Research Article

Digital Literacy and Long-Term Labor Outcomes: Impacts of the One Laptop per Child Program in Costa Rica

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Abstract

Technological skills are critical for high-productivity occupations. Between 2012 and 2017, a selected group of primary schools in Costa Rica were provided with one laptop per enrolled student. This paper evaluates this ambitious intervention by elucidating the effects on students' educational and labor market aspirations, school outcomes, and time allocation after six years of access to a computer with connectivity. Using baseline, midline, and endline primary data from program participants and a control group, and a difference-in-difference strategy, this study shows that the program influenced treated students to increase their school motivation, their target education completion, and their intention to migrate in adulthood. The results do not find conclusive evidence of positive change toward pursuing computer science-related occupations or office-based jobs. The findings show evidence of a significant increase in computer usage for treated children but no impacts on the time spent performing homework, outdoor activities, and home chores.

Keywords: Program Evaluation, Technology Adoption, Education Inputs, Economic Development, One Laptop per Child

Introduction

Digital literacy has become a critical skill for higher-productivity occupations. At the same time, using information and communication technologies (ICTs) has proven essential for improved and consistent educational provisions at every level. The uneven access to ICTs threatens to expand schooling gaps that will have significant long-term outcomes in the labor market and lead to broader social inequality. As an attempt to modernize the education system and as a response to public health hazards, governments have implemented policies to update public education by using digital media, such as computers in class, online platforms, projectors, audio devices, and digital materials, among other inputs. Understanding the implications of access to digital literacy in the school system is crucial for an assessment of both the education quality and future labor market outcomes.

Global labor research shows that ICT-related occupations have the highest productivity per worker, reflected through increased wages. According to Sachs (2019), both artificial intelligence programming and digital technologies overall will reduce the demand for unskilled labor and limit the dependence on labor-intensive occupations. This trend will affect less-developed countries that compete in the production of agricultural and manufacturing goods by paying lower wages. However, digital technologies can also allow for a substantial increase in per-worker productivity for a variety of goods and services when there is access and training in ICTs. Lower-income countries have the opportunity to train their labor force in ICTs to take advantage of these higher productivity occupations, as their main challenge is how to offer alternative income-generating opportunities to low-skilled workers who will face a lower labor demand.

ICT-related occupations require updated computer literacy capacities. In the present day, labor markets continue to thrive for those with skills in programming and robotization at the expense of occupations that heavily rely on manual work. The great divide has restructured occupational categories into routine-production workers, in-person service workers, and symbolic analysts. This last group relies heavily on ICT use and experiences the largest increase in wealth share (Warschauer and Matuchniak, 2010). The International Labour Organization (ILO) has warned of the disruptive nature of technological change and the potential for large-scale job destruction. In one of their research papers, Nübler (2016) warns of the unintentional consequences of technological change on the labor market and social cohesion, arguing that there is a need for public policy to guide societal learning and economic transformation. In a literature review conducted by Balliester and Elsheikhi (2018), the authors present calculations of jobs at risk of being automatized, which range from 20% to as high as 70% over the next 20 years.

In addition to the need for updated work skills, the 2020 global pandemic and the threat of future similar health hazards that could temporarily restrict mobility (including pollution and climate change) have accelerated the need for ICTs in school and the workspace (commonly known as remote learning and working, respectively). Those who do not have access to ICTs will find themselves educationally and socioeconomically vulnerable, while those who adapt to these changes are likely to improve their education and labor outcomes. Mandatory remote learning delivery has widened inequalities caused by heterogeneous socioeconomic status (SES). Students who have a computer and connectivity at home can receive differentiated education services over those who do not and are more affected by in-person class cancellations. The challenges associated with virtual education also include equity and access, testing and grading policy, graduation requirements, service provision to students with disabilities, portals, and materials, among others (Reich et al., 2020)

Most research on education quality has focused on topics such as teacher training, access to school, infrastructure, materials, and other classroom inputs, administrative reform, and monetary subsidies. However, there is not enough research documenting the causal effect of the development of technological skills on student performance and labor market outcomes. It is hard to imagine that a student without access to a computer will have the same occupational aspirations as another with computer access. In an attempt to raise awareness on this important topic, the World Bank has presented the concept of XXI century skills needed for future jobs. Training for these occupations is not always adequately developed under the existing school curricula, particularly in less developed countries. The main component of these skills is digital literacy, which requires access to inputs such as computers and smartphones with connectivity. For the case of Latin America, studies from the World Bank have warned of an overproduction of traditional vocations and skills, such as law, economics, accounting, and medicine, accompanied by an underproduction of XXI century skills (for more details, see Aedo & Walker, 2012).

Different programs have been designed to improve digital literacy in primary and secondary schooling. Many interventions sponsored the construction of computer laboratories in schools, while others included technological literacy classes in the curriculum. An intervention called the One Laptop per Child (OLPC) program focused its efforts on providing students with their own computer equipment for school use and home self-use. According to Ames (2019), the

OLPC program was initially promoted as an idealistic tool to drive social change by incorporating interphases designed for play, freedom, and connectivity into a laptop device for children. The author also highlights that three million laptops were distributed by 2019, eighty percent of them in Latin America. Latin American and Caribbean countries that have implemented OLPC programs include Brazil, Peru, Colombia, Uruguay, Haiti, Paraguay, Nicaragua, and Costa Rica (Nugroho & Londsale 2009). The OLPC interventions in these countries have been implemented in a similar way, with slight variation in the number of computers provided per student (one per student or a fixed number of students sharing), connectivity access, training offered, and after-school computer access.

The overarching goal of this paper is to evaluate the impact of the OLPC program implemented in Costa Rica. This intervention has been funded and implemented by the Quirós Tanzi Foundation since 2012 with an initial distribution of 1550 computers across 15 public primary schools within four low-income districts.[1] The program selected public primary schools that did not have computer laboratories and were located in communities with low access to technological inputs. Besides providing laptops for each student, the program installed internet connectivity in each school, provided teacher training, and offered bi-weekly maintenance for repairs.[2] Control schools were chosen from the same four low-income districts.

This paper intends to show how the OLPC program impacted students during the first six years of implementation, accounting for a full primary school cohort.[3] In late 2017, the implementer decided to retire the original stock of computers and agreed to support this endline evaluation of the program. The underlying hypothesis is that possessing a laptop computer generated causal effects on outcomes of computer usage, time allocation, and technological skills. The intervention is also expected to alter the access to information by the students, influencing their occupational aspirations.

The research questions guiding this evaluation are: A) What are the final outcomes generated on educational and labor market aspirations after six years of access to a computer with connectivity? B) How did the technological input affect the intermediate outcomes of altering the time allocation of the program participants, and C) How are these outcomes different for those students in secondary school? A difference-in-difference strategy is used to answer these questions. The changes in outcomes of treated students are compared to the changes of a control group serving as a counterfactual. The data comes from baseline data collected in 2012 from all students in the four targeted districts, as well as a 1-year follow-up data collection in 2013, and a final 6-year post-intervention data collection round that took place in late 2017.

Literature Review

[1] In 2013, 1,500 laptops were provided to 10 additional schools within the same 4 districts, completing the provision plan for these communities. Additional computers were distributed in future years to different areas of the country, which are not included in this study.

[2] Teachers across treatment and control schools had the same training and qualifications before the intervention.

[3] In late 2017, a representative 6th grade student (being a 1st grader in 2012) had a laptop during the entirety of the primary education years.

