative specification that produces identical results, is to restrict the sample to the first two waves using only treated schools. The causal impact of the CPE program (θ_1) can be estimated, under the traditional DID framework, using the group of schools in treatment 2 as the omitted category.

$$y_{i,t} = \tilde{\beta}_0 + \tilde{\beta}_1 C1_i + \tilde{\tau}_1 + \tilde{\theta}_1 T_{1i} \times \tau_1 + \epsilon_{i,t} \tag{1.4}$$

the test for homogeneity of the impact using as counterfactual non-recipients across treatment 1 and 2. Results for both subjects indicate that at elementary and high school the effect differs by treatment, but this conclusion does not hold for the middle school estimates. Evidence of heterogeneity by treatment is not conclusive because estimates for treatment 1 using non-recipients to control for trend in unobserved characteristics do not satisfy the common trends assumption.

Summing up, program's impact estimates indicates a small effect on academic test scores for all schooling levels, but there is evidence that treatment effect is not equal in both treatment groups. In language, for the 5^{th} grade there is a negative and precisely estimated impact on first treated schools of -0.05 standard deviations, independent of the counterfactual selected to account for the trend in unobservable characteristics. For the 9^{th} grade, no estimate is precisely estimated, and for the 11^{th} grade, there is no evidence of impact using the most reliable specification. In mathematics, there is no impact for the 5^{th} and 9^{th} grades, but there is a positive effect for the 11^{th} grade.

1.6.3 Heterogeneity by school size and location

The existence of complement and substitute resources in schools can create a differential impact of the CPE program, two measures related to resource availability are school size and location. For instance, bigger schools have a larger staff and other complementary resources like libraries and labs that can increase the effectiveness of computers on academic outcomes. Also, larger schools specialize their professors into specific subjects, being more qualified in the use of computers and related academic resources. The second source of heterogeneity inspected is location, schools in rural zones face higher restrictions in their access to other inputs like internet, public libraries, and high-quality teachers. In order to check this effect, interactions for school size dummy or a location dummy are added to equation 1.3. School size is defined as big if enrollment is above the median and small otherwise.

Columns 1 to 3 of table 1.6 show the treatment effect by school size, the upper panel corresponds to estimates of the effect on language. At 5^{th} grade, larger benefited schools reduces their score by 0.06 standard deviations while small schools increase their score by 0.08. Although this difference seems significant, it is not possible to reject the test that the program impact does not depend on school size as shown in column 3. Estimates of the program effect at the 9^{th} grade are similar by school size 0.001 and -0.009, then the F-test is not rejected with a p-value of 88%. In bigger schools in the 11^{th} grade, there is an increase of 0.007 standard deviations in the score, while there is a reduction of 0.025 in smaller schools. Both estimates are imprecisely estimated. Therefore, the F-test of homogeneity can not be rejected. For mathematics, lower panel, elementary test score for benefited schools with a higher enrollment reduces by 0.01 standard deviations and increases for smaller schools by 0.08. Again, the school size interaction reduces the precision of the estimates, and it is not possible to reject the homogeneity test of the effect by school size. Estimates for the 9^{th} grade indicate that bigger schools have an increase of 0.08 standard deviations in average test scores while there is a reduction of 0.08 in small schools, the F-test rejects the equality of the estimates. In the 11^{th} grade, larger treated schools have an increase of 0.07 standard deviations in their score, while smaller schools have a nonsignificant reduction of 0.01.

Columns 4 to 6, present estimates allowing a different program's impact by school location. For language at the 5^{th} grade, urban schools exhibit a significant decrease in their score of 0.08 standard deviations, while there is an increase of 0.04 standard deviations for schools in rural areas that is imprecisely estimated. The test of equality is rejected. For the 9^{th} grade, urban schools reduce their score by 0.02 standard deviations, while rural schools increase their score by 0.07. However, it is not possible to reject a homogeneous effect hypothesis for both locations. For the 11^{th} grade, rural schools increase their score by 0.03, while in urban schools reduce it by 0.02 standard deviations.

In mathematics for the 5^{th} grade, the treatment effect is not precisely estimated, althought it follows the trend observed in language. There is a reduction in scores for urban schools of 0.03 and an improvement in 0.05 for rural schools. Those impacts are statistically different with a p-value of 8.9%. For the 9^{th} grade, estimates indicate a positive impact on both tests in the 5^{th} and 9^{th} grades, but none of them are statistically different from zero, and test for homogeneity is not rejected. Finally, in the 11^{th} grade, there is a significant increase in the score for schools located in rural areas of 0.09 standard deviations, while this is only 0.019 in urban schools. The F-test rejects that effect is the same for both locations.[20]

[20] Also we inspected a more flexible estimation allowing both interactions at the same time, results were consistent with table 1.6, but standard errors were higher making it more difficult comparisons.

All in all, there is evidence at the 5^{th} grade that treatment effect differs by school location, with rural schools exhibiting higher benefit and that treatment effect for mathematics average score in the 9^{th} and 11^{th} test scores is a higher in bigger schools. Despite most of the estimates are not precisely estimated, some trends can be inferred from results. Two results support the idea that computers were allocated to schools where resources were scarce and computers helped to overcome deficit in other inputs. First, at the elementary school the effect on both subjects is higher in smaller schools and for all schooling levels, second the program's impact on rural schools is higher.

Additionally, results of a higher benefit for bigger schools in post elementary tests (9^{th} and 11^{th} grades) seems to support the idea that computers are more effective if they are complemented with other educational inputs available at school. The high standard error makes it difficult to compare and make statistical inference. Therefore, all remaining analysis is made using the whole group of schools.

1.6.4 Heterogeneity from exposure analysis

According to [5] existence of information technology (IT) in benefited schools is a key factor that determines the success of this programs. The longer the exposure to IT programs, the greater the impact on academic outcomes is expected, due for instance, to the fact that teachers might be able to integrate more efficiently computers into their classes. This section investigates whether there is heterogeneity of the treatment effect for schools in treatment 1. Alternative assumptions about the exposure are examined: a constant effect (column 5 of table 1.4), then the binary measure of treatment in equation 1.3 is replaced by a measure that accounts for the length of exposure using a linear, a quadratic and a non-parametric relationship between test scores and exposure. Similarity among the estimates for both groups suggests that the best candidate as comparison group is the second group of schools. Therefore, the effect is estimated with exposure varying between 1 and 3 years for benefited schools and no exposure for schools that got computers after 2005.

To compare estimates, table 1.7 summarizes the predicted benefit by the time of exposure. For language, only the last column corresponds to actual estimates. Estimates of the predicted benefit in columns 1 to 3 are constructed subtracting from the implied benefit the estimated change in the score between the first and second wave for schools in treatment 2.[21] The upper panel corresponds to the 5^{th} grade where results differ substantially by specification.

Assuming a constant effect, first column, there is a reduction of 0.05 standard deviations in the score of recipient schools, while the linear relationship also finds a negative effect of the program around 0.03, that diminishes with any additional year in the program. On the other hand, the quadratic model predicts an increasing effect from -0.097 in the first year to 0.009 standard deviations after being in the program for three years. Finally, column 4 indicates that under the non-parametric specification, estimates are non-statistically significant without a clear pattern for this effect. Schools exposed 1 year to the program experienced a reduction of 0.059

[21] Tables A.2 and A.3 in Appendix A present the estimated coefficients for linear and quadratic models, as well as the estimate of the change for schools in treatment two between the first and second waves.

standard deviations in their average score; the score increases by 0.003 in the second year, and -0.027 in the third year. The last row in this panel presents an F test to check whether estimates from columns 1 to 3 differ from those in column 4. Linear and constant specifications are adequate while quadratic estimates do not fit the data as well as the most flexible estimation.

For the 9^{th} grade, results indicate that longer exposure to the program reduces test score, but no estimate was statistically significant. Assuming a constant effect, there is an insignificant program's impact of -0.001. Restricting the relationship between exposure and test score to be linear, there is an adverse effect during the initial three years in the program ranging from -0.017 to -0.028. The quadratic trend shows that during the first two years score increase by 0.02 standard deviations, and it reduces by 0.036 after three years in the program. Finally, the non-parametric specification, indicates a positive impact during the first two years of about 0.06 standard deviations, that change sign to a reduction of 0.035 for the third year. According to the F tests, the hypothesis that fits from quadratic function and the constant specification are the same that the flexible estimation can not be rejected. However, the test rejects equality among the dummy and the linear specification.

For high school test scores, a reduction of 0.004 standard deviations is estimated under constant effect. The linear model estimates a positive impact that decreases with exposure from 0.023 to 0.008. The quadratic specification indicates a negative effect during the initial two years of exposure (-0.01 and -0.02 standard deviations), and a small positive effect after three years (0.03). The flexible specification indicates that schools reduce their score for one year in the program by 0.02 standard deviations and by 0.05 for schools more than one year in the program. F-tests indicate that constant, linear and quadratic specifications fit data as well as the dummy specification.

Table 1.8 presents the same set of results for mathematics. For the 5^{th} grade, there is a reduction of 0.01 standard deviations according to the constant specification, while there is an increasing effect of the program with exposure from -0.06 in the first year to 0.015. This increasing trend is also consistent with the quadratic specification where treatment effect ranges from -0.028 to 0.009. Finally, nonparametric estimates show an increase of the average score for schools treated in the first year of 0.02, 0.015 for the second year of exposure and a reduction of -0.035 in the third year. According to the test of homogeneity across estimates, only the constant and linear models fit the data as well as the dummy variables specification.

For the 9^{th} grade, under a constant effect, there is an increase of 0.03 in the score of recipient schools. The linear model also estimates that the program's impact is positive during the three initial years into the program around 0.03 standard deviations. A similar finding is obtained in the quadratic specification, with an impact of 0.046 in the first year, 0.054 in the second and 0.037 after three years in the program. Finally, the flexible specification shows that the estimated impact after two years is higher (0.172) than for the first (0.044) or the third year. The F-test rejects that constant, linear and quadratic specification are as good as the most flexible alternative. In the 11^{th} grade, the linear specification shows an increase of 0.05 standard deviations in treated schools test score. The linear model estimates an increasing in exposure benefit from -0.003 to 0.068 standard deviations and the quadratic specification shows an u inverted form for this relation from 0.056 in the first year to 0.028 after three years of receiving computers. The most flexible specification shows that benefit decreases from 0.059 for schools that receive computers one year after taking the test to 0.005 standard deviations for schools that got computers in 2002.

In summary, estimates for language indicates that allowing program effect to vary according to school's exposure, do not change substantial findings from the previous section for elementary, but a marked adverse impact is obtained for middle and high school test scores. However, most of the estimates are not precisely estimated. The majority of the treatment effects show a reduction in the elementary school and for the most flexible specification in the 11^{th} grade. The impact is positive for the 9^{th} grade. However, after three years in the program, there is no difference between the score of recipients and nonrecipients. In mathematics, for the 5^{th} grade, schools that participate in the program do not experience changes in their average score. On the other hand, tests for the 9^{th} and 11^{th} grades indicate that recipients experience an increase during the first two years in the program, and especially in the second year, but this impact disappears for the third year.

1.7 Discussion and Conclusions

This document presents several measures of computer benefits on academic achievement tests for 5^{th}, 9^{th} and 11^{th} grades test scores, under different assumptions the results do not support the hypothesis that computers improves learning and standardized test scores. Given differences in observable characteristics between recipients and non-recipients, the most reliable set of estimates is obtained comparing the effect on schools treated before 2006 with schools treated after that year used as reference. This effect is only statistically significant for language at the 5^{th} grade (-0.05) and for mathematics in the 11^{th} grade (0.05). For all schooling levels, analysis of the impact by school location indicate a higher treatment effect for rural schools than the estimated in urban recipients, but this estimate is only precisely estimated at the 5^{th} grade. Analysis by school size suggests that smaller schools are more benefited in elementary while, in the 9^{th} and 11^{th} grades treatment effect in bigger schools is higher, however the majority of those effects are not precisely estimated. Results in language including a measure of exposure to the treatment indicates that there is no difference between test scores for benefited schools and those from never recipients during initial 3 years, while in mathematics a positive effect is found during the two initial years into the program but this is effect declines to almost zero in the third year.

Some elements of the discussion about computers benefits on academic outcomes are similar to the previously presented by inclusion of calculators into learning practices, see for instance [43, 15] and [27]. At the time pocket calculators were introduced into teaching, instructors were concerned that their use will prevent students from learning crucial mathematical skills. However, there could be a benefit if students will take advantage of the time reduction due to the use of calculators and focus instead on studying fundamental concepts behind operations. Therefore, how technology is included into classes and daily practices is a key factor in order to analyze their impact. Computers are more complex than calculators, since they can develop a variety of activities, having effect on a broader range of skills, like writing, spelling and calculating math operations. Therefore, to boost the impact of any program related with computers and technology, it is customary to analyze the purpose and limitations of computers in each field. For the CPE program, the training phase was designed to teach instructors about computer possibilities in the classroom, increasing program's impact and allowing to integrate computers into teaching daily practices.

Findings in this paper and those of [7] are similar, they also found that there is no impact of the program, because in benefited schools use of computers only increases in computer science class. This association is not strange given that usually public schools in Colombia only are equipped with one computer lab room for all grades. Therefore, even if teachers want to use technology to teach or to instruct students to use computers at free time, it is physically impossible for students to take advantage of this resources. More motivated teachers can recommend students to search at home for specific learning resources but given that not all students have computers or access to internet, this teaching practices can not be enforced. Moreover, CPE program is not oriented to solve deficiencies in specific skills or subjects through a specific software, as in computer aided instruction, so it is not easy to determine a particular ability or subject to account for the benefits of the program. Because of that, this program is more closely related to increase computer literacy; findings of no impact of computers at school on pupil outcomes, are consistent with that literature as [47, 33] .

However, there are some methodological issues that make difficult to establish a direct link between this paper and [7]. First, test structure differs, they administered their own version of the SABER exams. This could be an issue for this study, if differences in test and cohorts are not completely captured by the time fixed effect. A second difference among students is that in this study is not possible to track students, so the estimates reflects an average for the school and do not include the effect of students who switch schools as a response to the program.[22] Third, evidence from [7] corresponds to all elementary students that are more representative of overall school improvement than data from SABER 5 9 and 11 used in this paper. From the data, it is not possible to separate for each school treatment effect between exposure and effect at different grades. However, results from this research can be representative of all elementary if effect across grades is constant, as it seems to be indicated by the small estimates independent of length of exposure found. Fourth, average exposure to the program differs from [7] because they focus on the short run effects of the program (18 months). Estimates from the flexible model suggest that in the majority of schooling levels and subjects effect does not differ after 2 years of being benefited by the program. Finally, there is a geographical difference while [7] focus on a specific region, while in this study results are obtained using schools from all Colombia's departments, with differences among regions of Colombia because for instance of teacher's training.

[22] [56] shows that under migration or switching of population, estimated effect of a program could be biased due to a number of factors: the compositional change in the students at schools benefited, the difference in the initial characteristics of the "migrants" and "residents" populations, the mean effect of the program in those sub-populations, and the change in the migrants population due to the selectivity of the new migrants. The direction of the bias will depend on the characteristics of the migrant population that is not possible to obtain from official records.

Results for the exposure effect using the non parametric specification can be compared to those obtained by [50], who found a small and imprecisely estimated impact for any recipient in the initial 3 years of the program. But, after four years their estimates indicate that benefited schools increase their score between 0.045 and 0.146 standard deviations. Estimates from both papers indicate a small impact of the program, even after allowing teachers to incorporate them into their teaching practices.

But this similarity must be considered with cautiones given some methodological differences. First, their study considers the effect of the program on aggregate SABER 11 test score, not only on mathematics and language, the impact of the CPE program can be related with score increases in other fields of knowledge. Second, their estimates are for high school test scores, there could be differences that suggest a differential effect by grade because of two reasons: high school students are more familiarized with computers use and because topics in high school are more complex requiring investigation and use of complementary sources. Third, students at elementary and high school are different by nature, there is a selection process that make that worst students dropout early and do not finish high school[23]. Fourth, high schools are located in more populated areas, usually characterized with better economic conditions and therefore with a higher access to other educational inputs, therefore if computers are complementary in the production function the rate of return on high school academic outcomes is presumed to be higher. Fifth, the assumptions about effect of non switchers are different, they restrict sample to non switchers i.e. to those students for whom, the benefit of stay is greater than that of leaving, therefore

[23] In 2006 and 2008, regulations punishing parents of students who stop their studies were promulgated, so this conclusion does not hold for the following period

estimated effect presents an upward bias. In contrast, in this paper due to the lack of student's information it is not possible to determine whether there is an upward or downward bias. Finally, there is a difference in schools used as counterfactual, while [50] control for unobserved trend using as counterfactual non-recipients, in this paper the group of control schools is conformed by the schools that got computers later.

Another plausible explanation to this non significant effect of computers on mathematics and language achievement tests, is that use of computers of the CPE program is not more effective than any other method used for teaching. This is true if CPE program has crowded out other educational inputs in order to get the computers, then would have recipient schools maintained initial allocation estimates would have found an increase in achievement, unfortunately it is not possible to test this hypothesis to with data available. The difference in estimates from school location and size, despite most of them are not statistically significant, leaves open the question of how other educational inputs available at school and effectiveness of the program are related. Although the main goal of the program was to increase use and access to computers so as reduce the digital gap in public schools, benefits of this policy are not exclusively on academic grounds, schools and society itself benefit from individuals with higher knowledge of IT, given that this eases communication, entertainment, and increases individual's skills and productivity for future jobs.

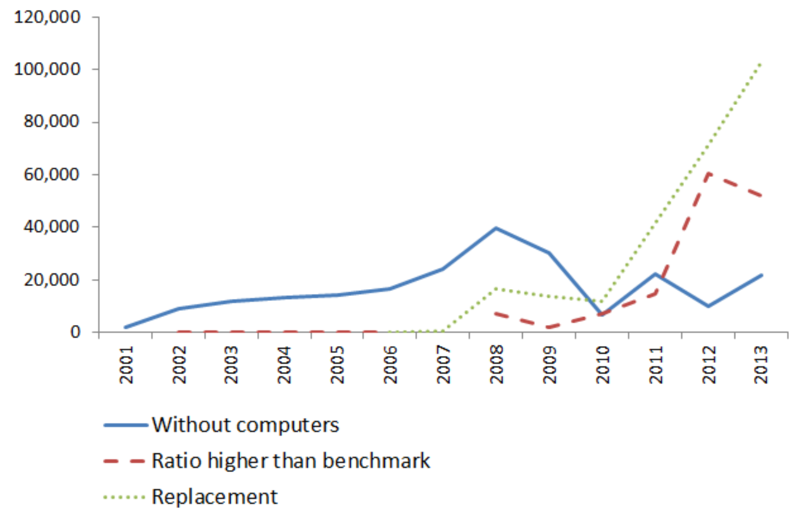

Figure 1.1: Computers granted by the program by type of recipient.

This figure presents the annual number of computers granted by the program according to three categories: schools without access to computers (solid blue line), schools with a limited number of computers (red dashed line) and schools with computers that are obsolete (pointed green line).

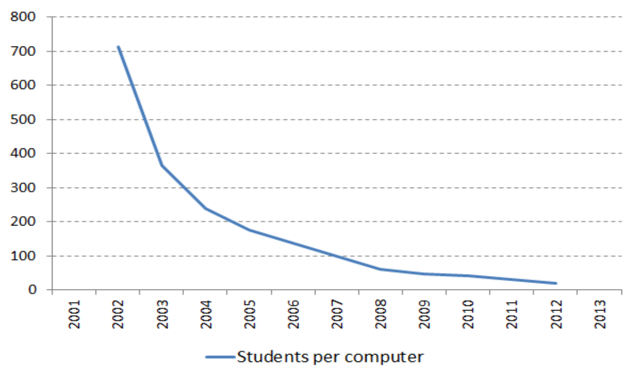

Figure 1.2: Ratio of total students to computers granted by the program.

This figure presents the ratio between enrolled students in all public institutions and the computers granted by the program, then it is a proxy for the impact of the program on students access to computers.

	Treatment 1	Treatment 2	Non-recipients
	5^{th} grade		
% rural	0.58	0.59	0.76
	(0.49)	(0.49)	(0.43)
% male	0.47	0.47	0.47
	(0.20)	(0.21)	(0.28)
Av Age	10.9	10.9	10.9
	(1.1)	(1.1)	(1.2)
Enrollment per grade	43.2	40.8	21.7
	(45.7)	(46.8)	(43.8)
School Enrollment	403.5	396.8	190.3
	(403.5)	(396.8)	(190.3)
N	2015	3870	10298
	9^{th} grade		
% rural	0.58	0.43	0.25
	(0.49)	(0.50)	(0.43)
% male	0.47	0.49	0.44
	(0.16)	(0.17)	(0.20)
Av Age	14.6	14.6	14.4
	(0.9)	(0.9)	(0.8)
Enrolment per grade	46.2	79.1	107.6
	(47.2)	(88.9)	(114)
School enrollment	588.8	793	1011.8
	(511.5)	(673)	(851.9)
N	1057	1641	1891
	11^{th} grade		
% rural	0.56	0.44	0.28
	(0.46)	(0.51)	(0.45)
% male	0.48	0.49	0.46
	(0.13)	(0.15)	(0.17)
Av Age	16.6	16.6	16.5
	(0.8)	(0.9)	(0.8)
Enrolment per grade	48.4	68.9	95.2
	(47.4)	(76.7)	(92.4)
School enrollment	605.2	798	1032.4
	(573.1)	(646)	(889.1)
N	741	1577	1273

This table presents the summary statistics for recipients of the program divided into two treatments. Treatment 1 refers to schools that were benefited by the program prior to 2006, while Treatment 2 refers to school that got computers in 2006 or later. Control group corresponds to all schools that never got computers from the CPE program. Standard deviations are presented in parentheses.

Table 1.1: descriptive statistics.

	Without additional controls	With department trends
Language		
5^{th} grade		
Coefficient	-0.0427***	-0.0102
Standard error	(0.011)	(0.0114)
R^2	0.004	0.091
N	25281	25281
9^{th} grade		
Coefficient	-0.0554***	0.0105
Standard error	(0.0166)	(0.0161)
R^2	0.004	0.134
N	6699	6699
11^{th} grade		
Coefficient	0.0712***	-0.00413
Standard error	(0.0085)	(0.0086)
R^2	0.013	0.212
N	10773	10773
Mathematics		
5^{th} grade		
Coefficient	-0.0137	0.0127
Standard error	(0.0123)	(0.0126)
R^2	0.002	0.122
N	25455	25455
9^{th} grade		
Coefficient	-0.0744**	0.0207
Standard error	(0.0227)	(0.0216)
R^2	0.005	0.161
N	6702	6702
Coefficient	0.0264***	-0.0057
Standard error	(0.0079)	(0.0085)
R^2	0.006	0.087
N	10773	10773

This table presents alternative specifications of equation 1.1 including covariates to control for other educational reforms. First column, corresponds to estimate from a model with school and time effects. Column 2 includes department trend to proxy for the change in promotion conditions for teacher.

Table 1.2: Estimates of the treatment effect assuming an homogeneous impact

	Homogeneous impact	Impact for treatment 1 schools	Impact for treatment 2 schools	Test for homogeneity of the impact
	α	α_1	α_2	F test
		Language		
5^{th} grade	-0.01	-0.042**	0.014	0
	(0.011)	(0.015)	(0.014)	
9^{th} grade	0.011	-0.025	0.030	0.03
	(0.016)	(0.0230	(0.018)	
11^{th} grade	-0.004	0.015	-0.011	0.09
	(0.009)	(0.014)	(0.009)	
		Mathematics		
5^{th} grade	0.013	0.032	-0.002	0.09
	(0.013)	(0.017)	(0.0150	
9^{th} grade	0.021	-0.034	0.050*	0.01
	(0.022)	(0.031)	(0.025)	
11^{th} grade	-0.006	0.046**	-0.023*	0
	(0.009)	(0.014)	(0.010)	

This table presents alternative measures of the impact of the CPE program, using as counterfactual schools that never got computers. α in column (1) corresponds to the estimate from a model with school and time effects where the impact of the program is constant, equation 1.1. Relaxing that assumption columns (2) and (3) measure the impact of the program for schools under treatments 1 and 2, equation 1.2. Column Four presents the F test and its p-value that estimates from columns 2 and 3 are equal.

Table 1.3: Heterogeneity of the program impact by group of schools treated

	Impact for treatment 1 schools	Impact for treatment 2 schools	Impact for treatment 1 schools	Impact for treatment 2 schools	Impact for treatment 1 schools
	α_1	α_2	β_1	$\beta_4 - \beta_3$	$\beta_1 - \beta_3$
			Language		
5^{th} grade	-0.0424**	0.0143	-0.0591**	0.028*	-0.055***
	(0.015)	(0.014)	(0.018)	(0.016)	(0.019)
9^{th} grade	-0.025	0.0296	0.021	-0.01	-0.001
	(0.023)	(0.018)	(0.029)	(0.023)	(0.027)
11^{th} grade	0.0152	-0.0108	-0.0640***	0.038***	-0.004
	(0.014)	(0.009)	(0.016)	(0.011)	(0.016)
			Mathematics		
5^{th} grade	0.0321	-0.00199	0.0989***	-0.058***	-0.011
	(0.017)	(0.015)	(0.020)	(0.018)	(0.021)
9^{th} grade	-0.0336	0.0500*	0.0208	-0.003	0.034
	(0.031)	(0.025)	(0.039)	(0.031)	(0.036)
11^{th} grade	0.0456**	-0.0234*	0.101***	-0.057***	0.051***
	(0.014)	(0.009)	(0.016)	(0.011)	(0.016)

This table presents alternative measures of the impact of the CPE program allowing heterogeneity by treatment, Columns 1 to 4 use as counterfactual never recipients. Columns (1) and (2) measures impact of the program for schools under treatments 1 and 2, from equation 1.2. Columns (3) and (4) also compute those estimates, allowing treatment 2 schools to have a different trend than non-recipients. Column (5) presents estimates of the impact for the first group of treated schools, using as counterfactual schools in treatment 2.

Table 1.4: Impact of the program by treatment

		Common trends assumption for treatment 2 schools	Impact homogeneous independent of exposure	Equality of impact for treatments 1 and 2
		β_3=0	$\beta_1 = \beta_2$	$\beta_1 = \beta_4 - \beta_3$
		Language		
5^{th}	F test	0.07	4.21	11.15
	p-value	0.797	0.04	0.001
9^{th}	F test	0.87	9.55	0.55
	p-value	0.351	0.002	0.46
11^{th}	F test	31.51	72.53	25.86
	p-value	0	0	0
		Mathematics		
5^{th}	F test	38.17	8.26	30.11
	p-value	0	0.004	0
9^{th}	F test	0.17	17.38	0.18
	p-value	0.681	0	0.672
11^{th}	F test	22.41	28.27	63.12
	p-value	0	0	0

This table presents the F tests for restrictions that make equation 1.3 and 1.1, to be equal. First column present F test to check if schools in treatment 2 have the same trends that never treated schools. Column 2, presents test for assumption that effect is constant and independent of exposure for schools in treatment 1. Column 3 presents the test of equality of the treatment effect for schools treated before and after 2006.

Table 1.5: F tests for assumptions in Equation 1.2

	Size			Location		
	Big	Small	F test p-value	Urban	rural	F test p-value
			Language			
5^{th} grade	-0.058	0.081	0.374	-0.083	0.036	0.004
	(0.019)	(0.157)		(0.023)	(0.033)	
9^{th} grade	0.001	-0.009	0.883	-0.021	0.07	0.136
	(0.007)	(0.063)		(0.032)	(0.053)	
11^{th} grade	0.007	-0.025	0.403	-0.023	0.03	0.254
	(0.007)	(0.075)		(0.036)	(0.051)	
			Mathematics			
5^{th} grade	-0.014	0.076	0.595	-0.029	0.047	0.089
	(0.021)	(0.17)		(0.026)	(0.037)	
9^{th} grade	0.081	-0.088	0.062	0.015	0.095	0.335
	(0.041)	(0.081)		(0.042)	(0.071)	
11^{th} grade	0.067	-0.008	0.036	0.019	0.092	0.105
	(0.019)	(0.029)		(0.013)	(0.038)	

This table presents estimates of heterogeneity in the program's impact by school size and location for schools in treatment 1, using as reference schools in treatment 2. An interaction for school size is included in equation 1.3 in columns 1 and 2, and for location in columns 3 and 4.

Table 1.6: Heterogeneity of the program's impact by school size and location

	constant	linear	quadratic	Non parametric
			5^{th} grade	
1 year	-0.055	-0.025	-0.097	-0.059
2 years	-0.055	-0.029	-0.089	0.003
3 years	-0.055	-0.033	0.009	-0.027
F	1.45	1.1	9.1	
p-value	0.231	0.296	0.003	
			9^{th} grade	
1 year	-0.001	-0.017	0.015	0.064
2 years	-0.001	-0.023	0.010	0.06
3 years	-0.001	-0.028	-0.036	-0.035
F	1.38	2.6	0.83	
p-value	0.252	0.109	0.363	
			11^{th} grade	
1 year	-0.004	0.023	-0.009	-0.016
2 years	-0.004	0.015	-0.016	-0.049
3 years	-0.004	0.008	0.031	-0.049
F	0.43	0.64	1.64	
p-value	0.512	0.424	0.202	

This table presents predicted benefits by length of exposure for schools in treatment 1 between the first and second wave using four measures of exposure:a constant effect, linear and quadratic trends and a non parametric specification for the relationship between test scores and exposure. As comparison group, it is used the group of schools in the second part of the treatment.

