The Impact of a One Laptop per Child Program on Learning: Evidence from Uruguay[1]

Resumen

En este artículo se presenta evidencia sobre el impacto en el desempeño en matemáticas y lectura del programa Un Computador por Niño con mayor despliegue y el único implementado a escala nacional: el Plan Ceibal en Uruguay. Se cuenta con la fecha exacta de entrega de la laptop para cada estudiante de la muestra. Ello habilita a utilizar los días de exposición al Plan Ceibal como una medida de la intensidad del tratamiento. Empleamos una estrategia de diferencias en diferencias incluyendo efectos fijos a nivel de individuoyaislamos el efecto del programa de una potencial heterogeneidad en la tasa a la que las escuelas de Montevideo y el resto del Uruguay logran mejoras en el desempeño de sus estudiantes en ausencia del programa. Nuestros resultados sugieren que en los primeros dos años de su implementación, el programa no tuvo efectos en los puntajes de matemáticas y lectura.

Palabras clave: tecnología, educación, evaluación de impacto

Abstract

We present evidence on the impact on students´ math and reading scoresof one of the largest deploymentsof a One Laptop PerChild programand the only one implemented at a national scale: Plan Ceibal in Uruguay. We have the exact date of laptop delivery for every student in the sample. This gives us the ability to use a continuous treatment, where days of exposure are used as a treatment intensity measure. We use a difference-in difference strategy including fixed effects at the individual level and identify the effect of the program net of potential heterogeneity in the rate schools located in Montevideo and the rest of Uruguaygain improvements on student's achievement over time in the absence of the OLPC program. Our results suggest that in the first two years of its implementation the program had no effects on math and reading scores.

1.Introduction

In recent years many countries have made substantial investments in One Laptop per Child (OLPC) programs, while others are about to start implementing this type of interventions.As their name describes, OLPC programs provide students with a laptop designed to promote learning.It has been argued that computers may impact on educational outcomes by tailoring contents to the need of each student(Hornbeck, 1991; Koedinger et al. (1997) cited by Bulman and Fairlie(2015); Fullan and Langworthy (2013)).In addition, they may increase the amount of instruction students receive as students can use computer aided instructional programs also without the direct supervision of teachers (Cuban, 1993; Barrow Markman and Rouse, 2009; cited by Bulman and Fairlie (2015)). Also, Hornbeck (1991),Cuban (2003) and Fullan and Langworthy (2013)argue that because of their interactive nature computer aided instruction may motivate children's learning more than traditional methods and enhance self-directed learning.[2] Instead, Belo Ferreira and Telag (2014) propose a model in which time spent using computers may be unproductive. This paper contributes to the study of the effect of OLPC programs on students reading and math scores using a quasi-experimental design and data from Uruguay, the first country to implement anOLPC program at a national scale (Plan Ceibal) and currently one of the largest deployments with one million laptops delivered.[3]

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[2] Hornbeck (1991), cited by Cuban (1993) p. 188, writes "The computer motivates. It is nonjudgmental. It will inform a student of success or failure without saying by word or deed that the student is good or bad. The computer individualizes learning, permitting mastery at one's own pace. In most instances, the learner has far more autonomy than in many other teacher directed settings....Such generic qualities allow the learner more often than not to be in charge. This is a quality missing in the lives of many students, especially those who are at-risk, due to environmental, physical, mental or language disabilities."

[3] Public primary school students and teachers (and more recently junior high students) were provided with a laptop and internet access. By October 2013, Plan Ceibal had distributed one million laptops. This figure is larger than the number of beneficiaries because XOs are exchanged for more powerful laptops when students reach junior high.

Although relatively abundant, the literatureon the effects of the use of computers on educational outcomes is still mixed.Fairlie and Robinson (2013) find that the use of computers at home has no effect on children's educational outcomes, while Vigdor and Ladd (2010) and Malamud and Pop-Eleches (2011) report a negative effect. Similarly, Angrist and Lavy (2002) study the impact of computers at school and find a negative impact, while Machin et al. (2007) find the contrary.

Banerjee et al. (2007) concentrate on the impact of specific software on math and find a substantial positive effect. Unfortunately, the effect is short-lived and disappears within a year of the end of treatment. Carrillo et al. (2010) evaluate a project that provides computer-aided instruction in math and reading and find a positive effect in math and no effect in reading. By means of a randomized controlled trial evaluation Mo et al. (2013) analyze the impact of an intervention in 13 migrantschools of Beijing. The intervention involved the distribution of laptops with learning/remedial software installed, plus a single training session on the use of the computer. No training to teachers as to how to use computers to improve the learning/teaching process was provided. The authors find a positive effect on math (only significant at the 10% level) but no effect on reading.