The literature on education program evaluation has analyzed interventions such as teachers' incentives, vouchers to increase school choice, grants, and decentralization (see Glewwe and Kremer, 2006 & Muralidharan et al., 2012). Novel research on school inputs has focused on understanding how the provision of computers and other technologies influences test scores. Angrist & Lavy (2002) found that a computer distribution program in Israel led to very low effects on test scores, while Banerjee et al. (2007) found that computer use during mathematics classes in Indian schools elevated test scores for math but not for other subjects. Not all results are as encouraging regarding school performance. Malamud & Pop-Eleches (2011) show how providing computers in Romania led students to allocate more time to playing video games and lowered test scores. Zheng et al. (2016) conducted a meta-analysis of ten different one-to-one laptop computer programs in K-12 education in the United States. They find that these programs generally deliver positive effects in English, writing, mathematics, and science. Nogry & Varly (2018) co-studied an OLPC intervention in Madagascar and found that the laptop became a very important part of the children's routine, mostly used for playing games, listening to music, watching videos, sharing content, and doing their homework.

Empirical studies of computer provision in Latin America have found little to no effects on school performance measures. They commonly argue that the lack of connectivity, teacher training, and guidance to students on best computer usage limited any potential change in performance (see Barrera-Osorio & Linden (2009), Cristia et al. (2012) & Beuermann et al. (2012) for further details of OLPC evaluations in Colombia and Peru). Ames (2019) evaluated the OLPC intervention in Paraguay within 2 phases. In the first phase, an adequate level of complementary support to the laptops led to modest improvements in both math and reading tests, while in the second phase, the lack of this support led to no effects from the program regarding test scores. The author argues that the lack of complementary infrastructure, teacher support, and maintenance hinders the effectiveness of the program and is cause of OLPC failure. For the case of the OLPC intervention in Costa Rica, Meza-Cordero (2017) showed that after one year of laptop provision and adequate support structure, students increased their computer usage both in school and at home, allocated less time to homework and outdoor activities, and did not increase their school performance.

ICT literacy is also expected to lead to long-term outcomes as education and training are the main inputs for human capital accumulation and labor productivity. The existing literature on school completion reveals that an additional year of schooling can be translated to an increase in earnings of 9 percent, a result that has been consistent globally over the last six decades (Psacharopoulos & Patrinos, 2018). However, it is far from clear that the incorporation of ICTs in the school curriculum and the information on returns to education is used by students (and their parents) when optimizing their education completion target.

Appadurai (2004) argues that in the context of poverty, development and cultural change are personal and future-oriented, originating from economic calculations that involve needs, wants, and aspirations. Access to information helps the individual update these aspirations to become more realistic. In this context, students would optimize their choice of education completion contingent on labor market aspirations to improve their lifetime well-being. Jensen (2010) studied the changes in aspirations after providing information to students in the Dominican Republic to test the accuracy of students' desired occupations and salary perceptions.

Through an experiment involving eighth graders, the author finds that students who obtained information on the measured returns to education completed between 0.2 and 0.35 additional years of schooling. This finding suggests that students underestimate the returns from education and that this misperception leads to an undersupply of skilled labor that slows down development. Zheng et al. (2014) conducted a study in the United States to measure the effects of computers on fifth-graders interest in science, technology, engineering, and mathematics (STEM). They conclude that computer-based instruction is likely to increase students' motivation for STEM-related professions. This paper about the OLPC program in Costa Rica intends to fill gaps in the existing literature by providing empirical evidence on the long-term effects of ICT access and training on education completion and labor market aspirations.

Data

The data comes from three primary data collection rounds constituting a panel of 7,571 observations. Baseline data was collected in 2012 before the first lot of computers was distributed. A questionnaire was given to the population of 25 schools in the four districts where the participating schools were located, plus three schools from neighboring districts that were very similar based on socioeconomic characteristics. Students from 15 schools started participating in the program in 2012, while students from 10 schools started one year later, and students from the three schools in neighboring districts never joined the program. The total number of surveys at baseline was 3,022 students.

The second round of surveys took place one year after baseline and included the same students plus the incoming first graders, totaling 3,587 students.[4] The third round of surveys was conducted during the last month of classes in 2017, capturing exactly six school years of exposure for those who received a computer in 2012 (and five years of exposure to those who received it in 2013). This final round was targeted at students that had the computer for at least four years. Thus, only students in fourth, fifth, and sixth grade of primary school were surveyed. Additionally, a sample of students participating in the program during primary school and were attending a nearby secondary school were tracked and interviewed. In this final round, 3,962 students were given a survey to be filled out individually and in person. 692 of them in grades 4 through 6 of primary school and 270 in secondary school. Figure 1 summarizes the data collection timeline.

Figure 1: Timeline of the Data Collection

February 2012	*February 2013*	*October 2017*
Baseline Survey was Applied	1-Year Follow-up Survey Applied	Endline Survey was Applied
Laptops were Distributed to 15 Primary Schools	Laptops were Distributed to 25 Primary Schools (15 that started in 2012 + 10 additional schools)	

The three survey instruments administered were nearly identical. However, due to the young age of the respondents at the baseline and 1-year follow-up, the questionnaire included specific questions for students and other questions for parents. The third round was designed to

[4] 10 control schools became treatment schools in 2013

have only students as respondents since only students in grade 4 and higher were interviewed. The first section of the questionnaire gathered socio-demographic information from the household, such as the individual's name, ID, phone number, age, gender, size of their household, number of children in their household, family income, expenses on the children, gender of the head of the household, education completion, and whether there was access to a computer and internet at home. The second section of the questionnaire contained questions on future aspirations, such as the student's educational objective and desired occupation, their preference for the child to continue living in the same town in adulthood, and school motivation. The third and final section focused on time allocation, including the time that the parents spent helping the children with their homework, time that the student spent performing homework, home duties, outdoor activities, weekly computer use by the child and other family members, and functions for which the computer is believed to be useful.

Figure 2 presents the fraction of households with computer and internet access during 2012, 2013, and 2017. The figure shows a positive trend for both computer and internet access across time, which is consistent for both treatment and control groups. Figure 3 presents the trends for educational and occupational aspirations. Occupational aspirations were cataloged according to the first two digits of the current International Standard Classification of Occupations (ISCO-08) from the ILO. These cataloged occupations were then divided into occupations considered to be white-collar and non-white-collar. White collar jobs take place in an office environment and require a professional degree where a computer is a necessary tool (including government officials and medical practitioners). White-collar occupations were disaggregated into computer science and engineering-related occupations. Non-white collar jobs are mostly part of manufacturing and agricultural labor, relying on the use of industrial machinery and physically intensive activities. In 2012, over 77 percent of students wanted to complete a college or vocational degree. This number increased in 2017 by approximately 12 percentage points. The aspiration for white-collar occupations remained nearly constant during the study period, ranging from 75 percent to 69 percent. Notably, the proportion of students who desire to work in computer science or engineering increased substantially, from 12 percent to 18 percent.