Table 1.7: Estimated exposure effect for language

	constant	linear	quadratic	Non parametric
			5^{th} grade	
1 year	-0.011	-0.061	-0.028	0.020
2 years	-0.011	-0.023	0.009	0.015
3 years	-0.011	0.015	0.009	-0.035
F	0.81	7.12	1.92	
p-value	0.369	0.001	0.167	
			9^{th} grade	
1 year	0.034	0.024	0.046	0.044
2 years	0.034	0.025	0.054	0.172
3 years	0.034	0.025	0.037	-0.021
F	3.14	3.72	2.29	
p-value	0.078	0.055	0.132	
			11^{th} grade	
1 year	0.051	-0.003	0.056	0.059
2 years	0.051	0.033	0.080	0.048
3 years	0.051	0.068	0.028	0.005
F	4.06	3.87	1.02	
p-value	0.045	0.051	0.314	

This table presents predicted benefits by length of exposure for schools in treatment 1 between the first and second wave using four measures of exposure:a constant effect, linear and quadratic trends and a non parametric specification for the relationship between test scores and exposure. As comparison group, it is used the group of schools in the second part of the treatment.

Table 1.8: Estimated exposure effect for mathematics

CHAPTER 2

NONLINEARITIES IN THE EFFECT OF INCOME ON CHILD OUTCOMES.

ABSTRACT

This paper presents an approach to test nonlinearities in the effect of income on child outcomes controlling for endogeneity of income due to measurement error and unobserved fixed and transitory factors. Using the NLSY79 data, quadratic, logarithmic and spline specifications are inspected. Results are inconclusive and show that the data are consistent with linear and logarithmic specifications of the relationship between income and math and reading tests of cognitive abilities.

2.1 Introduction

Governments have implemented income support programs that expand households' budget constraints. One motivation for such programs is to improve academic performance, success in school and future productivity of children from disadvantaged households ([26]). An important issue in evaluating these programs is determining whether an additional dollar has the same impact on child outcomes for a family with an annual income at the low end of the distribution as it would have for a family in the upper end. The economics literature has focused on estimating the effect of income on child outcomes, without much consideration of whether the effect differs across the income distribution.

According to [49], if the income-outcome relationship is non linear, but a linear model is estimated, the estimate can be expressed as a weighted average of the marginal impact of income at different points of the distribution, different estimators such as OLS and IV implicitly weight marginal effects at any given part of the income distribution differently. The design of public cash transfers should account for the effect of income on child outcomes over the whole income distribution, so the government can redirect resources to the population with higher marginal benefits from this additional income. For instance, if there are diminishing returns to income, the marginal impact of subsidies for households at the mean of the income distribution can be close to zero. Thus, it is possible to reduce their cash transfers without hurting child outcomes and redistribute that money to increase poorer households' subsidies or program coverage. It is also important to identify nonlinearities in scenarios where the government increases the program's budget, because it would be desirable to increase cash transfers for households at the low end more than for other households benefited by the program.

Some studies have shown that there is a higher effect of income for groups with lower permanent income. Those estimates usually correspond to robustness checks of the baseline specifications, as in [1] or [22]. More direct evidence of nonlinearities in this relationship has been provided for instance by [11], who found an increasing income effect with the wage rate and with non labor income. In contrast, evidence of a diminishing income effect can be found in [55] and [26]. However, these studies do not control for the endogeneity of income to child outcomes as a result of unobserved heterogeneity.

This paper analyzes nonlinearities in the relationship between income and child outcomes. The main contribution is to relax the linearity assumption by specifying more flexible forms of the income - child outcomes relationship. The paper investigates whether non linear functional forms such as quadratic, splines and logarithmic provide evidence of nonlinearity. If there is evidence that the effect differs across the income distribution, estimates from this paper will be useful for policy design.

Estimates of the income effect are obtained following the approach of [22]. Their approach uses instrumental variables derived from changes over time in the Earned Income Tax Credit (EITC) to address identification challenges created by permanent and year to year changes in unobserved family characteristics that affect household income, parental behaviour, and child outcomes. The EITC provides income support to low and moderate income households, so it is a useful source of identification of non-linearities of the effect of income on child achievement in such households. In this paper, this framework is preferred since fixed effects estimators used in previous literature do not account for the endogeneity of income shocks and exacerbate measurement error bias.

This paper is divided into seven sections including this introduction. The second presents a literature review on non linearities of the income and child outcome relationship. In the third section a conceptual framework of the economics behind the relationship is provided. The fourth section describes the approach and assumptions used by [22] extended to the case of a quadratic specification. In the fifth section, results from a Monte carlo experiment are presented to analyze whether changes in the EITC provide identification if the true relationship between child outcomes and income is quadratic, cubic, logarithmic or piece-wise linear. According to the Monte carlo results, the proposed approach works well if the true model is given by a quadratic, logarithmic or a piece-wise linear specification. The sixth section describes the data used in the estimation. The seventh section, presents the estimates of the impact of parental income on mathematics and language using the NLSY79 data. In this section, only the specifications for which the proposed approach show enough power to detect nonlinearities are presented.

The Estimates do not provide evidence of a quadratic or spline relationship, while there is evidence that the data are consistent with a logarithmic relationship that exhibits diminishing returns to income. However, it is not possible to rule out linearity.

2.2 Literature review

There are two main strands identified by [42] in the analysis of the relationship between income and child outcomes. The first approach analyzes the reduced form effect of income on educational and behavioural outcomes: [11, 22, 51, 28]. The second focuses on the effect of financial constraints on educational achievement and skill formation: [48, 44, 16]. This literature review will focus on the first strand because this article will contribute to this field of the literature.

[11] used a fixed effects strategy to deal with the endogeneity of income caused by fixed unobservables family or child characteristics. The author analyzes the impact of current and permanent income on child outcomes, using the National Longitudinal Study of Youth (NLSY79).[24] [25] He found that a $10000 increase in real permanent income improves child outcomes by 0.8% to 1.5% of a standard deviation. This effect is very small and higher than the effect of "temporary income" which is even smaller, suggesting that only large income transfers would affect current child development.

The author investigates whether the effect is constant for different levels of the wage rate and nonlabor income, finding a nonlinear and increasing effect for PPVT and BPI. PPVT increases by 5% of a standard deviation for children in households in the lowest wage rate category while it increases 14% for children from households in the highest category of wage. The nonwage income effect on child outcomes also varies for each category inspected. The estimates result from a proxy approach in which the Armed Forces Qualification Test (AFQT) score is included to control for unobserved factors that affect both child outcomes and income.[26] However, those estimates might be biased because this proxy does not account for endogeneity caused by unobserved factors.

[24]Current income is defined as previous year income, and permanent income is computed as the average income between 1979 and 1991

[25]Outcomes analyzed include: Behavioural Problem Index (BPI), Peabody Individual Achievement tests of mathematics and reading recognition, Peabody Picture Vocabulary Test (PPVT), Verbal Memory Parts A and B, and the Motor and Social development

[26]The Armed Forces Qualification Test, or AFQT is a test collected in the NLSY79, that is similar to the test score applied to determine eligibility for enroll in the armed services. This test includes four sections taken from the Armed Services Vocational Aptitude Battery (ASVAB): Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning, and Mathematics Knowledge.

[22] address endogeneity caused by both permanent and transitory sources of unobserved heterogeneity. Transitory income may create a challenge for identification. For instance, a shock that decreases labor demand might force households to work part time, causing a reduction in income and this reduction may also increase stress at home which affects child outcomes. Their approach uses first differences to remove the bias caused by permanent unobserved characteristics related with the permanent component of income, and changes in EITC generosity over time as an instrument to deal with transitory income endogeneity. The authors use the NLSY79 focusing on the income effect on cognitive achievement. Estimates indicate that $1000 additional income increases math-reading achievement by about 6% of a standard deviation using current income. This estimate is larger in order of magnitude than estimates from a child fixed effects approach. For instance, the income effect is 4 to 7 times greater than findings in [11].

The authors estimate separately the effect of income according to mother's education, race, AFQT, marital status and child's age and gender. Although these classifications are not designed to study nonlinearities, those categories in most of the cases roughly correspond to a division into low and high income households. Their estimates suggest that the effect is higher for children with a mother with high school or less (5.4% of a standard deviation) than for children whose mother has a higher educational achievement (1.6%). Also the income effect for children whose parents are not married is higher (8.1%) than the effect for children of married couples households (4.3%). Moreover, their estimates indicate that the effect of income is higher for young children (12 years or less), children of mothers with low AFQT test score, children from households with non white parents and children from single parents. Although those differences provide evidence of a non constant effect, the high standard errors of the estimates do not allow one to reject the null hypothesis of equality of estimates across subgroups. This evidence is not a strict test of nonlinearity given that the correlation between these characteristics and income is not perfect.

[1] analyze a transfer program from a casino opening in 1996 in rural North Carolina. A portion of the profits from the casino was distributed to all American Indians living close to the casino. This criterion is independent of household characteristics, current employment status, and earned income. The authors find a positive effect on child educational attainment and a reduction in criminality. The effect differs by initial household poverty status. Their estimates suggest that for a household that was previously in poverty the educational achievement increases between 0.44 and 1.13 years, but only from 0.05 to 0.17 if the household was not in poverty. This positive relation also is reflected in the probability of high school graduation, which increases by 0.29 to 0.39 for households previously in poverty and by 0.01 to 0.13 for household that had not experienced poverty.

[55] found that adoptees achievement is similar to that of a couple's birth children. The authors claim that this is evidence of the positive effect of income, given that adoptees usually come from financially constrained households and that adoptive parents are from higher income households. However, there are diminishing returns with respect to income. For instance for a family in the 30^{th} percentile of the income distribution, educational achievement increases by 1.36 years while it only increases

0.89 for a family located in the median.

[49] analyze nonlinearities in the relationship between income and child outcomes. The authors show that traditional estimates from OLS, IV and FE can be expressed as a weighted average of the marginal effect on the subgroups of income included. The authors decompose the difference in estimates using these econometric techniques into two factors. The first factor is due to the distribution of weights, and the second is due to the marginal effects of income for each subgroup. Estimates of the effect of income from these techniques differ because the weights from each methodology differ, even if the assumptions for their validity hold. In the empirical application with Norwegian administrative data, the authors found that there is a quadratic relationship between parental income and IQ, years of education, and high school dropout rate. Additionally, they found that under a linear specification the IV estimator places low weight on the high marginal effect for poorer households. This is due to the fact that the instrument used in their IV estimation is an oil boom that mainly affects households in richer locations and therefore assigns little weight to the population in the lower part of the distribution.

These studies provide evidence that children in households with higher income develop more skills and have better academic outcomes. Moreover, the majority of the evidence suggests a non linear relationship, with higher returns for children in lower income or more disadvantaged households. However, the estimates from the previous research did not determine how the income effect varies across the distribution. Usually, those estimates were performed to check the validity of the baseline estimates and to highlight that benefits from income can be greater in financially constrained households. However as [49] show, estimates based on a linear specification of the causal impact of income represent a weighted income effect across the income distribution. If the true impact is nonlinear, a linear model will produce an estimate that represents the weighted average of the effect, with weights that depend on the source of identification.

2.3 Conceptual Framework

Parents interested in their children's future will invest time and money in the development of physical and mental health, as well as in cognitive and non cognitive skills of their children. [51] focus on two channels identified in previous research through which income affects child outcomes. The first channel, known as the *resource channel*, assumes that income affects the availability at home of essential inputs to children's development such as food, books, computers, and music and sports lessons. In an economic model, this channel operates through the budget constraint. The second channel, which has received less attention in the economics literature, is the *family process channel*, which assumes that income affects parental stress, and stress negatively affects parental behaviour, relationships among family members, and therefore family functioning. In an economic model this channel can be represented in different ways. Stress may be included as a negative input into the child outcome production function. Stress may affect other inputs' productivity in the child outcome equation. For instance, time devoted to children will be less productive for more stressed parents. Stress could be a consequence of the disadvantages of a low permanent income, and parents in more disadvantaged households will always be more stressed. Alternatively, stress can be due to fluctuations in income, and adverse shocks to income like job loss. These channels are not mutually exclusive and affect the amount and quality of inputs entering into the education production function of children.

From an economic point of view the demand for books, child care, and services such as music classes can be derived as the solution of a standard optimization problem according to household preferences, the education or child outcome production function and the time and budget constraints. In this framework, it is important to distinguish between the effect of permanent and transitory income in the decision making process. If households are able to borrow against future earnings, the optimal level of education would be entirely determined by the present value of income streams. However, if households can't borrow against future income, optimal investments are restricted to the income available at each period. This situation could generate an under investment in the children's human capital in poor households that are more financially constrained [8]. This constraint means that in these households the marginal rate of return on human capital exceeds the marginal rate of return on assets, but in households that do not face a liquidity constraint those two rates of return are equal. This model suggests an income effect that differs across the income distribution.

Finally, household income is correlated with other characteristics, such as parental education or skills that affect the child outcome production function and contribute to children's skill formation. Thus, households with higher income will also have more favorable environments for child development, and more able parents. This will create an upward bias in estimates of the income effect if these factors are unobserved. A mother or child fixed effects estimator can remove this endogeneity as long as these factors remain constant over time.

2.4 Empirical specification

In this paper, a reduced form approach similar to those used in studies discussed above is used to evaluate the effect of income on child achievement. This strategy has the advantage that it does not restrict the effect of income to operate through specific mechanisms such as the budget constraint, but it is unable to identify the mechanisms through which income operates. The approach follows [22] closely. An outcome for child i at age a, y_{ia}, depends on observable permanent characteristics x_i, an unobserved permanent child effect μ_i, time varying characteristics w_{ia}, and total family income net of taxes, and transfers, I_{ia}. We begin with a quadratic specification of income, which can be interpreted as a second order approximation to an unknown function.

$$y_{ia} = x_i'\alpha_a + w_{ia}'\beta + I_{i,a}\delta_1 + I_{i,a}^2\delta_2 + \mu_i + \epsilon_{yia}. \tag{2.1}$$

Estimating Equation 2.1 by OLS will give biased estimates for δ_1 and δ_2 if income is endogenous. For instance, household income may be correlated with unobservable conditions at home, like parent skills, educational background and health that affect child outcome even if family income increases. Taking first differences will remove any bias caused by such constant factors.

$$\Delta y_{ia} = x_i'\alpha + \Delta w_{ia}'\beta + \Delta I_{i,a}\delta_1 + \Delta I_{i,a}^2\delta_2 + \Delta\epsilon_{yia}, \tag{2.2}$$

where $\alpha = \alpha_a - \alpha_{a-1}$ is the effect on achievement of the fixed characteristics, which is assumed to be independent of age. An additional bias that will remain in OLS estimates of Equation 2.2 comes from the correlation between transitory shocks to income and changes in unobservable characteristics crucial for child outcomes. Following [22] the change in income, $\Delta I_{i,a}$ is instrumented using the change in EITC generosity over time. As EITC is a factor that determines after tax income, changes in this variable are correlated with changes in household income for benefited households. Moreover, changes in the EITC schedule are not related to family characteristics and child achievement so this instrument is exogenous. Therefore, IV estimation will provide a consistent estimate of the impact of income on child achievement for low income households. The proposed instrument is the expected change in income due to changes in the EITC, derived as follows.

Parental income can be expressed as the sum of pretax income P_{ia}, the EITC transfer $\chi_a^{S_{ia}}(P_{ia})$ minus taxes $\tau_a^{S_{ia}}(P_{ia})$. [27] The instrument proposed by [22] is:

$$\Delta\chi_a^{IV}(P_{i,a-1}) \equiv \chi_a^{S_{i,a-1}}(\hat{E}[P_{i,a}|P_{i,a-1}]) - \chi_{a-1}^{S_{i,a-1}}(P_{i,a-1}), \tag{2.3}$$

[27] Superscript s_{ia} denotes the specific EITC schedule faced by the child's family, which depends on the age and the number of dependent children in the family (one or more than one child).

where $\hat{E}[P_{i,a}|P_{i,a-1}]$ is the expected value of current pre-tax income given once-lagged pretax income. Thus the proposed instrument uses individual information available in the previous period, as well as child outcomes. This instrument is determined by family income evolution and changes over time in the EITC schedule. The first factor may be correlated with unobserved changes in family characteristics that affect child outcomes, while the last component is expected to be exogenous. In this context, the variety of changes over time in the EITC schedule that differentially affect households along the income distribution, identify the income effect.

Following [68], the square of income is instrumented using a two step estimator. First, the linear projection of income on the exogenous variables $\hat{I}$ is estimated. Then, this estimate is squared, $\hat{I}^2$, and used as instrument for I^2. This instrument is useful when there is a linear relationship between the endogenous regressor and the instrument. These two terms are expected to be valid instruments, because the EITC is determined by the government, and its schedule does not depend on child outcomes. Also, it could represent up to 40% of the total income for families, so it is likely to be a strong instrument for households at the lower end of the income distribution. However, this does not guarantee that those two instruments provide consistent estimates of the parameters of interest. Therefore, in order to check for the power and usefulness of those instruments a Montecarlo experiment mimicking the key features of [22] is presented in the next section.

An additional source of bias is caused by the fact that current outcomes may be correlated with lagged income. Therefore, in order to remove any bias it is proposed to include into the child outcome equation a control function for lagged income, $\Phi(P_{i,a-1})$. The final specification of the differenced child outcome equation is:

$$\Delta y_{ia} = x_i'\alpha + \Delta w_{ia}'\beta + \Delta I_{i,a}\delta_1 + \Delta I_{i,a}^2\delta_2 + \Phi(P_{i,a-1}) + \eta_{ia}. \tag{2.4}$$

This specification accounts for the fact that changes in the EITC affect differently the population depending on their location in the income distribution. [22] proposed that this relationship may be captured by a very flexible function, to guarantee that $E_a[\Delta\epsilon_{yia}|P_{i,a-1}, \Delta\chi_a^{IV}] = \Phi(P_{i,a-1})$ and therefore that estimates for δ_1 and δ_2 obtained from Equation 2.4 by IV are consistent. In their application they use the same function as $\hat{E}[P_{i,a}|P_{i,a-1}]$, but it is possible to include any function. For instance, [34] include a 10 piece-spline in the first lag of income. In [22] this function is not collinear with the first stage estimates because the EITC structure (phase-in, flat and phase-out zones) provides a non linearity. Implicit in this reasoning to guarantee identification is the assumption of the stability of the relationship between child development shocks and lagged income, so it is independent of age: $E_a[\Delta\epsilon_{yia}|P_{i,a-1}, P_{ia}] = E[\Delta\epsilon_{yia}|P_{i,a-1}, P_{ia}]$. Also, it is necessary to have a stationary process for income, i.e. $g(P_{i,a-1}, P_{ia}) = g(P_{i,a'-1}, P_{ia'})$ for all a, a'.

2.5 Identification of the income effect using the EITC

Theoretically the EITC satisfies the exclusion and validity restrictions for a valid instrument in the linear case, thus it is expected that transformations of this variable are also valid instruments. However, empirically there is still a question of whether failure to reject a linear specification is due to the fact that the set of instruments is not powerful enough or if it is because in fact the relation is linear. This section presents the set up and results of a Montecarlo experiment in order to check whether the proposed instruments will provide identification of the causal impact of income on child outcomes in Equation 2.4. This section aims to provide evidence on two questions: *(i)* if the true model is nonlinear in income, will the IV estimate correctly reject the null hypothesis of a linear effect?, and *(ii)* if the true effect is linear, will the IV estimate correctly fail to reject linearity?.

The artificial data is constructed to guarantee comparability with [22]. Subsection 2.5.1 presents how total household income and the EITC are constructed. The next subsections analyze several nonlinear specifications between child outcomes and income, using parameters in each functional form taken from estimates in [22]. Also, in each subsection additional instruments and the estimates under four scenarios of endogeneity are presented. Subsection 2.5.2 presents quadratic and cubic specifications. In subsection 2.5.3 two piecewise specifications are inspected, and in subsection 2.5.4 the logarithm of income is used. Finally subsection 2.5.5 presents a summary.

2.5.1 Montecarlo Setup

This subsection provides a description of how earned income, taxable income, and non taxable income are constructed in a Montecarlo so as to create comparable samples to the one used by [22]. It is assumed that there are 4,000 children observed every 2 years from 1985 to 1999, similar to the baseline sample. Earned income $E_{i,a}$ is defined as the sum of 5 components: an autoregressive component $E'_{i,a}$, an individual effect μ_i, a time effect δ_t, an endogenous component $endo_{i,a}$, and a shock $\epsilon_{Ii,a}$.[28] The autoregressive component captures changes in wages due to factors that grow at a constant rate, such as work experience, and it includes any shock to parental productivity whose effect does not disappear in the same period. In order to generate this autoregressive process, it is assumed that earned income for 1985 is generated by the following process $E'_{i0} \sim exp(normal(0, 0.9))$, and observations after 1985 follow an AR(1) process $E'_{ia} = 0.12 + 0.96 * E'_{i,a-1} + n(0, 0.9)$. Earned income can be written as:

$$E_{i,a} = 1.3 + E'_{ia} + \mu_i + \delta_t + 0.5 * endo_{i,a} + 1.1 * \epsilon_{I,i,a}, \tag{2.5}$$

where the fixed effect μ_i is drawn from a uniform distribution between -3.45 and 3.45, and the mean and standard deviations match estimates of the individual effects from [22], using a similar specification. $endo_{i,a} \sim iidN(0, 1)$ refers to the component of income that is endogenous, i.e. it is not observed by the researcher and affects both child outcomes and income. $\epsilon_I \sim iidN(0, 2.2)$. δ_t are time fixed effects that capture differences in productivity and economic conditions over the years, and are also set

[28]Earned income includes wages and salaries for both members of the couple if the child lives with both parents.

to match the estimates of [22].

Finally, in order to construct total household income it is necessary to include two additional components. The first is unearned income (UEI), which refers to income derived from sources other than regular employment. The second is non-taxable income (NTI),which refers to the income that by federal or state laws is exempt from taxes.[29] Those variables are constructed to match the structure of correlation among those 3 variables in [22]. For NTI construction, two cases are considered that depend on whether there is a positive value for earned income or not.

$$NTI = \begin{cases} \mu_{0_{I_0}} + \nu_{I_0,t} & \text{if } E_{i,a} = 0 \\ \mu_{0_{I_{>0}}} + \mu_1 \times E_{i,a} + \nu_{I_{>0},t} & \text{if } E_{i,a} > 0. \end{cases}$$

The same strategy is used to construct the unearned income, UEI. With the variables for household income previously defined, the EITC and taxes are computed using the Taxsim program provided by the National Bureau of Economics Research (NBER). Total income is defined as the sum of pretax income $P_{i,a}$ and the EITC benefit $\chi_a^{S_{i,a}}(P_{ia})$, minus state and federal taxes before credits $\tau(P_{ia})$.

$$I_{i,a} = P_{i,a} + \chi_a^{S_{i,a}}(P_{ia}) - \tau(P_{ia}), \tag{2.6}$$

where $\tau(P_{i,a})$ refers to the taxes paid by the family of child i at age a and $\chi_a^{S_{i,a}}(P_{ia})$ is the EITC benefit for the family of child i at age a under the schedule $S_{i,a}$. The EITC

[29]The authors construct Unearned Income as the sum of income from business, farm, interest, net rental and other regular sources. They also include in this category unemployment compensation and social security payments. Non Taxable income includes veterans benefits, worker compensation or disability payments, welfare payments (including food stamps, Supplementary Security Income, and other public assistance), and child support.

schedule depends on the number of children or dependents, which is set to match the distribution in the original data(Table 2.1). In the simulation there are 3 factors that are held constant over time: number of dependent children, state of residence, and marital status.[30] Table 2.2 presents a comparison of the statistics between [22] and those from the simulation. The mean of earned income, the percentage of households without earned income, and the correlation among EI, UEI and NTI are similar to those in [22]. However, there are differences in the standard deviation of earned income, with a lower dispersion in the simulated data. The standard deviation is $32400 from the Montecarlo and $35900 in the real data. Also, the percentage of households that received an EITC in the simulation, 0.23, is lower than in the real data, 0.30. This difference can increase the standard error of the estimates in the first stage and in the final specification.

2.5.2 Quadratic and cubic relationship

In order to facilitate interpretation and comparison of their estimates [22] standardized the child outcomes to have a mean 0 and standard deviation 1. For a quadratic income effect, the standardized child outcome y_{ia} is given by:

$$y_{ia} = \delta_0 + I_{i,a}\delta_1 + I_{i,a}^2\delta_2 + 10 * \mu_i + \theta \times endo_{i,a} + (1-\theta) \times \epsilon_{y,i,a}, \tag{2.7}$$

where $\epsilon_{y,i,a} \sim iidN(0,1)$ and the correlation between $\epsilon_{I,i,a}$ and $\epsilon_{y,i,a}$ is zero. For simplicity, the non-constant unobserved component of the child outcome will be denoted

[30]There are two marital statuses related to tax purposes: single or joint.

as $u_{i,a} = \theta \times endo_{i,a} + (1-\theta) \times \epsilon_{y,i,a}$, and is constructed as a weighted average between the endogenous component and an outcome shock. Thus θ represents the percentage of the transitory error term that is accounted for by the endogenous component; that is, the extent of endogeneity.

In the analysis, the values for the parameters are set to $\delta_1 = 0.08$ and $\delta_2 = -0.0008$. These parameters imply that an additional dollar for a family with annual income of $50,000 dollars deflated to year 2000 will have no impact on child outcomes. After that threshold, the selected parameters imply a negative marginal effect. As it is not expected that additional income will ever reduce a child's development, it was assumed that the marginal effect of income is zero for parental income in excess of $50,000. In order to focus on determining whether the instruments are able to identify the true parameters of the quadratic relationship, the sample is restricted to children with parental annual income lower than $50,000. This truncation does not affect the exogeneity or relevance of the EITC.

We start by examining estimates from Equation 2.7 using the montecarlo described for 400 replications.[31] In Table 2.3, the left column describes which estimator is used and whether the Φ function is included. There are four estimation strategies: (1) ordinary least squares OLS; (2) OLS with Φ, which removes any bias due to the correlation of current child outcomes and lagged income; (3) IV, which addresses the endogeneity coming from income shocks, and (4) IV with Φ, which accounts for both endogeneity of income shocks and the correlation between child outcomes and lagged

[31] Results for a higher number of replications are similar.

income.

Each column reports estimates for different assumptions about the extent of endogeneity: no endogeneity ($\theta = 0$), small ($\theta = 0.25$), medium ($\theta = 0.50$), and large ($\theta = 0.75$). In all four assumptions, the variance of u, $V(u)$ was set to match that of [22], so in this exercise the explained component of the child outcome is held constant while the degree of endogeneity changes. An additional tool to obtain a sense of the magnitude of the endogeneity is the percentage of the variance of the child outcome $V(y)$ that is accounted for by the unobserved *endo* variable, $\frac{\theta^2 V(endo)}{V(y)}$ (first row of the third panel). This percentage is 0% in the best case scenario, 10.5% with small endogeneity, 21.7% with medium endogeneity, and 33.8% with large endogeneity, the worst case scenario considered.

The first panel presents the results of estimating linear specifications, that is $I^2_{i,a}$ is an omitted variable. Without endogeneity, first column, OLS, OLS Φ, and IV Φ provide consistent estimates of δ_1. Moreover, to guarantee consistency of the IV estimate, it is crucial to include the Φ function in the second stage. The bias from IV is 0.053 (66%) while only 0.002 (2.5%) with IV Φ. Allowing for endogeneity, the bias of the OLS Φ estimator increases with the extent of endogeneity. Thus the bias is 0.0044 (5%), for small endogeneity, 0.011 (14%) for medium, and 0.018 (23%) under large endogeneity. Finally, the bias of the IV Φ estimates is smaller (-0.001, 0.0004, and 0.002, for the same scenarios). However, those estimates do not capture the entire effect of income, since this specification omits the quadratic effect.

The second panel presents estimates from the same four econometric strategies assuming a quadratic specification. In all specifications without endogeneity, the estimates for the linear and the quadratic effect of income are consistent. Thus, any inference about the effect of income across the distribution will be adequate; however, the standard errors of the parameters using instrumental variables are higher than those from OLS. Allowing endogeneity, OLS Φ estimates of the linear parameter (δ_1) are biased by 0.005, 0.010, and 0.015 under small, medium, and large endogeneity. Those values imply an upward bias of 6.3%, 12.5%, and 18.8%. Estimates of the quadratic parameter (δ_2), are also upward biased by 5.7%, 11.1%, and 16.9%. Using IV Φ estimation technique estimates become consistent. The bias of the linear parameter is reduced to 2.9%, 4.8%, and 6.8% under small, medium, and large endogeneity. The bias for estimates of δ_2 is also reduced and ranges from 1.6% with small endogeneity to 7.2% under large endogeneity. The trend of an increasing bias with the more endogeneity allowed in the child outcome equation is explained by the increasing correlation between the unobserved component of income Δ_u and the instrument. A more detailed explanation is provided in Appendix A.