So far, the evidence in the field of OLPC impact evaluation comes from only one study implemented in Peru. Cristia et al. (2012) report results from a large-scale randomized control trial (RCT) evaluation of an OLPC program in 319 public schools in small and poor communities of rural Peru. Most treated schools had no access to internet and the distribution of laptops was not coupled with training to teachers on how they may use computers to improve teaching and learning. Treatment and controls were followed for 15 months. The authors find no

effect on either math or reading, though some statistically significant impact on cognitive skills, as measured by a Raven's Progressive Matrices test, was detected.[4]

Unlike the study by Cristia et al. (2012), our study is not particularly targeted to evaluate the impact of the OLPC program in the context of rural schools in poor communities. Instead, our evaluation survey delivers a representative sample of all schools in Uruguay, both rural and urban. We use a difference-in-difference strategy (DiD) to estimate the impact of Plan Ceibalon educational achievement. The analysis exploits the fact that the rollover of the program was based on geographic criteria and not on students' school performance. The exact date at which each student received the laptop is available. This gives us the ability to calculate with no error a continuous measure of treatment as the number of days that each student has been exposed to the program by the time of the follow-up date (normalized to years). We control for potential systematic differences in school improvement over time between schools in Montevideo (the capital of Uruguay) and the rest of Uruguay. Also, given that there is some within-school variation in hand-in dates, we are able to control, keeping an individual fixed-effects framework, for potential heterogeneity in the rate schools gain improvements on student's achievement over time in the absence of the OLPC program (i.e. we allow each school to follow a different learning growth curve over time due to unobservable time-varying heterogeneity).

Our main estimates are based on a panel of students first contacted in October 2006 when they attended third grade in primary school and subsequently followed-up in October 2009, when most of them were attending sixth grade (i.e. final year of primary school). By the end of 2009,

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[4]There is a second study on Nepal not currently available online (Sharma, 2012). This study uses a DiD estimator applying a quasi-experimental design and reports a negative effect on reading but no effect on math.

all primary school students had received their laptops but while some had been exposed to the program for almost two years, others had been treated for less than a month. This variation in the intensity of treatment is what allows us to identify the causal effect of the Ceibal program on children's scores, net of observable and unobservable individual characteristics and controlling for potential systematic differences in regional or school educationalimprovements over time. Findings suggest the program had no impact on either reading or math scores. These findings also hold if the within-school treatment variation is discarded and the impact of the program is estimated analyzing a panel of schools that exploits only the between-school treatment variation and allows exclusively for heterogeneity in the learning growth curve of Montevideo and the rest of Uruguay in the absence of the OLPC program.The study provides a hint on why we observe no effect on scores as we have information on laptops' main use in class and observe that teachers use the laptop mainly to search for information in the web.Also, teacher training has so far been optionalwhile as Fullan et al. (2013) argue the challenge is to train teachers continuously to achieve permanent use of laptops and their incorporation into pedagogical practices.

The rest of the paper is organized as follows. Section 2 describes the program and data. Section 3 discusses the identification strategy. Section 4 reports results. Finally, Section 5 concludes.

2. Data and background information

2.1 OLPC program in Uruguay: Plan Ceibal

Plan Ceibal'skey objective is to promote digital inclusion among Uruguayan children.[5]It also intendsto improve learning both at school and at home.[6]Public primary school students and teachers (and more recently junior high students) are provided with a laptop and internet access.[7] Students who were granted a laptop (XO) while in primary school are encouraged to exchange it for standard laptops during junior high.[8]By October 2013, Plan Ceibal had distributed one million laptops and had benefitted approximately 625,000 students with an estimated cost of 180 dollars per laptop.[9] The number of laptops distributed is larger than the number of beneficiaries because XOs are exchanged for more powerful laptops when students reach junior high.

The project provides schools and other areas such as public squares with wireless internet connection. Students take the laptops home and can often access internet either through the school'swi-fi or through free internet available at public places. The software installed in laptops containsstandard programs to write, make calculations, programming environment (Tortugarte, Etoys, Scratch, Pippy), browse the web (Navegar), draw and design (Tuxpaint, Pintar), study geography (Geo gebra/ Dr. Geo, Conozco Uruguay), take photos and make videos, produce and

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[5]Ceibal stands for*Conectividad Educativa de Informática Básica para el Aprendizaje en Línea.*
[6] Presidential decrees April 18th 2007 and December 15th 2008.
[7]In Uruguay, public education is widespread. Approximately 80% of primary school children attend public schools.
[8] XO is a type of laptop used by OLPC programs.
[9] The number of beneficiaries excludes pre-school students. Laptops are also provided to pre-school students although they do not take them home.

edit sounds (Tam tam mini, Sara), learn English (English for fun),play games (Laberinto), as well as books.

The initiative was launched in a pilot province in 2007.[10]During the first semester of 2008 laptops were distributed mostly in schools in the western provinces and in the eastern provinces during the second semester of 2008, reaching Montevideoand Canelones (a province nearby Montevideo)in 2009. By October 2009, all students and teachers in public primary school had been granted a laptop (UNESCO, 2011, p.34).The government decided to begin distributing laptops in the rest of the provinces and end up in the capital, Montevideo, in order to shift the focus which has always favored centralism (Balaguer, 2010).