Figure 2: Computer and Internet Access

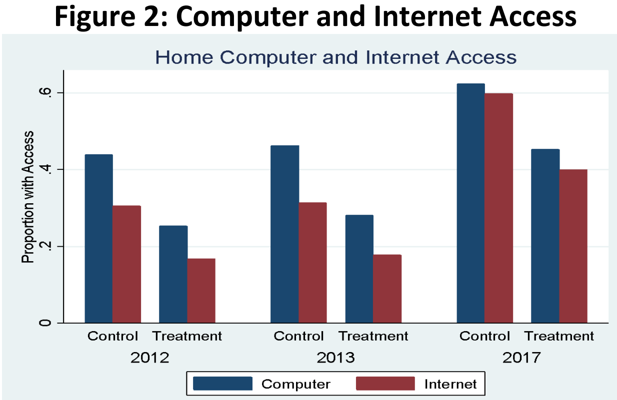

Figure 3: Student Aspirations

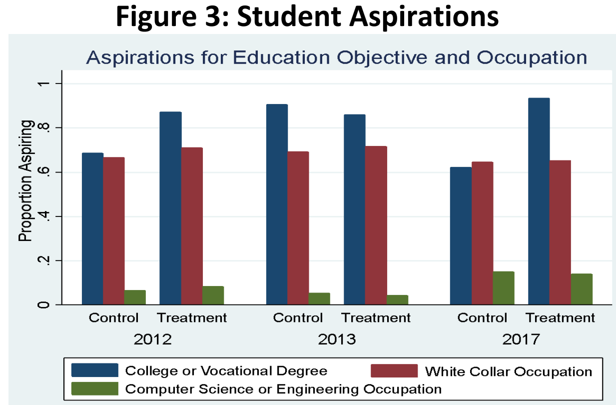

Table 1 presents the descriptive statistics for the socioeconomic characteristics collected each year. The first column for each data collection round shows results for the entire sample, while the second and third columns present the statistics for the treatment and control groups, respectively. Both groups were equivalent in observable characteristics at baseline (see Meza-Cordero, 2017 for baseline analysis). The 2012 and 2013 student surveys have a mean age of 9.6 years for primary school students. The 2017 survey presents an average age of 12.20 years, a considerable increase by design given that this round gathered information from students in grades 4, 5, and 6 of primary school and those attending secondary school.

The average household size was consistent throughout the six years of the study, with nearly five members on average, out of which 2 were children under age 12. The head of the household is male in approximately 70 percent of the cases. As noted in Figure 2, there is an upward trend in computer and internet access at the household level. The availability of computers at home increased from 31 percent in 2012 to 49 percent in 2017. Internet connectivity in the house more than doubled in this period, increasing from 21 percent to 44 percent. It is also important to point out that 81 percent of the households in 2017 reported having at least one person other than the beneficiary student using a computer (an increase of 15 percent during the six years of the study).

Weekly hours of computer use at home was 3.35 in 2012, with a considerable difference across groups because the treatment group was selected in areas with lower computer access. The number of hours dropped to 1.92 in 2017, in part because students in secondary school had to return their laptop when graduating from primary school. Weekly hours of computer use outside of the house show a similar pattern, decreasing from 1.98 to 0.92 during the six years of the study. Hours performing outdoor activities and doing homework also decreased from 6.14 to 4.05 and from 5.70 to 3.01, respectively. The education objective remained near constant with a mean aspiration of 3, mapping a desire to complete university.

Empirical Strategy

The effects of the computer provision program are identified by comparing the outcomes of the treated students to a counterfactual. The unbiased effects of the intervention are estimated through a difference in difference (DID) strategy that quantifies and subtracts the time trends of the control schools (to serve as the counterfactual trend for treatment schools). Y_i is defined as the outcome variable for student i. The outcome variables for future aspirations include a white-collar occupation plan, education level objective, school motivation, intended area of residence, and intent to pursue a career in a computer science related field. The outcome variables for weekly time allocations include time using a computer at home, time using a computer outside of the home, total time using a computer, time performing outdoor activities, time doing homework, time performing household chores, and time of other household members using a computer. T=0 is defined as the baseline period, and T=1 is the endline period. D=1 denotes the students that belong to the treatment schools, while D=0 denotes the students in the control schools.

Table 1: Descriptive Statistics

		2012						2013						2017					
		All		Treatment		Control		All		Treatment		Control		All		Treatment		Control	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Socio-Demographic	Age	9.60	(2.11)	9.24	(2.08)	9.79	(2.10)	9.58	(2.14)	9.47	(2.21)	9.69	(2.04)	12.20	(2.00)	12.50	(2.06)	11.23	(1.42)
	Sex	1.48	(0.50)	1.46	(0.50)	1.49	(0.50)	1.49	(0.50)	1.48	(0.50)	1.50	(0.50)	1.50	(0.50)	1.51	(0.50)	1.49	(0.50)
	Age Head Household	36.10	(8.50)	35.93	(8.65)	36.20	(8.41)	35.70	(7.86)	35.19	(7.41)	35.72	(7.91)	37.00	(6.63)	39.00	(4.24)	35.00	(9.90)
	Male Head Household	0.72	(0.45)	0.72	(0.45)	0.71	(0.45)	0.72	(0.45)	0.73	(0.44)	0.69	(0.47)	0.67	(0.46)	0.69	(0.46)	0.61	(0.49)
	Education Head Household	1.87	(1.35)	1.83	(1.35)	1.90	(1.34)	1.82	(1.28)	1.78	(1.32)	1.79	(1.12)	1.50	(1.00)	2.00	(1.41)	1.00	(0.00)
	Household Size	4.87	(1.68)	4.95	(1.77)	4.81	(1.61)	4.72	(1.66)	4.72	(1.64)	4.72	(1.67)	4.97	(1.76)	4.96	(1.76)	4.99	(1.78)
	Household Kids	1.89	(1.23)	1.94	(1.15)	1.84	(1.31)	1.83	(1.18)	1.81	(1.18)	1.81	(1.13)	1.57	(1.53)	1.51	(1.50)	1.82	(1.61)
	Computer Home	0.31	(0.46)	0.30	(0.46)	0.33	(0.47)	0.33	(0.47)	0.31	(0.46)	0.46	(0.50)	0.49	(0.50)	0.45	(0.50)	0.62	(0.49)
	Internet Home	0.21	(0.41)	0.21	(0.41)	0.22	(0.41)	0.21	(0.41)	0.21	(0.41)	0.31	(0.46)	0.44	(0.50)	0.40	(0.49)	0.60	(0.49)
	Other Member Comp. Use	0.66	(0.47)	0.64	(0.48)	0.69	(0.46)	0.67	(0.47)	0.67	(0.47)	0.81	(0.39)	0.81	(0.39)	0.80	(0.40)	0.86	(0.35)
Computer & Time Use	Computer Home	3.35	(5.24)	1.93	(4.51)	4.11	(5.45)	3.87	(5.48)	4.22	(6.18)	4.48	(5.20)	1.92	(3.80)	1.82	(3.62)	2.24	(4.31)
	Computer Outside	1.98	(6.80)	0.60	(1.89)	2.71	(8.20)	1.97	(4.12)	2.22	(4.85)	2.17	(3.82)	0.92	(2.39)	0.84	(2.07)	1.18	(3.21)
	Hours Outdoors	6.14	(6.23)	6.82	(7.02)	5.47	(5.28)	5.76	(6.64)	5.72	(7.16)	4.65	(4.64)	4.05	(4.86)	4.12	(4.89)	3.74	(4.73)
	Hours Homework	5.70	(4.39)	6.41	(4.52)	5.05	(4.16)	5.15	(4.70)	5.18	(5.24)	4.66	(3.71)	3.01	(3.63)	2.90	(3.33)	3.49	(4.69)
	Hours Home Duties	3.17	(4.35)	3.03	(4.08)	3.31	(4.62)	2.86	(3.75)	2.82	(3.81)	2.28	(2.76)	3.93	(4.99)	3.95	(4.87)	3.84	(5.49)
	Hours Parent Help	5.20	(5.26)	6.03	(5.86)	4.41	(4.48)	4.97	(6.06)	5.17	(7.34)	4.54	(4.47)	2.11	(3.80)	1.80	(3.10)	3.44	(5.74)
	Hours Computer Others	4.53	(10.03)	5.45	(11.49)	3.57	(8.15)	4.01	(9.24)	4.00	(9.02)	5.25	(10.90)	2.49	(5.20)	2.28	(4.96)	3.38	(6.03)
Aspirations	School Enjoyment	9.09	(1.66)	9.26	(1.33)	9.00	(1.80)	9.08	(1.77)	9.12	(1.74)	8.93	(1.88)	7.96	(2.57)	8.33	(2.05)	6.78	(3.56)
	College Education	3.07	(0.65)	3.07	(0.60)	3.08	(0.70)	2.93	(0.82)	2.86	(0.87)	3.05	(0.73)	3.16	(0.59)	3.18	(0.54)	3.06	(0.75)
	White Collar Job	0.77	(0.46)	0.74	(0.44)	0.71	(0.45)	0.75	(0.43)	0.75	(0.43)	0.75	(0.43)	0.69	(0.46)	0.70	(0.46)	0.67	(0.47)
	Computer Science Job	0.11	(0.31)	0.12	(0.32)	0.10	(0.29)	0.09	(0.29)	0.09	(0.28)	0.10	(0.30)	0.18	(0.39)	0.18	(0.39)	0.18	(0.39)
	Observations	2876		1094		1890		3579		1439		1578		962		737		225	