Table 2.4 presents estimates assuming that child outcomes and income has a linear relationship. The true effect of income is $\delta_1 = 0.08$. In this scenario, estimates in the first panel assume the correct specification. Without endogeneity all the estimation techniques except IV provide consistent estimates. Including endogeneity, the bias from OLS and OLS Φ is higher than the one from IV Φ, which ranges from 0.0004, under small endogeneity to 0.0015 in the large endogeneity case. This fact provides evidence that the instrument is powerful enough to guarantee consistent estimates, even under higher extents of endogeneity. In the second panel of the table, a mis-specified regression is estimated assuming a quadratic relationship. This panel is useful to understand whether the generated data and the instruments can correctly fail to reject linearity. Under the four estimation techniques, the bias of the estimates of the linear impact of income is similar in magnitude to those in the first panel. Regarding the estimate of the misspecified variable, i.e. the inclusion of the squared of income, the mean estimate is close to zero and with a high standard error. Thus, the null hypothesis of linearity will be correctly not rejected. Therefore, if the true relationship between income and child outcome is linear, a linear IV Φ is the most appropriate technique of estimation, providing the closest representation of the true effect. Additionally, if a quadratic term is incorrectly included, estimates correctly will not reject the null hypothesis of a linear impact of income.

An additional criteria useful to evaluate the adequacy of the approach for identification is the power of the test. This measures the probability of correctly rejecting a specification given that the alternative relationship is true. Using the data from the Montecarlo it is possible to compute the distribution of the test statistics under linearity and a quadratic effect, so as to compute the type II error and the power of the test. For the linear specification the power of the test goes from 0.958 without endogeneity to 0.935 while it goes from 0.89 to 0.87 for the quadratic specification.

Additionally a cubic relationship was inspected, in which the term I^3 is added to Equation 2.7.[32] The results show that the IV estimator is not able to identify the parameters. Estimates under linear or quadratic specifications are inconsistent, even without endogeneity, while if a cubic relationship is estimated only the estimate of the cubic effect of income is significant.

2.5.3 Piecewise function

Higher order polynomial relationships inspected in the previous subsection impose a marginal effect of income that varies for each value of income. Another alternative that allows for nonlinearities in the child outcome equation is to divide educational inputs into two "types": basic and complementary. Basic inputs are those goods and services demanded in all households and can be related with basic living conditions. While complementary inputs refer to classes, books and other material that only richer households can afford.

In this setting low income households, those which income is below some threshold I^*, can not afford complementary goods and therefore only demand basic inputs. The marginal effect of income for low income households is a function of the marginal impact of basic inputs that is constant across the income distribution. Richer households have an income above the threshold and demand both type of inputs. For them, the marginal impact of income is composed of the marginal effect of basic inputs and the marginal impact of complementarity inputs that is constant for all the values of income above the threshold. A relationship that represents this setting is

[32]The cubic of the linear projection of income was used as instrument for the cubic of income.

constructed using two linear functions. It allows for two marginal impacts of income, one for households with annual income between 0 and the threshold or knot I^*, and another marginal effect for households with higher income that will reflect the effect of both complementary and basic inputs demanded. This specification is known in the literature as a piecewise relationship with one knot and is defined as:

$$y_{ia} = \delta_0 + I_{i,a}\gamma_1 + I2_{i,a}\gamma_2 + 10\mu_i + \theta \times endo_{i,a} + (1-\theta) \times \epsilon_{y,i,a}, \tag{2.8}$$

where, $I2_{i,a} = \begin{cases} I_{i,a} - I^* & \text{if } I_{i,a} > I^* \\ 0 & \text{if } I_{i,a} \leq I^* \end{cases}$

The marginal effect of income on child outcomes for households with an annual income below the threshold is γ_1 while it is $\gamma_1 + \gamma_2$ if the annual household income is greater than \$15000. If the effect is actually linear then γ_2 must be equal to 0. In this context, a negative value of γ_2 implies that the basic inputs into the education production function are more productive than the complementary inputs. To guarantee identification, two instruments are required given that I and $I2$ are endogenous. The first instrument considered is the same as that in [22] while the second instrument is the increase in EITC if annual benefit during the previous period is greater than \$1500, which is $\Delta\chi \times 1(\chi_{i,a-1} > \chi^* = 1500)$. The selection of the knot aims to keep the nonlinearity in the relationship between EITC benefits and earnings, because this nonlinearity contributes to the identification of the parameters. As can be seen in Figure 2.1, the knots that define the phase-in, flat, and phase-out zones of the EITC schedule do not change considerably over time. As a consequence, the shape of two-year changes of the EITC in Figure 2.2 is similar to the shape in levels with minor differences in the marginal tax rates and the location of the knots. By these two factors the proposed division will not affect the linearity of the new instrument.

Table 2.5 presents estimates of linear and piecewise specifications of child outcomes generated by Equation 2.8. The values of the parameters are $\gamma_1 = 0.075$ and $\gamma_2 = -0.02$ which implies a marginal impact of income for poor households of 0.065 and 0.055 for richer households values consistent with a concave relationship between income and child outcomes. In the first panel, the estimation assumes a linear relationship.[33] The OLS estimate of 0.061 is closer to the effect of income for households with annual income lower than \$15000, than to the effect for richer households (0.045). The IV estimate of 0.054 underestimates the marginal effect of income for poor households and overestimates for richer households. OLS and IV estimates have a low standard error and in consequence are significant, independent of the extent of endogeneity allowed in the child outcome equation.

The second panel presents OLS and IV estimates of a piecewise specification with one knot. If the estimation is performed by OLS, the estimate of γ_1 is significant and downward biased (around 16%) and the estimate of γ_2 is also significant and upward biased (around 28%). Those estimates hold under all extents of endogeneity and imply that the predicted effect of income is under estimated for the whole distribution and only the predicted marginal effect of income above the knot ($\gamma_1 + \gamma_2$) is close to the real value. Finally, OLS estimates reject the linearity assumption. IV estimates of γ_1 are downwardly biased, with a bias ranging from 1% to -11%, and the estimates

[33]From now on, only estimates that include the Φ function are presented, since it is clearly important in achieving consistency of the estimates.

of γ_2 are upwardly biased with a bias ranging between 0% and 20%. Despite these biases, the predicted effect of income is closer to the true value than that estimated using OLS. Additionally, the t-statistic of both parameters decreases with the extent of endogeneity and IV estimates reject the hypothesis that the effect for households with an annual income greater than $15000 is lower than the effect for the poorer households.

Finally, if the proposed approach is useful to test for non linearities, a true linear relationship must reject non linearities. Estimation of linear as well as one knot spline specifications are presented in the Table 2.6, where the effect of income is $\delta_1 = 0.08$. The first panel reproduces the results already presented in the polynomial specifications and are included as comparison. OLS estimates are upward biased while IV correctly estimates the effect of income under all extents of endogeneity. The second panel, presents the estimates of a spline specification with one knot. OLS estimate of γ_1 is upward biased and the bias is increasing with the extent of endogeneity. γ_2 estimates are practically zero and imprecisely estimated, in all scenarios considered. Estimation by IV also predicts an impact close to the real one, given that the parameter γ_1 has a small downward bias that ranges from -1.0% to -7.25%, and γ_2 is small and imprecisely estimated all the cases.

The results of the power analysis indicate that when the linear specification is tested it correctly rejects 95.3% of the times data generated by a spline specification in the scenario without endogeneity. Similar values of the power are found for all values of endogeneity. On the other hand, the power of the spline specification indicates that in 92% of the times, it correctly rejects data generated by a linear process between child outcomes and income. This power of the test is almost constant in all scenarios of endogeneity.

A second specification that has three marginal effects of income is constructed by allowing two knots I_1^* and I_2^* in the relationship between income and child outcomes was also inspected.[34] In this case the Montecarlo results indicate that the impact of income is underestimated for the entire distribution under a linear specification. Under a spline specification IV estimates are biased but follow closely the real effect; however, the effect of income is not precisely estimated. So, this approach is not useful to identify a spline relationship with two knots.

2.5.4 Logarithmic relationship

In this subsection, we explore a specification that is linear in the logarithm of income. This specification has diminishing returns to income and the marginal effect of income varies across the whole distribution. The relationship is given by:

$$y_{ia} = \delta_0 + log(I_{i,a})\phi_1 + 10 * \mu_i + \theta \times endo_{i,a} + (1-\theta) \times \epsilon_{y,i,a}, \tag{2.9}$$

where $log(I_{i,a})$, denotes the natural logarithm of income. The assumed value of $\phi_1 = 0.65$. Table 2.7 presents the estimates for specifications where the child outcome

[34]The two additional instruments are constructed in a similar way to the one knot case, using $\Delta\chi \times 1(\chi_{i,a} > \chi_1^* = 800)$ and $\Delta\chi \times 1(\chi_{i,a} > \chi_2^* = 1500)$ in addition to the instrument defined in [22].

is a linear function of the actual level of income or its logarithm, using the endogeneity values described in the previous tables. The first panel presents estimates of a linear relationship. The OLS Φ do not capture the impact of income, for instance without endogeneity the estimate of 0.0254 is closer to the marginal impact at the mean 0.203% than to the true parameter. Estimates of the impact of income under the different extents of endogeneity analyzed are similar, so assuming a linear relationship will not convey a good estimate of income's impact at all points of the income distribution. Additionally, it is possible to reject the null hypothesis that income has no effect on child outcomes. Using an Instrumental Variable approach, the estimated impact of income increases to 3.5% and the hypothesis of no impact of income is rejected under all extents of endogeneity. The instrument used in the IV estimation is the same proposed by [22].

The second panel presents estimates of the correct specification. Without endogeneity, the OLS estimates are upward biased by 2.2%, 4.5%, and 6.8% under small, medium and large endogeneity. OLS estimates are significant at standard levels and close to the true impact of income. On the other hand, IV estimates are significant and have a small bias (%3.9), thus the estimated and true income effects are close. In this panel the change in the logarithm of income is instrumented using the expected change in the logarithm of income due to the EITC, that is $\Delta log\big(\chi_a^{IV}(P_{i,a-1})\big) \equiv log\big(\chi_a^{S_{i,a-1}}(\hat{E}[P_{i,a}|P_{i,a-1}])\big) - log\big(\chi_{a-1}^{S_{i,a-1}}(P_{i,a-1})\big)$. [35]

[35] As the logarithm of 0 is not defined, to allow the instrument to be defined for all households the EITC benefits for non recipients were assumed to be $1.

The power of the test for the linear specification is 0.93 for the specification without endogeneity and has a slight decline to 0.89 in the scenario with large endogeneity. The power of the logarithmic is about the same, from 0.92 to 0.89 in the same scenarios.

2.5.5 Summary

This section assesses the usefulness of the EITC as instrument in identifying the causal impact of income under alternative nonlinear specifications of the relationship between income and child outcomes. The Montecarlo results suggest that if the true effect is quadratic, piecewise with one knot, or logarithmic the approach achieve identification while if the true relationship is cubic or piecewise with two knots the proposed approach is not able to identify the parameters that define the correct relationship.

2.6 Data

This article uses data from the NLSY79 and the Children of the NLSY. The sample is defined to be the same as in [22] in order to replicate their estimates and compare their estimates with specifications in which the effect is nonlinear. Also, this sample guarantees the adequacy of the EITC as instrument. Including more years will reduce the relevance due to the big increases in taxes in the Tax Reform Act of 1986 and in the two Bush cuts in 2001 and 2003. In addition, this selection guarantees that changes in EITC were unanticipated and therefore exogenous to household decisions.[36] Thus, in that period increments in EITC are correlated with increments in income, however after 2000 this relationship vanishes given that the EITC schedule has few changes. In order to check whether including recent waves of the NLSY79 affects the estimates, appendix C presents a comparison of the estimates of the quadratic specification using the original sample and information from 1988 to 2012. Findings indicate that including more years reduces the estimated effect of income and its statistical significance.

The NLSY79 is an ongoing survey performed annually between 1979 and 1994, and biennially since 1994. It is based on a nationally representative sample of 12686 men and women who were between 14 and 21 years old in 1979. It collects detailed information about income, assets, program participation, labor force, and education, among other demographic and individual characteristics. The Children of the NLSY allows researchers to follow the children born to NLSY79 female respondents and includes cognitive assessments for math, language of each child as well as demographic and development characteristics. Child outcomes are available for children 5 years old and older on a biennial basis since 1986, while demographic, educational, labor market, and income variables are captured in the main NLSY79.

There are some features highlighted by [22] of using this data: *(i)* it is possible to link children to their mothers, which guarantees that they can be assigned to the correct household income and other characteristics, *(ii)* it is possible to follow children over time, which helps to control for child fixed effects, and *(iii)* the design of the

[36] If households have perfect foresight about taxes and benefits they would include them into their optimization and decisions, so the EITC would become a variable under their control.

NLSY includes an over-sample of minorities, who usually have a lower annual income and therefore the NLSY has a relatively high percentage of the eligible population and EITC recipients.

The Peabody Individual Achievement Tests (PIAT) are selected as child outcomes. These tests evaluate children's ability in a variety of skills in the mathematics and reading sections: oral reading, word recognition, mathematics, and the ability to derive meaning from printed words. Test scores are measured in a scale with a mean of 100 and a standard deviation of 15 for each age, but in order to interpret and compare estimates obtained in this article with previous studies child outcomes are re-standardized to have zero mean and a standard deviation of one.

Total parental income is computed as the sum of three components: earned income, unearned income, and non taxable income, for the respondent and her spouse. Earned income corresponds to all wages and salaries received in the calendar year of reference. Unearned income includes all income derived from business and farm, unemployment, savings, net rental, and social security. Finally, Nontaxable income corresponds to all veteran benefits, worker compensation, and disability payments, and income from welfare/AFDC, food stamps, Supplemental Security Income or other public assistance and child support. However, in the program participation section, it is not recorded whether a household receives EITC benefits. [22] assume that all households take the credit given that [60] shows that between 80% and 87% of the eligible families take the credit.

The final piece of information corresponds to the EITC benefits and taxes computed using the TAXSIM code developed by [32], and available at the National Bureau of Economic Research web page (http: www.nber.org/taxsim). This code computes a microsimulation of the US state and federal tax income system based on a large sample of actual returns, but it has some limitations.[37]

The sample is restricted to children observed at least for two consecutive survey years between 1988 and 2000, with valid information for household characteristics and income. Children from the oversamples of poor white families and military families are excluded. The sample is limited to children in households that do not experience a change in marital status between interviews. Household formation and dissolution create changes not only in income but in other family characteristics that may be correlated with income. All monetary measures are expressed in 2000 dollars, using the CPI-U as the deflator. As some of the income variables are missing in some years, the authors proposed an imputation procedure to maintain representability of the sample. [38] With all these considerations the final sample includes 4412 children observed 2.2 times each on average.

[37]For instance, it is assumed that "families with few or no property tax deductions and modest income were renters, and estimated their rent based on consumer expenditures data...", "Tax payers without state identification (because their income exceeded $200000 were assigned randomly to states" [32]. Additionally, the following aspects are omitted from the simulator: state tax liabilities generated by interest from municipal debts, interest from federal securities are included as part of the interest income variable, non-itemizers are treated as renters for the purpose of calculating rent and property tax credits, itemized deductions for non itemizers are treated as zero by the tax state calculators, and taxpayer gross income is used as a measure of gross income for the total household income.

[38]The details of the imputation procedure are provided in the online appendix of [22]

2.7 Estimation

This section presents estimates from linear, quadratic, logarithmic, and spline specifications. The proposed approach accounts for different sources of endogeneity, such as measurement error, permanent unobserved heterogeneity, and temporary unobserved shocks. Due to the restrictions to accessing the Geocode information of the NLSY79 imposed by the data information policies, in the estimations presented in this section only the federal EITC benefits are used. Two specifications that nest the linear effect, a quadratic and piecewise with one knot, are inspected in subsections 2.7.1 and 2.7.2. In subsection 2.7.3 a linear relationship with respect to the log of income is presented.

2.7.1 Quadratic Specification

Table 2.8 presents estimates of quadratic and linear specifications for: math and reading, math, reading recognition, and reading comprehension. The first column presents the estimates of the parameters δ_1 and δ_2 of Equation 2.4. The estimate of the linear impact of income (7.7%) is significant and bigger than the estimate of 6.5% under a linear specification, column 2; however, that difference is not significant in statistical terms. In addition, the negative estimate of δ_2 is consistent with a diminishing return to income effect, and implies that income has a positive marginal effect for households with annual income lower than $39000. However, this estimate is not precisely estimated at the standard levels and therefore the null hypothesis of a linear effect is not rejected.

Estimates of income effect on mathematics and reading comprehension standardized test scores are similar to those discussed for math and reading. The estimates imply a diminishing returns pattern, with a significant estimate of the linear impact of income but the quadratic effect of income is not precisely estimated. Finally, results suggest that income has a lower effect on reading recognition test scores (5% of a standard deviation) than on any other test. In conclusion, despite indicating that the marginal effect of income is bigger for households at the low end of the income distribution the high standard error does not allow us to reject linearity. Thus, estimates in column two are preferred to describe the relationship between child outcomes and income.

In the third column the estimates of [22] of the effect of income on these outcomes are presented. These values are directly comparable to the ones presented in the second column and show that there is no statistical or economical difference in the values, the standard error and their significance. Thus this paper successfully replicates the previous work.

2.7.2 Piecewise with one knot

This section presents OLS and IV estimates of a spline specification with one knot, using $15000 as the value of the knot. The first column of table D.1 presents the OLS estimates. Results show that an increase of $1000 in income lead to an increase on math and reading test score of 0.31% of a standard deviation for children in households with low income, and increases by 0.20% for children in households with annual income higher than the knot. Estimates of the impact on math achievement are similar in magnitude. For achievement in reading recognition estimates predict a small effect of income increases at the low end (0.05% of a standard deviation) and an increase around 0.33% for richer households.

Finally, increases of $1000 in annual income would increase reading comprehension test score by 0.4% of a standard deviation for children in households below the knot, and reduce scores by 1.37% for children in households with an annual income above the knot. The small effect of income on improving tests scores is similar to previous findings in research that only dealt with the endogeneity caused by constant unobserved factors e.g. [11]. However, the high standard errors for the estimates imply that is not possible to reject the hypothesis that income has no effect on any of the child outcomes mentioned.

The second column presents the IV estimates. A $1000 increase in income will increase mathematics and reading scores by 5.6% of a standard deviation for low income households and by 3.0% for high income households; [39] As a result of such cash transfer, math test scores would also increase by 5.3% of a standard deviation for low income and by 3.3% for children in higher income households. In both cases test scores exhibit a diminishing returns pattern to income, however it is not possible the reject the null hypothesis of linearity. Standardized scores for reading recognition also increase as a result of income support, by 4.3% if the household has a lower annual

[39] The two variables associated with income are instrumented using [22]'s instrument and the interaction described in section 2.5.3 using $1500 as the knot value for the EITC.

income than the threshold and by 4.6% if income is above to the knot.

Results suggest that cash transfers are positive to increase reading comprehension scores. Children in low income households will increase their scores by 5.7%, similar to the one experienced by children in richer households 5.8%. These estimates imply that income support policies improve child achievement, and that there is no a difference between the effect income effect for households above the knot given that γ_2 is not precisely estimated. In conclusion, there is no evidence that the relationship between income and the child outcomes analyzed here follows a spline specification.

Results discussed in this subsection are not sensible to changes in the value of the knot for income selected. As is shown in appendix D selecting the value of the knot for income close to the mean of the income for benefitted households does not change the main inference. First, in all scenarios it is not possible to reject the linearity of the relationship between income and child outcomes and second, the predicted effect of income is similar under the alternative knots.

2.7.3 Logarithmic specification

This subsection analyzes a logarithmic relationship between income and child outcomes. Table 2.10 presents estimates of Equation 2.9 for achievement tests in math and reading. One advantage of this specification is that increments in income never hurt child outcomes. OLS estimates in the first column indicate that income has a positive effect on the combined measure of math and reading and reading comprehension, and hardly improves math and reading recognition standardized test scores.

The marginal impact of income ranges from 0.18% to 0.35% of a standard deviation for children in households with an annual income of $10000. These findings are consistent with an economically insignificant effect of income in previous research that only addresses the endogeneity of permanent income.

The IV estimate of the effect of the logarithm of income on math and reading is precisely estimated at 0.663. For math and reading comprehension, a similar value for the effect of the logarithm of income is estimated, while the estimate of ϕ_1 on reading recognition is lower (0.407). All those effects are precisely estimated and convey evidence of a diminishing marginal effect.

The existence of nonlinearities may lead to inconsistent estimates of the income effect across the distribution, when a linear specification is used. In the quadratic and spline cases, to test for nonlinearities it was enough to test whether including an additional function of income adds useful information information about the impact of income. However, as the logarithmic and linear specifications are non nested, to establish which specification is preferred it is necessary to test for the correct functional form of the relationship between child outcomes and income. [23] proposed two alternatives of the J test, that allows us to compare non nested specifications.

The first alternative consists of four steps. *(i)* Estimate the logarithmic model and use the estimates of the coefficients to obtain the predicted value of the child outcome $\hat{Y}_{Log}$.*(ii)* Estimate the linear model and obtain the predicted value $\hat{Y}_{Lin}$. *(iii)* Add $\hat{Y}_{Log}$ into the linear specification, and obtain the t-statistic for the null hypothesis that the coefficient associated with this variable is zero. *(iv)* Add the $\hat{Y}_{Lin}$ into the logarithmic specification, and obtain the t-statistic for the null hypothesis that the coefficient associated with this variable is zero. The last two steps investigate whether the prediction of the other model adds relevant information. There are four possible results, of which two are non conclusive: reject or fail to reject both of the two null hypotheses in steps (iii) and (iv). The other two possible outcomes, one hypothesis is rejected while the other is not, favors the model that adds information to the estimate.

The second J-test involves only three steps: *(i)* Estimate the linear model and obtained R^2_{lin}, *(ii)* estimate a hybrid model including all the explanatory variables of the linear and logarithmic models, and obtain the R^2_N, and *(iii)* to check whether the logarithmic model is "better" than the linear specification. The null hypothesis is that the the parameter associated with $log(I)$ is equal to zero. This is similar to a nested problem, where the two R^2 can be compared using an F test. Then if the $F - statistic$ is lower than the critical value the linear model is selected over the logarithmic specification and if the $F - statistic$ is greater than the critical value the logarithmic model would be preferred. [40] If there is only one variable different in the models, both J tests are equal. Finally, to improve the properties in small sample it is recommended to use bootstrapping in order to obtain the small sample properties of the estimates in both tests. Results of this test in Table 2.11 suggest that it is not possible to reject that either the linear specification or the logarithmic specification.

[40]The F-statistic for this test is given by $F = \frac{R^2_N - R^2_{lin}}{(1-R^2_N)/(N-k-3)}$. Where k is the number of variables included in both models, N is the total sample size

2.8 Discussion

This paper presents an extension of [22] to allow for nonlinearities in the effect of income on cognitive child achievement in low and moderate income households that are benefitted by the EITC. Results of estimating by OLS the logarithmic and spline specifications in which only large transfers of income affect child outcomes, are consistent with previous findings of literature that only address unobserved confound factors that are constant over time. Dealing also with the endogeneity caused by correlated shocks, income has an economically significant role in improving child outcomes and evidence of nonlinearities is found under the three relationships inspected in this paper. However, the estimates fail to reject the linear specification that is the main relationship used in empirical research.

[49] are the first authors that report a nonlinear effect of income given by quadratic relationship. Their estimates show a diminishing effect of income on years of education, IQ, and the high school dropout rate using Norwegian administrative data. Using the estimates from their paper in figure 2.3 the relationship between parental income and these outcomes is presented, using the standardized parental income to facilitate comparison. Cash transfers have a positive effect for children on the three outcomes in households with an annual income lower than 3 standard deviations. Also, the marginal effect of income is double for children in households in which annual income is one standard deviation than in households with an annual income of two standard deviations.

Figure 2.4 presents the effect of income on reading and math standardized test scores for the US, using the estimates of a quadratic effect presented in subsection 2.5.2. Scores in math and reading, reading comprehension and math would be benefitted by cash transfers for children which parental income is below 1.9 standard deviations. Income support improves reading recognition scores for children in households which annual income below 1.3 standard deviations. The effect on child outcomes for children in households with one standard deviation is double the effect for children in households with annual income of one and a half standard deviations, suggesting that the marginal effect of income declines more quickly than in the Norwegian case. Although the estimates in this paper are not precisely estimated, results suggest that the income effect does vary across the income distribution. Moreover, standardized test scores are less affected than long term outcomes like the IQ, years of education and the dropout rate.

Estimates in subsection 2.7.3 provide evidence that the relationship between cognitive achievement and parental income can be described by linear or logarithmic specifications. Those two alternative relationships imply a different analysis of how to allocate cash transfers. If the true relationship is logarithmic, allocating higher amounts of money to poorer households would be the preferred policy design given the diminishing effect of income. On the other hand, if the linear specification is the one that captures the effect of income, efficient allocation of resources is independent of income given that the effect on rich and poor households is the same.

To understand how the income effect varies across the income distribution under a logarithmic specification, each column of table 2.12 presents the percentage of a standard deviation that each of the child outcomes will increase if annual household income is increased by \$1000, for some selected values of annual income. [41] The combined measures of math and reading, reading comprehension, and math will increase by 13% of a standard deviation, and reading recognition by 8% for children in households with an annual income of \$5000. The marginal impact of income for children which parental income is \$10000 is closer to the impact predicted under linear estimates, presented in the final row of the table. Thus if the relationship is nonlinear the marginal effect is underestimated for children in households with parental income below that value. Additionally, cash transfers for low income households are more efficient than those at the mean of the income distribution and income support have little impact on child outcomes for children in households with annual income over \$20000.

The findings in this paper also have implications for cash transfer policy design. Under a logarithmic relationship as the marginal benefit of income is higher at the low end, it is more efficient to allocate higher amounts of income to poorer households than for instance the design of the phase-in and flat zones of the EITC. However, the main objective of this tax credit is not to provide income support to improve child outcomes but to create incentives for households with children to supply labor. A redesign of the EITC to be consistent with both goals would be done by keeping its phase-in and flat zones but increasing the marginal benefits at a steeper rate for

[41] In this case the impact on child outcomes of increasing annual income $I_{i,a}$ by \$1000 is $\frac{\phi_1}{I_{i,a}}$ of a standard deviation.

households in the phase in zone and the benefits to households in the flat zone. In this strategy, households would have a higher incentive to increase their labor supply and they would receive higher benefits. Child outcomes would be positively affected and more inputs can be bought.On the other hand, if the true relationship is linear, in the design of the EITC the weight of improving child achievement decreases given that cash transfers are equally productive at all income levels. Thus, only on redistributional grounds would cash transfers at the low be preferred.

Number of Children	Proportion
1	0.119
2	0.391
3	0.299
4	0.119
5	0.045
6	0.016
7	0.009
8	0.004

This table presents the distribution of the number of children or dependents used to compute the EITC, over the generated samples.

Table 2.1: distribution of dependents or children

	DL	Simulation
Mean Earned Income	34115	34807
Sd Earned Income	35902	32447
% without Earned Income	15.4	18.1
%EITC recipiency	29.6	23.5
Corr(EI,UEI)	0.19	0.22
Corr(EI, NTI)	-0.42	-0.43
Corr(UEI, NTI)	-0.07	0.06

This table presents the basic statistics from the data used in [22] and the montecarlo experiment using 400 replications. Income variables are measured in 2000 dollars.