It should be noted that Ceibal is an institution that reports directly to the President. As such, it is not part ofthe *AdministraciónNacional de EducaciónPública* (ANEP), the central authority responsible for education in Uruguay. While this feature speeded the implementation of the program, it also implied that the coordination with teachers has not been as fluent as it would have been desired. Right from the start, there were optional courses available for teachers (both in-person and online). Training was only compulsory for school inspectors and teachers who applied as external consultants to support schoolsin the process of incorporation of laptops in the teaching process (*Maestros Dinamizadores*).[11]Plan Ceibal did not entail formal parental involvement until 2012. Since then on, some schools that were assigned a Ceibal Support Teacher (*Maestro de ApoyoCeibal*), organized workshops involving relatives and people that live

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[10] The first province that received laptops by the end of 2007, Florida, was selected to be the first because it is situated close to Montevideo.

[11] From 2012 onwards, ANEP created the role of *Maestro de ApoyoCeibal* (MAC), assigning a teacher to each school to provide support in terms of technologies of information and communication. Training for this kind of teachers is compulsory.

in the neighborhood who are interested in learning how to use the laptop. Theseworkshopshave been implemented in very few schools so far.

The data set we analyze includes a survey among students, family, teachers and school principals regarding Plan Ceibal which was carried out in October 2009. According to this survey,by 2009 87% of school principals had internet access at school but connectivity did not allow every grade in a school to connect simultaneously. In fact, 83% of school principals argued that less than 50% of students in a school could connect at the same time. Principals' perceptions of the impact of Ceibal were extremely positive in all aspects, especially in regardto students' motivation to work in class and learning (see Table A.1 in the Annex). As for teachers, 59% answered that they used a computer in a daily basis.Regarding the students surveyed, 65%of the students' households owned a personal computer or a laptop (other than Ceibal's laptop) and 47% had internet access either through broadband or through Ceibal's wireless signal.Almost all parents answered that the students used the Ceibal laptop at home and 80% also used another computer (see Table A.2 in the Annex).

2.2 Data

We use panel data from students evaluated both in 2006and 2009. Both waves included math and reading standardized tests together with questionnaires to students, their families, teachers and the schoolprincipals. The first wave corresponds to the SERCE evaluation (*Segundo Estudio Regional Comparativo y Explicativo*) designed by UNESCOand implemented in October 2006.

By that time, the students analyzed in this paper were attending third grade.[12]The second wavecorresponds to the *V EvaluaciónNacional de Aprendizajes* carried out in October 2009 by ANEP. Both studies are representative at the national level. Among the sample of schools evaluated, ANEP included schools that had participated in the SERCE evaluation in order to build a panel.From 6222 students in public schools that had participated in the SERCE evaluation in October 2006, 2645 also participated in the *EvaluaciónNacional de Aprendizajes* in 2009. By that time, the majority was attending the last year of primary school.Students that had participated in the evaluation in 2006 and had in the meantime repeated a grade (i.e. that were attending 4th or 5th grade),were also evaluated in 2009.

Student identification numbers and full names were available for schools that participated in the October 2009 evaluation.This enabled us to match 92% of students in public schools who were both evaluated in 2006 and 2009with the administrative records of Plan Ceibal. The administrative records contain the exact date in which each student received his/her laptop. Table 1 shows the distribution of observations matched by geographic location, month and year of receipt. In order to assess whether the rollout of the program is exogenous, we plot average reading and math scores in 2006 (prior to the implementation of Plan Ceibal) by the date when most children in each school received the laptop. That is, Figure 1.1 and 1.2 show average reading and math scores, respectively where the x axis represents schools in the order in which they received the laptop from Plan Ceibal. We also include baseline repetition rates by the date when most children in each school received the laptop in Figure A.1. As these figures suggest the rollout criteria does not seem to be correlated with prior educational outcomes.
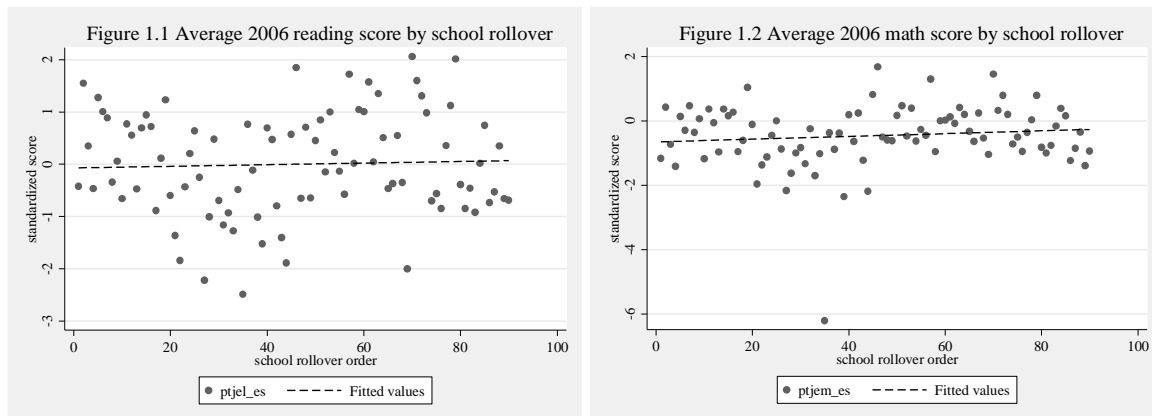
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[12]This evaluation was performed in sixteen Latin American countries plus one state in Mexico to students attending third and sixth grade. We concentrate on those students that were attending third grade because only this cohort was evaluated again when attending sixth grade.