Notes: This table reports descriptive statistics of sociodemographic characteristics and outcomes of interest. The mean for each variable is reported with the associated standard error in parenthesis. Columns 1-6 reflect year 2012, columns 7-12 reflect year 2013, and columns 13-18 reflect year 2017. For each year, the first columns include both groups, while the next columns are disaggregated to present the treatment and the control group, respectively.

Equation (1) represents the equation used to obtain the DID estimators:

$$Y = \alpha + \beta D + \delta T + \gamma DT + \phi X_0 + \varepsilon \quad (1)$$

Where X_0 is a set of baseline control variables. These variables include age, age squared, gender, gender of the head of the household, having a computer and internet at home, having used a computer in the past, size of the household, and number of children in the household. Equation 1 is first estimated through repeated cross-sections of data, where the parameter γ captures the ATT. However, given that individuals were followed over time, a panel data strategy with the following structure will also be used:

$$Y_{it} = \alpha + \beta D_i + \delta T + \gamma D_i T + \phi X_i + \mu_i + \varepsilon_{it} \quad (2)$$

Where μ_i represents any unobservable fixed effects for individual i, and the effects of the baseline control variables, ϕ_t, are allowed to change with time. By subtracting the baseline period from the post-intervention period at the individual level, any time-invariant fixed effects are eliminated, resulting in the following equation:

$$\Delta Y_i = \delta + \gamma D_i + \sigma X_i + \eta_i \quad (3)$$

Where σ is equal to $\Delta\phi$ and η_i is equal to $\Delta\varepsilon_i$. Since D_i is the dummy variable indicating treatment, γ will indicate the average treatment effect on the treated. Finally, a time series strategy is implemented for the case of treated students that were tracked and found attending a local secondary school. Continuous variables are estimated through ordinary least squares, while dichotomous variables are estimated with logistic regression. The robustness of the results is analyzed for these three strategies.

Results

The results present an analysis estimating repeated cross sections for primary school students only. This structure has 1889 baseline observations: 1053 treatment and 836 control. It also leverages 707 endline observations: 497 treatment and 210 control. These observations include students from grades 1 through 3, for which baseline data was collected in 2012, plus students that were interviewed in 2013 when they started school (1st graders). The endline observations include students who were in grades 4 through 6 in 2017 at the time of the interview.

Repeated Cross Sections for Primary School Students

Aspirations

The results for student aspirations are presented in Table 2. The estimates show positive but not statistically significant program effects on a preference for white-collar aspirations. There is a positive and statistically significant effect showing that program participants have a higher education aspiration and are more motivated to finish school. There is a negative effect on desiring to continue living in the country, showing that many students want to move (presumably to the metropolitan area). However, this effect is not statistically significant. Finally, specific occupational aspirations in computer science or engineering are analyzed, yet no significant effects are found.

Table 2: Student Future Aspirations and Plans - Cross-Sections

	White Collar Aspiration (1)	College Aspiration (2)	School Motivation (3)	Same County (4)	Informatics Aspiration (5)
Treatment Group	0.320***	-0.253	0.136*	0.740	0.0149
	(0.117)	(0.219)	(0.0638)	(0.480)	(0.0184)
Time Trend	-0.751***	-5.978***	-7.293***	-0.836***	0.0311***
	(0.0938)	(1.342)	(0.432)	(0.300)	(0.00689)
Program Effect	**0.164**	**6.767*** **	**6.449*** **	**-0.872**	**0.0503**
	(0.356)	**(1.459)**	**(0.498)**	**(0.549)**	**(0.0340)**
Age Baseline	0.191	0.589	0.198	-0.0739	0.0155
	(0.231)	(0.459)	(0.276)	(0.344)	(0.0401)
Age Squared Baseline	-0.0144	-0.0403	-0.0166	-7.98e-05	-0.000873
	(0.0161)	(0.0264)	(0.0163)	(0.0199)	(0.00249)
Gender	1.932***	-0.122	0.355***	-0.844*	-0.0830***
	(0.159)	(0.175)	(0.0322)	(0.493)	(0.00631)
Gender HH Head	-0.0556	0.0744	-0.0601	0.0612	-0.00365
	(0.108)	(0.194)	(0.0795)	(0.0895)	(0.0115)
Family Size Baseline	-0.0241	-0.00700	0.0285	0.0469	-0.00673
	(0.0398)	(0.0542)	(0.0161)	(0.0398)	(0.00508)
Family Kids Baseline	0.00968	-0.133*	-0.0114	-0.0105	-0.00381
	(0.0399)	(0.0794)	(0.0358)	(0.0424)	(0.00398)
Computer at Baseline	-0.0711	0.996***	0.177	-0.161	-0.0143
	(0.156)	(0.257)	(0.147)	(0.138)	(0.0176)
Internet at Baseline	0.151	-0.211	-0.0921	-0.0112	0.0207
	(0.173)	(0.315)	(0.139)	(0.137)	(0.0133)
Computer Use Other	-0.101	-0.0545	-0.0774	-0.146	0.0175
	(0.176)	(0.158)	(0.112)	(0.110)	(0.0217)
Computer Use Past	-0.142*	0.00365***	-0.00048***	0.00471***	-6.62e-05***
	(0.0827)	(0.00124)	(7.49e-05)	(0.00156)	(1.73e-05)
Constant	-2.209**	0.536	8.232***	2.434*	0.155
	(0.892)	(2.112)	(1.178)	(1.440)	(0.138)
Observations	1,707	1,788	1,784	1,784	1,788
R-squared			0.402		0.036

Notes: This table reports estimates from a regression of future plans and aspirations of the students on an indicator for being assigned a laptop computer and a set of covariates using repeated cross sections for primary school students only. Covariates include age, age squared, gender, gender of the head of the household, size of the household, number of children in the household, having a computer and/or internet at baseline, other household members that use computers, and having used a computer in the past. Binary variables have a value equal to 1 for "yes" and equal to 0 for "no" (aspiring to a white-collar occupation, planning to attend college, staying in the same county, and planning to study an informatics-related major, columns 1, 2, 4 and 5 respectively). Column 3 contains school motivation and is a numeric value. The regression models are estimated using a logit regression for binary variables and ordinary least squares for numeric variables. Standard errors are presented in the parenthesis below each estimate. Significance levels for the estimates are determined as: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Time Allocation

Table 3 shows the weekly time allocation of the students. The beneficiary students reallocated their time so that computer use and homework time increased at the expense of hours outdoors and home duties. The effect on computer use at home is statistically significant, showing an increase of approximately four additional hours per week. All other effects are not statistically significant.