Table 2.2: Basic statistics

Model	parameter	Without $\theta = 0$	Small $\theta = 0.25$	Medium $\theta = 0.50$	Large $\theta = 0.75$
			Linear Estimates		
OLS	δ_1	0.077	0.084	0.092	0.1
		(0.001)	(0.001)	(0.001)	(0.001)
OLS,Φ	δ_1	0.077	0.084	0.091	0.098
		(0.001)	(0.001)	(0.001)	(0.001)
IV	δ_1	0.133	0.156	0.179	0.202
		(0.005)	(0.004)	(0.004)	(0.005)
IV,Φ	δ_1	0.078	0.079	0.08	0.082
		(0.003)	(0.002)	(0.002)	(0.002)
			Quadratic estimates		
OLS	δ_1	0.08	0.085	0.09	0.095
		(0.002)	(0.001)	(0.001)	(0.001)
	δ_2	-0.000794	-0.000728	-0.000661	-0.000596
		(0.000032)	(0.000024)	(0.000019)	(0.000018)
OLS, Φ	δ_1	0.08	0.085	0.09	0.095
		(0.001)	(0.001)	(0.001)	(0.001)
	δ_2	-0.000801	-0.000755	-0.000711	-0.000665
		(0.000021)	(0.000017)	(0.000015)	(0.000015)
IV	δ_1	0.08	0.103	0.127	0.15
		(0.007)	(0.006)	(0.006)	(0.007)
	δ_2	-0.000801	-0.001112	-0.001422	-0.001732
		(0.000105)	(0.000087)	(0.000086)	(0.000101)
IV, Φ	δ_1	0.081	0.082	0.084	0.085
		(0.02)	(0.016)	(0.015)	(0.018)
	δ_2	-0.00081	-0.000788	-0.000765	-0.000743
		(0.00047)	(0.000387)	(0.000357)	(0.000406)
			Bias and Endogeneity measure		
$\frac{\theta^2 V(endo)}{V(y)}$		0	0.105	0.217	0.338
$\frac{\sigma_u}{\sigma_I}$		0.0025	0.032	0.039	0.073
$\frac{\sigma_u}{\sigma_I 2}$		0	0.000001	0.000004	0.000007

This table presents the estimates of a Montecarlo experiment using 400 replications using a quadratic relationship between parental income and child outcomes. The parameters as set $\delta_1 = 0.08$ and δ_2=-0.0008.The first panel correspond to estimates of a linear model, that is misspecified because it ignores the quadratic term. Estimates of a quadratic specification are presented in the second panel. The last panel present two alternative measures of the size of the endogeneity, as the percentage of the child outcome variance that is attributed: *(i)* to the endogenous term ($\theta \times endo$) and *ii)* to the unobserved component of child outcomes. Additionally, the third and four rows present the bias of Equation B.1 due to the ratio between the variance of the unobserved component and the endogenous variable.

Table 2.3: Estimates of linear and quadratic models from data generated by a Montecarlo assuming a quadratic model 400 replications

Model	parameter	Without	Small	Medium	Large
			Linear Estimates		
OLS	δ_1	0.08	0.083	0.086	0.088
		(0.001)	(0.001)	(0.001)	(0.001)
OLS,Φ	δ_1	0.08	0.082	0.085	0.087
		(0.001)	(0.001)	(0.001)	(0.001)
IV	δ_1	0.08	0.084	0.089	0.093
		(0.004)	(0.004)	(0.004)	(0.004)
IV,Φ	δ_1	0.08	0.08	0.081	0.081
		(0.004)	(0.004)	(0.004)	(0.004)
			Quadratic estimates		
OLS	δ_1	0.08	0.083	0.086	0.09
		(0.002)	(0.002)	(0.002)	(0.002)
	δ_2	-0.000002	-0.000007	-0.000013	-0.000018
		(0.00003)	(0.000031)	(0.000032)	(0.000033)
OLS, Φ	δ_1	0.08	0.083	0.086	0.089
		(0.001)	(0.002)	(0.002)	(0.002)
	δ_2	-0.000002	-0.000006	-0.000009	-0.000013
		(0.000064)	(0.000065)	(0.000067)	(0.00007)
IV	δ_1	0.079	0.097	0.114	0.131
		(0.022)	(0.022)	(0.023)	(0.024)
	δ_2	-0.000002	0.000071	0.000144	0.000218
		(-0.000105)	(-0.000106)	(-0.00011)	(-0.000116)
IV, Φ	δ_1	0.081	0.08	0.079	0.079
		(0.058)	(0.058)	(0.06)	(0.062)
	δ_2	-0.000023	0.000006	0.000034	0.000062
		(0.001382)	(0.001401)	(0.001439)	(0.001494)
			Bias and Endogeneity measure		
$\frac{\theta^2 V(endo)}{V(y)}$		0	0.084	0.183	0.296

This table presents the estimates of a Montecarlo experiment using 400 replications using a linear relationship between parental income and child outcomes, with $\delta_1 = 0.08$. The first panel correspond to estimates of a linear model, that is misspecified because it ignores the quadratic term. Estimates of a quadratic specification are presented in the second panel. The last panel present two alternative measures of the size of the endogeneity, as the percentage of the child outcome variance that is attributed: *(i)* to the endogenous term ($\theta \times endo$) and *ii)* to the unobserved component of child outcomes. Additionally, the third row presents the bias of Equation B.1 due to the ratio between the variance of the unobserved component and the parental income.

Table 2.4: Estimates of linear and quadratic models from data generated by a Montecarlo assuming a linear model 400 replications

Model	parameter	Without $\theta = 0$	Small $\theta = 0.25$	Medium $\theta = 0.50$	Large $\theta = 0.75$
		Linear Estimates			
OLS,Φ	δ_1	0.061	0.063	0.064	0.065
		(0.0005)	(0.0004)	(0.0003)	(0.0002)
IV,Φ	δ_1	0.0544	0.0546	0.0548	0.055
		(0.003)	(0.002)	(0.002)	(0.002)
		spline estimates			
OLS, spline, Φ	γ_1	0.0546	0.0553	0.0553	0.056
		(0.002)	(0.0013)	(0.0013)	(0.0007)
OLS, spline, Φ	γ_2	-0.0144	-0.0137	-0.0137	-0.013
		(0.0021)	(0.0014)	(0.0014)	(0.0007)
IV, spline, Φ	γ_1	0.0657	0.0631	0.0598	0.0579
		(0.0247)	(0.0241)	(0.0241)	(0.0247)
IV, spline, Φ	γ_2	-0.02	-0.0189	-0.0172	-0.016
		(0.008)	(0.0074)	(0.0069)	(0.0069)

This table presents the estimates of a Montecarlo experiment using 400 replications using a spline relationship between parental income and child outcomes with one knot. The parameters are set as $\gamma_1 = 0.06$, and γ_2=-0.02. The first panel correspond to estimates of a linear model, that is misspecified because it ignores the quadratic term. Estimates of a spline specification with one knot are presented in the second panel.

Table 2.5: Estimates of linear and spline models from data generated by a Montecarlo assuming a spline model with one knot 400 replications

Model	parameter	Without $\theta = 0$	Small $\theta = 0.25$	Medium $\theta = 0.50$	Large $\theta = 0.75$
		Linear Estimates			
OLS,Φ	δ_1	0.0799	0.0821	0.0851	0.0872
		(0.0005)	(0.0006)	(0.0007)	(0.0008)
IV,Φ	δ_1	0.08	0.0802	0.0804	0.0806
		(0.0035)	(0.0038)	(0.0041)	(0.0042)
		spline estimates of a relationship with one knot			
OLS, spline Φ	γ_1	0.0803	0.0815	0.0828	0.084
		(0.0022)	(0.0017)	(0.0015)	(0.0018)
	γ_2	-0.0004	0.0003	0.001	0.0017
		(0.002)	(0.0016)	(0.0014)	(0.0017)
IV, spline, Φ	γ_1	0.0792	0.0781	0.0761	0.0742
		(0.0191)	(0.016)	(0.0148)	(0.0158)
	γ_2	0.0007	0.0078	0.0149	0.022
		(0.0157)	(0.0135)	(0.0125)	(0.0132)

This table presents the estimates of a Montecarlo experiment using 400 replications using a linear relationship between parental income and child outcomes. The main purpose is to determine whether the simulated data and the Iv approach proposed is able to not reject the null hypothesis of linearity. The parameters is $\delta_1 = 0.08$. The first panel correspond to estimates of a linear model, that is misspecified because it ignores that income has different effect across the income distribution. Estimates of a spline specification with one knot are presented in the second panel.

Table 2.6: Estimates of linear and spline models from data generated by a Montecarlo assuming a linear model 400 replications

Model	parameter	Without $\theta = 0$	Small $\theta = 0.25$	Medium $\theta = 0.50$	Large $\theta = 0.75$
			Linear Estimates		
OLS,Φ	δ_1	0.0254	0.0264	0.0274	0.0283
		(0.0003)	(0.0003)	(0.0002)	(0.0002)
IV,Φ	δ_1	0.0348	0.0349	0.035	0.0351
		(0.0019)	(0.0019)	(0.0019)	(0.002)
			logarithmic estimates		
OLS,Φ, log	ϕ_1	0.6495	0.6643	0.6791	0.6939
		(0.0037)	(0.0031)	(0.0029)	(0.0033)
IV, logl	ϕ_1	0.6248	0.6248	0.6247	0.6247
		(0.1289)	(0.1286)	(0.1285)	(0.1287)

This table presents the estimates of a Montecarlo experiment using 400 replications using a logarithmic relationship between parental income and child outcomes. The parameters as set $\phi_1 = 0.65$. The first panel correspond to estimates of a linear model, that is misspecified because it ignores the quadratic term. Estimates of a quadratic specification are presented in the second panel.

Table 2.7: Estimates of linear and logarithmic models from data generated by a Montecarlo assuming a logarithmic model 400 replications

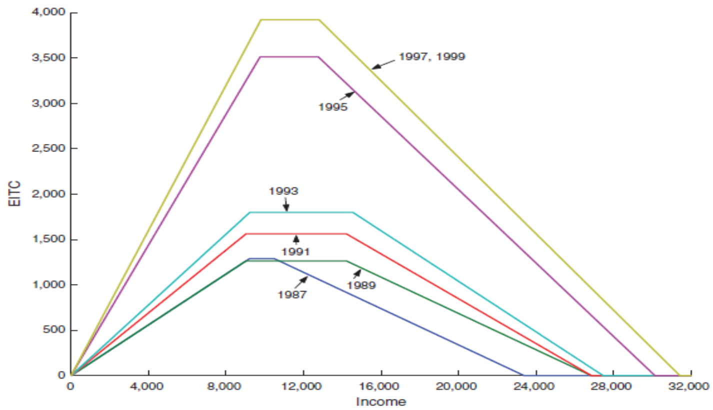

Figure 2.1: EITC schedule

Source [22].

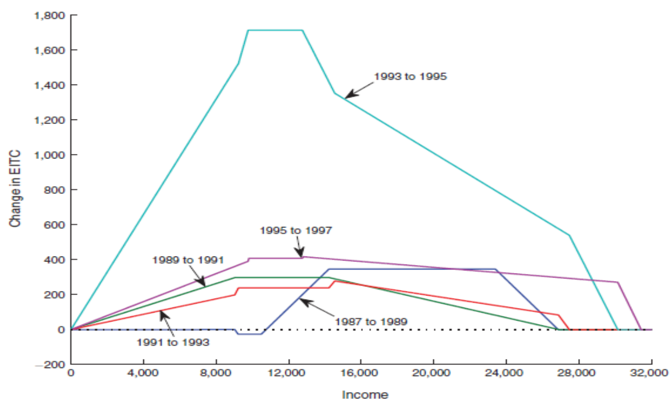

Figure 2.2: Two year changes in EITC schedule

Source [22].

Coefficient	Quadratic	Linear	Dahl-Lochner
	Math and reading		
δ_1	0.078^{*}	0.063^{*}	0.0610^{*}
	(0.036)	(0.029)	(0.0251)
δ_2	-0.001		
	(0.002)		
	Math		
δ_1	$0.075^{\dagger}$	0.060^{*}	0.0582^{*}
	(0.041)	(0.028)	(0.0273)
δ_2	-0.001		
	(0.002)		
	Reading recognition		
δ_1	$0.051^{\dagger}$	$0.038^{\dagger}$	$0.0359^{\dagger}$
	(0.030)	(0.020)	(0.0195)
δ_2	-0.001		
	(0.001)		
	Reading comprehension		
δ_1	$0.073^{\dagger}$	0.063^{*}	0.0613^{*}
	(0.039)	(0.029)	(0.364)
δ_2	-0.001		
	(0.002)		

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

This table presents estimates of Equation 2.7 of quadratic and linear specifications. As instruments are used the expected change in income due to changes in EITC and the squared of the linear prediction of income on that instrument.

Table 2.8: IV FE estimates of a quadratic specification

Coefficient	OLS	IV
	Math and reading	
ϕ_1	0.0031	0.0559
	(0.002)	(0.030)
ϕ_2	-0.0011	-0.026
	(0.001)	(0.065)
	Math	
ϕ_1	0.0033	0.0534
	(0.003)	(0.034)
ϕ_2	-0.0018	0.144
	(0.0231)	(0.5613)
	Reading recognition	
ϕ_1	0.0005	0.043
	(0.002)	(0.026)
ϕ_2	0.0028	-0.0206
	(0.009)	(0.063)
	Reading comprehension	
ϕ_1	0.0040	0.0574
	(0.003)	(0.034)
ϕ_2	-0.0177	0.0010
	(0.017)	(0.003)

Significance levels: † : 10% $*$: 5% $**$: 1%

This table presents estimates of Equation 2.8. For income the knot is estimated at $15000, while for the instrument the value of the knot is $1500.

Table 2.9: IV FE estimates of a one knot spline

Coefficient	OLS	IV
	Math and reading	
ϕ_1	0.0315^{**}	0.663^{**}
	(0.0116)	(0.228)
	Math	
ϕ_1	0.0182	0.635^{*}
	(0.0146)	(0.277)
	Reading recognition	
ϕ_1	0.0265	0.407^{*}
	(0.0172)	(0.201)
	Reading comprehension	
ϕ_1	0.0357^{*}	0.648^{*}
	(0.0173)	(0.274)

Significance levels: † : 10% $*$: 5% $**$: 1%

This table presents estimates of Equation 2.9.

Table 2.10: IV FE estimates of a logarithmic relationship

Child outcome	H_0 linear	H_0 Logarithmic
Math & reading	2.37	-1.39
	(3.29)	(3.42)
Math	4.19	-3.28
	(5.78)	(7.35)
Reading comprehension	-2.6	3.54
	(11.46)	(15.73)
Reading recognition	3.58	-2.64
	(4.67)	(4.86)

This table presents the results of the four steps J test proposed by [23] The first column presents the coefficient and standard error of the step *iv*, that is the true model is linear. The second column presents the coefficient and standard error of the step *iii*, that is the true model is logarithmic.

Table 2.11: J specification test for comparing linear and logarithmic models

Household income	Math - Reading	Math	Reading Recognition	Reading Comprehension
5	13.25	12.7	8.14	12.95
10	6.63	6.35	4.07	6.48
15	4.42	4.23	2.71	4.32
20	3.31	3.17	2.04	3.24
25	2.65	2.54	1.63	2.59
30	2.21	2.12	1.36	2.16
35	1.89	1.81	1.16	1.85
40	1.66	1.59	1.02	1.62
45	1.47	1.41	0.9	1.44
50	1.33	1.27	0.81	1.3
linear	6.5	6.2	4.0	6.3

This table presents the increase as percentage of a standard deviation on child outcomes of increasing annual household income in $1000. Predicted effect is computed using estimates in table 2.10.

Table 2.12: Marginal effect of Income under a logarithmic relationship

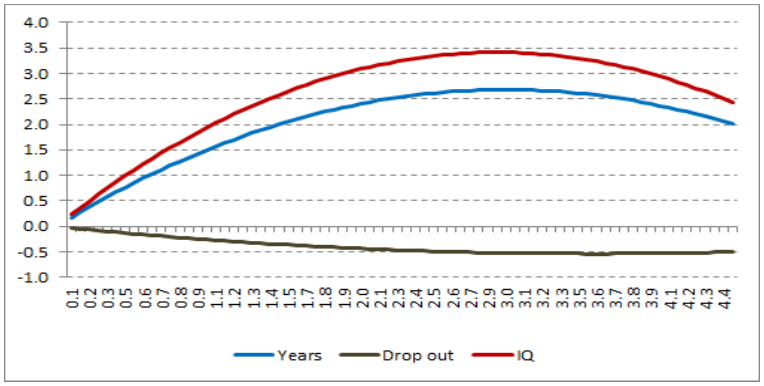

Figure 2.3: Effect of parental income on child outcomes

The Figure presents the effect of parental income using Instrumental Variables for Norwegian administrative data, [49]. Parental income is measured in standard deviations to facilitate comparison.

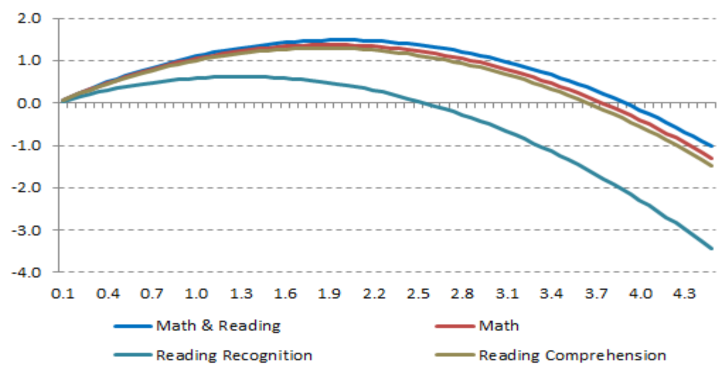

Figure 2.4: Effect of parental income on child outcomes

The Figure presents the effect of parental income using estimates in table 2.7.1. Parental income is measured in standard deviations to facilitate comparison.

CHAPTER 3

THE EFFECT OF PARENTAL CONFLICT ON SKILLS AND CHILD AND ADULT OUTCOMES.

ABSTRACT

This paper investigates the effect of parental conflict on child development, being conflict a non-tangible input related to family functioning. The evolution of cognitive and non-cognitive skills over childhood is estimated using data from the National Longitudinal Survey of Youth 1979. Results show that higher conflict reduces skill accumulation and years of education completed. Cognitive development is more affected during early childhood while non-cognitive development is at later ages. Effect of conflict on years of education completed is lower than the effect of material investments and similar to the effect of parental time.

3.1 Introduction

Child development is one of the most widely studied topics in the economics literature because it is a crucial factor that determines the development and productivity of an economy. Economics has a role through the design of policy aimed to reduce inequalities in academic, socio-emotional, and labor outcomes of individuals. A first strand of the research related to this topic includes reduced form studies that estimate the effect of improving conditions at disadvantaged households on achievement and adult outcomes. The analysis focus on the effect of two type of programs: *(i)* providing better inputs, evaluating the effect of programs such as Headstart or Abecedarian

([21, 12]) and *(ii)* providing income support ([11, 22, 1]). A second strand of the literature models the key elements of intertemporal household decision making incorporating utility from child achievement (e.g. [24, 64]).

Since [17, 19], the theoretical framework used by economists includes concepts from psychology aiming to capture how cognitive and non-cognitive or socio-emotional skills are accumulated over childhood and how they determine child achievement, IQ, wages, and years of education among other adult outcomes. In this framework, skill formation depends on the previous level of skills and investment in educational inputs such as books, tuition, and additional classes ([17, 18]), parental time ([4, 3]), and family background ([20]).

Family functioning and it's effect on skill accumulation, child achievement, and subsequent labor outcomes have been studied in psychology but have not been fully incorporated in economics. There is evidence of the effect of family functioning on cognitive accumulation but there is no previous research on its impact on the evolution of non-cognitive skills. Family functioning is an intangible input that affects child well-being and can be assessed directly using self-evaluation or indirectly through behaviors like parental conflict ([62]). Exposure to conflict influences children through parenting and parents' psychological well-being (e.g. [29, 30]).[42] It is likely that children in households with higher conflict have a less favorable environment. Their parents will have a lower commitment to provide financial resources, buy educational inputs, and provide time to help their children. Thus, parental conflict is a negative

[42] The factor is closely associated with parental stress, which is recognized in the economic literature as one of the channels through which income can affect child outcomes (e.g. [51].)

input that might be included into the technology of skill formation. The Dynamic Systems Theory in psychology describes child development as a cumulative process, where the child is exposed to a changing environment that affects child learning. Moreover, parental investments, parental conflict, and all other factors that contribute to learning interact in each stage to determine human capital acquisition (e.g. [53]).

In economics research, parental conflict has been incorporated in models of divorce and the negative effect of divorce on children (e.g. [64]). The lower scores on cognitive achievement tests of children in divorced households compared to children in stable households has been widely studied in the child development literature. Parental conflict is associated with a higher probability of divorce and directly impact skill formation. For instance, [64] shows that cognitive achievement of children exposed to conflict is lower than the achievement of children in conflict-free households regardless of marital status. [35] conclude that parental conflict is a good predictor of child adjustment problems (aggression, anxiety, withdrawal, depression, and low-self esteem). These results attest that parental conflict affects both cognitive and non-cognitive skills.

The objective of this paper is to analyze how parental conflict affects cognitive and non-cognitive skill accumulation and adult outcomes. A measure of parental conflict is incorporated into the production function for cognitive and non-cognitive skill formation developed by [20]. This framework uses a value added skill production function that incorporates material inputs (books, lessons), time, and other parental investments. It is natural to extend the model to include parental conflict as an additional input.

Parental conflict is measured using a latent factor model based on a set of questions from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79) that capture whether the respondent and her spouse argue about each of nine topics: children, money, chores and responsibilities, showing affection, religion, leisure time, drinking, other women, and the respondent's relatives. These questions have been used to describe whether parents accommodate to a conflict-free relationship or not. Thus, we can measure the effect of that decision on cognitive skills (e.g. [52, 64]). Previous studies use an arbitrarily constructed index of conflict while in this paper we identify the optimal weights of each source of argument in the form of a factor that explains whether parents harmonize or not. Thus, lower levels of this factor reflect an increase in parental conflict at home.

This paper contributes to the literature on cognitive and non-cognitive skill formation by including parental conflict, which is an input that may undermine conditions at home and the effectiveness of public policy. It extends the models of [19, 17] and [20]. This paper also makes two contributions to the literature on the effect of parental conflict on child achievement (eg. [64] and [52]). First, unlike those papers we analyze the effect of conflict on both cognitive and non-cognitive skills. Second, this paper estimates the effect of parental conflict on a child's subsequent long-term outcomes such as years of education and adult earnings.

The estimation of the technology of skill formation follows [20]'s approach. They describe cognitive and non-cognitive skill as low dimensional latent variables based on child achievement test scores. Additionally, noisy measures of parental time, investment goods, and parental time are used to construct latent investment levels. This approach does not rely on a single measure of skill accumulation, given that test scores are affected not only by skills but also by environmental factors (eg [38]). Another advantage is that this methodology reduces the demands on the Instrumental Variable approach, diminishing the number of instruments necessary to guarantee identification.

The estimated technology of skill formation is consistent with previous findings in literature: (i) there is self-productivity of skill production: skills accumulated in one period persist in child development, (ii) there is dynamic complementarity of time, material investments, and parental conflict. Moreover, reductions in parental conflict increase cognitive and non-cognitive skill development as well as child schooling achievement. Cognitive skill is more responsive when parental conflict is reduced during early childhood while non-cognitive skill is more responsive to reductions when a child is over 4 years. If parental conflict is reduced 10% for the entire childhood for a child in an average family his school achievement would increase by 0.4 years.

After this introduction, a review of the economics literature on child development and skill accumulation is presented. In section 3 the conceptual framework is described. In section 4 a description of the identification under different assumptions about endogeneity is presented. In section 5 the Children of the NLSY79 (CNLSY) and NLSY79 data used in this paper is analyzed. Section 6 presents and discusses the estimates of the effect of parental conflict on child skill accumulation and child and adult outcomes. Finally, section 7 concludes.

3.2 Literature Review

Child development is a central topic of economic and policy discussions because child development affects productivity and it is connected to the economic decisions made in the household. The economics literature has analyzed this topic from different perspectives. One set of studies analyzes the short and long run effects of programs aimed to improve inputs or budget at disadvantaged households (e.g. [11, 1, 22]). These studies do not estimate the technology of skill formation. Instead, they investigate how income support and government programs affect outcomes such as cognitive and non-cognitive test scores, adult earnings, and high school graduation.

A second approach focuses on structural models in which utility-maximizing households take their labor supply and child investments in an intertemporal setting (e.g. [24, 10, 48]). The utility function includes the child outcomes as an argument. This framework is useful to simulate the effects of counterfactual economic policies. However, the policy simulations that come from structural models can be questionable, because of the assumptions about the utility function, budget constraint, production function, and expectations.

This paper belongs to a third set of studies which focus on how human capital is accumulated over childhood in a dynamic setting. Instead of focusing on the reduced form effects on specific outcomes of increase resources or income. The approach estimates the production functions of cognitive and non-cognitive skills, thus, it is closer to the second strand because those are structural equations. These studies build on the conceptual framework of [9], which describes how parents invest in inputs to boost skill acquisition during childhood.

[66] estimate several specifications of the production function of cognitive achievement using as determinants of skill accumulation the entire history of lagged home and school inputs, parents ability, and unobserved endowments. The authors find evidence of a value-added model augmented with information on lagged inputs, home environment, and mother's ability. These last two factors are important to explain differences in test scores in early childhood.

[17] build on and generalize [9] by incorporating multiple skills, differences in input productivity across stages of development, and dynamic complementarities in skill formation. They classify skills as cognitive (mathematics, reading) and non-cognitive (perseverance, motivation, self-esteem, self-control), which are accumulated over several periods of childhood. These skills are powerful determinants of wages, schooling, teen pregnancy, smoking, and crime, among other measures of adult economic and social success.

[20] generalize the work in [19] by allowing for a nonlinear specification of the skill formation production function, which relaxes the assumption that early and late investments are perfect substitutes. In addition, they include cognitive and non-cognitive skills of parents as inputs into the skill formation equations.

[3] analyze skill formation in early childhood using a randomized intervention in Colombia, also relaxing the perfect substitutability assumption. This intervention aims to boost development, growth, and hemoglobin levels by providing stimulation and micronutrient supplementation to help. Their findings were consistent with the literature that a child's current stock of cognitive and non-cognitive skills fosters the development of future skills, and that all inputs are complementary in the production of future skills. In addition, the authors incorporate parental time as an input. Results suggest that material investments are more important for cognitive skill accumulation while time is more important socio-emotional skill development.

This paper extends [20] by including into the technology a latent factor from the questions of the NLSY79 that describe the incidence and frequency of conflicts. Low values of the factor indicates higher parental conflict. This paper includes the effect of parental conflict on non-cognitive skill, interacting with material inputs, parental time, and parental skills.

In sum, the literature has shown that child development depends on investments of goods and time. Additionally, the literature has incorporated parental skills as an input into the development technology. However, child development is also affected by psychological factors like family functioning. For instance, [51] argue that family functioning is a channel through which income affects cognitive achievement. [64] finds evidence that parents that do not accommodate to a conflict-free relationship negatively affect cognitive achievement. This paper presents evidence that higher levels of parental conflict adversely affect cognitive and non-cognitive development, as well as adult outcomes.

3.3 Conceptual Framework

This section describes how human capital (cognitive θ_t^C and non-cognitive θ_t^N skills) is determined over T periods of childhood by the production functions of cognitive (f_s^C) and non-cognitive (f_s^N) skills, which are assumed to be monotone and increasing in their arguments, twice continuously differentiable, and are described by the following equations:

$$\theta_{t+1}^C = f_s^C(\theta_t^C, \theta_t^N, \theta_t^I, \theta_t^{PC}, \theta_t^\tau, \theta^{CP}, \theta^{NP}, \eta_t^C) \tag{3.1}$$

and

$$\theta_{t+1}^N = f_s^N(\theta_t^C, \theta_t^N, \theta_t^I, \theta_t^{PC}, \theta_t^\tau, \theta^{CP}, \theta^{NP}, \eta_t^N). \tag{3.2}$$

Skills are accumulated in each period $t = 1, ..., T$, according to the production function of the stage s. Accumulation depends on the levels of both skills at the beginning of the period, two investment inputs: θ_t^I, which represents purchased goods and services, and θ_t^τ the time that parents spend with their children. It also depends on parental conflict θ_t^{PC} and two fixed inputs: parental cognitive and non-cognitive abilities θ^{CP}, θ^{NP}. Finally, η_t^C and η_t^N represent unobserved shocks to skill. In this specification each variable is a scalar that denotes a latent factor for the skills, parental investments, parental conflict, or parental skills.

Parental investments θ_t^I represents all material goods such as books that help the learning process. Parental time θ_t^τ captures another important dimension of parental investments as shown by [4]. If parents spend time at home they can monitor and enforce children's homework and in general help them with school.

Parental conflict, θ_t^{PC} is the result of parental interaction. [64] treats conflict as the result of parental decisions to accommodate to a conflict-free relationship or not to accommodate and have a relationship with conflict. In this paper, conflict is not restricted to be dichotomous; instead it is a latent factor determined by several dimensions of couple behaviour. High levels of conflict are hypothesized to directly affect skill accumulation and to affect the productivity of other inputs.

Parents with higher cognitive θ^{CP} and non-cognitive θ^{NP} skills can teach their children better than parents with low skills. These variables are related to home background. Both parental skills are treated as fixed, which is consistent with the assumption that skills are only accumulated during childhood.

The production function parameters are stable during each stage (s) of childhood, but can change between stages. This flexibility captures that some stages may be more productive in the production of skills, and therefore skill accumulation can be manipulated at different ages. To determine what stage is better to increase skills it is useful to incorporate sensitive and critical periods for investments, as defined in [45]. Stages that are more efficient for skill accumulation are called sensitive periods. Thus, t^* is a sensitive period if at the same level of inputs investments are more productive in stage t^* than in $s \neq t^*$.

$$\left.\frac{\partial \theta^C_{t+1}}{\partial \theta^I_{t^*}}\right|_{\theta^C=\bar{\theta}^C,\theta^N=\bar{\theta}^N,\theta^I_1=i_1,\ldots,I_t=i_t} > \left.\frac{\partial \theta^C_{t+1}}{\partial \theta^I_{s}}\right|_{\theta^C=\bar{\theta}^C,\theta^N=\bar{\theta}^N,\theta^I_1=i_1,\ldots,I_t=i_t}$$

A period t^* is critical if it is the only period in which investments are productive.

$$\frac{\partial \theta^C_{t+1}}{\partial \theta^I_{t^*}} > 0$$

and $\forall s \neq t^*$

$$\frac{\partial \theta^C_{t+1}}{\partial \theta^I_{s}} \equiv 0$$

Following [20] in the empirical analysis we divide childhood into two stages. The first one describes how human capital is accumulated for children up to 4 years of age while the second stage captures skill accumulation for children 5 years and older.