Table 1. Percentage of students by date of laptop receipt and geographic area

	Rest of the country			Montevideo		
	2007	2008	2009	2007	2008	2009
January		0,35%				
February						
March			0,04%			
April		3,73%	9,91%		0,04%	
May		7,94%	5,03%			
June		9,03%	0,18%			7,52%
July		2,85%				11,21%
August		0,00%	0,11%		4,29%	13,15%
September		3,20%	0,11%		0,04%	8,05%
October		4,18%	0,04%			0,14%
November		4,89%				
December	3,90%	0,11%				
Total	3,90%	36,27%	15,40%		4,36%	40,07%

Note: The delivery date includes day, month and year. For the purpose of this table observations are aggregated by month and year

Figure 1. Baseline averageschool scores by Plan Ceibal rollover order (2006)

Figure 1.1 Average 2006 reading score by school rollover

Figure 1.2 Average 2006 math score by school rollover

Within a school, laptops were distributed to most students on the same day and those who were absent on that day received it later. The within-school variation in hand-in dates explains slightly more than 2% of the total hand-in date variation in our sample.To test whether having received

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the laptop late within a school is correlated with any individual observable characteristic, we estimate a probit model including school fixed effects and clustering standard errors at the school level (see Table 2). No variable appears to be statistically significant.

Table2. Probability of receiving the laptop later than the rest of the students in a school

Probability of receiving the laptop later than the rest of the students in a school	
Standardisedreading score	-0.1050
	(0.076)
Standardisedmath score	-0.0761
	(0.097)
Male	-0.0181
	(0.083)
Mother's education: Did not finish primary	0.2256
	(0.199)
Mothers' education: Junior high	0.1445
	(0.225)
Mothers' education: Secondary school or College	0.1310
	(0.240)
Information about mother's education is missing	0.2754
	(0.231)
Number of persons living at home	-0.0043
	(0.028)
Information about persons living at home is missing	-0.0121
	(0.229)
Studentwork	0.2125
	(0.154)
Information about student work is missing	0.0341
	(0.154)
Schoolfixedeffects	Yes
Obs.	1888

Standard errors are clustered at the school level.
*** p<0.01, ** p<0.05, * p<0.1

Table 3presents descriptive statistics for those students who participated in both evaluations and for whom we have information on the date they received the laptop. Reading and math tests were standardized to mean 0 and standard deviation equal to 1.

Table 3. Descriptive statistics

Definition	October 2006			October 2009		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Standardisedreading score	2057	0,00	1,00	2057	0,00	1,00
Standardisedmath score	2080	0,00	1,00	2080	0,00	1,00
Days exposed to the program up to the date of the reading test, normalized to years	2057	0,00	0,00	2057	0,71	0,51
Days exposed to the program up to the date of the math test, normalized to years	2080	0,00	0,00	2080	0,72	0,51
Male; 0 otherwise	2080	0,52	0,50	2080	0,52	0,50
Mother's education: Did not finish primary school; 0 otherwise	2080	0,11	0,31	2080	0,08	0,28
Mothers' education maximum level completed: Primary school; 0 otherwise	2080	0,43	0,50	2080	0,42	0,49
Mothers' education maximum level completed: Junior high (9 years of schooling); 0 otherwise	2080	0,21	0,41	2080	0,25	0,43
Mothers' education maximum level completed: Secondary school or College; 0 otherwise	2080	0,13	0,33	2080	0,14	0,35
Information about mother's education is missing; 0 otherwise	2080	0,12	0,32	2080	0,11	0,32
Number of persons living at home; 0 if information is missing	2080	4,07	2,92	2080	4,59	2,39
Information about persons living at home is missing; 0 otherwise	2080	0,24	0,43	2080	0,10	0,30
Number of primary schools that participated in the evaluation	90			90		

Note: Estimates also include variables regarding year of birth, number of books at home, number of rooms, access to drinkable water, phone, cable, dvd, microwave, washing machine, dishwasher, internet and computer at home. Also information regarding whether the student works and is paid for that and regarding household type. For those whose information on number of persons in the house is missing the variable persons has been recoded to 0.