Table 3: Student Weekly Time Allocation - Cross-Sections

	Computer Total (1)	Computer Home (2)	Computer Outside (3)	Home Duties (4)	Hours Outdoors (5)	Hours Homework (6)	Use Others (7)
Treatment Group	-3.861	-3.085*	-0.786	5.839	4.444	-11.50	-0.845
	(2.594)	(1.614)	(1.121)	(10.44)	(5.949)	(14.22)	(10.59)
Time Trend	-5.152	-4.452*	-0.750	-0.343	3.113	-24.83	-5.775
	(3.070)	(2.143)	(0.986)	(5.222)	(6.585)	(13.96)	(9.473)
Program Effect	**4.281**	**3.820***	**0.477**	**-4.005**	**-12.45**	**17.81**	**-2.475**
	(2.881)	**(1.816)**	**(1.204)**	**(9.060)**	**(8.115)**	**(16.10)**	**(13.91)**
Age Baseline	1.638	1.295*	0.404	11.31	-5.100	-7.261	11.82
	(1.355)	(0.614)	(1.071)	(15.36)	(8.234)	(15.85)	(14.08)
Age Squared Baseline	-0.100	-0.0829**	-0.0210	-0.448	0.370	0.609	-0.487
	(0.0790)	(0.0352)	(0.0656)	(0.900)	(0.522)	(1.138)	(0.798)
Gender	0.372	-0.0185	0.414	4.114	-0.423	-4.250	6.513
	(0.535)	(0.211)	(0.488)	(5.887)	(2.494)	(7.616)	(6.389)
Gender HH Head	-0.517	-0.0552	-0.477	-7.031	0.521	-0.647	-6.760**
	(0.511)	(0.194)	(0.537)	(8.796)	(3.823)	(5.741)	(2.727)
Family Size Baseline	-0.185	-0.00506	-0.188	0.374	-2.393***	-1.906	-0.108
	(0.128)	(0.0515)	(0.115)	(1.823)	(0.736)	(1.154)	(1.571)
Family Kids Baseline	0.298*	0.218	0.0922*	-2.932*	1.237	-1.233	-4.755**
	(0.146)	(0.123)	(0.0473)	(1.576)	(0.979)	(2.102)	(1.927)
Computer at Baseline	1.134	1.776***	-0.634	-8.904	1.217	-6.791*	-8.853
	(0.853)	(0.426)	(0.725)	(6.431)	(3.154)	(3.157)	(8.011)
Internet at Baseline	0.246	0.311	-0.0916	-6.438	0.706	7.997**	4.997
	(0.398)	(0.293)	(0.211)	(5.535)	(3.984)	(3.288)	(7.941)
Computer Use Other	1.107	0.0995	1.020	5.769	-2.948	-18.38	8.095
	(0.650)	(0.248)	(0.633)	(8.483)	(5.001)	(13.32)	(5.520)
Computer Use Past	-0.0014***	-0.0011**	-0.000288	-0.0096	-0.0080	-0.0087	-0.0039
	(0.000366)	(0.000378)	(0.000443)	(0.00641)	(0.00701)	(0.00924)	(0.00506)
Constant	-0.659	-1.311	0.448	-42.18	38.37	80.33	-38.97
	(6.912)	(3.391)	(4.357)	(53.91)	(33.12)	(49.78)	(53.31)
Observations	1,788	1,768	1,761	1,735	1,729	1,713	1,729
R-squared	0.085	0.145	0.018	0.012	0.004	0.012	0.012

Notes: This table reports estimates from a regression of weekly time allocation of the students on an indicator for being assigned a laptop computer and a set of covariates using repeated cross sections for primary school students only. Covariates include age, age squared, gender, gender of the head of the household, size of the household, number of children in the household, having a computer and/or internet at baseline, other household members that use computers, and having used a computer in the past. All columns contain numeric values regarding total hours using a computer, hours using a computer at home, hours using a computer outside, hours on home duties, hours performing outdoor activities, hours performing homework, and hours of computer use by other family members. The regression models are estimated using ordinary least squares. Standard errors are presented in the parenthesis below each estimate. Significance levels for the estimates are determined as: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel Data for Primary School Students

The second data structure used is a panel of primary school students tracked and interviewed in 2017. The baseline data used for all students is from 2012, with the only exception being the incoming class of first graders in 2013. The panel consists of 410 observations, of which 158 are treatment students, and 47 are control students.

Aspirations

Table 4 shows the effects on future aspirations and plans. There is little to no effect on white-collar aspirations, but the other four measures are statistically significant. Education aspirations and school motivation increased, showing an increased interest in higher levels of formal education completion. There is a negative effect on wanting to stay in the same county, which means that the treated students want to migrate, presumably to the metropolitan area, where there are more jobs in manufacturing and services. There is a positive and statistically significant effect on computer science job aspirations, meaning that more students trained with a laptop during primary school intend to pursue a career in computer-related disciplines.

Table 4: Students' Future Aspirations and Plans - Panel

	White Collar Aspiration (1)	College Aspiration (2)	School Motivation (3)	Same County (4)	Informatics Aspiration (5)
Program Effect	**-0.0670**	**1.027*** **	**6.269*** **	**-0.196** **	**0.0916***
	(0.0762)	**(0.0607)**	**(0.230)**	**(0.0757)**	**(0.0471)**
Age Baseline	1.200***	-0.315**	-0.696	0.0863	0.151
	(0.288)	(0.136)	(0.887)	(0.161)	(0.197)
Age Squared Baseline	-0.0878***	0.0204*	0.0454	-0.00822	-0.00880
	(0.0183)	(0.00936)	(0.0574)	(0.00891)	(0.0114)
Gender	-0.0710	0.0381	-0.153	0.142	-0.0711
	(0.157)	(0.0441)	(0.333)	(0.0951)	(0.0712)
Gender HH Head	0.0809	0.0137	-0.130	-0.00235	-0.0212
	(0.0742)	(0.0761)	(0.394)	(0.103)	(0.0384)
Family Size Baseline	-0.00135	-0.00192	0.0537	0.00747	-0.0156
	(0.0240)	(0.00833)	(0.0742)	(0.0379)	(0.00903)
Family Kids Baseline	0.00577	0.0113	-0.0608	0.0442	0.00751
	(0.0501)	(0.0179)	(0.0787)	(0.0496)	(0.0114)
Computer at Baseline	-0.202	-0.0629	0.0840	0.283**	0.0181
	(0.120)	(0.0677)	(0.378)	(0.0944)	(0.0772)
Internet at Baseline	0.225**	-0.0256	-0.250	-0.194	0.0157
	(0.0780)	(0.0666)	(0.349)	(0.136)	(0.0466)
Computer Use Other	0.391**	-0.166	-0.739	-0.196**	0.0627**
	(0.123)	(0.150)	(0.912)	(0.0666)	(0.0234)
Computer Use Past	-0.160*	-0.0615	0.332	0.147	0.0183
	(0.0743)	(0.0451)	(0.394)	(0.0829)	(0.0412)
Constant	-4.197**	0.446	-4.268	-0.882	-0.513
	(1.443)	(0.509)	(3.994)	(0.499)	(0.945)
Observations	173	197	191	191	197
R-squared	0.098	0.587	0.640	0.101	0.031

Notes: This table reports estimates from a regression of future plans and aspirations of the students on an indicator for being assigned a laptop computer and a set of covariates using a panel of students that were surveyed while in primary school. Covariates include age, age squared, gender, gender of the head of the household, size of the household, number of children in the household, having a computer and/or internet at baseline, other household members that use computers, and having used a computer in the past. Binary variables have a value equal to 1 for "yes" and equal to 0 for "no" (aspiring to a white-collar occupation, planning to attend college, staying in the same county, and planning to study an informatics-related major, columns 1, 2, 4 and 5 respectively). Column 3 contains school motivation and is a numeric value. The regression models are estimated using a logit regression for binary variables and ordinary least squares for numeric variables. Standard errors are presented in the parenthesis below each estimate. Significance levels for the estimates are determined as: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Time Allocation

The estimates for weekly time allocations are presented in Table 5. There is an increase of 11.3 additional hours of computer use per week. These hours consist of 8.4 hours at home and 2.8 outside. Estimates for hours on home duties, outdoors, homework, and of computer use by others are omitted due to the lack of consecutive observations for the control group.