The technology described in equations 3.1 and 3.2 allows for a dynamic interdependence or complementarity: children with greater abilities at young ages learn more in subsequent periods. Dynamic complementarity for investments occurs when the skills acquired in $t-1$ make current investments θ^I_t more productive $\partial^2\theta^C_{t+1}/\partial\theta^C_t\partial\theta^I_t > 0$. This has two important implications for policy design. First, divergence in skills may appear at early ages. Second, early interventions are in general more effective than later remediation (e.g. [17, 40]).

Finally, cognitive and non-cognitive skills accumulated during childhood determine adult human capital. Thus, human capital is characterized by the stock of cognitive and non-cognitive skills at $T+1$. It is the main determinant of adult success, measure in outcomes such as child achievement, high school completion, teen pregnancy, and adult earnings, among others. Then, the adult outcome Q_j can be described as a function of the skills accumulated over childhood.

$$Q_j = g_j(\theta^C_{T+1}, \theta^N_{T+1}, \nu) \tag{3.3}$$

The function g_j is assumed to be continuously differentiable and reflect that skills positively affect the majority of life outcomes with different effect in the labor market outcomes or other areas.

3.4 Identification and Estimation

3.4.1 specification

Following [19] and [20], the identification and estimation of the latent inputs, skills, and the production function uses a dynamic factor analysis. This factor model has a state space representation and is estimated using the Kalman Filter.[43] The

[43] The Kalman filter is an algorithm that uses a series of measurements observed over time, containing some measurement error or statistical noise, and produces estimates of latent or underlying variables, see for instance [39].

filter consists of two sets of equations: measurement and transition. The measurement equations capture the relationship between observed noisy measures of parental investments and skills and the latent factors, and are given by:

$$Z_{t,j}^{M} = \mu_{t,j}^{M} + \alpha_{t,j}^{M}\theta_{t,j}^{M} + \epsilon_{t,j}^{M}, \tag{3.4}$$

with $j = 1, ..., J$, $t = 1, ..., T$

$Z_{t,j}^{M}$ represents the $j - th$ observed measure for latent factor M at time t. M refers to cognitive and non-cognitive skills (θ_t^C, θ_t^N), investments, parental conflict, and time $(\theta_t^I, \theta_t^{PC}, \theta_t^{\tau})$ and parental cognitive and non-cognitive skill $(\theta_t^{CP}, \theta_t^{NP})$, that is $M = \{C, N, I, PC, \tau, CP, NP\}$. $\alpha_{t,j}^{M}$ are factor loadings and $\epsilon_{t,j}^{M}$ is a measurement error assumed to be uncorrelated across the measures. The transition equations can be written in matrix form as as:

$$\Theta_{t+1} = G_t\Theta_t + \nu_t \tag{3.5}$$

with $\Theta_t = vec\{\theta_t^C, \theta_t^N, \theta_t^{PC}, \theta_t^I, \theta^{CP}, \theta^{NP}\}$. The transition equations capture the dynamic behaviour of the system. In the case of the skill accumulation equations they represent the production functions. See appendix F for a discussion of the application of the Kalman filter to this model.

Factor loadings in equation 3.4 are identified under the assumption that the measurement errors $\epsilon_{t,j}^{M}$ are uncorrelated across t and that there are at least two measurements of each latent factor per period. Using covariance restrictions and normalizing one factor loading $(\alpha_{t,1}^{M} = 1)$ for each latent variable and for all t it is possible to estimate the remaining factors loadings using the covariances of the observed measurements.[44] The joint distribution of all latent variables $\{\theta_t^C, \theta_t^N, \theta_t^{PC}, \theta_t^I, \theta^{CP}, \theta^{NP}\}$ is identified using the approach suggested by [58, 59].

The estimation of equations 3.1 and 3.2 requires the specification of a functional form. Following [20] a constant elasticity of substitution production function (CES) is used. This allows to compare results with previous findings. The CES nests perfect substitutability ([19]) as well as the Cobb-Douglas technology. The CES function is defined by the following equation:

$$\theta_{t+1}^k = \left[\gamma_{sk1}(\theta_t^c)^{\phi_{sk}} + \gamma_{sk2}(\theta_t^N)^{\phi_{sk}} + \gamma_{sk3}(\theta_t^I)^{\phi_{sk}} + \gamma_{sk4}(\theta_t^{PC})^{\phi_{sk}} + \gamma_{sk5}(\theta^{CP})^{\phi_{sk}} + \gamma_{sk6}(\theta^{NP})^{\phi_{sk}} \right]^{\frac{1}{\phi_{sk}}} e^{\eta_{kt+1}} \tag{3.6}$$

where $\gamma_{skl} \geq 0$ and $\sum_1^6 \gamma_{skl} = 1$. Each γ_{skl} represents the share or relative importance of a factor in the production of skill k in stage s, $k \in \{C, N\}$, $t = \{1, 2..., T\}$, $s \in \{1, 2\}$. The errors are assumed to be normally distributed: $\eta_{kt} \sim N(0, \delta_{\eta s}^2)$. If the parameter $\phi_{sk} = 1$ the elasticity of substitution is infinite and inputs perfectly substitutes each other according to their productivity γ_{skl} in producing cognitive and non-cognitive skills. If $\phi_{sk} = -\infty$ the elasticity of substitution is 0, thus all inputs are complements and necessary to accumulate skills in the period. If $\phi_{sk} = 0$, the

[44] Using the normalization $\alpha_{t,1}^C = 1$, for all t the covariance of the first measurement for the cognitive skills between periods t and $t+1$ is: $Cov(Z_{t,1}^C, Z_{t+1,1}^C) = Cov(\theta_t^C, \theta_{t+1}^C)$. In addition, the covariance of the second measurement on cognitive skills in t and the first measurement in $t+1$ can be expressed as: $Cov(Z_{t,2}^C, Z_{t+1,1}^C) = \alpha_{t,2}^C Cov(\theta_t^C, \theta_{t+1}^C)$. If the left and right hand terms on the first equation are different from zero, it is possible to compute the loading $\alpha_{t,2}^C$ by dividing the second equation by the first one.

production function is Cobb Douglas and inputs are imperfect substitutes.

In previous research, test scores are used as measures of outcomes, but those are not invariant to affine transformations. One of [17]'s innovations is to define a cardinal scale for cognitive and non-cognitive skills by anchoring results to school attaintment. To have a better understanding of the relative importance of cognitive and non-cognitive skills, investments, time and parental conflict at different stages of the life cycle, it is desirable to anchor skills in a common scale. Here, estimates of the parameters are anchored to school attaintment Q at age 25. Using the equation for adult outcomes we have:

$$Q = \mu + \alpha^C \theta^C_{T+1} + \alpha^N \theta^N_{T+1} + \epsilon \tag{3.7}$$

The scale of the factors θ^C, θ^N is unknown, so for affine transformations, the parameters α^C, α^N, and μ will adjust. However, the scale of $\delta^C \theta^C_{T+1}$ and $\delta^N \theta^N_{T+1}$ is uniquely determined by its effect on child school attaintment, that is $\frac{\partial Q}{\partial \theta^I_t} = \alpha^C \frac{\partial \theta^C_{T+1}}{\partial \theta^I_t}$ and $\frac{\partial y}{\partial \theta^I_t} = \alpha^N \frac{\partial \theta^N_{T+1}}{\partial \theta^I_t}$. Child school achievement is measured in years avoiding reliance on test score metrics which are arbitrary.

In [20], parental time investments are measured as ordinal scales with integer values from 1-5. However, the responses indicate how often in a year the investment occurs. Using the categorical value as if they were ordinal assumes that each category measure the intensity in which input is used but this is clearly not true. Thus, in order to measure parental time precisely the categories are replaced by their equivalents in times per year. For instance, if the child sees family or friend once per month or once per week the variable *number of times per year* is equal to 12 or 52.

3.4.2 Unobserved heterogeneity

Estimates of the technology and adult outcomes equations will be biased if unobserved fixed or transitory variables that influence investment choice are correlated with unobservables in the production functions. First, we analyze how to deal with constant heterogeneity assuming that the error term in the skill technology equation has two components: a time-invariant unobserved factor π and an *i.i.d.* error term ν_t. We account for correlation of π and the inputs using a similar approach to the one used to identify factor loadings in the measurement equations. Using the adult outcome equation 3.7 it is possible to impose restrictions on the covariance between observed adult outcomes and measurements of investments.[45]

Endogeneity can also be caused by transitory shocks that affect both the accumulation of skills and parental investment. For instance, to reduce the effect of a negative health shock, parents may compensate by increasing the use of educational inputs, parental time or by reducing parental conflict. Endogeneity arises because parental investment decisions are made knowing the transitory shock. In this case, the error term of the technology equation is divided into a time-varying unobserved heterogeneity factor π_t that can be correlated with the vector (θ, I_t, θ_P) and an *i.i.d.* error term ν_t. To deal with this endogeneity, [20] proposed to use an approach similar

[45] Rewriting 3.7, we have $Q_j = \alpha_{jC}\theta^C_{T+1} + \alpha_{jN}\theta^N_{T+1} + \alpha_{j\pi}\pi + \epsilon_j$. π is an unobserved fixed component that is correlated with the latent factors. Then, it is possible to write the covariance between adult outcomes and measurements as: $Cov(Q_j, Z^C_{t,j}) = \alpha_{jC}Cov(\theta^C_t, \theta^C_{T+1}) + \alpha_{jN}Cov(\theta^C_t, \theta^N_{T+1}) + \alpha_{j\pi}Cov(\theta^C_t, \pi)$. Using at least 3 adult outcomes, and the covariances with cognitive and non-cognitive measurements it is possible to identify factor loadings α_{jC}, α_{jN} and $\alpha_{j\pi}$.

to a control function. If the unobserved shock is serially correlated, it will be correlated with θ_t due to the correlation between past investments and skill accumulation.[46]

Then, to guarantee identification it is necessary to find instruments: variables that affect investment decisions and parental conflict but that are not directly related with cognitive and non-cognitive skill accumulation. As variables that exogenously shift resources, [20] proposed lagged values of income y_t. These instruments for θ_t, work well if the transitory shock is independent of $\theta_t^C, \theta_t^\tau$ and the past and present values of y_t. [3] proposed to use the average female and male wages in the child's village, household wealth at the baseline survey, and an indicator variable for whether the mother was married.

In this paper, following [22] the Earned Income Tax Credit is used as an instrument. The EITC is an antipoverty program initiated in the mid-1990's. Low wage working households get tax relief, increasing their budget. Parental income at period t can be expressed as the sum of pretax income P_{it} and the EITC transfer $\chi_t^{S_{it}}(P_{it})$, minus taxes $\tau_t^{S_{it}}(P_{it})$.[47] Using their approach, the proposed instruments are the expected EITC income given once-lagged pretax income $(\chi_t^{S_{i,t-1}}(\hat{E}[P_{i,t}|P_{i,t-1}]))$ and the EITC benefit in the previous period $\chi_{t-1}^{S_{i,t-1}}(P_{i,t-1})$. Those instruments use individual information available in the previous period, so by assumption they are orthogonal to any shock that affects current income, as well as child outcomes. This instrument is

[46] If the unobserved heterogeneity is *i.i.d.*, each one of the investments $\theta_t^I, \theta_t^\tau$ and parental conflict θ_t^{PC} can be identified using a similar strategy to the one presented in the identification of the factor loadings and permanent endogeneity. Exploiting covariance restrictions between the observed investments and skills in addition to the restrictions on cognitive and non-cognitive covariances.

[47] Superscript s_{it} denotes the specific EITC schedule faced by the child's family, which depends on the age and the number of dependent children in the family (one or more than one child).

determined by family income evolution and changes over time in the EITC schedule. In this context, the changes in EITC generosity over time that differentially affect households along the income distribution contributes to identification. Figure 3.1 shows the big increases in EITC generosity during 1988 to 2000, with the highest expansion between 1993 and 1995. Given that the EITC schedule is determined by federal and state governments it is not expected to be affected by cognitive and non-cognitive skills of children, so it is exogenous. Also, it could represent up to 40% of the total income for families, so it is likely to be a strong instrument for households at the lower end of the income distribution.

Additionally, it is proposed to use other parts of the federal tax system as instruments. Taxes also affect resources available at home and they are not related with child skills. Therefore. it is possible to define as additional instruments the expected tax given once-lagged pretax income ($\tau_t^{S_{i,t-1}}(\hat{E}[P_{i,t}|P_{i,t-1}])$) and the tax in the previous period $\tau_{t-1}^{S_{i,t-1}}(P_{i,t-1})$. With parental conflict, material investments and parental time there are three endogenous variables. Therefore, we have four instruments, thus satisfying the rank condition.

An additional source of bias is caused by the fact that current investments, parental time and conflict may be correlated with lagged income. Therefore, in order to remove bias [22] proposed to include a control function for lagged income, $\Phi(P_{i,t-1})$. This specification accounts for the fact that changes in the EITC and taxes affect differently the population depending on their location in the income distribution. [22] proposed a fifth order polynomial to capture this relationship. However, any other functional form is possible. For instance, [34] include a 10 piecewise in the first lag of income. In [22] this function is not collinear with the first stage estimates because the EITC structure (phase-in, flat and phase-out zones) provides a non linearity.

3.5 Data

The model is estimated using data from the NLSY79 and the children of the NLSY79 (CNLSY). The NLSY79 is an ongoing survey conducted annually between 1979 and 1994, and biennially since 1996. It is based on a nationally representative sample of 12686 men and women who were between 14 and 21 years old in 1979. It collects detailed information about income, assets, program participation, labor force, and education, among other demographic and individual characteristics. The Children of the NLSY79 started in 1986 and includes information for children born to female respondents of the NLSY79 about cognitive and non-cognitive assessments, demographics, home environment, and development. [48]

Following [20] only first born white children were studied. This restriction is motivated by the differences between the cognitive and non-cognitive outcomes for children by race found by [66]. In addition, the sample is restricted to households with married or cohabitating couples where the questions about arguments are observed. This may bias estimates because it omits children whose parents do not live

[48] Information about school inputs that could be relevant for skill formation is not recorded in the NLSY79.

together as a consequence of high levels of conflict.[49] In order to avoid this potential bias the inverse of the mills ratio is included into the estimation of the skill technology following the two step procedure proposed by [41].

Appendix G presents a comparison between the sample data used by [20] and the sample of first born white children used here. There are two factors that create differences in the samples. First, [20] use 2208 first born white children out of the 2810 that are available in the survey. There is no documentation on which additional criteria they used to get their final sample. And second, their data on cognitive and non-cognitive achievement tests seem to be standardized to be mean 0 and standard deviation 1, but there is no reference on how the standardization was performed.[50] In order to determine whether the results presented here are directly comparable with their results, in section G.2 of the appendix compares both descriptive statistics and estimates of the baseline models in [20].

Results of these comparisons show that cognitive and investment measurements are pretty similar despite the difference in the sample size. On the other hand, there are some differences in the descriptive statistics of non-cognitive skills with respect to their sample that may be attributed to the differences in the standardization method. Estimates of the technology parameters using my comparison sample are very similar so it is reasonable to assume that findings reported here can be directly compared to

[49]Material investments, parental time are expected to be more productive for skill development in households where both parents live together given that this shows commitment to a long term relationship.

[50]In this document the standardization was made for each period including all the respondents of the CNLSY, which brings the descriptive statistics closest to their data.

those of [20]. The next subsection describes the sample of first born white children in households with married or cohabitating couples.

3.5.1 Descriptive statistics of the sample

The sample used in this study consists of 1,679 first born white children who live in a household with married or cohabitating parents. Due to the frequency of the NLSY79 and the CNLSY, the unit of analysis is a two year period. Table 3.1 describes the periods of development and observations available. Differences in the number of observations per period are explained by the rate of response and the fact that not all children are observed in each wave. There are three characteristics worth mentioning. First, the lower number of observations on children in the first period, between 0 and 11 months is due to the biennial periodicity of the survey. Second, the lower number of observations for children between 1 and 4 years (periods 1 and 2) is explained because in 1986 some of the children were already 5 years or older. Finally, the decline in the number of observations for children between 11 and 14 years (periods 7 and 8) is explained because in 2012 not all children have completed their childhood. The next subsections describe the measurements used as indicators of skills and inputs for all periods of development. More detailed statistics are found in the appendix E.

Cognitive skill

The first panel of table 3.2 summarizes measures of child cognitive skills. For children up to 4 years the Motor and Social Development Scale, the Parts of the Body

Score, the Memory for Location Score, and the Peabody Picture Vocabulary Test are used, normalized to mean zero and standard deviation 1. Thus, if the average value of cognitive measurements is positive it indicates that first born white children of married parents do better in these tests than the rest of the sample. This fact is consistent with [65]'s findings.

Non-cognitive measurements

The Second panel of table 3.2 presents the measures of non-cognitive skills. They are divided into two batteries of questions. For children up to 4 years, the Temperament Scale is used. It is composed of mother reported responses to questions about *activity, predictability, fearfulness, positive affect, and friendliness.* For children over 4 years, components of the Behavioural Problem Index (BPI) are used to measure non-cognitive achievement. The BPI is designed to measure the frequency, range, and type of childhood behavior problems. These are categorical variables indicating whether a given statement about behaviour is: often true, sometimes true, or not true. In the analysis the following subscores are used: *(i) antisocial*, *(ii) anxious/depressed*, *(iii) headstrong*, *(iv) hyperactive*, *(v) peer problems.*

First born white children have a higher sociability and compliance score, as indicated by a mean higher than 0. Also, first born white children present antisocial and head strong scores above the mean, indicating that they are more affected by those problems. On the other hand, their hyperactive and conflict scores are lower than for the rest of CNLSY respondents.

Inputs and Time - Investments

The third panel of table 3.2 presents the CNLSY measures of parental investment that are collected in the Home Observation Measurement of the Environment - Short Form (HOMESF). This form collects information about home environment, planned events, and family surroundings that influence the emotional support and the stimulation received by children. The information collected can be classified into variables that capture material or time investments. The following measures of parental investments are used: the number of books the child has, the number of push/pull toys, the number of soft/role play toys, number of magazines, whether the child has a tape recorder/CD player, whether the child has musical instrument, whether the family receives a daily newspaper, whether the child receives special lessons/activities, whether the child is taken to musical performances.

Time measurements include the number of times the child was praised last week, and the number of times positive things were said to the child last week, how often the child gets out of the house, how often the mother reads to the child, how often the child eats with mom/dad, how often mom talks to the child from work, how often the child is taken to a museum, and how often the child sees family and friends. All these are categorical variables, but are associated with time frequencies (1 time per week, or 1 time per year) so it is possible to create a new variable that measures annual frequency. This will reflect more accurately the time that parents devote to their children. [51]

[51] The following variables are converted: How often child gets out of house, how often the mother reads to the child, how often child eats with mom/dad, how often mom talks to child from work, how often child is taken to museum, and how often the child sees family friends.

Parental conflict

Starting in 1988, the NLSY79 measures parental conflict using reports by female respondents about disputes at home over a variety of topics related to family functioning. Respondents reported how frequently they argue with their partner about the following items: *chores and responsibilities, money, children, leisure time, showing affection to each-other, drinking, religion, other women, and her or his relatives.*[52]

The fourth panel of table 3.2 reports the mean, standard deviation, and observations for each source of conflict at each period. The responses in the NLSY79 are categorical and they are reported as: 1-often, 2-sometimes, 3- hardly ever, and 4-never, so values closer to 4 indicate that conflict is low. The most frequent subjects of conflict are: chores, children, and money. There are few couples that argue over drinking, other women, religion and relatives. These findings hold for all periods of childhood. Thus, the latent factor will reflect parents commitment to a conflict-free relationship, with lower levels of the factor reflecting parental conflict.

Taxes and EITC

We use the EITC and federal taxes as instruments. To compute those variables we define total household as the sum of three components: earned income, unearned income, and non taxable income, for the respondent and her spouse. Earned income is the sum of all wages and salaries received in the calendar year of reference. Unearned

[52]There are other questions related to parental conflict available in the NLSY79. However, their availability is lower. Those questions are: the degree of satisfaction in the current relationship (e.g. degree of happiness)and whether biological parents of children over 9 years argue.

income includes income derived from business and farm, unemployment, savings, net rental, and social security. Finally, nontaxable income corresponds to veteran benefits, worker compensation, disability payments, and income from welfare/AFDC, food stamps, Supplemental Security Income, and other public assistance, and child support.

Using these three variables the EITC and federal taxes are computed using the TAXSIM code developed by [32] and available at the National Bureau of Economic Research web page (http: www.nber.org/taxsim). This code computes a microsimulation of the US state and federal tax income system based on a large sample of actual returns. We assume that all eligible households take the credit. This is based on [60], who shows that between 80% and 87% of the eligible families take the credit. Income from tax corresponds to the federal income tax before credits, which includes tax on taxable income, special treatment of capital gains, and 15% rate phase-out. The EITC provides income support for low income households, so it provides enough variation for identifying parameters in low income households. On the other hand, taxes affect the entire income distribution, providing instruments relevant to the middle and the high end of the income distribution.

3.6 Estimates of the technology of skill formation

This section presents estimates of the technology of skill formation under two specifications. Subsection 3.6.1 extends [20] by specifying two investments inputs: material and time. We compare the results with [3] who also separately include time and material investments. In subsection 3.6.2 parental conflict is added to the specification. In both subsections three sets of estimates are presented, corresponding to three assumptions about the relationship between the unobservables in the investment equations and in the technology equations: no endogeneity, permanent endogeneity and unrestricted endogeneity.

3.6.1 Time and material investments

Cognitive skill accumulation

Estimates of the technology of cognitive skill formation are presented in table 3.3. Each column corresponds to a different assumption about the unobserved heterogeneity. The upper panel refers to the parameters for cognitive accumulation from birth up to 4 years and the lower panel describes the estimates of the skill technology for children over 4 years.

Consistent with previous research, the most important determinant of skill accumulation is the previous level of the skill, especially during the second stage. The relative importance for cognitive skill accumulation of the previous level of cognitive skills in the first stage (γ_{sC1}) ranges from 38.9% to 42.3%, while it ranges from 80.9% - 88.7% in the second stage. There is a small cross productivity during early childhood; non-cognitive skills contribute to cognitive skill accumulation (γ_{sC2} ranges from 3.0% to 4.4%). Similar result to [3] and [20], who found a positive effect of non-cognitive skill on cognitive skill accumulation for children under 5 years.

Parental investments are important for cognitive skill accumulation, with a higher impact during the first stage. Thus, cognitive skill accumulation is sensitive to early investments. For children up to 4 years both investments have a high importance regardless of the specification of the unobserved heterogeneity. During the second stage, material and time investment productivities diminish considerably. Material investments are more important than time investments in both stages, with a relative importance almost double. Estimates of the material investment share (γ_{sC4}) range from 3.4% to 4.9% and estimates of the time investment share (γ_{sC3}) range from 0.9% to 2.4% in second stage. [3] also found that material investment has a higher productivity in cognitive accumulation. However, the estimates of investment share are higher in this paper than in their paper, which reported relative importance of material investments of 8% vs 0.8% of time.

The sum of the shares of time and material inputs is bigger than the effect of the single latent investment factor reported by [20]. Relative participation of inputs for cognitive development during the first stage of childhood using one factor was 23.1%, 16.1%, and 26.1% under no heterogeneity, permanent, and time varying heterogeneity. Using two separate factors, the importance of the sum of investments ($\gamma_{sC3} + \gamma_{sC4}$) is 45.0%, 37.3%, and 42.5% under the same scenarios of endogeneity. The relative importance during the second stage is also larger when disaggregating investments into material and time. While in [20] importance of investments ranges from 2.0% to 4.4%, using two latent factors it ranges from 4.3% to 7.2%.

The estimates of the elasticity of substitution are significantly higher during the first stage of development ranging from 1.7 to 2.43. In the second stage, estimates range from 0.39 to 0.42. Therefore, low levels of cognitive skills at early stages can be compensated by increasing parental time or material investments. Given this fact and the self-productivity of cognitive skills, public policy may alleviate cognitive deficits in early childhood.

Non-cognitive skill accumulation

Estimates of the technology of non-cognitive skill formation are presented in table 3.4, which has the same format as the previous table. Self-productivity is high and therefore the previous level of non-cognitive skill is the most important input into accumulation during the first stage. Its relative importance ranges from 52.1% to 54.7% and it increases for children over 4 years ranging from 78.8% to 82.7%. Cognitive skills do not contribute to the production of non-cognitive skills in either stage, as in [20].

Parental investments are important for non-cognitive skill accumulation, especially during the first stage. The time share ranges from 9.7% to 13.7% and the material investment share from 12.8% to 16.8%. (similar finding to [3]). For children 5 years and older the effect of parental time diminishes to 3%. Also, there is a reduction in material investment importance in the second stage, where it ranges from 8.9% to 10.4%.

As was the case for cognitive skills, decomposing investment into two latent factors increase the total importance of parental investments. For children under 5 years, the relative importance of the latent factor of all investments in [20] ranges from 6.5% to 20.9%, while the sum of their relative importance ranges from 22.5% to 30.5% using two factors. During the second stage, the share using one factor ranges from 5.1% to 5.5%, and with two factors it increases to 11.9% - 13.4%. The share of investment material goods is 12.7% and for time it is 14.9%. For children 5 and more years, importance of investments also increase from 5.5% to 11.8% (3% for time and 8.9% for material investments). Therefore, we can conclude that using two latent factors captures additional information about skill accumulation technology.

3.6.2 The effect of parental conflict

Cognitive technology

Table 3.5 presents estimates of the cognitive production function parameters for the two stages of development. The table is organized in the same way as tables 3.3 and 3.4. The main results for cognitive accumulation are similar to the findings in Table 3.3. The previous level of cognitive skill is the most important determinant of cognitive skill accumulation. The other factors in order of importance are: material investments, parental time and parental conflict and there is a small impact of parental non-cognitive skills and previous level of non-cognitive skills. During the second stage the importance of the initial level of cognitive skills increase and all other factors reduce considerably its importance.

Columns 1 and 2 of table 3.7 present the elasticity on cognitive accumulation of all factors. Elasticities are evaluated at the mean and for all cognitive production factors estimates indicate that skill accumulation is inelastic. The first panel presents results without unobserved heterogeneity, while the second and third panel address permanent and time varying heterogeneity. During the first stage, cognitive accumulation is most responsive to changes in the initial level of cognitive skill. The elasticity ranges from 0.39 to 0.46, and it increases to 0.44 to 0.53 for children over 4 years. Responsiveness of cognitive skill to changes in material investments for children up to 4 years old are about 0.2 without unobserved heterogeneity and with time varying heterogeneity, and 0.31 allowing for permanent heterogeneity. Cognitive skills are slightly more responsive for older children, with elasticities that range from 0.21 to 0.40. A reduction in parental conflict increases cognitive skills in both stages of development with elasticities of about 0.1. Increments in parental time have a similar effect on cognitive skill accumulation in both stages of development with elasticities of about 0.1. Higher parental skills have a small impact on cognitive accumulation, with elasticity around 0.06. Finally, non-cognitive skill have no impact under none and permanent unobserved heterogeneity.

Parental conflict is important for cognitive accumulation in both stages. However, development is more sensitive in early childhood. Moreover, the level of parental conflict is more important than non-cognitive skills and parental skills. The elasticities show that reductions in parental conflict are the third factor in order of importance for cognitive development with a value around 0.10 during childhood.

Non-Cognitive accumulation

Table 3.6 presents estimates of non-cognitive accumulation with findings that are consistent with those discussed in the previous subsection. The lagged value of non-cognitive skills is the most important for the development of non-cognitive skills. Shares for parental non-cognitive skills, parental time, material investments and parental conflict are about 0.10. Non-cognitive development is not affected by cognitive skills in the previous period or by parental cognitive skills.

Columns 3 and 4 of table 3.7 present the elasticity on non-cognitive accumulation. As was the case for cognitive accumulation self-productivity is the most important factor for development, elasticity is 0.5 for both stages of development. Higher levels of parental cognitive skills increase child non-cognitive being the second factor in order of importance, its elasticity is up to 0.23 addressing for time varying unobserved heterogeneity. Increases in parental time or material investments as well as reductions in parental conflict have a smaller effect on non-cognitive development with elasticities around 0.10. Finally, responsiveness to cognitive skills and parental cognitive skills is almost zero.

The evolution of non cognitive skills depends on the level of parental conflict. Development is more sensitive in early childhood with a share that ranges from 0.083 to 0.124, while it decreases during the second stage to 0.05. The relative importance of parental conflict is higher on non-cognitive than on cognitive accumulation. The estimated elasticity shows that reductions in conflict are important for accumulation and responsiveness is almost the same in both stages of development with a similar effect to parental investments.