3. Methodology

The identification strategy exploits the fact that we observe laptop hand-in dates for almost everyindividual in the panel. Our treatment variable is the number of days exposed to the program, reflecting the intensity of the treatment. To facilitate the interpretation, we normalize this variable into years of exposure. We start by estimating the following model:

$$Y_{ist} = X_{ist}\boldsymbol{\gamma} + \beta T_{ist} + \delta_t + c_i + u_{ist} \qquad (1)$$

whereY_{ist} represents the test score of individual$i$ at school s in wave t; $i=1,...,N$, $s=1,...,90,$and $t=2006, 2009.$$T_{ist}$ is the treatment variable that reflects the number of days(in terms of years) the student has had the laptop by t. X_{ist} are time-varying characteristics, $\delta_t$is a dummy indicator of year 2009,c_i are individual fixed effects, and u_{ist} is the idiosyncratic error term. In all models we considered the explanatory variables to be exogenous. In other words, we assume that the condition $E(u_{ist}|X_{is}, T_{ist}, \delta_t, c_i) = 0$ is met. Also, for every model we report robust standard errors (i.e. we use the White-Huber-Eiker estimator of the covariance matrix) clustered at the school level. The model is fitted by fixed-effects. We work with a balanced panel at the individual level because we only have two waves and are implementing a fixed-effects estimator.

The specification in equation (1) assumes that schools follow a common trend as in the standard differences-in-differences model. However, given that there is some within-school variation in hand-in dates, we relax the common trend assumption and allow for heterogeneity in the rate schools gain improvements on student's achievement over time in the absence of the OLPC

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program (i.e. we allow each school to follow a different learning growth curve over time due to unobservable time-varying heterogeneity). This strategy allows us to control for potential time-varying heterogeneous shocks to schools – for instance, changes in the school management style over time – that otherwise would be interpreted as part of the Plan Ceibal's treatment effect.

$$Y_{ist} = X_{ist}\gamma + \beta T_{ist} + \delta_t + \pi_s \times \delta_t + c_i + u_{ist} \quad (2)$$

Equation (2) enables to control for changes in school level time-varying unobserved heterogeneity relative to the baseline period by including interactions between school dummies and the time dummy $\pi_s \times \delta_t$ (Wooldridge 2002, p. 267). Model (2) is also estimated by individual fixed effects.

However, the within school variation in laptops hand-in dates is not large. Because there is evidence that suggests that there are differential trends over time betweenMontevideo (the capital) and the rest of Uruguay (see Table5), we would like to control for the likely event that schools in Montevideo and schools in the rest of Uruguay gain improvements in achievement at different rates in the absence of the OLPC program. In other words, we would like to control for potential time-varying shocks to schools that are different in the capital and the rest of Uruguay:

$$Y_{ist} = X_{ist}\gamma + \beta T_{ist} + \delta_t + Montevideo \times \delta_t + c_i + u_{ist} \quad (3)$$

whereMontevideo represents a dummy indicating schools located in the capital. Equation (3) enables to control for changes in region level time-varying unobserved heterogeneity relative to

the baseline period by including interaction terms between the Montevideo dummy and year 2009. Again, model (3) is estimated by individual fixed effects. Robust standard errors clustered at the school level are reported.

We also implement a robustness check using an estimator that does not exploit the within-school variation of the treatment. Namely, we collapse the data at the school level to form a balanced panel of schools for the years 2006 and 2009. In this specification the dependent and control variables are mean averages at the school level. The estimated model is:

$$Y_{st} = X_{st}\boldsymbol{\gamma} + \beta T_{st} + \delta_t + Montevideo \times \delta_t + c_s + u_{st} (4)$$

which is fitted by fixed effects at the school level. Robust standard errors clustered at the school level are reported.

4. Results

Table 4 reports results from estimating a fixed effects model at the individual level (Eq. 1 in Section 3) including time-varying regressors. Standard errors are clustered at the school level. Time varying characteristics include: the number of persons living in the house, the number of rooms in the house, access to drinking water, access to durable goods (telephone, cable tv, dvd, microwave, washing machine and dishwasher) and a dummy that indicates whether the child works. Under this model, there seems to be a positive and significant effect in math: one year of exposure to Plan Ceibal would increase math scores in 0.16 standard deviations. When we

consider only observations from the provinces excluding Montevideo, although the magnitude of the coefficient is similar, the effect is no longer significant.Note that variation in time of exposure to Ceibal holds even after excluding Montevideo with a maximum of exposure of almost two years and a minimum of almost days as the second test took place in October 2009 (see Table 1).

Table 4. Individual fixed effects (2006-2009).

	Allprovinces						**Excluding Montevideo**
Dependent variable: reading scores							
Treatment (days of exposure normalized to years)	0.0428	0.0350	0.0320	0.0319	0.0337	0.0313	0.059
	(0.051)	(0.051)	(0.050)	(0.051)	(0.049)	(0.050)	(0.083)
Observations	4,114	4,114	4,114	4,114	4,114	4,114	2338
Number of students	2,057	2,057	2,057	2,057	2,057	2,057	1169
Dependent variable: math scores							
Treatment (days of exposure normalized to years)	0.1632***	0.1619***	0.1613***	0.1604***	0.1632***	0.1623***	0.1543
	(0.053)	(0.053)	(0.053)	(0.054)	(0.054)	(0.055)	(0.104)
Observations	4,160	4,160	4,160	4,160	4,160	4,160	2338
Number of students	2,080	2,080	2,080	2,080	2,080	2,080	1169
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of persons at house (time-varying)	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of rooms at home (time-varying)	No	No	Yes	Yes	Yes	Yes	Yes
Drinkable water at home (time-varying)	No	No	No	Yes	Yes	Yes	Yes
Durable goods at home variables (time-varying)	No	No	No	No	Yes	Yes	Yes
Work (time-varying)	No	No	No	No	No	Yes	Yes