Table 5: Student Weekly Time Allocation - Panel

	Computer Total (1)	Computer Home (2)	Computer Outside (3)	Home Duties (4)	Hours Outdoors (5)	Hours Homework (6)	Use Others (7)
Program Effect	**11.30*** **	**8.417*** **	**2.847*** **	-	-	-	-
	(0.740)	**(0.540)**	**(0.286)**	-	-	-	-
Age Baseline	2.600	1.111	1.440	-	-	-	-
	(2.211)	(1.687)	(1.321)	-	-	-	-
Age Squared Baseline	-0.147	-0.0636	-0.0795	-	-	-	-
	(0.123)	(0.0948)	(0.0759)	-	-	-	-
Gender	0.0344	-0.167	0.228	-	-	-	-
	(0.840)	(0.690)	(0.279)	-	-	-	-
Gender HH Head	-0.205	0.0461	-0.232	-	-	-	-
	(0.491)	(0.356)	(0.196)	-	-	-	-
Family Size Baseline	-0.224	-0.273	0.0582	-	-	-	-
	(0.204)	(0.161)	(0.0510)	-	-	-	-
Family Kids Baseline	0.469	0.506*	-0.0297	-	-	-	-
	(0.329)	(0.269)	(0.117)	-	-	-	-
Computer at Baseline	1.362	1.268	0.148	-	-	-	-
	(1.265)	(0.750)	(0.634)	-	-	-	-
Internet at Baseline	0.00811	-0.561	0.474	-	-	-	-
	(0.800)	(0.548)	(0.436)	-	-	-	-
Computer Use Other	-1.645	-1.675	0.0298	-	-	-	-
	(1.952)	(1.390)	(0.682)	-	-	-	-
Computer Use Past	2.463**	1.932**	0.604	-	-	-	-
	(1.010)	(0.656)	(0.437)	-	-	-	-
Constant	-24.48**	-14.32**	-10.22	-	-	-	-
	(8.509)	(5.961)	(5.862)	-	-	-	-
Observations	197	191	188	-	-	-	-
R-squared	0.460	0.478	0.216	-	-	-	-

Notes: This table reports estimates from a regression of weekly time allocation of the students on an indicator for being assigned a laptop computer and a set of covariates using a panel of students that were surveyed while in primary school. Covariates include age, age squared, gender, gender of the head of the household, size of the household, number of children in the household, having a computer and/or internet at baseline, other household members that use computers, and having used a computer in the past. All columns contain numeric values regarding total hours using a computer, hours using a computer at home, hours using a computer outside, hours on home duties, hours performing outdoor activities, hours performing homework, and hours of computer use by other family members. The regression models are estimated using ordinary least squares. Standard errors are presented in the parenthesis below each estimate. Columns 4 – 6 are omitted due to lack of observations in both periods. Significance levels for the estimates are determined as: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Pooled Cross Sections: Primary School Students & Secondary School Students.

A larger sample is obtained when pooling together primary and secondary school students. All primary school students (grades 1-6) interviewed at baseline are included. The observations are kept for students with information for 2012 and/or 2013, accounting for 4911 observations in total. All observations gathered in 2017 are included, which include grades 4-6 in primary school and 7-11 in secondary school, accounting for 962 individuals.

Aspirations

Table 6 shows the results for student aspirations when pooling together the entire sample. The results are very consistent with what was found for primary school students. No statistically significant changes were found for white collar aspirations, higher education completion, school motivation, and moving out of the county in adulthood. Additionally, no change was found when narrowing for computer science occupation aspirations, although the results show that girls are less likely to aspire to these careers. These effects are consistent with previous results and were expected as primary school students represent the largest proportion of the sample.

Table 6: Primary and Secondary Student's Aspirations - Pooled

	White Collar Aspiration (1)	College Aspiration (2)	School Motivation (3)	Same County (4)	Informatics Aspiration (5)
Treatment Group	0.346***	-0.145	0.132*	0.665*	0.0213
	(0.130)	(0.144)	(0.0712)	(0.395)	(0.0186)
Time Trend	-0.329***	-4.098***	-6.623***	-0.616**	0.111***
	(0.115)	(0.309)	(0.469)	(0.310)	(0.0226)
Program Effect	**0.0973**	**4.762*****	**5.292*****	**-0.936****	**-0.0110**
	(0.193)	**(0.395)**	**(0.462)**	**(0.393)**	**(0.0296)**
Age Baseline	0.218	0.322	0.0519	-0.157	0.0269
	(0.175)	(0.261)	(0.136)	(0.220)	(0.0151)
Age Squared Baseline	-0.00675	-0.0174	-0.00954	0.00215	-0.000547
	(0.00898)	(0.0135)	(0.00753)	(0.0119)	(0.000784)
Gender	1.723***	-0.0361	0.283***	-0.923*	-0.0942***
	(0.152)	(0.105)	(0.0407)	(0.486)	(0.00790)
Gender HH Head	-0.0630	0.119	0.0147	0.0421	-0.0262*
	(0.0550)	(0.110)	(0.0835)	(0.0842)	(0.0135)
Family Size Baseline	-0.0576**	-0.0758	0.0434***	0.0376*	-0.0106***
	(0.0225)	(0.0513)	(0.0125)	(0.0203)	(0.00287)
Family Kids Baseline	0.000596	-0.000726	0.00111***	-0.00177***	-0.000140***
	(0.00124)	(0.000707)	(8.36e-05)	(0.000617)	(1.72e-05)
Computer at Baseline	-0.0306	0.640***	0.0111	-0.0727	0.0131
	(0.138)	(0.171)	(0.118)	(0.113)	(0.0141)
Internet at Baseline	0.187*	-0.0167	-0.0342	-0.0258	0.0311*
	(0.0954)	(0.241)	(0.0755)	(0.107)	(0.0139)
Computer Use Other	0.0872	0.256**	-0.0611	-0.153*	0.00944
	(0.0992)	(0.126)	(0.0690)	(0.0814)	(0.0187)
Computer Use Past	-0.00151	-0.00147	-9.55e-06	0.00676	-8.55e-05
	(0.00211)	(0.00173)	(0.000602)	(0.00697)	(5.02e-05)
Constant	-2.733***	0.872	8.875***	3.070***	0.105*
	(0.742)	(1.333)	(0.649)	(0.965)	(0.0559)
Observations	3,090	3,221	3,207	3,213	3,221
R-squared			0.270		0.053

Notes: This table reports estimates from a regression of future plans and aspirations of the students on an indicator for being assigned a laptop computer and a set of covariates pooling data of all students in primary and in secondary school. Covariates include age, age squared, gender, gender of the head of the household, size of the household, number of children in the household, having a computer and/or internet at baseline, other household members that use computers, and having used a computer in the past. Binary variables have a value equal to 1 for "yes" and equal to 0 for "no" (aspiring to a white-collar occupation, planning to attend college, staying in the same county, and planning to study an informatics-related major, columns 1, 2, 4 and 5 respectively). Column 3 contains school motivation and is a numeric value. The regression models are estimated using a logit regression for binary variables and ordinary least squares for numeric variables. Standard errors are presented in the parenthesis below each estimate. Significance levels for the estimates are determined as: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Time Allocation

The effects on time allocation are consistent with those found for primary school students. Table 7 shows a positive and statistically significant computer use increase of approximately 5 hours, 3.9 of them at home. There are no statistically significant effects on the other variables.