3.6.3 Effects of reductions in parental conflict.

Table 3.8 presents the estimation of child school achievement as a function of cognitive and non-cognitive skills accumulated by age of 14 (equation 3.3). In this subsection only results for the model that addresses time varying heterogeneity are presented, given the similarity in the estimates of the parameters of the technology. Estimates show that both skills are key for child achievement, and non-cognitive skill has a higher effect. However, those estimates can not be understood without including the technology and measurement equations.

To fully understand the implications of these parameters it is useful to simulate the whole model and show how cognitive skill, non-cognitive skill, and years of schooling react to a reduction in parental conflict. We simulate the impact of a 10% reduction in parental conflict (about one quarter of a standard deviation). In the simulation it was assumed that investments, parental time, and parental skills are at their average values. We start by considering the impact of reducing conflict in one period of childhood. The upper panel of table 3.9 presents the impact of such reductions. Column 1 describes the period in which the reduction in conflict is made, columns 2 and 3 show the percentage increase in each skill, while column 4 shows the increase in years of education. For instance, a reduction in parental conflict only in the first period increases cognitive skill by 0.18%, non-cognitive skill by 0.13%, and school achievement by 0.02 years.

Reduction of conflict during early childhood (periods 1-3) increases cognitive skill between 0.18% and 0.75%, while for children over 4 years cognitive skill increases between 0.10% and 0.17%. Thus the benefits of reducing parental conflict are two or three times higher during early childhood. The highest increment occurs for children between 3 and 4 years old. The increasing pattern of the effect of reducing parental conflict is due to the dynamic complementarity. That is, there is a higher productivity of investments, time, and non-conflict because of preexisting levels of cognitive skills. Reductions in parental conflict increase non cognitive skills between 0.13% and 0.42% during early childhood. Higher increases in non-cognitive skills are observed during the second stage of development, between 0.25% and 0.51%. Despite this fact, the increment predicted for children aged 3 and 4 years (0.42%) is also important and similar in magnitude to the effect on children between 11 and 12 years (0.49%). As stated in the introduction, parental conflict shows a higher impact on non-cognitive accumulation. Finally, those increments lead to an increase in years of education between 0.02 and 0.07 if the reduction in conflict is made in one period of the early childhood and between 0.02 and 0.05 if parental conflict is reduced in one period of the second stage (over 4 years). The highest increments are presented when the child is 3-4 years old and between 13-14 years. This finding is again consequence of the dynamic complementarity that the technology exhibits.

As public policies usually focus on more than one period, we present the effects of reducing parental conflict during the first, second stages, or during the entire childhood in the lower panel of the table. Estimates indicate that cognitive skill increase by 1.29%, non-cognitive skill by 0.79%, and children complete 0.13 additional year in school if parental conflict is reduced during early childhood by 10% (for children up to 4 years). If the reduction is exclusively during the second stage (5 years and older), cognitive skill increase by 0.67%, non-cognitive by 1.87% and child achievement by 0.18 years. While if parents reduce their conflict during the entire childhood, cognitive skill increase by 2%, non-cognitive skill by 2.68%, and child achievement by 0.31 years. These findings suggest a higher impact of reductions in conflict on cognitive skills during the first stage, while the impact is higher on the second stage for non-cognitive skills, that is consistent with [19, 20].

An additional tool to get a better understanding of the parental conflict effect is to compare with the effect of investments and parental time. Table 3.10 presents the effect of 10% increments in investments or in parental time on cognitive skill, non-cognitive skill, and years of education. The table is organized in a similar way to table 3.9, where columns 2-4 describe the effect of increments in investments and columns 5-7 to increments in parental time. Increments of 10% in investments leads to a increase in cognitive skill between 0.26% and 1.08% during early childhood and between 0.33% and 0.61% for older children. That is, increasing investments has an effect 1.4 times higher than reducing parental conflict during early childhood, and 3.2 times higher for older children. A 10% increment in investments lead to increases in non-cognitive skill between 0.23% and 0.71%, for children up to 4 years and between 0.45% and 0.93% for children over 4 years. Thus, increments in investments are about 1.75 times more "productive" than reductions in parental conflict. Finally, a 10% increment in one period of early childhood in investment leads to 0.3-0.10 additional years, that is 1.5 higher than the effect of reducing conflict. If the increase in investment is made for a child over 4 years, years of education are expected to increase between 0.05 and 0.10. This effect is 1.5 times higher than reducing parental conflict in early childhood and 2.1 times higher for older children.

The same comparison can be made between reductions in parental conflict and increments in parental time. We see that for children up to 4 years, increments in parental time are less effective in increasing cognitive skill than reducing parental conflict. But, effect of increments in parental time is about 1.35 times higher than that of reducing time for older children. For non-cognitive skills, the parental time effect is 1.2 times higher in early childhood than that of parental conflict and it is smaller (0.74 times) during the second stage of development. Reductions in parental conflict have about 80% of the effect of increases in time on early non-cognitive accumulation and about 1.3 times for older children. Finally, the effect of increasing parental time on years of education is about the same to reductions in parental conflict during the first stage and about 0.86 times during the second stage.

3.7 Discussion

This paper extends [20] by including the effect of parental conflict on the evolution of cognitive and non-cognitive skills. Conflict is a non-tangible input that is associated with family functioning, and has been discussed in psychology and mainly mentioned in economics as a key factor shaping development. Using the NLSY79 data a CES production function for skills is estimated. Results indicate that reductions in parental conflict increase cognitive and non cognitive development. The productivity of conflict reduction on early cognitive accumulation is lower than the productivity of material inputs or time, but it is bigger than the effect of parental skills or the effect of non-cognitive skills. The productivity of parental conflict for non cognitive skills is similar to that of parental time, but is less important than self or material investments productivity. Parental conflict also affects older child development. For children over 5 years it is the third factor in order of importance for cognitive and non-cognitive skill acquisition with a similar share as material investments. The productivity of parental conflict is higher on non-cognitive accumulation than on cognitive skills for both stages of child development.

The effect of parental conflict on development is lower than the effect of material investments. That difference in effect is higher for cognitive skills, given that investments are more productive in cognitive development. on the other hand, effect of reducing conflict is similar to the effect of increasing time spend with parents.

The simulation shows that reductions in parental conflict are positive for cognitive accumulation, specially during early childhood. This finding is consistent with research that found a higher substitution for cognitive accumulation during the first stage and with research that show that cognitive accumulation is sensitive in that stage (e.g. [19]). Therefore, low levels of initial cognitive skills can be compensated by increments in material investments or parental time, or by a reduction in parental conflict. Thus, public policy aimed to alleviate cognitive skill gaps may focus on improving those conditions.

Parental conflict has a higher impact on non-cognitive accumulation. The simulation shows that reductions in conflict have a higher increment on non-cognitive skill accumulation than in cognitive development, and that its impact affects both stages of development, specially the second. This result can be explained given that substitutability is slightly higher during the second stage. Then, public policy and parental decisions have a role not only during early childhood as in the case for the development of cognitive skill. These findings for human capital development are consistent with the literature on the evolution of cognitive and personality traits (eg [13, 61]).

period	Age range	observations
1	< 1	492
2	1 -2	1195
3	3 -4	1376
4	5 -6	1526
5	7 -8	1642
6	9 -10	1636
7	11 -12	1537
8	13 -14	1436

This table describes the sample size available for the estimation in each one of the periods of development. The sample corresponds to first born white children who live in a household where parents are married or cohabitate.

Table 3.1: Sample by period of development

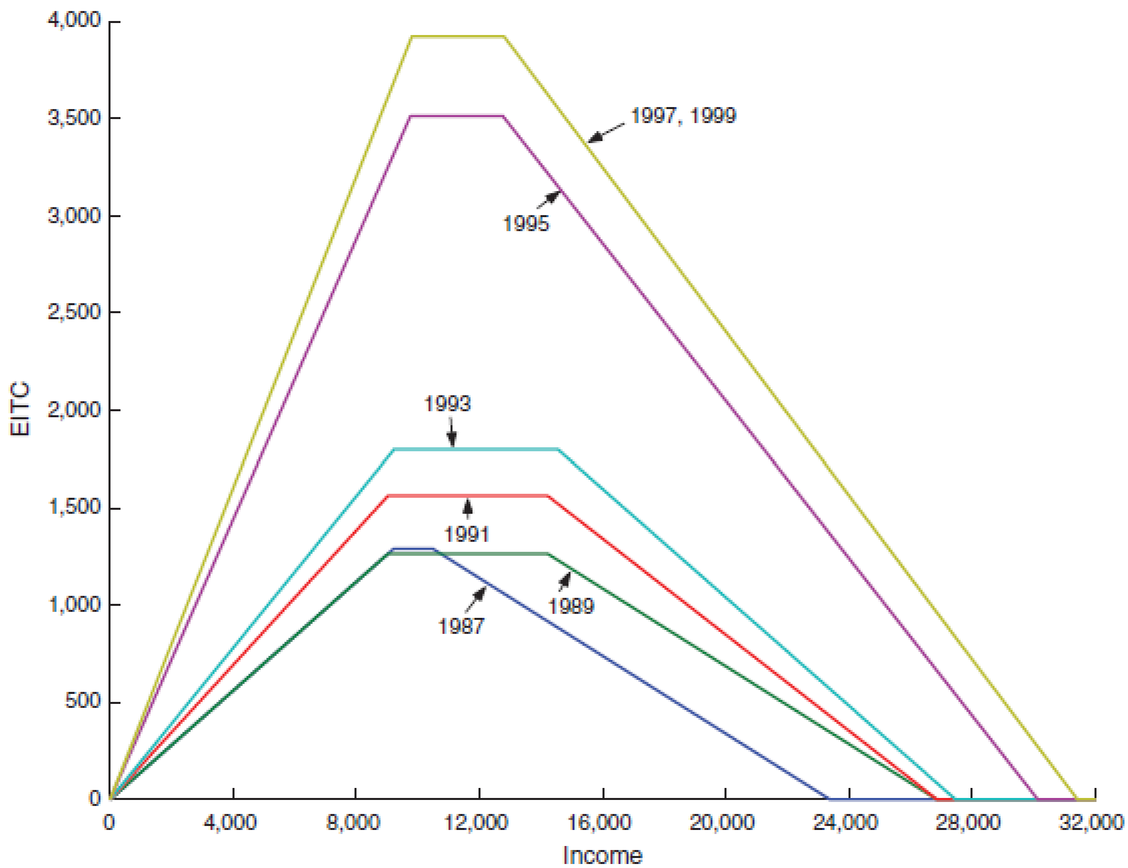

Figure 3.1: Federal EITC schedules For Families with two or more children

Source [22].

	Observations	Mean	Std error
		Cognitive Skills	
Weeks of Gestation	1623	3.882	0.238
Weight at Birth	1654	3.332	0.565
Motor-Social Development Score	2122	0.168	0.933
Body Parts	298	0.327	0.996
Memory for Locations	353	0.194	0.958
PIAT Math	6058	0.36	0.949
PIAT Reading Recognition	6039	0.331	0.965
PIAT Reading Comprehension	5902	0.375	0.97
		Non-cognitive Skills	
Difficulty	207	0.04	1.028
Friendliness	225	0.192	0.933
Compliance	1464	0.165	0.926
Insecure Attachment	1518	0.002	0.86
Sociability	1232	0.201	0.964
Antisocial	6974	0.182	0.88
Anxiety	7089	0.09	0.982
Headstrong	7091	0.118	0.962
Hyperactive	7090	-0.013	0.931
Conflict	7100	-0.007	0.9
		Parental Investments	
Child Has Musical Instrument	5058	0.605	0.479
Child Has Tape Recorder/CD Player	1541	0.855	0.35
Child Is Taken to Musical Performances	5052	2.752	0.964
Child Receives Special Lessons/Activities	5052	0.752	0.427
Family Receives Daily Newspaper	5057	0.572	0.502
How Often Child Eats With Mom/Dad	7723	2.162	0.958
How Often Child Gets Out of House	1894	5.965	1.639
How Often Child Is Taken to Museum	5824	2.348	0.874
How Often Child Sees Family Friends	5037	5.07	1.636
How Often Mom Reads to Child	5067	4.84	1.2
How Often Mom Talks to Child From Work	976	1.544	0.67
Number of Books	7783	3.871	0.468
Number of Magazines	1543	3.404	1.33
Number of Push/Pull Toys	976	0.591	5.518
Number of Soft/Role Play Toys	974	1.683	11.731
Number of Times Praised Child Last Week	3632	3.037	2.248
Number of Times Said Positive Things Last Week	3555	3.784	1.949
		Conflict Variables	
Affection	7202	3.004	0.913
Children	7167	2.63	0.806
Chores	7204	2.446	0.821
Drinking	7194	3.626	0.7
Free time	7200	2.987	0.871
Money	7203	2.607	0.883
Other women	7193	3.864	0.438
Religion	7201	3.646	0.629
Relatives	7198	3.275	0.821

This table presents the descriptive statistics of the variables used as proxies of latent skills, investments and parental conflict. The sample correspond to first born white children who live in a household where parents are married or cohabitate. Test scores are standardized-by-period values of the raw scores provided in the NLSY79.

Table 3.2: Descriptive Statistics for cognitive measurements

		Unobserved heterogeneity		
		None	Permanent	Time Varying
	First Stage			
Cognitive Skills	γ_{sC1}	0.408 (0.043)	0.389 (0.039)	0.423 (0.036)
non-cognitive Skills	γ_{sC2}	0.03 (0.046)	0.041 (0.035)	0.044 (0.125)
Time	γ_{sC3}	0.188 (0.058)	0.168 (0.048)	0.191 (0.061)
Material investments	γ_{sC4}	0.262 (0.063)	0.205 (0.039)	0.234 (0.041)
Parental Cognitive	γ_{sC5}	0.067 (0.029)	0.073 (0.019)	0.047 (0.021)
Parental Non-Cognitive	γ_{sC6}	0.046 (0.017)	0.123 (0.036)	0.061 (0.035)
Complementarity	ϕ_{sC}	0.589 (0.23)	0.412 (0.143)	0.552 (0.273)
Elasticity of substitution		2.433	1.7	2.23
	Second Stage			
Cognitive Skills	γ_{sC1}	0.887 (0.041)	0.809 (0.038)	0.861 (0.037)
non-cognitive Skills	γ_{sC2}	0.01 (0.032)	0.004 (0)	0.03 (0.048)
Time	γ_{sC3}	0.009 (0.002)	0.023 (0.006)	0.024 (0.006)
Material investments	γ_{sC4}	0.034 (0.006)	0.049 (0.007)	0.035 (0.006)
Parental Cognitive	γ_{sC5}	0.043 (0.015)	0.071 (0.027)	0.038 (0.022)
Parental Non-Cognitive	γ_{sC6}	0.017 (0.005)	0.045 (0.014)	0.02 (0.008)
Complementarity	ϕ_{sC}	-0.652 (0.006)	-0.582 (0.006)	-0.501 (0.007)
Elasticity of substitution		0.605	0.632	0.666

This table presents the estimates of the technology for cognitive skills extending [20] by decomposing parental investments between material and time inputs as discussed in section 3.6.1. The first panel refers to the cognitive technology from birth up to 4 years, while the second panel describes the technology for children over 4 years. Each column describes a different assumption over the correlation between unobservables in parental investments and those in cognitive and non-cognitive skills. The first column presents estimates without addressing endogeneity, the second column address for permanent endogeneity and the last column deal with time-varying endogeneity.

Table 3.3: Technology of cognitive skill formation time and investments

Unobserved heterogeneity		None	Permanent	Time Varying
	First Stage			
Cognitive Skills	γ_{sN1}	0 (0.001)	0.004 (0.003)	0 (0.001)
non-cognitive Skills	γ_{sN2}	0.547 (0.19)	0.544 (0.173)	0.521 (0.18)
Time	γ_{sN3}	0.121 (0.049)	0.097 (0.03)	0.137 (0.052)
Material Investments	γ_{sN4}	0.163 (0.057)	0.128 (0.035)	0.168 (0.061)
Parental Cognitive	γ_{sN5}	0.028 (0.013)	0.035 (0.019)	0.029 (0.021)
Parental Non-Cognitive	γ_{sN6}	0.142 (0.052)	0.202 (0.098)	0.125 (0.046)
Complementarity	ϕ_{sN}	-1.422 (0.23)	-1.17 (0.33)	-1.03 (0.273)
Elasticity of substitution		0.412	0.461	0.493
	Second Stage			
Cognitive Skills	γ_{sN1}	0.003 (0.02)	0.001 (0.001)	0.001 (0.002)
non-cognitive Skills	γ_{sN2}	0.827 (0.282)	0.788 (0.268)	0.826 (0.282)
Time	γ_{sN3}	0.03 (0.012)	0.03 (0.011)	0.029 (0.011)
Material Investments	γ_{sN4}	0.089 (0.034)	0.104 (0.039)	0.097 (0.036)
Parental Cognitive	γ_{sN5}	0.01 (0.003)	0.02 (0.014)	0.02 (0.037)
Parental Non-Cognitive	γ_{sN6}	0.031 (0.012)	0.059 (0.022)	0.028 (0.011)
Complementarity	ϕ_{sN}	-1.03 (0.34)	-0.747 (0.31)	-0.645 (0.296)
Elasticity of substitution		0.492	0.572	0.608

This table presents the estimates of the technology for non-cognitive skills extending [20] by decomposing parental investments between material and time inputs as discussed in section 3.6.1. The first panel refers to the non-cognitive technology from birth up to 4 years, while the second panel describes the technology for children over 4 years. Each column describes a different assumption over the correlation between unobservables in parental investments and those in cognitive and non-cognitive skills. The first column presents estimates without addressing endogeneity, the second column address for permanent endogeneity and the last column deal with time-varying endogeneity.

Table 3.4: Technology of non-cognitive skill formation time and investments

	Unobserved heterogeneity	None	Permanent	Time Varying
	First Stage			
Cognitive Skills	γ_{sC1}	0.433 (0.039)	0.374 (0.04)	0.449 (0.068)
Non Cognitive Skills	γ_{sC2}	0.012 (0.061)	0.062 (0.023)	0.035 (0.018)
Time	γ_{sC3}	0.129 (0.045)	0.108 (0.038)	0.099 (0.034)
Material Investments	γ_{sC4}	0.242 (0.056)	0.199 (0.032)	0.164 (0.034)
Parental Cognitive	γ_{sC5}	0.072 (0.028)	0.069 (0.02)	0.083 (0.03)
Parental Non-Cognitive	γ_{sC6}	0.043 (0.015)	0.08 (0.028)	0.056 (0.024)
Parental Conflict	γ_{sC7}	0.07 (0.029)	0.109 (0.033)	0.113 (0.044)
Complementarity	ϕ_{sC}	0.544 (0.188)	0.38 (0.117)	0.47 (0.205)
Elasticity of substitution		2.192	1.612	1.887
	Second Stage			
Cognitive Skills	γ_{sC1}	0.857 (0.063)	0.779 (0.048)	0.817 (0.067)
Non Cognitive Skills	γ_{sC2}	0.004 (0.004)	0.003 (0.001)	0.017 (0.065)
Time	γ_{sC3}	0.009 (0.003)	0.005 (0.001)	0.017 (0.007)
Material Investments	γ_{sC4}	0.035 (0.007)	0.05 (0.007)	0.053 (0.007)
Parental Cognitive	γ_{sC5}	0.037 (0.015)	0.062 (0.026)	0.057 (0.025)
Parental Non-Cognitive	γ_{sC6}	0.018 (0.006)	0.039 (0.013)	0.025 (0.007)
Parental Conflict	γ_{sC7}	0.041 (0.012)	0.061 (0.02)	0.024 (0.006)
Complementarity	ϕ_{sC}	-1.345 (0.558)	-1.041 (0.514)	-1.17 (0.605)
Elasticity of substitution		0.426	0.489	0.461

This table presents the estimates of the technology for cognitive skills including parental conflict as discussed in section 3.6.2. The first panel refers to the cognitive technology from birth up to 4 years, while the second panel describes the technology for children over 4 years. Each column describes a different assumption over the correlation between unobservables in parental investments and those in cognitive and non-cognitive skills. The first column presents estimates without addressing endogeneity, the second column address for permanent endogeneity and the last column deal with time-varying endogeneity.

Table 3.5: Technology of Cognitive skill formation including parental conflict

Unobserved heterogeneity		None	Permanent	Time Varying
	First Stage			
Cognitive Skills	γ_{sC1}	0.003 (0.039)	0.002 (0.04)	0.001 (0.068)
Non Cognitive Skills	γ_{sC2}	0.525 (0.134)	0.482 (0.149)	0.549 (0.296)
Time	γ_{sC3}	0.114 (0.041)	0.096 (0.029)	0.104 (0.036)
Material Investments	γ_{sC4}	0.122 (0.024)	0.099 (0.013)	0.132 (0.027)
Parental Cognitive	γ_{sC5}	0.021 (0.007)	0.048 (0.015)	0.032 (0.01)
Parental Non-Cognitive	γ_{sC6}	0.085 (0.036)	0.163 (0.075)	0.086 (0.04)
Parental Conflict	γ_{sC7}	0.127 (0.05)	0.103 (0.028)	0.097 (0.032)
Complementarity	ϕ_{sC}	-1.53 (0.538)	-1.42 (0.508)	-1.17 (0.519)
Elasticity of substitution		0.395	0.413	0.461
	Second Stage			
Cognitive Skills	γ_{sC1}	0.001 (0.031)	0.002 (0.028)	0.003 (0.021)
Non Cognitive Skills	γ_{sC2}	0.796 (0.068)	0.767 (0.06)	0.819 (0.07)
Time	γ_{sC3}	0.043 (0.015)	0.038 (0.013)	0.034 (0.011)
Material Investments	γ_{sC4}	0.079 (0.015)	0.087 (0.015)	0.068 (0.01)
Parental Cognitive	γ_{sC5}	0.004 (0.002)	0.002 (0.003)	0.002 (0.001)
Parental Non-Cognitive	γ_{sC6}	0.026 (0.008)	0.042 (0.013)	0.029 (0.011)
Parental Conflict	γ_{sC7}	0.05 (0.021)	0.061 (0.018)	0.046 (0.018)
Complementarity	ϕ_{sC}	-1.02 (0.392)	-0.791 (0.33)	-0.831 (0.396)
Elasticity of substitution		0.495	0.558	0.546] [0.3 cm]

This table presents the estimates of the technology for non-cognitive skills including parental conflict. The first panel refers to the non-cognitive technology from birth up to 4 years, while the second panel describes the technology for children over 4 years. Each column describes a different assumption over the correlation between unobservables in parental investments and those in cognitive and non-cognitive skills. The first column presents estimates without addressing endogeneity, the second column address for permanent endogeneity and the last column deal with time-varying endogeneity.

Table 3.6: Technology of Non-cognitive skill formation including parental conflict

	Cognitive		Non-cognitive	
	First Stage	Second Stage	First Stage	Second Stage
No Unobserved heterogeneity				
Cognitive Skills	0.46	0.53	0	0
Non Cognitive Skills	0.03	0.04	0.56	0.56
Time	0.09	0.1	0.1	0.11
Investments	0.18	0.21	0.1	0.1
Parental Cognitive	0.08	0.09	0.03	0.03
Parental Non-Cognitive	0.05	0.06	0.1	0.1
Parental Conflict	0.11	0.13	0.09	0.09
Permanent Unobserved heterogeneity				
	First	Second	First	Second
Cognitive Skills	0.41	0.51	0	0
Non Cognitive Skills	0.01	0.02	0.54	0.53
Time	0.11	0.14	0.11	0.12
Investments	0.31	0.4	0.08	0.08
Parental Cognitive	0.07	0.08	0.02	0.02
Parental Non-Cognitive	0.04	0.05	0.09	0.1
Parental Conflict	0.07	0.09	0.13	0.13
Time Varying Unobserved heterogeneity				
Cognitive Skills	0.39	0.44	0	0
Non Cognitive Skills	0.07	0.08	0.49	0.5
Time	0.1	0.11	0.08	0.08
Investments	0.21	0.24	0.06	0.06
Parental Cognitive	0.05	0.05	0.04	0.04
Parental Non-Cognitive	0.08	0.09	0.22	0.23
Parental Conflict	0.11	0.12	0.1	0.1

This table presents the elasticity of the inputs into cognitive and non-cognitive accumulation. Columns 1 and 2 refer to the elasticity during the first and second stage of cognitive skills, Columns 3 and 4 refer to the elasticity during the first and second stage of non-cognitive skills. The upper panel corresponds to the estimates without correcting for unobserved heterogeneity, while estimates correcting for permanent and time varying unobserved heterogeneity are presented in the middle and lower panels.

Table 3.7: Elasticity of the variables into the Technology of Human Capital

Variable	Coefficient	(Std. Err.)
Cognitive	1.234**	(0.060)
Non-Cognitive	1.654**	(0.057)
Intercept	9.297**	(0.032)
N	1679	
R^2	0.301	
$F_{(2,1676)}$	537.202	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 3.8: Estimation of years of schooling

Period/stage	Cognitive skill	Non- Cognitive Skill	Years of schooling
	Reductions of 10% in parental conflict for one period		
1	0.18%	0.13%	0.02
2	0.37%	0.23%	0.04
3	0.75%	0.42%	0.07
4	0.1%	0.25%	0.02
5	0.12%	0.3%	0.03
6	0.13%	0.36%	0.03
7	0.15%	0.43%	0.04
8	0.17%	0.51%	0.05
	Reductions of 10% in parental conflict for stages		
1	1.29%	0.79%	0.13
2	0.67%	1.87%	0.18
1-2	1.98%	2.68%	0.31

This table presents a simulation of the impact of reductions of 10% in parental conflict on skill accumulation and child achievement. Estimates are based on the model that addresses time-varying heterogeneity and estimates of the child achievement equation. Columns 1 and 2 shows the percentage increase in each skill while column 3 shows the increase in the years of education.

Table 3.9: Impact of reductions of Parental conflict on Skill accumulation and years of schooling

	Increment of 10% in investments			Increment of 10% in time		
Period/stage	Cognitive	Non- Cognitive	Child Achievement	Cognitive	Non- Cognitive	Child Achievement
	Effect of increment for periods					
1	0.26%	0.22%	0.03	0.15%	0.16%	0.02
2	0.53%	0.4%	0.06	0.31%	0.29%	0.04
3	1.08%	0.71%	0.11	0.62%	0.51%	0.07
4	0.33%	0.45%	0.05	0.13%	0.18%	0.02
5	0.38%	0.54%	0.06	0.15%	0.22%	0.02
6	0.45%	0.65%	0.07	0.18%	0.26%	0.03
7	0.52%	0.77%	0.09	0.21%	0.32%	0.04
8	0.61%	0.93%	0.1	0.24%	0.38%	0.04
	Effect of increment for stages					
1	1.86%	1.35%	0.2	1.08%	0.96%	0.13
2	2.34%	3.42%	0.39	0.92%	1.38%	0.15
1-2	4.3%	4.85%	0.59	2.02%	2.37%	0.29

This table presents a simulation of the impact of reductions of 10% in parental conflict on skill accumulation and child achievement. Estimates are based on the model that addresses time-varying heterogeneity and estimates of the child achievement equation. Columns 1 and 2 shows the percentage increase in each skill while column 3 shows the increase in the ears of education.

Table 3.10: Impact of increments of investments and time on skill and years of education

APPENDIX A

ESTIMATES OF THE EFFECT OF THE CPE PROGRAM

$T1 \times \tau_1$	-0.0591**
	(0.0184)
$T1 \times \tau_2$	-0.0212
	(0.0195)
$T2 \times \tau_1$	-0.00416
	(0.0161)
$T2 \times \tau_2$	0.0234
	(0.0179)
τ_1	0.409
	(0.2449)
τ_2	0.722
	(0.4895)
$Antioquia \times trend$	-0.161
	(0.2448)
$Atlantico \times trend$	-0.306
	(0.2463)
$Bogota \times trend$	-0.441
	(0.2449)
$Bolivar \times trend$	-0.513*
	(0.2451)
$Boyaca \times trend$	-0.227
	(0.2453)
$Caldas \times trend$	-0.33
	(0.2455)
$Caqueta \times trend$	-0.453
	(0.2462)
$Cauca \times trend$	-0.500*
	(0.2453)
$Cesar \times trend$	-0.371
	(0.2452)
$Cordoba \times trend$	-0.478
	(0.2449)
$Cundinamarca \times trend$	-0.306
	(0.245)
$Choco \times trend$	-0.744**
	(0.2473)
$Huila \times trend$	-0.352
	(0.2451)
$Laguajira \times trend$	-0.622*
	(0.2474)
$Magdalena \times trend$	-0.614*
	(0.2459)
$Meta \times trend$	-0.411
	(0.2456)
$Nortedesantander \times trend$	-0.28
	(0.2453)
$Sucre \times trend$	-0.496*
	(0.2452)
$Tolima \times trend$	-0.336
	(0.2456)
$Arauca \times trend$	-0.151
	(0.2478)
$Casanare \times trend$	-0.268
	(0.2463)
$Putumayo \times trend$	-0.342
	(0.2466)
$Sanandres \times trend$	-0.134
	(0.2614)
$Amazonas \times trend$	-0.187
	(0.3068)
$Guainia \times trend$	-0.179
	(0.2786)
$Guaviare \times trend$	-0.263
	(0.2569)
$Vaupes \times trend$	-0.0934
	(0.2759)
$Vichada \times trend$	-0.051
	(0.265)
constant	-0.0288***
	(0.0048)
R^2	0.092
N	25281

This table presents the estimated coefficients of equation 1.3 for language at 5^h grade.