Standard errors are clustered at the province level.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4does not control for potential heterogeneity in the rate schools gain improvements on student's achievement over time in the absence of the OLPC program across the country. To evaluate the existence of pre-existing differences in trajectories among regions we use data from the educational authority (ANEP) on teacher seniority (percentage of teachers with less than 5 years of seniority) for all public schools in Uruguay.We estimate the effect of differential trends by region on teacher seniority at the school level by including two dummy variables: Montevideox2006 and Montevideox2007, as well as time dummies and school fixed effects. Robust standard errors clustered at the school level are reported. We observe a differential evolution of teacher seniority in Montevideo and the rest of the country during 2007, significant at the 1% level (see Table 5). This suggests equation 1 should not be estimated without controlling for divergent trajectories among regions. Otherwise, the treatment variable is confounded with the pre-existent differences in learning trajectories across schools.

Table 5. Testing for the importance of regional changes across time in seniority

with school fixed effects

Dependent variable: seniority (% teachers with less than 5 years of experience)	2005-2006-2007
Montevideo*Year 2006	-1.252
	(1.287)
Montevideo*Year 2007	-4.999***
	(1.427)
Observations	6,551
Number of schools	2,340
Time dummies	Yes
Schoolfixedeffects	Yes

Source: own estimates using Monitor Educativo (ANEP).

Standard errors are clustered at the school level.

*** p<0.01, ** p<0.05, * p<0.1

To address this issue, we then estimate an individual fixed effects model including school-time dummies (Eq. 2 in Section 3, Table 6). Under this specification, treatment effects in math are no longer significant.The possibility of including school-time dummies is due to the presence of a 2% within school treatment variation. However, given that this variation is not large and thereby standard errors increase significantly,in the last column of Table 6we substitute school-time dummies for a Montevideo-time dummy (Eq. 3 in Section 3). The results represent our preferred specification and also show that the effect in math is not significant.Under this specification, standard errors are comparable to those of Cristia et al. (2012) for math.

Table 6.Individual fixed effects including school-time dummy or Montevideo-time dummy

(2006-2009)

Dependent variable: reading scores							
Treatment (days of exposure normalized to years)	-0.0544	-0.0142	-0.0104	-0.0029	-0.0008	-0.0027	-0.0664
	(0.408)	(0.402)	(0.389)	(0.387)	(0.395)	(0.388)	(0.110)
Observations	4,114	4,114	4,114	4,114	4,114	4,114	4,114
Number of students	2,057	2,057	2,057	2,057	2,057	2,057	2,057
Dependent variable: math scores							
Treatment (days of exposure normalized to years)	-0.1658	-0.1561	-0.1582	-0.1620	-0.1513	-0.1601	0.0394
	(0.283)	(0.289)	(0.279)	(0.281)	(0.280)	(0.282)	(0.096)
Observations	4,160	4,160	4,160	4,160	4,160	4,160	4,160
Number of students	2,080	2,080	2,080	2,080	2,080	2,080	2,080
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-time dummies	Yes	Yes	Yes	Yes	Yes	Yes	No
Montevideo-time dummy	No	No	No	No	No	No	Yes
Number of persons at house (time-varying)	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of rooms at home (time-varying)	No	No	Yes	Yes	Yes	Yes	Yes
Drinkable water at home (time-varying)	No	No	No	Yes	Yes	Yes	Yes
Durable goods at home variables (time-varying)	No	No	No	No	Yes	Yes	Yes
Work (time-varying)	No	No	No	No	No	Yes	Yes

Standard errors are clustered at the provincelevel.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

We then discardthe within-school treatment variation to estimate the impact of the program by collapsing data at the school level (Eq. 4 in Section 3, Table 7). When exploiting only the between-school treatment variation and allowing for heterogeneity in the learning growth curves of Montevideo and the rest of Uruguay in the absence of the OLPC program (i.e. including a Montevideo-time dummy), we do not observe any significant impact on reading or math.Also, if

we estimate the model excluding Montevideo (thereby without including a Montevideo-time dummy) we do not find a significant effect in math either and the magnitude drops substantially.