Table 7: Primary and Secondary Student's Weekly Time Allocation - Pooled

	Computer Total (1)	Computer Home (2)	Computer Outside (3)	Home Duties (4)	Hours Outdoors (5)	Hours Homework (6)	Use Others (7)
Treatment Group	-4.597**	-3.080*	-1.547*	2.035	4.173	-16.58	-4.525
	(1.990)	(1.425)	(0.811)	(8.460)	(7.990)	(18.87)	(14.07)
Time Trend	-5.264*	-4.000*	-1.322*	-1.144	-8.623	-23.67*	-19.39
	(2.560)	(1.997)	(0.687)	(5.189)	(5.010)	(11.33)	(11.50)
Program Effect	**4.902***	**3.879***	**1.035**	**-4.088**	**-4.067**	**15.83**	**5.619**
	(2.608)	**(1.963)**	**(0.796)**	**(9.074)**	**(7.720)**	**(18.88)**	**(14.06)**
Age Baseline	1.010	0.609	0.475	10.48	1.667	0.217	27.86
	(0.835)	(0.369)	(0.560)	(7.631)	(6.832)	(7.045)	(20.57)
Age Squared Baseline	-0.0399	-0.0247	-0.0189	-0.538	-0.0332	0.0612	-1.441
	(0.0416)	(0.0196)	(0.0261)	(0.422)	(0.341)	(0.418)	(1.073)
Gender	0.0156	-0.255	0.279	4.066	0.248	0.0738	3.565
	(0.362)	(0.157)	(0.309)	(4.110)	(3.494)	(6.322)	(1.985)
Gender HH Head	0.159	0.144	0.00200	-4.836	-3.571	-10.52*	-1.399
	(0.612)	(0.291)	(0.405)	(6.675)	(3.542)	(4.681)	(6.301)
Family Size Baseline	0.0269	-0.0241	0.0555	0.0825	-1.599**	-2.377	-0.983
	(0.187)	(0.0751)	(0.156)	(1.840)	(0.632)	(1.443)	(1.668)
Family Kids Baseline	-0.00395*	-0.00275	-0.00128*	0.389***	0.190	-0.0357*	0.377***
	(0.00208)	(0.00181)	(0.000693)	(0.0606)	(0.174)	(0.0177)	(0.0655)
Computer at Baseline	1.007	1.780***	-0.811	-4.346	3.303	-4.973	-6.351
	(0.648)	(0.326)	(0.650)	(5.178)	(6.735)	(5.607)	(11.90)
Internet at Baseline	-0.0992	0.189	-0.298	-8.246	-4.040	0.455	-2.802
	(0.497)	(0.292)	(0.255)	(6.024)	(7.744)	(4.593)	(10.00)
Computer Use Other	1.450*	0.196	1.299	5.633	5.602	-8.496	7.592**
	(0.723)	(0.171)	(0.784)	(6.548)	(3.599)	(5.071)	(2.547)
Computer Use Past	0.00453	0.00437	0.000126	-0.00816	-0.000425	-0.00934	0.319
	(0.00539)	(0.00508)	(0.000442)	(0.00821)	(0.00489)	(0.00656)	(0.331)
Constant	0.0859	1.026	-1.239	-39.42	8.913	59.03	-107.1
	(6.491)	(3.111)	(3.912)	(33.33)	(35.13)	(35.49)	(82.91)
Observations	3,221	3,174	3,177	3,166	3,143	3,110	3,145
R-squared	0.095	0.137	0.031	0.037	0.010	0.010	0.030

Notes: This table reports estimates from a regression of weekly time allocation of the students on an indicator for being assigned a laptop computer and a set of covariates pooling data of all students in primary and in secondary school. Covariates include age, age squared, gender, gender of the head of the household, size of the household, number of children in the household, having a computer and/or internet at baseline, other household members that use computers, and having used a computer in the past. All columns contain numeric values regarding total hours using a computer, hours using a computer at home, hours using a computer outside, hours on home duties, hours performing outdoor activities, hours performing homework, and hours of computer use by other family members. The regression models are estimated using ordinary least squares. Standard errors are presented in the parenthesis below each estimate. Significance levels for the estimates are determined as: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Secondary School Students

The final set of results considers only secondary school students. A panel of 227 students interviewed in 2012 while in primary school were found in secondary schools within neighboring districts in late 2017. All of them were part of treatment schools, so a difference-in-difference estimation is not feasible. The estimation strategy used is ordinary least squares with a treatment dummy variable indicating the year. An issue that arises is that this model does not capture a time trend, which makes it a biased result that must be interpreted with caution.

Aspirations

Table 8 presents the effects on secondary school students' aspirations. The time trend plus program effect for secondary school students shows no effect on aspirations for white-collar occupations. The effect on aspiring to attend college or vocational training is positive and statistically significant. School motivation is now negative and statistically significant. Planning to stay in the same county remains negative and statistically significant, which indicates the students' wishes to move out in adulthood. A positive and statistically significant effect is found when looking into aspirations that include only computer science and engineering. An additional finding is that girls are less likely to be the ones aspiring to these occupations.

Table 8: Secondary School Student's Aspirations – Time Series

	White Collar Aspiration (1)	College Aspiration (2)	School Motivation (3)	Same County (4)	Informatics Aspiration (5)
Time Trend + Program Effect	**-0.0402**	**0.793******	**-2.109******	**-1.363******	**0.160******
	(0.290)	**(0.236)**	**(0.106)**	**(0.188)**	**(0.0325)**
Age Baseline	1.312	-1.482	-0.318	-0.855	-0.100
	(1.429)	(0.951)	(1.144)	(1.503)	(0.152)
Age Squared Baseline	-0.0523	0.0719*	0.00259	0.0388	0.00856
	(0.0757)	(0.0435)	(0.0583)	(0.0778)	(0.00771)
Gender	1.317***	-0.161	0.270	-0.923***	-0.157***
	(0.225)	(0.315)	(0.155)	(0.177)	(0.0347)
Gender HH Head	0.150	0.0793	0.233	-0.0880	-0.0334
	(0.179)	(0.608)	(0.305)	(0.0996)	(0.0237)
Family Size Baseline	-0.316***	-0.212	-0.0723	0.0416	-0.0355**
	(0.100)	(0.206)	(0.0633)	(0.106)	(0.0136)
Family Kids Baseline	0.0333	-0.289*	0.0327	-0.0989	0.00106
	(0.0707)	(0.169)	(0.0805)	(0.105)	(0.0158)
Computer at Baseline	0.507**	0.721	0.138	0.153	0.103
	(0.245)	(0.607)	(0.417)	(0.253)	(0.0934)
Internet at Baseline	-0.219	0.105	-0.408*	-0.468*	-0.0111
	(0.240)	(0.615)	(0.216)	(0.262)	(0.0295)
Computer Use Other	-0.232	-0.350	0.0514	0.455***	0.0961***
	(0.482)	(0.362)	(0.155)	(0.137)	(0.0201)
Computer Use Past	-0.499***	-0.779*	0.264	0.0204	-0.0293
	(0.173)	(0.450)	(0.143)	(0.203)	(0.0309)
Constant	-5.932	12.99***	11.56*	6.903	0.617
	(6.199)	(4.717)	(5.461)	(7.333)	(0.695)
Observations	321	325	324	324	325
R-squared			0.305		0.155