Table A.1: Estimates for language at 5^{th} grade

	linear specification	quadratic specification
	$5^{th} grade$	
linear term	-0.00399	-0.126***
	(0.008)	(0.032)
quadratic term		0.0448***
		(0.011)
change in treatment 2 schools	-0.0076	-0.0129
	(0.013)	(0.014)
	9^{th} grade	
linear term	-0.00563	0.0542
	(0.013)	(0.049)
quadratic term		-0.02
		0.0173
change in treatment 2 schools	0.0000384	0.00743
	(0.019)	(0.019)
	11^{th} grade	
linear term	-0.00919	-0.0791**
	(0.007)	(0.030)
quadratic term		0.0248*
		(0.011)
change in treatment 2 schools	-0.0319***	-0.0349***
	(0.009)	(0.009)

This table presents the estimates used in the construction of table 1.7 in the paper. Column 1 correspond to the estimates of the marginal effect of being in the program using a linear specification while estimates in column 2 impose a quadratic functional form to the effect of duration of the program.

Table A.2: Exposure to the program linear and quadratic estimations Language

	linear specification	quadratic specification
	$5^{th} grade$	
linear term	0.0375***	0.0937**
	(0.009)	(0.035)
quadratic term		-0.0187
		(0.012)
change in treatment 2 schools	0.0715***	0.0771***
	(0.015)	(0.015)
	9^{th} grade	
linear term	0.00012	0.0458
	(0.017)	(0.066)
quadratic term		-0.0125
		(0.023)
change in treatment 2 schools	-0.0232	-0.0114
	(0.026)	(0.026)
	11^{th} grade	
linear term	0.0371***	0.140***
	(0.007)	(0.029)
quadratic term		-0.0386***
		(0.011)
change in treatment 2 schools	0.0469***	0.0511***
	(0.009)	(0.009)

This table presents the estimates used in the construction of table 1.8 in the paper. Column 1 correspond to the estimates of the marginal effect of being in the program using a linear specification while estimates in column 2 impose a quadratic functional form to the effect of duration of the program.

Table A.3: Exposure to the program linear and quadratic impact for mathematics

APPENDIX B

ANALYSIS OF THE BIAS AND VARIANCES USING INSTRUMENTAL VARIABLES.

Results in Table 2.3 are as expected in terms of the findings of IV performance. As has been shown in the econometrics literature, standard errors of IV estimates are higher than those from OLS (e.g. [14]). In the framework developed in this simulation, the standard error of the estimates is increasing with the extent of the endogeneity allowed in the child outcome equation. Additionally, the increasing bias can be explained considering the *plim* of the IV estimates. Consider, for instance, the *plim* of the linear impact of income ([68]):

$$plim\ \delta_1^{IV} = \delta_1 + \frac{\sigma_{\Delta u}}{\sigma_{\Delta I}} \frac{cor(\Delta\chi(), \Delta u)}{cor(\Delta\chi(), \Delta I)} \tag{B.1}$$

IV estimates will be inconsistent if the sample correlation between the instrument $\Delta\chi()$ and Δu is nonzero. There are two factors that determine the size of the bias from the estimates. The first factor is the existence of weak instruments, i.e. instruments that explain a small portion of the endogenous variable (e.g. [36, 2, 37, 67, 63]). In the equation above, this factor is captured by the correlation between the instrument and the endogenous variable $cor(\Delta\chi(), \Delta I)$, while in the multiple instruments case this relationship is associated with the partial R^2 between the instruments and the endogenous variable. Small values of this factor may create a bias that can be even greater than the bias of the OLS estimates. In the Monte Carlo framework presented here, the first stage R^2 is about 0.02 for both endogenous variables: income and its square, a value that is similar to the first stage partial R^2 of [22].[53] The correlation between the instruments and the child outcome is below 0.02 for the different extents of endogeneity considered. Those values imply that the quotient $\frac{cor(\Delta\chi(),\Delta u)}{cor(\Delta\chi,\Delta I)}$ ranges

[53]In this exercise, there are no additional covariates in the first stage, so the R^2 and the partial R^2 are the same.

from 0.2 to 0.6.

The second source of bias, which has received less attention in research, is the ratio between the variance of the unobserved component and the endogenous variable $\frac{\sigma_{\Delta u}}{\sigma_{\Delta_I}}$. This term is not observable in practice and in this simulation is held constant. Thus the bias in the estimation is mainly due to the higher extent of endogeneity allowed in the non observed component, due to the increase in the sample correlation between the error term and the instrument. In summary, if the true effect of income is quadratic, a small bias in the estimates of the linear impact of income is generated by omitting the quadratic term in the estimation. Including in the estimation the quadratic term, OLS estimates of the linear and quadratic parameters are biased, and the size of the bias depends on the degree of endogeneity in the child outcome. The IV Φ estimates are much less biased than the OLS estimates for both endogenous variables I, and I^2, and the standard error estimate allows us to reject the linearity hypothesis of the effect of income.

Model	parameter	Without $\theta = 0$	Small $\theta = 0.25$	Medium $\theta = 0.50$	Large $\theta = 0.75$
			Linear specification		
OLS,Φ	δ_1	0	2.5	6.3	8.7
IV,Φ	δ_1	0	0	1.3	1.3
			Quadratic specification		
OLS, Φ	δ_1	0	6.3	12.5	18.8
	δ_2	0.1	-5.6	-11.1	-16.9
IV, Φ	δ_1	1.3	2.5	5	6.3
	δ_2	1.3	-1.5	-4.4	-7.1
			One-knot spline specification		
OLS, Φ	γ_1	-16	-15	-15	-14
OLS, Φ	γ_2	-40	-42.9	-42.9	-45.7
IV, Φ	γ_1	1	-5	-10	-16
IV, Φ	γ_2	0	-11.4	-25.7	-40
			Logarithmic specification		
OLS Φ	ϕ_1	-0.1	2.2	4.5	6.8
IV	ϕ_1	-3.9	-3.9	-3.9	-3.9

This table presents all the bias from the estimates of a Montecarlo experiment using 400 replications

Table B.1: Bias of the estimates from a Montecarlo assuming 400 replications

APPENDIX C

COMPARISON OF THE ESTIMATES INCLUDING DATA UP TO 2000

This appendix compares the estimates using the NLSY79 data between 1988 and 2012 and the sample used by [22]. Their sample focus on the period 1988 to 2000, given that the major expansions in the EITC occurred between 1987 and 1999, as presented in graph 2.2. In that period it is clear that changes in EITC generosity affect income of recipients. However, after 2000 EITC benefits remain almost constant, then it may be the case that changes in income and EITC are not related, reducing the power of the instrument to identify the true relationship.[54]

To check this hypothesis table C.1 presents the estimates of the quadratic specification for the relationship between income and child achievement in math and reading. Column 1 presents the estimates using [22] sample (presented in table 2.8), while column 2 shows the estimates adding the NLSY79 waves from 2002 up to 2012. Adding recent data has two main effects on estimates and their significance. The first effect is a reduction in the estimate of the linear impact of income δ_1 which is at least 1% lower than the estimate using the original sample. The second effect is an increase of the standard error for both parameters. Therefore, the t statistic is lower in the specification with more data, and at the 5% of significance it is not possible to reject the hypothesis that income has no effect on child cognitive achievement. At the 10% of significance only the linear effect of income is significant, providing evidence of a linear relationship between income and math and the combination of math and reading.

[54] As mentioned in the data section an additional reason of [22] to select this period is to focus solely on EITC expansions, rather than mixing up with the effect of tax changes such as Tax Reform act of 1986 the two Bush tax cuts in 2001 and 2003.

Moreover, differences in the estimates may occur if there is no stability of two relationships required for identification. First, between child development shocks and lagged income $E_a[\Delta\epsilon_{yia}|P_{i,a-1}, P_{ia}] = E[\Delta\epsilon_{yia}|P_{i,a-1}, P_{ia}]$ and second in the stationary relationship between current income and the previous period income $g(P_{i,a-1}, P_{ia}) = g(P_{i,a'-1}, P_{ia'})$. In the original sample the time span is 12 years, thus economic conditions and unobservables are expected to be more stable than in a 24 years span.

Coefficient	DL sample	sample 2012
	Math and reading	
δ_1	0.078*	0.065†
	(0.036)	(0.043)
δ_2	-0.001	-0.001
	(0.002)	(0.003)
	Math	
δ_1	0.074†	0.062†
	(0.041)	(0.048)
δ_2	-0.001	-0.000
	(0.002)	(0.004)
	Reading recognition	
δ_1	0.050†	0.039
	(0.030)	(0.037)
δ_2	-0.001	-0.000
	(0.001)	(0.002)
	Reading comprehension	
δ_1	0.072†	0.061
	(0.039)	(0.045)
δ_2	-0.001	-0.001
	(0.002)	(0.003)

Significance levels : † : 10% $*$: 5% $**$: 1%

This table compares the estimates of Equation 2.7 using data up to 2000 and 2012 of a quadratic specification of the relationship of income and child test scores. As instruments are used the expected change in income due to changes in EITC and the squared of the linear prediction of income on that instrument.

Table C.1: Estimates using DL data and data up to 2012 Quadratic specification

APPENDIX D

SENSITIVITY ANALYSIS OF THE KNOT FOR INCOME.

This appendix presents the estimates of the one knot spline relationship between child outcomes and income at considering 4 values for the knot of income ($10000, $12500, $12500, and $15000). Those values were chosen to capture a point in the middle of the distribution of benefitted households to have good sample size above and below the threshold. Columns 1 to 4 present the estimates of an OLS regression that only addressed the permanent endogeneity. For instance for math and reading combined, the effect of increasing annual income by $1000 is small (ranging between 0.3% and 0.4%), for all values of the knot, thus income hardly affect test scores. Also, it is not possible to reject the linearity, that is $\gamma_2 = 0$, although those estimates imply a decreasing effect of income on child scholastic achievement. These conclusions can be extended to other achievement tests, where the linearity assumption can not be rejected and income effect ranges from 0.3% to 0.4% for math, from 0.4% to 0.5% for reading comprehension and is about 0.1% for reading recognition.

Columns 5 to 8 present estimates addressing for transitory endogeneity. Despite some estimates show a nonlinear impact of income, the null hypothesis of linearity can not be rejected due to the high standard error. Therefore, the estimated impact of income is the same for low and moderate income households γ_1 and it is stable independent of the value selected for the knot. Math and reading test increases between 5.6% to 6.8%, math from 5.2% to 6.2%, reading from 5.1% to 5.7% and reading recognition from 4.2% to 4.8%.

In conclusion, estimates under OLS and IV are not sensitive to the value selected as the knot for income. Under OLS estimates indicate an small impact of income, while addressing transitory endogeneity there is evidence that increases in income will increase achievement. However, it is not possible to reject the linearity.

‘

Coefficient	**OLS**				**IV**			
I^*	10	12.5	15	17.5	10	12.5	15	17.5
				Math and reading				
γ_1	0.0042†	0.0039†	0.0031	0.0029	0.0676†	0.0632†	0.0559*	0.0563*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.033)	(0.032)	(0.030)	(0.028)
γ_2	-0.0014	-0.0013	-0.0011	-0.001	-0.012	-0.015	-0.013	-0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.032)	(0.035)	(0.033)	(0.028)
				Math				
γ_1	0.0039†	0.0036†	0.0033	0.003	0.0619†	0.0563†	0.0534†	0.0521†
	(0.002)	(0.002)	(0.002)	(0.002)	(0.036)	(0.034)	(0.034)	(0.033)
γ_2	-0.0020	-0.0019	-0.0018	-0.0019	-0.0136	-0.011	-0.0101	-0.0095
	(0.002)	(0.002)	(0.002)	(0.002)	(0.069)	(0.068)	(0.063)	(0.054)
				Reading recognition				
γ_1	0.0006	0.0005	0.0005	0.0004	0.0483†	0.0451†	0.043	0.0423†
	(0.003)	(0.002)	(0.002)	(0.002)	(0.027)	(0.025)	(0.026)	(0.027)
γ_2	0.0032	0.0035	0.0028	0.0025	0.0010	0.0023	0.0032	0.0036
	(0.008)	(0.007)	(0.009)	(0.006)	(0.021)	(0.024)	(0.024)	(0.019)
				Reading comprehension				
γ_1	0.0049	0.0047	0.004	0.0038	0.0574†	0.0543†	0.0504†	0.0509†
	(0.003)	(0.004)	(0.003)	(0.003)	(0.033)	(0.033)	(0.034)	(0.035)
γ_2	-0.0017	-0.0018	-0.0016	-0.0015	-0.0028	-0.0012	-0.0010	-0.0008
	(0.0016)	(0.0018)	(0.0017)	(0.0018)	(0.004)	(0.004)	(0.003)	(0.004)

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

This table presents estimates of Equation 2.8. For different values of the knot of income (I^* measured in thousands of dollars), while for the instrument the value of the knot is \$1500.

Table D.1: Sensitivity analysis of the knot for income

APPENDIX E

DESCRIPTIVE STATISTICS

	Observations	Mean	Std deviation
		First period	
Weeks of Gestation	1623	3.882	0.238
Weight at Birth	1654	3.332	0.565
Motor-Social Development Score	211	0.15	1.003
		Second period	
Motor-Social Development Score	1014	0.121	0.967
Body Parts	298	0.327	0.996
Memory for Locations	353	0.194	0.958
		Third period	
Motor-Social Development Score	897	0.226	0.879
Peabody Picture Vocabulary Test	685	0.612	0.945
		Fourth period	
Peabody Picture Vocabulary Test	760	0.532	0.893
PIAT Math	1015	0.308	1.048
PIAT Reading Recognition	995	0.289	1.024
PIAT Reading Comprehension	948	0.272	0.969
		Fifth period	
PIAT Math	1359	0.328	0.974
PIAT Reading Recognition	1362	0.276	1.078
PIAT Reading Comprehension	1310	0.299	1.077
		Sixth period	
PIAT Math	1322	0.343	0.909
PIAT Reading Recognition	1326	0.352	0.944
PIAT Reading Comprehension	1308	0.396	0.936
		Seventh period	
PIAT Math	1228	0.386	0.928
PIAT Reading Recognition	1223	0.367	0.914
PIAT Reading Comprehension	1209	0.42	0.936
		Eight period	
PIAT Math	1134	0.437	0.902
PIAT Reading Recognition	1133	0.37	0.857
PIAT Reading Comprehension	1127	0.475	0.925

This table presents the descriptive statistics of the variables used as proxies of cognitive ability in the estimation of the child technology. The sample correspond to first born white children who live in a household where parents are married or cohabitate. Variables correspond to the standardized-by-period values of the raw scores provided in the NLSY79.

Table E.1: Descriptive Statistics for cognitive measurements

	Observations	Mean	Std deviation
		First period	
Difficulty	207	0.04	1.028
Friendliness	225	0.192	0.933
		Second period	
Compliance	265	0.235	0.932
Insecure Attachment	289	-0.021	0.88
Sociability	400	0.316	0.919
		Third period	
Compliance	1199	0.15	0.925
Insecure Attachment	1229	0.007	0.855
Sociability	832	0.145	0.985
Antisocial	321	0.17	0.882
Anxiety	321	0.037	0.99
Headstrong	319	0.144	0.977
Hyperactive	321	0.014	0.927
Conflict	322	-0.098	0.853
		Fourth period	
Antisocial	1348	0.157	0.877
Anxiety	1354	0.01	0.98
Headstrong	1356	0.071	0.978
Hyperactive	1355	-0.028	0.942
Conflict	1358	-0.123	0.838
		Fifth period	
Antisocial	1408	0.139	0.908
Anxiety	1441	0.085	1.037
Headstrong	1437	0.09	0.978
Hyperactive	1439	-0.043	0.955
Conflict	1441	-0.064	0.938
		Sixth period	
Antisocial	1394	0.154	0.886
Anxiety	1408	0.07	1.01
Headstrong	1412	0.105	0.978
Hyperactive	1412	-0.044	0.929
Conflict	1414	-0.063	0.925
		Seventh period	
Antisocial	1298	0.213	0.848
Anxiety	1323	0.02	1.014
Headstrong	1323	0.034	0.983
Hyperactive	1322	-0.092	0.945
Conflict	1321	-0.039	0.966
		Eight period	
Antisocial	1205	0.261	0.877
Anxiety	1242	0.292	0.855
Headstrong	1244	0.3	0.879
Hyperactive	1241	0.153	0.877
Conflict	1244	0.308	0.84

This table presents the descriptive statistics of the variables used as proxies of non-cognitive ability in the estimation of the child technology. The sample correspond to first born white children who live in a household where parents are married or cohabitate. Variables correspond to the standardized-by-period values of the raw scores provided in the NLSY79.

Variables from the temperament scale is used for children up to 4 years (Difficulty, friendliness and sociability)

Variables from the Behavioural Problem Index are used for children 5 years old or older (Antisocial, Anxiety, Headstrong, Hyperactive, Conflict).

Table E.2: Descriptive Statistics for non-cognitive measurements

	Observations	Mean	Std deviation
		First period	
How Often Child Gets Out of House	230	5.24	2.14
Number of Books	231	2.59	1.2
How Often Mom Reads to Child	226	3.03	2.07
Number of Soft/Role Play Toys	231	1.169	8.23
Number of Push/Pull Toys	230	0.15	2.98
How Often Child Eats With Mom/Dad	217	3.29	2.13
How Often Mom Talks to Child From Work	223	1.59	0.77
		Second period	
How Often Child Gets Out of House	754	6.42	1.1
Number of Books	753	3.82	0.5
How Often Mom Reads to Child	747	5.32	1.11
Number of Soft/Role Play Toys	743	1.843	12.82
Number of Push/Pull Toys	746	0.727	6.3
How Often Child Eats With Mom/Dad	748	2.01	0.84
How Often Mom Talks to Child From Work	753	1.53	0.64
		Third period	
How Often Child Gets Out of House	185	6.44	1.05
Number of Books	963	3.99	0.34
How Often Mom Reads to Child	964	5.43	1
How Often Child Eats With Mom/Dad	962	2.04	0.83
Number of Magazines	779	3.35	1.35
Child Has Tape Recorder/CD Player	778	0.84	0.37
		Fourth period	
How Often Child Gets Out of House	725	5.6	2.19
Number of Books	1067	3.99	0.4
How Often Mom Reads to Child	1065	5.21	1
How Often Child Eats With Mom/Dad	1061	2.07	0.9
Number of Magazines	764	3.46	1.31
Child Has Tape Recorder/CD Player	763	0.87	0.33
How Often Child Is Taken to Museum	1059	2.32	0.97
Child Has Musical Instrument	298	0.49	0.5
Family Receives Daily Newspaper	299	0.56	0.5
Child Receives Special Lessons/Activities	297	0.66	0.47
Child Is Taken to Musical Performances	298	2.08	0.95
How Often Child SeesFamily Friends	297	5.421	1.432
Number of Times Praised Child Last Week	208	2.632	2.432
Number of Times Said Positive Things Last Week	171	4.09	2.042

This table presents the descriptive statistics of the variables used as proxies of the inputs in the estimation of the child technology.The sample correspond to first born white children who live in a household where parents are married or cohabitate.

Table E.3: Descriptive Statistics for inputs measurements

	Observations	Mean	Std deviation
		Fifth period	
Number of Books	1183	3.99	0.34
How Often Mom Reads to Child	1184	4.77	1.24
How Often Child Eats With Mom/Dad	1174	2.1	0.9
How Often Child Is Taken to Museum	1181	2.43	0.88
Child Has Musical Instrument	1178	0.48	0.5
Family Receives Daily Newspaper	1178	0.58	0.5
Child Receives Special Lessons/Activities	1178	0.7	0.46
Child Is Taken to Musical Performances	1180	2.045	0.891
How Often Child SeesFamily Friends	1178	5.451	1.423
Number of Times Praised Child Last Week	787	2.84	2.121
Number of Times Said Positive Things Last Week	801	3.751	1.921
		Sixth period	
Number of Books	1229	3.93	0.39
How Often Mom Reads to Child	881	3.9	1.46
How Often Child Eats With Mom/Dad	1223	2.13	0.93
How Often Child Is Taken to Museum	1232	2.43	0.86
Child Has Musical Instrument	1229	0.59	0.49
Family Receives Daily Newspaper	1230	0.58	0.52
Child Receives Special Lessons/Activities	1227	0.76	0.42
Child Is Taken to Musical Performances	1225	2.091	0.93
How Often Child SeesFamily Friends	1224	5.032	1.812
Number of Times Praised Child Last Week	925	3.12	2.42
Number of Times Said Positive Things Last Week	823	3.781	1.94
		Seventh period	
Number of Books	1209	3.86	0.53
How Often Child Eats With Mom/Dad	1197	2.21	0.97
How Often Child Is Taken to Museum	1207	2.33	0.84
Child Has Musical Instrument	1207	0.69	0.46
Family Receives Daily Newspaper	1206	0.57	0.49
Child Receives Special Lessons/Activities	1205	0.8	0.4
Child Is Taken to Musical Performances	1205	2.032	0.934
How Often Child SeesFamily Friends	1194	4.923	1.912
Number of Times Praised Child Last Week	854	3.05	2.231
Number of Times Said Positive Things Last Week	859	4.03	1.942
		Eight period	
Number of Books	1148	3.78	0.62
How Often Child Eats With Mom/Dad	1141	2.28	1.05
How Often Child Is Taken to Museum	1145	2.22	0.83
Child Has Musical Instrument	1146	0.69	0.46
Family Receives Daily Newspaper	1144	0.56	0.5
Child Receives Special Lessons/Activities	1145	0.77	0.42
Child Is Taken to Musical Performances	1144	5.121	1.112
How Often Child SeesFamily Friends	1144	4.781	1.432
Number of Times Praised Child Last Week	858	3.212	2.151
Number of Times Said Positive Things Last Week	901	3.523	1.971

This table presents the descriptive statistics of the variables used as proxies of the inputs in the estimation of the child technology. The sample correspond to first born white children who live in a household where parents are married or cohabitate.

Table E.4: Descriptive Statistics for investment inputs measurements

	affection	children	chores	drinking	free time	money	other women	religion	relatives
First period									
Mean	3.31	3.47	2.66	3.7	3.2	2.85	3.92	3.74	3.37
std	(0.89)	(0.75)	(0.8)	(0.63)	(0.83)	(0.89)	(0.34)	(0.54)	(0.79)
N	239	209	239	239	239	239	238	239	238
Second period									
Mean	3.03	2.9	2.33	3.65	2.94	2.63	3.91	3.66	3.23
std	(0.92)	(0.82)	(0.82)	(0.69)	(0.88)	(0.91)	(0.38)	(0.62)	(0.83)
N	599	596	599	598	599	599	599	599	598
Third period									
Mean	3.01	2.66	2.4	3.61	2.89	2.58	3.89	3.66	3.18
std	(0.9)	(0.78)	(0.79)	(0.72)	(0.89)	(0.86)	(0.38)	(0.6)	(0.86)
N	836	835	836	833	836	836	835	835	836
Fourth period									
Mean	2.97	2.59	2.38	3.63	2.88	2.59	3.88	3.64	3.24
std	(0.9)	(0.82)	(0.82)	(0.7)	(0.89)	(0.89)	(0.39)	(0.62)	(0.85)
N	914	915	915	914	914	914	914	914	914
Fifth period									
Mean	3	2.62	2.45	3.61	2.98	2.61	3.87	3.63	3.23
std	(0.9)	(0.78)	(0.8)	(0.72)	(0.87)	(0.88)	(0.42)	(0.66)	(0.84)
N	1081	1080	1081	1080	1081	1081	1079	1080	1080
Sixth period									
Mean	2.97	2.53	2.42	3.61	2.98	2.54	3.83	3.62	3.27
std	(0.93)	(0.81)	(0.82)	(0.71)	(0.87)	(0.88)	(0.52)	(0.66)	(0.84)
N	1148	1148	1149	1148	1149	1148	1147	1149	1149
Seven period									
Mean	3.01	2.57	2.5	3.65	3.06	2.62	3.84	3.66	3.33
std	(0.92)	(0.82)	(0.83)	(0.65)	(0.85)	(0.89)	(0.5)	(0.61)	(0.79)
N	1200	1199	1200	1198	1198	1200	1197	1200	1197
Eight period									
Mean	2.98	2.52	2.51	3.61	3.06	2.63	3.85	3.64	3.36
std	(0.92)	(0.82)	(0.86)	(0.73)	(0.87)	(0.88)	(0.44)	(0.64)	(0.77)
N	1185	1185	1185	1184	1184	1186	1184	1185	1186

This table presents the descriptive statistics of the variables used to proxy parental conflict in the estimation of the child technology. The sample correspond to first born white children who live in a household where parents are married or cohabitate.

Table E.5: Descriptive Statistics for parental conflict measurements

APPENDIX F

KALMAN FILTER AND STATE SPACE REPRESENTATION

This section describes the state space representation of the estimation problem. This is a widely used representation in economics and factor analysis. The first subsection describes a Gaussian linear model of the technology of skill formation used in the seminal paper by Cunha and Heckman (2008). The second subsection extends the analysis to allow for nonlinearities in the transition equation used in Cunha et al (2010).

F.1 Gaussian linear model

In this representation the state variables $\theta = \{\theta_t^C, \theta_t^N, \theta_t^{PC}, \theta_t^{\tau}\}$ that are not directly observed can be reconstructed considering their relationship with the measured data Z_t.

$$Z_t = X\beta_t + \alpha_t\theta_t + \epsilon_t \tag{F.1}$$

Equation F.1 is the measurement equation and relates the observed variables to the unobserved skills and factors. where $Z_{t(p_t,1)}$ is the vector of $p_t masure$ observed measurements, $\theta_{t(5,1)}$ is the vector of unobserved skills and inputs, and α_t is the matrix of factor loadings. $\epsilon_{t(p_t,1)}$ denotes the measurement disturbances, $X_{t(p_t,m)}$ is a vector of m exogenous variables, $\beta_{t(m,1)}$ is the vector of associated coefficients, and $\epsilon \sim N(0, H_t)$. The dynamic of the skills and investments in [19] is described by:

$$\theta_{t+1} = G_t\theta_t + \eta_t, \tag{F.2}$$

where $\eta_{t(5,1)}$ denotes the transition disturbances, G_t is and $\eta_t \sim N(0, Q_t)$. Equation F.2 is called the transition equation and describes how current skills and parental investments affect tomorrow's child skills.

The state space representation is defined by equations F.1, F.2 and the initial condition of the system, which is assumed to be drawn from a joint normal distribution.

$$\theta_1 \sim N(a_1, P_1) \tag{F.3}$$

The matrices α_t, H_t, G_t, Q_t are called the system matrices. The system is estimated using the Kalman filter, a computational algorithm can solve state space models using the conditional likelihood of the measurements.

$$p(z) = p(z_1) \prod_{t=2}^{T} p(z_t | z_{t-1,\ldots,z_1})$$

Because of the linearity and normality of the model, the likelihood of $p(z)$ is normal, each $p(z_t|z_(t-1),, z_1)$ also has the likelihood of a normal variable. In order to characterize this function, the mean and variance of each $z_{t+1}|z_t,, z_1$ can be obtained recursively using the Kalman Filter. Then from equation F.1.

$$E[Z_{t+1}|X, z_t] = X\beta + \alpha_t E[\theta_t|z_t]$$

$$P_{t+1} = Var[Z_{t+1}X, Z_t] = \alpha_t Var[\theta_{t+1}|Z_t]\alpha_t' + H_t$$

[39] summarizes the Kalman filter for equations F.1 - F.3 as:

$$\nu_t = z_t - \alpha_t \theta_t$$

$$F_t = \alpha_t P_t \alpha_t' + H_t$$

$$K_t = P_t \alpha_t'$$

$$E[\theta_{t=1}|Y_t] = G_t E[\theta_t Y_{t-1}] + K_t F_t^{-1} \nu_t$$

$$P_{t+1} = G_t(P_t - K_t F_t^{-1} K_t') G_t' + Q_t$$

The solution of the filter can be summarized as follows:

1. The initial conditions $E[\theta_1], Var[\theta_1]$ for the state vector are defined.

2. The state vector for period 2 is predicted $E[\theta_2|\theta_1]$ using the transition equation.

3. The state vector is updated with the information up to period 2 $E[\theta_2|z^2]$ using the measurement equation.

Steps 2 and 3 are repeated recursively for time periods $t = 3, , T$.