Table 7. Exploiting solely between school variation

	Allprovinces		Excluding Montevideo
Dependent variable: reading scores			
Treatment (days of exposure normalized to years)	0.0879	-0.0124	0.0496
	(0.058)	(0.103)	(0.118)
Observations	180	180	120
Number of schools	90	90	60
Dependent variable: math scores			
Treatment (days of exposure normalized to years)	0.1344*	-0.0604	-0.0174
	(0.069)	(0.116)	(0.146)
Observations	180	180	120
Number of schools	90	90	60
Time dummies	Yes	Yes	Yes
Montevideo-time dummy	No	Yes	No
Number of persons at house (time-varying)	Yes	Yes	Yes
Number of rooms at home (time-varying)	Yes	Yes	Yes
Drinkable water at home (time-varying)	Yes	Yes	Yes
Durable goods at home variables (time-varying)	Yes	Yes	Yes
Work (time-varying)	Yes	Yes	Yes

Standard errors are clustered at the schoollevel.
*** p<0.01, ** p<0.05, * p<0.1

Finally, we test for heterogeneous effects across children with differentmother's educationunder the main specification in Table 6(including aMontevideo-time dummy) and do not find any effects either in reading or math (see Table 8).

Table 8. Heterogeneous effects by mother education

	Reading	Math
Treatment (years)	-0.0618	-0.0335
	(0.113)	(0.139)
Treatment (years) * Mom's education: Primary school	-0.0069	0.1256
	(0.093)	(0.104)
Treatment (years) * Mom's education: Junior high	-0.0096	0.0205
	(0.110)	(0.099)
Treatment (years) * Mom's education: Secondary school or College	0.1727	-0.0188
	(0.126)	(0.114)
Treatment (years) * Mom's education is missing	-0.2640	0.1609
	(0.173)	(0.161)
Observations	4.114	4,160
Individuals	2.057	2,080
Time dummies	Yes	Yes
Montevideo-time dummy	Yes	Yes
Number of rooms at home (time-varying)	Yes	Yes
Drinkable water at home (time-varying)	Yes	Yes
Durable goods at home variables (time-varying)	Yes	Yes
Work (time-varying)	Yes	Yes

Standard errors are clustered at the school level.

*** p<0.01, ** p<0.05, * p<0.1

Tables A.3and A.4 in the Annex attempt to provide some hints regarding the reason why Plan Ceibal does not seem to have had an impact on reading and math. First, the use of laptops in class is not widespread across all public schools (see Table A.3). Second, Table A.4suggests that students use their laptops in class mostly to search information from internet (68% answered that looking for information in the net is the most frequent use of the laptop in class) rather than for

training using drills and exercises.[13] The fact that laptops are used in class mainly to download information suggests that impacts on reading and math should not be expected.

6. Conclusion

In this paper, we apply panel data analysis to estimate the impact of Plan Ceibal (a nationwide OLPC program implemented in Uruguay) on reading and math skills. Precise information of the date in which each student received the laptop is available. There seem to be differential trends in the evolution of educational inputs among regions. For this reason, we identify the effect of the program net of potential heterogeneity in the rate schools located in Montevideo and the rest of Uruguay gain improvements on student's achievement over time in the absence of the OLPC program across the country. Given that there is some variation in the date of laptop delivery across individuals within the same school, we also run an alternative specification where we allow each school to follow a different learning growth curve over time due to unobservable time-varying heterogeneity.

Our findings suggest that the program did not have an impact on reading and math scores. This is in line with most of the literature on the impact of computers on learning, in which either no effects or negative effects are found (Angrist and Lavy 2002; Vigdor and Ladd, 2010; Malamud and Pop-Eleches, 2011; Cristia et al., 2012 and Fairlie and Robinson, 2013). A particularly important feature of the program is that teacher training has been, up to now, optional. Furthermore, when analyzing descriptive data on the frequency of laptop use during class and the

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[13] The fact that a significant percentage of students answer that the main use of the laptop in class is to play games should not be interpreted necessarily as indicating that the laptops cause a distraction for learning, as laptops contain some games developed for educational purposes.

tasks for which computers are used in class, we observe that every-day use of laptops in class is not widespread across all public schools. Besides, laptops' main use in class is to search for information in the internet rather than for training using drills and exercises. Thesecharacteristics provide a hint on why it is reasonable not to find an effect on these skills.

Both Nesta (2012) and Fullan and Langworthy (2013) highlight that technology cannot impactlearning unless the teaching-learning process is transformed.In order to impactlearning, technology must no longer be conceived as a tool to gather information, but rather as a tool that radically changes the teachingand learning process. In this context, the role of teachers should no longer be to transmit knowledge but to convey learning attitudes, support peer learning, and help children in converting information into knowledge (Nesta, 2012; Fullan and Langworthy, 2013).Fullanand Langworthy (2013) suggest that technology affects learning only when it is used as a tool for stimulating intrinsic motivation and for creating commitment to continuous improvement of the teaching- learning process, as well as when it is used as a tool for improving communication and collective work between teacher and students. According to these authors, technology playsan important role in enhancing self-directed learning because it allows active students to construct knowledge and meaning by searching and conducting enquiries using the internet as a major source of information. Technology can also provide instant feedback and improve communication between teachers and students, potentially taking the learning experience beyond the classroom. However, despite all the advantages and promises that computer-aided learning make potentially available, Fullan and Langworthyremind us that at the end the teaching-learning process is intrinsically human. As such, technology can only bear its fruits when both students and teachers interact with the machine in a sustained and imaginative

way that transforms the teaching-and-learning process to improve understanding and development of skills.