Notes: This table reports estimates from a regression of future plans and aspirations of the students on an indicator for being assigned a laptop computer and a set of covariates using a time series strategy for treatment students surveyed in primary school and again in secondary school. Covariates include age, age squared, gender, gender of the head of the household, size of the household, number of children in the household, having a computer and/or internet at baseline, other household members that use computers, and having used a computer in the past. Binary variables have a value equal to 1 for "yes" and equal to 0 for "no" (aspiring to a white-collar occupation, planning to attend college, staying in the same county, and planning to study an informatics-related major, columns 1, 2, 4 and 5 respectively). Column 3 contains school motivation and is a numeric value. The regression models are estimated using a logit regression for binary variables and ordinary least squares for numeric variables. Standard errors are presented in the parenthesis below each estimate. Significance levels for the estimates are determined as: * p < 0.05, ** p < 0.01, *** p <0.001

Time Allocation

Analysis of treatment secondary school students shows a positive and statistically significant effect of using a computer at home. Considering that these students participated in the OLPC program but no longer have an OLPC laptop in secondary school, we can infer that they purchased a computer at home. Given the single difference strategy used in this estimation, it must be noticed that this result could also be a consequence of a time trend of more computers at home during adolescence. Table 9 shows no statistically significant effects on computer use outside or home chores. There is a negative and statistically significant effect on hours outdoors and hours doing homework. Note that these effects could be a result of time trends.

Table 9: Secondary School Students Weekly Time Allocation – Time Series

	Computer Total (1)	Computer Home (2)	Computer Outside (3)	Home Duties (4)	Hours Outdoors (5)	Hours Homework (6)	Use Others (7)
Time Trend + Program Effect	**0.437**	**0.588***	**-0.213**	**1.453**	**-13.93****	**-9.404****	**-7.776***
	(0.311)	**(0.262)**	**(0.219)**	**(0.983)**	**(5.581)**	**(3.120)**	**(3.679)**
Age Baseline	-1.836	-3.201**	1.209	-0.122	-2.530	28.64*	35.34
	(1.760)	(1.323)	(0.896)	(2.117)	(30.40)	(13.80)	(23.41)
Age Squared Baseline	0.103	0.165**	-0.0535	0.0180	0.385	-1.334*	-1.774
	(0.0831)	(0.0611)	(0.0411)	(0.108)	(1.667)	(0.647)	(1.187)
Gender	-0.265	-0.324	0.0306	0.353	-2.878	-5.975*	6.707***
	(0.505)	(0.407)	(0.225)	(0.345)	(2.163)	(2.983)	(1.953)
Gender HH Head	0.114	0.0135	0.0614	-0.251	-11.20***	-7.018**	-2.089**
	(0.272)	(0.172)	(0.196)	(0.448)	(3.027)	(2.454)	(0.652)
Family Size Baseline	-0.0939	-0.191	0.0906	0.215	-3.676	-2.255***	3.507**
	(0.158)	(0.124)	(0.0620)	(0.292)	(2.529)	(0.646)	(1.247)
Family Kids Baseline	-0.474*	-0.341**	-0.159	0.273	8.714	4.757**	-2.040
	(0.251)	(0.123)	(0.128)	(0.245)	(4.978)	(1.510)	(1.308)
Computer at Baseline	1.208**	1.279***	-0.0431	-0.342	-1.216	-7.154*	3.536***
	(0.446)	(0.350)	(0.182)	(0.358)	(1.602)	(3.557)	(0.776)
Internet at Baseline	1.987***	1.790***	0.262***	-0.389***	3.469*	-4.028	6.674**
	(0.293)	(0.223)	(0.0771)	(0.0879)	(1.837)	(2.842)	(2.126)
Computer Use Other	0.521	0.462	0.179	-0.374	12.19***	9.604**	2.385
	(0.590)	(0.449)	(0.160)	(0.734)	(3.544)	(4.056)	(3.018)
Computer Use Past	-2.092***	-1.336***	-0.656**	-1.583***	9.700	1.509	4.617*
	(0.416)	(0.310)	(0.216)	(0.222)	(6.399)	(1.870)	(2.031)
Constant	13.53	19.35**	-5.192	4.028	-2.110	-122.2*	-197.8
	(8.563)	(6.570)	(4.423)	(11.08)	(139.1)	(65.38)	(121.9)
Observations	325	319	319	323	322	319	319
R-squared	0.183	0.193	0.049	0.069	0.039	0.031	0.027

Notes: This table reports estimates from a regression of weekly time allocation of the students on an indicator for being assigned a laptop computer and a set of covariates using a time series strategy for treatment students surveyed in primary school and again in secondary school. Covariates include age, age squared, gender, gender of the head of the household, size of the household, number of children in the household, having a computer and/or internet at baseline, other household members that use computers, and having used a computer in the past. All columns contain numeric values regarding total hours using a computer, hours using a computer at home, hours using a computer outside, hours on home duties, hours performing outdoor activities, hours performing homework, and hours of computer use by other family members. The regression models are estimated using ordinary least squares. Standard errors are presented in the parenthesis below each estimate. The lack of information from a control group does not allow for a difference in difference strategy, so the results are found using a time series specification in which a time trend could bias the estimate. Significance levels for the estimates are determined as: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Limitations

This study has limitations from the challenges in locating program participants (and the control group) 6 years after the program started. A potential source of bias arises from the fact that most students found and interviewed in 2017 are still in the education system and in the same study districts. Those who were not found may be systematically different from those who were. For example, students who did not perform well in school may have dropped out and were not found. Another limitation is that it was extremely hard to find students in secondary school that participated in the OLPC program or that were in the original control group. The total sample size of secondary school students is 255, which is smaller than ideal. Because of this limited number of observations, it was impossible to execute a difference-in-difference approach for the secondary school subsample.

Conclusion

This paper investigates if education policy should consider incorporating technological equipment as school inputs and teaching students how to develop digital literacy skills from an early age in order to better their education completion and labor market outcomes. Due to the nature of the OLPC program, there was expected to be an increase in students' interest in computer science aspirations and their pursuit of white-collar occupations. The results suggest that treated students increased their school motivation and interest in pursuing higher education levels. However, except for secondary school students, the findings show no effects on aspirational changes toward computer science disciplines and white-collar occupations. This result may be because these primary school students are very young and have not yet received information about the returns to education for each occupation. It is important to mention that the findings suggest that treated students increased their intention to migrate out of their district, presumably to attend college in the city or to pursue a job not provided locally.

This paper's second area of focus analyzed the role of a computer in a student's daily activities. The findings show that the program has statistically significant positive impacts on hours of computer use across all groups and specifications. For the case of hours performing household chores, no significant effects were identified. Negative and statistically significant impacts on hours outdoors and doing homework were found only for secondary school students. The results obtained display robustness across repeated cross-sections and panel data strategies, presenting little change in the sign of the coefficients and statistical significance. Future research will help explain the lack of effects regarding aspirations on computer science disciplines and white-collar occupations. Further studies are needed to shed light about the effectiveness and efficiency of the program through a cost-benefit analysis, as well as to calculate the effects of laptops and other devices with connectivity on education outcomes through remote learning.

Acknowledgments

I thank the Quirós Tanzi Foundation for allowing me to evaluate their project. All opinions and any errors are solely my own.

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