F.2 Nonlinearities in the transition equation

The assumption of a linear transition equation can be relaxed to consider more general forms of the transition equation.

$$\theta_{t+1} = f(\theta_t) + \eta_t \tag{F.4}$$

If f is nonlinear the Kalman Filter of the state space model of equations F.1,F.4 and F.3 is unsuitable. Cunha et al (2010) proposed to use the Unscented Kalman filter to solve this model.[55] The main assumption is that both $p(\theta_t|Z^t)$ and $p(\theta_{t+1}|Z^t)$ are

[55] Another methodology, the Extended Kalman Filter uses the first-order Taylor series approximation of the function f. However, the results are only accurate results until the first order while the Unscented Kalman filter results in approximations that are accurate to the third order for Gaussian inputs for all nonlinearities

accurately approximated by a normal random variable with mean $a_{t+k,t} = E[\theta_{t+k}|Z^t]$ and variance $P_{t+k,t} = Var[\theta_{t+k}|Z^t]$ for $k \in 0, 1$.

An additional concern is given by the fact that the state vector could have a non-symmetric and/or multimodal distribution. As a solution [20] consider a more flexible approximation that uses a mixture of normal. Denoting the probability density of the normal variable l as $\phi(\theta_t; a_{l,t+k,t}, P_{l,t+k,t})$, we have:

$$p(\theta_{t+k}Z^t) \sum_{l=1} \tau_{l,t}\phi(\theta_t; a_{l,t+k,t}, P_{l,t+k,t}), \tag{F.5}$$

with $\tau_{l,t}$ as the weights, such that $\tau_{l,t} \in [0, 1]$ and $\sum_{l=1} \tau_{l,t} = 1$.

The update step of the filter is just like the Kalman Filter. First, it is necessary to compute the updated density for each element of the mixture.

$$Z_{l,t} = E_l[z_t X, Z^t] = X\beta_t + E_l[\alpha_t\theta_t]$$

Then the updating equations for the mean and the variance are:

$$a_{l,t,t} = a_{l,t,t-1} + K_{l,t}(z_t - \hat{z}_{l,t})$$

$$P_{l,t,t} = P_{l,t,t-1} + K_{l,t}F_{l,t}K'_{l,t}$$

With

$$K_{l,t} = Cov(\theta_t, z_t|X, z^{t-1})F^{-1}_{l,t}$$

$$F_{l,t} = Var(x_t\beta + \alpha_t\theta_t) + H_t$$

Finally the weights of each density are given by:

$$\tau_{t,r} = \frac{\tau_{r,t-1}\phi(z_t; \hat{z}_{r,t}, F_{r,t})}{\sum l = 1^L[\tau_{l,t-1}\phi(z_t; \hat{z}_{l,t}, F_{l,t}]} \qquad r \in \{1, ., L]$$

Using the mixture of normal as an approximation of the density $p(\theta_t|Z^t)$ and the transition equation F.4 it is possible to compute the one-step prediction density $p(\theta_{t+1}|Z^t)$.

$$a_{l,t+1,t} = E_l[\theta_{t+1}|y^t] = E_l[f(\theta_t) + \eta_t Z^t] = E_l[f(\theta_t)Z^t]$$

$$P_{l,t+1,t} = Var_l[f(\theta_{t+1})|y^t] = Var_l[f(\theta_t) + \eta_t Z^t] = Var_l[f(\theta_t)|Z^t] + Q_{t+1}$$

Thus

$$p(\theta_{t+1}|z^t) \sum_{l=1} [\tau_{l,t}\phi(z_t; a_{l,t,t}, P_{l,t,t})]$$

Using the formulas for predicting and updating, it is possible to compute the Unscented Kalman Filter for a nonlinear transition equation, repeating the algorithm described for the linear gaussian model.

APPENDIX G

COMPARISON WITH [20]

G.1 Descriptive statistics

This subsection presents the comparison between the data provided by [20] in their online appendix and the sample of first born white children from the NLSY79. As was stated in the data section there are two factors that explain differences in the descriptive statistics between the first born white children of the CNLSY and the sample used in this paper. First, the [20] sample consists of 2208 first born white children. However, using this criteria, I find 2810 children. It is not possible to establish in their document or appendix additional restriction imposed to match the data used in this document and their sample. After considerable exploration, it was not possible to attribute the difference in sample size to differences in the year of birth or any other observable characteristic. This difference is present in all the measures for skill, inputs and parental time.

The second factor that may create differences in the estimates is the standardization procedure for cognitive and non-cognitive measurements. From the descriptive statistics in [20] it is reasonable to assume that achievement test scores are standardized, given that their mean is close to zero and the standard deviation is close to 1. However, there is no documentation in their paper on which procedure was used to standardized these variables or which variable of the CNLSY was used to measure cognitive and non-cognitive achievement. Standardization in this paper was made separately for each period of childhood using all the respondents of the CNLSY, this procedure provides the closest values to the ones provided in [20] appendix.

Table G.1 presents a summary of the NLSY79 cognitive measurements considered. Columns 1-3 refers to the statistics of the sample used by [20]. In columns 4-6 the statistics for my sample are given. There are more observations in column 4 than in column 1, especially for children over 6 years old (periods 5-8 of childhood). The mean and standard deviation of all cognitive measures are similar in both samples, so it seems that both samples are similar in observable characteristics. Thus the difference in the sample and the standardization seem to have no impact on the variables that measure cognitive skills.

Table G.2 presents the comparison of the descriptive statistics for non-cognitive measurements. The table is organized in a similar way to table G.1 and the standardization of columns 4-6 follows the same procedure. The number of observations also increase in this case, especially for children over 4 years (periods 4-8 of childhood). In this case there are some perceptible differences between the variables in the two samples. Statistics for children up to 2 years old are similar. The standardized scores for the conflict show differences for children between 3 and 10 years old (periods 3 - 6). Additionally, there are some differences in the standardized hyperactive score for children 9 years or older (periods 6 - 8). All other descriptive statistics are similar. Then the small differences in this table are driven by the change in the sample size given the similarity of the statistics in the previous table, that differences are originated by the standardization procedure is unlikely.

Tables G.3 and G.4 present the comparison of the inputs and parental time variables used by [20] and the sample used in this paper. Descriptive statistics for variables used as input measurements are equal in both samples, despite the change in sample size. Then the two samples are similar with respect to the variables used as inputs. On the table, variables that represent frequencies over a year are converted because that is the way they are used in the empirical analysis, this is the reason that there are differences on the table.

In conclusion, there are no tangible differences in statistics for cognitive and input measurements indicating that both sample share observable characteristics and that the standardization procedure seems to work. Differences in parental time measures are attributable to the conversion from categories to frequencies over year. There are differences in some non-cognitive measures that may be attributed to the change in the sample size. Then it is expected to have some differences in the estimates of the technology of skill accumulation with respect to [20], but those differences are not expected to be huge.

G.2 estimates of the technology

This sub-appendix test for changes in the estimates due to changes in the sample size and the standardization procedure with respect to the original sample presented in [20]. This is done analyzing the estimates of the technology of skill production under three different assumptions about the relationship between unobservables of the investment equations and the unobservable in the technology equations. Table G.5 presents the estimates assuming that there is no correlation between the unobservable components of investment equations and those in cognitive and non-cognitive accumulation. The first panel correspond to the estimates from cognitive skills, columns 1 and 2 presents the estimates from table 2 of [20], while columns 3 and 4 presents the estimates using the sample defined of white first born children defined in the previous section. Their findings suggest that for children up to 4 years cognitive skill accumulation mainly depend on the previous level of cognitive skill, investments and parental non-cognitive skills. While in the second stage, cognitive skills in the previous period determine about 90% of the cognitive skill accumulation. Moreover, that there is an effect of non-cognitive skills during this first stage, but they do not affect skill accumulation for children over 5 years old.

The second panel of the table presents the estimates of the technology of non-cognitive skills. During the firs period of childhood previous level of non-cognitive skills, parental non-cognitive skills and parental investment are the key determinants of skill formation. During the second period of childhood, non-cognitive accumulation depends primarily on the laged value of non-cognitive skills. Their evidence suggest that cognitive skills do not affect in any of the two stages. The parameters estimated using both samples are similar therefore the conclusions described hold under the sample used in this paper, and the standardization procedure used does not affect the main results.

Tables G.6 and G.7 present estimates of the technology of skill formation allowing for permanent and transitory endogeneity and these estimates are comparable to those described in subsection 3.4.2. The tables are organized in a similar way to the previous one. In both scenarios, under a permanent heterogeneity (table G.6) and with time varying heterogeneity (table G.7) the estimates of the parameters using the sample in this paper are close to those presented by [20]. Therefore we can conclude that the changes in the sample size and the change in the standardization do not impose change in the descriptive statistics nor in the estimates, then any extension using the sample in this paper is comparable to [20] results.

	CH 2010			First Born - White		
	Observations	Mean	Std error	Observations	Mean	Std error
			First period			
Weeks of Gestation	2118	3.878	0.234	2585	3.881	0.234
Weight at Birth	2159	3.345	0.561	2697	3.321	0.561
Motor-Social Development Score	209	0.123	0.998	222	0.161	0.997
			Second period			
Motor-Social Development Score	1043	0.094	0.968	1110	0.112	0.963
Body Parts	317	0.267	1.002	338	0.298	1.001
Memory for Locations	373	0.221	0.939	402	0.173	0.965
			Third period			
Motor-Social Development Score	915	0.185	0.923	1011	0.21	0.902
Peabody Picture Vocabulary Test	738	0.543	0.954	792	0.578	0.946
			Fourth period			
Peabody Picture Vocabulary Test	809	0.475	0.907	911	0.502	0.9
PIAT Math	1101	0.271	1.04	1217	0.278	1.029
PIAT Reading Recognition	1074	0.246	1.016	1190	0.259	0.99
PIAT Reading Comprehension	1025	0.241	0.98	1132	0.251	0.956
			Fifth period			
PIAT Math	1433	0.285	0.976	1619	0.305	0.966
PIAT Reading Recognition	1433	0.222	1.054	1621	0.254	1.064
PIAT Reading Comprehension	1383	0.246	1.058	1556	0.272	1.065
			Sixth period			
PIAT Math	1379	0.321	0.911	1600	0.32	0.896
PIAT Reading Recognition	1380	0.299	0.945	1602	0.316	0.935
PIAT Reading Comprehension	1361	0.337	0.936	1577	0.368	0.929
			Seventh period			
PIAT Math	1238	0.372	0.92	1514	0.354	0.913
PIAT Reading Recognition	1236	0.342	0.915	1510	0.346	0.912
PIAT Reading Comprehension	1221	0.392	0.932	1494	0.397	0.935
			Eight period			
PIAT Math	1063	0.425	0.922	1385	0.407	0.91
PIAT Reading Recognition	1064	0.336	0.876	1385	0.349	0.859
PIAT Reading Comprehension	1056	0.427	0.937	1377	0.449	0.932

This table presents the comparison of the descriptive statistics for measurements of cognitive skills between the sample used in [20] and first born white children from the CNLS.
Columns 1-3 are taken from the online appendix of their document while columns 4-6 correspond to the standardized-by-period values of the raw scores provided in the NLSY79.

Table G.1: Comparison with sample in [20]: Cognitive Skills

	CH 2010			First Born - White		
	Observations	Mean	Std error	Observations	Mean	Std error
			First period			
Difficulty	207	0.046	1.035	219	0.029	1.025
Friendliness	224	0.183	0.92	237	0.205	0.926
			Second period			
Compliance	274	0.213	0.926	291	0.229	0.938
Insecure Attachment	299	0.033	0.888	316	-0.014	0.9
Sociability	422	0.281	0.911	454	0.297	0.917
			Third period			
Compliance	1253	0.119	0.941	1368	0.127	0.939
Insecure Attachment	1282	0.015	0.869	1402	0.021	0.857
Sociability	893	0.1	1.002	964	0.117	0.988
Antisocial	353	0.073	0.983	377	0.088	0.96
Anxiety	353	0.124	1.092	377	0.1	1.055
Headstrong	351	0.161	0.99	374	0.186	0.993
Hyperactive	352	0.084	0.991	376	0.076	0.976
Conflict	354	0.004	0.975	378	-0.028	0.934
			Fourth period			
Antisocial	1453	0.093	0.937	1611	0.104	0.92
Anxiety	1461	-0.066	1.033	1619	0.063	1.014
Headstrong	1462	0.099	0.997	1620	0.11	0.987
Hyperactive	1461	0.01	0.973	1619	0.004	0.959
Conflict	1463	0.064	0.906	1622	-0.091	0.872
			Fifth period			
Antisocial	1489	0.083	0.951	1684	0.099	0.938
Anxiety	1517	0.135	1.063	1721	0.132	1.057
Headstrong	1512	0.124	0.995	1716	0.128	0.987
Hyperactive	1513	0.011	0.975	1717	-0.001	0.961
Conflict	1517	0.011	0.988	1721	-0.025	0.967
			Sixth period			
Antisocial	1422	0.112	0.929	1677	0.105	0.927
Anxiety	1438	0.098	1.032	1696	0.119	1.03
Headstrong	1444	0.110	0.995	1703	0.136	0.982
Hyperactive	1443	0.042	0.941	1703	-0.013	0.94
Conflict	1446	0.035	0.962	1705	-0.028	0.958
			Seventh period			
Antisocial	1293	0.137	0.932	1596	0.131	0.921
Anxiety	1321	0.076	1.045	1627	0.086	1.034
Headstrong	1319	0.067	1.009	1626	0.091	0.999
Hyperactive	1321	0.069	0.96	1627	-0.042	0.958
Conflict	1319	0.016	1.028	1626	0.008	1.011
			Eight period			
Antisocial	1125	0.117	0.971	1484	0.122	0.946
Anxiety	1138	0.088	1.053	1515	0.093	1.046
Headstrong	1143	0.070	0.998	1518	0.081	0.995
Hyperactive	1138	0.044	0.974	1514	-0.044	0.965
Conflict	1142	0.024	1.033	1519	0.025	1.026

This table presents the comparison of the descriptive statistics for measurements of non-cognitive skills between the sample used in [20] and first born white children from the CNLS. Columns 1-3 are taken from the online appendix of their document while columns 4-6 correspond to the standardized-by-period values of the raw scores provided in the NLSY79.

Variables from the temperament scale is used for children up to 4 years (Difficulty, friendliness and sociability) Variables from the Behavioural Problem Index are used for children 5 years old or older (Antisocial, Anxiety, Headstrong, Hyperactive, Conflict).

Table G.2: Comparison with sample in [20]: Non-cognitive Skills

	CH 2010			First Born - White		
	Observations	Mean	Std error	Observations	Mean	Std error
First period						
Number of Books	229	2.59	1.198	243	2.58	1.2
Number of Soft/Role Play Toys	229	1.17	0.83	243	1.16	8.12
Number of Push/Pull Toys	228	0.15	0.29	24	0.15	2.93
How Often Child Gets Out of House	228	3.6	1.55	242	5.25	2.14
How Often Mom Reads to Child	223	3.09	2.09	237	3.05	2.09
How Often Child Eats With Mom/Dad	212	3.62	2.12	228	3.36	2.14
How Often Mom Talks to Child From Work	221	4.43	0.73	235	1.58	0.75
Second period						
Number of Books	1125	3.6	0.787	1214	3.59	0.8
Number of Soft/Role Play Toys	1114	1.84	1.30	1199	1.83	12.82
Number of Push/Pull Toys	1115	0.67	0.54	1203	0.68	5.95
How Often Child Gets Out of House	1125	4.42	1	1214	6.28	1.26
How Often Mom Reads to Child	1120	4.99	1.41	1208	4.98	1.44
How Often Child Eats With Mom/Dad	1086	4.89	1.12	1174	2.12	1.15
How Often Mom Talks to Child From Work	1123	4.48	0.63	1212	1.52	0.65
Third period						
Number of Books	1027	3.93	0.325	1438	3.94	0.42
Number of Magazines	1023	3.25	1.38	1116	3.22	1.39
Child Has Tape Recorder/CD Player	1022	0.77	0.42	1115	0.77	0.42
How Often Child Gets Out of House	1023	3.72	1.00	322	6.26	1.24
How Often Mom Reads to Child	1026	5.20	1.04	1439	5.27	1.1
How Often Child Eats With Mom/Dad	986	4.80	1.18	1383	2.19	1.2
Fourth period						
Number of Books	1117	3.944	0.301	1636	3.95	0.42
Number of Magazines	718	3.164	1.42	1207	3.15	1.42
Child Has Tape Recorder/CD Player	716	0.81	0.39	1203	0.81	0.39
Child Has Musical Instrument	392	0.43	0.50	421	0.44	0.5
Family Receives Daily Newspaper	393	0.51	0.50	422	0.51	0.51
Child Receives Special Lessons/Activities	392	0.58	0.49	420	0.58	0.49
Times Praised Child Last Week	273	2.52	2.35	285	2.74	2.42
Times Said Positive Things Last Week	233	3.93	1.93	192	4.05	2.03
How Often Child Gets Out of House	717	3.62	1.00	736	5.83	2.04
How Often Mom Reads to Child	1116	5.04	1.03	1635	5.06	1.05
How Often Child Eats With Mom/Dad	1054	4.68	1.33	1544	2.38	1.41
How Often Child Is Taken to Museum	1110	2.25	0.98	1623	2.24	0.98
Child Is Taken to Musical Performances	393	1.94	0.84	421	2.12	0.95
How Often Child SeesFamily Friends	395	3.90	1.18	421	5.36	1.39

This table presents the comparison of the descriptive statistics for measurements of inputs between the sample used in [20] and first born white children from the CNLS.

Table G.3: Comparison with sample in [20]: Inputs

	CH 2010			First Born - White		
	Observations	Mean	Std error	Observations	Mean	Std error
			Fifth period			
Number of Books	1525	3.95	0.28	1736	3.96	0.41
How Often Mom Reads to Child	1525	4.59	1.26	1736	4.61	1.3
How Often Child Eats With Mom/Dad	1476	4.55	1.41	1692	2.5	1.49
How Often Child Is Taken to Museum	1521	2.37	0.92	1732	2.37	0.93
Child Has Musical Instrument	1522	0.44	0.50	1730	0.45	0.5
Family Receives Daily Newspaper	1522	0.53	0.50	1730	0.53	0.51
Child Receives Special Lessons/Activities	1519	0.63	0.48	1727	0.63	0.48
Child Is Taken to Musical Performances	1516	1.92	0.83	1728	1.95	0.84
How Often Child Sees Family Friends	1517	3.79	1.19	1730	5.34	1.35
Times Praised Child Last Week	955	2.93	2.25	1113	2.86	2.26
Times Said Positive Things Last Week	910	3.85	1.89	1023	3.79	1.89
			Sixth period			
Number of Books	1176	3.89	0.41	1229	3.93	0.39
Child Has Musical Instrument	1174	0.52	0.50	1229	0.59	0.49
Family Receives Daily Newspaper	1176	0.51	0.50	1230	0.58	0.52
Child Receives Special Lessons/Activities	1172	0.71	0.46	1227	0.76	0.42
Times Praised Child Last Week	809	2.91	2.27	925	3.12	2.42
Times Said Positive Things Last Week	779	3.71	1.89	823	3.78	1.94
How Often Mom Reads to Child	725	3.92	1.41	881	3.9	1.46
How Often Child Eats With Mom/Dad	1143	4.49	1.49	1223	2.13	0.93
How Often Child Is Taken to Museum	1174	2.35	0.87	1232	2.43	0.86
How Often Child SeesFamily Friends	1176	3.73	1.23	1224	5.03	1.81
Child Is Taken to Musical Performances	1175	1.93	0.85	1225	2.09	0.93
			Seventh period			
Number of Books	1322	3.82	0.49	1635	3.83	0.57
Child Has Musical Instrument	1323	0.62	0.49	1632	0.63	0.48
Family Receives Daily Newspaper	1320	0.52	0.50	1629	0.52	0.50
Child Receives Special Lessons/Activities	1321	0.75	0.43	1630	0.75	0.43
Times Praised Child Last Week	967	3.13	2.15	1342	3.15	2.16
Times Said Positive Things Last Week	964	3.57	1.91	1341	3.46	2.05
How Often Child Eats With Mom/Dad	1268	4.35	1.51	1594	2.72	1.60
How Often Child Is Taken to Museum	1322	2.29	0.86	1632	2.29	0.86
Child Is Taken to Musical Performances	1323	1.93	0.80	1632	1.99	0.82
How Often Child SeesFamily Friends	1321	3.66	1.21	1629	3.74	1.11
			Eight period			
Number of Books	1142	3.70	0.62	1525	3.73	0.65
Child Has Musical Instrument	1140	0.64	0.48	1523	0.65	0.48
Family Receives Daily Newspaper	1139	0.51	0.50	1521	0.51	0.50
Child Receives Special Lessons/Activities	1142	0.74	0.44	1524	0.74	0.44
Times Praised Child Last Week	856	3.20	2.15	1195	3.204	2.29
Times Said Positive Things Last Week	897	3.48	1.95	1286	3.423	1.98
How Often Child Eats With Mom/Dad	1086	4.23	1.58	1493	2.87	1.68
How Often Child Is Taken to Museum	1137	2.18	0.84	1520	2.19	0.84
Child Is Taken to Musical Performances	1141	1.92	0.86	1523	2.07	0.91
How Often Child SeesFamily Friends	1142	3.51	1.23	1520	4.32	1.42

This table presents the comparison of the descriptive statistics for measurements of inputs between the sample used in [20] and first born white children from the CNLS.

Table G.4: Comparison with sample in [20]: inputs

		CH 2010		This paper	
	Parameter	first stage	second Stage	first stage	second Stage
		Cognitive Skill Accumulation			
Cognitive Skills	γ_{sC1}	0.487 (0.030)	0.902 (0.014)	0.434 (0.041)	0.879 (0.018)
non-cognitive Skills	γ_{sC2}	0.083 (0.026)	0.011 (0.005)	0.099 (0.028)	0.014 (0.009)
Investments	γ_{sC3}	0.231 (0.024)	0.020 (0.006)	0.242 (0.025)	0.011 (0.015)
Parental Cognitive skills	γ_{sC4}	0.050 (0.013)	0.047 (0.008)	0.067 (0.018)	0.056 (0.010)
Parental Non-Cognitive skills	γ_{sC5}	0.148 (0.030)	0.020 (0.010)	0.158 (0.046)	0.04 (0.014)
Complementarity Parameter	ϕ_{sC}	0.611 (0.240)	-1.373 (0.168)	0.572 (0.27)	-1.421 (0.18)
Elasticity of substitution		2.569	0.421	2.336	0.413
variance of shocks	δ^2_{sC}	0.165 (0.007)	0.097 (0.003)	0.171 (0.009)	0.101 (0.005)
		Non-Cognitive Skill Accumulation			
Cognitive Skills	γ_{sN1}	0.000 (0.025)	0.008 (0.010)	0.001 (0.029)	0.003 (0.013)
non-cognitive Skills	γ_{sN2}	0.649 (0.034)	0.868 (0.011)	0.671 (0.038)	0.901 (0.013)
Investments	γ_{sN3}	0.146 (0.027)	0.055 (0.013)	0.141 (0.029)	0.051 (0.016)
Parental Cognitive skills	γ_{sN4}	0.022 (0.011)	0.000 (0.007)	0.019 ()	0.001 ()
Parental Non-Cognitive skills	γ_{sN5}	0.183 (0.031)	0.069 (0.017)	0.167 (0.035)	0.044 (0.018)
Complementarity Parameter	ϕ_{sN}	-0.674 (0.324)	-0.695 (0.274)	-0.691 (0.334)	-0.718 (0.291)
Elasticity of substitution		0.597	0.590	0.591	0.582
variance of shocks	δ^2_{sN}	0.189 (0.012)	0.103 (0.004)	0.197 (0.014)	0.112 (0.006)

This table presents the estimates of the technology of skill formation assuming that there is no permanent nor transitory components that affects both skill formation and investment. Columns 1 and 2 corresponds to estimates from table 2 in [20] and columns 3 and 4 to the obtained using the sample defined in this paper.

Table G.5: Technology of skill formation assuming no endogeneity

	Parameter	CH 2010 first stage	CH 2010 second Stage	This paper first stage	This paper second Stage
		Cognitive Skill Accumulation			
Cognitive Skills	γ_{sC1}	0.479 (0.026)	0.831 (0.011)	0.445 (0.028)	0.803 (0.015)
non-cognitive Skills	γ_{sC2}	0.070 (0.024)	0.001 (0.005)	0.087 (0.029)	0.003 (0.006)
Investments	γ_{sC3}	0.161 (0.015)	0.044 (0.006)	0.173 (0.019)	0.0521 (0.008)
Parental Cognitive skills	γ_{sC4}	0.031 (0.013)	0.073 (0.008)	0.041 (0.018)	0.085 (0.010)
Parental Non-Cognitive skills	γ_{sC5}	0.258 (0.029)	0.051 (0.014)	0.254 (0.033)	0.0568 (0.017)
Complementarity Parameter	ϕ_{sC}	0.313 (0.134)	-1.243 (0.125)	0.381 (0.149)	-1.349 (0.158)
Elasticity of substitution		1.457	0.446	1.613	0.426
variance of shocks	δ^2_{sC}	0.176 (0.007)	0.087 (0.003)	0.181 (0.009)	0.091 (0.006)
		Non-Cognitive Skill Accumulation			
Cognitive Skills	γ_{sN1}	0.000 (0.026)	0.000 (0.010)	0.001 (0.031)	0.001 (0.012)
non-cognitive Skills	γ_{sN2}	0.585 (0.032)	0.816 (0.013)	0.627 (0.036)	0.841 (0.016)
Investments	γ_{sN3}	0.065 (0.021)	0.051 (0.006)	0.057 (0.025)	0.043 (0.009)
Parental Cognitive skills	γ_{sN4}	0.017 (0.013)	0.000 (0.008)	0.021 (0.018)	0.005 (0.010)
Parental Non-Cognitive skills	γ_{sN5}	0.333 (0.034)	0.133 (0.017)	0.293 (0.031)	0.11 0.019()
Complementarity Parameter	ϕ_{sN}	-0.61 (0.215)	-0.551 (0.169)	-0.65 (0.231)	-0.62 (0.181)
Elasticity of substitution		0.621	0.645	0.606	0.617
variance of shocks	δ^2_{sN}	0.222 (0.013)	0.101 (0.004)	0.198 (0.015)	0.121 (0.006)

This table presents the estimates of the technology of skill formation assuming that there is an unobserved permanent component that affects both skill formation and investment. Columns 1 and 2 corresponds to estimates from table 4 in [20] and columns 3 and 4 to the obtained using the sample defined in this paper.

Table G.6: Technology of skill formation allowing for permanent endogeneity

		CH 2010		This paper	
	Parameter	first stage	second Stage	first stage	second Stage
		Cognitive Skill Accumulation			
Cognitive Skills	γ_{sC1}	0.485 (0.031)	0.884 (0.013)	0.440 (0.029)	0.849 (0.021)
non-cognitive Skills	γ_{sC2}	0.062 (0.026)	0.011 (0.005)	0.091 (0.027)	0.016 (0.006)
Investments	γ_{sC3}	0.261 (0.026)	0.044 (0.011)	0.252 (0.029)	0.031 (0.013)
Parental Cognitive skills	γ_{sC4}	0.035 (0.015)	0.051 (0.008)	0055 (0.013)	0.072 (0.011)
Parental Non-Cognitive skills	γ_{sC5}	0.157 (0.033)	0.011 (0.012)	0.162 (0.035)	0.031 (0.014)
Complementarity Parameter	ϕ_{sC}	0.585 (0.225)	-1.220 (0.149)	0.61 (0.241)	-1.37 (0.162)
Elasticity of substitution		2.410	0.450	2.569	0.421
variance of shocks	δ^2_{sC}	0.165 (0.007)	0.098 (0.003)	0.149 (0.009)	0.091 (0.005)
		Non-Cognitive Skill Accumulation			
Cognitive Skills	γ_{sN1}	0.000 (0.028)	0.002 (0.011)	0.000 (0.025)	0.010 (0.009)
non-cognitive Skills	γ_{sN2}	0.602 (0.034)	0.857 (0.011)	0.649 (0.031)	0.867 (0.014)
Investments	γ_{sN3}	0.209 (0.031)	0.051 (0.006)	0.146 (0.029)	0.054 (0.009)
Parental Cognitive skills	γ_{sN4}	0.014 (0.013)	0.000 (0.008)	0.022 (0.019)	0.000 (0.007)
Parental Non-Cognitive skills	γ_{sN5}	0.175 (0.033)	0.037 (0.021)	0.183 (0.039)	0.069 (0.018)
Complementarity Parameter	ϕ_{sN}	-0.464 (0.263)	-0.522 (0.214)	-0.571 (0.313)	-0.602 (0.263)
Elasticity of substitution		0.683	0.657	0.597	0.590
variance of shocks	δ^2_{sN}	0.203 (0.012)	0.102 (0.003)	0.189 (0.014)	0.110 (0.005)

This table presents the estimates of the technology of skill formation assuming that there is an tim varying component that affects both skill formation and investment. Columns 1 and 2 corresponds to estimates from table 5 in [20] and columns 3 and 4 to the obtained using the sample defined in this paper.

Table G.7: Technology of skill formation allowing for time varying endogeneity

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