Plan Ceibal has taken on board these aims in the last few years, incorporating many programs that help teachers use the laptop in class.[14] The students analyzed in this study received their laptops when Plan Ceibal had just started and, thereby, did not benefit from the recent changes in the program while in primary school. In future research it would be particularly interesting to evaluate the impact on learningas well as on other outcomes of the new resources that Ceibal has now made available.

An important clarification is due. The fact that we do not find significant effects of the use of computers on children's reading and math scores does not mean that using a computer for learning at school is futile. Clearly, there may be cognitive skills other than the ones tested in math and reading exams that computers help developing. For instance, other studies have found a positive impact on cognitive skills based on Raven's Progressive Matrices test (Malamud and Pop-Eleches, 2011; Cristia et al., 2012).

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[14] For instance, as was mentioned before, nowadays each school has a teacher whose role is to support others in the use of the laptop. Also, laptops are now used to perform online tests designed by the education authority. Teachers can immediately access the test questions and results and work on strengthening the identified problems.

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Appendix

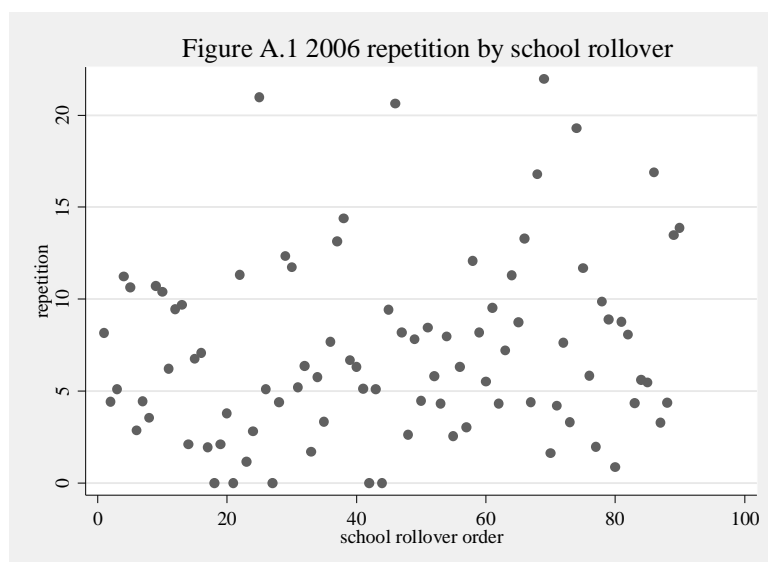**Figure A.1. Baseline repetition rates by Plan Ceibal rollover order (2006)**

Figure A.1 2006 repetition by school rollover

Table A.1. In your opinion, what was the impact of Plan Ceibal in your school? Question asked to school principals.

	Positive	Negative	Didnotinfluence	Don'tknow
Attendance	31,3%		68,4%	0,3%
Students' motivation to work in class	86,0%		13,0%	1,0%
Students' motivation to do homework	72,4%		18,1%	9,5%
Organization of work in class	60,5%	14,1%	20,3%	5,1%
Behavior	63,3%		36,1%	0,5%
Students' self-esteem	84,3%		5,9%	9,8%
Learning	85,8%		11,5%	2,7%
Teachers'motivation to work in class	77,1%		20,5%	2,5%
Parents' schoolinvolvement	53,6%		46,2%	0,2%

Source: V Evaluación Nacional de Aprendizajes, ANEP 2009,
weighted.

Table A.2. Who uses a computer at home? Question asked to parents.

Who uses a computer at home?	Ceibal laptop	Anothercomputer
Thestudentbeingevaluated	97,3%	79,7%
His/her younger siblings who do not have their own Ceibal laptop	30,2%	36,2%
His/her older siblings who do not have their own Ceibal laptop	33,6%	56,6%
His/hermother	40,5%	70,3%
His/herfather	23,8%	56,0%
Others	13,5%	24,2%

Source: V Evaluación Nacional de Aprendizajes, ANEP 2009, weighted.

Table A.3. Frequency of laptop use in class (October 2009)

	In your reading classes: How often do you use the laptop?	In your math classes: How often do you use the laptop?
Every day or almost every day	37,6%	26,0%
One up to three times per week	38,0%	25,4%
Less than once per week	24,3%	48,6%

Source: V Evaluación Nacional de Aprendizajes, ANEP 2009, weighted.

Table A.4. Main laptop use in classand at home (October 2009)

	School	Home
Search information in the internet	67,5%	40,1%
Write a text	13,1%	5,0%
Spreadsheet	0,2%	0,0%
Calculator	0,8%	0,2%
Send emails	1,3%	1,9%
Play	11,5%	38,6%
Chat	2,7%	8,6%
Other	2,9%	5,6%

Source: V Evaluación Nacional de Aprendizajes, ANEP 2009, weighted.