



New Technologies in Households: Is there an Educational Payoff? Evidence from Argentina

Nuevas tecnologías en los hogares: ¿Hay una recompensa educativa? Evidencias para Argentina

María Marta Formichella^a, María Verónica Alderete^b, Gisela Di Meglio^c

^a IIESS, Universidad Nacional del Sur- CONICET; Departamento de Economía, UNS. Argentina.
<https://orcid.org/0000-0002-2057-0938> mformichella@iieess-conicet.gob.ar

^b IIESS, Universidad Nacional del Sur- CONICET; Departamento de Economía, UNS. Argentina.
<https://orcid.org/0000-0002-9617-7526> mvalderete@iieess-conicet.gob.ar

^c Departamento de Análisis Económico, Universidad Complutense de Madrid, Madrid, España
<https://orcid.org/0000-0001-6184-167X> gdimeglio@ccee.ucm.es

ARTICLE INFO

Key words:

ICT
School achievements
Secondary Education
Matching
Argentina

Palabras clave:

TIC
Rendimiento educativo
Educación secundaria
Emparejamiento
Argentina

ABSTRACT

Information and Communication Technologies (ICT) are now deeply embedded in educational systems across both developed and developing countries. However, research on the impact of ICT on educational outcomes is still inconclusive. This paper examines whether computers with Internet access at student's home has a payoff in terms of mathematics, reading and science scores. Moreover, it assesses the effects of ICT in households on school failure. To do so, the research employs a matching procedure using the PISA database available for Argentina. Results show that educational performance increases between 2.5% and 3.5% among the group of students with a home computer connected to the Internet, depending on the skill considered and the matching method employed. Furthermore, ICT access at home reduces school failure by between 8% and 18%. These findings would support public policies recently implemented in the region aimed at the universalization of ICT.

RESUMEN

Las nuevas Tecnologías de Información y Comunicación (TIC) están actualmente arraigadas en los sistemas educativos de los países desarrollados y en desarrollo. Sin embargo, la investigación académica sobre el impacto de las TIC en el rendimiento educativo todavía no es concluyente. Por ello, este artículo examina si disponer de ordenador con acceso a Internet en los hogares de los estudiantes tiene una recompensa en las puntuaciones obtenidas en matemáticas, lectura y ciencia. Además, analiza el efecto de disponer de TIC en el hogar sobre el fracaso escolar. A tal fin, la investigación emplea un procedimiento de emparejamiento utilizando la base de datos PISA disponible para Argentina. Los resultados muestran que, entre el grupo de estudiantes con un ordenador doméstico con conexión a Internet, el rendimiento educativo aumenta entre el 2,5% por ciento y el 3,5%, dependiendo de la competencia considerada y del método de emparejamiento empleado. Además, el acceso a TIC en el hogar reduce el fracaso escolar entre el 8% y el 18%. Estos hallazgos podrían validar aquellas políticas públicas recientemente implementadas en la región con el objetivo de la universalización de las TIC.

1. Introduction

Argentina is leading the expansion of Information and Communication Technologies (ICT) in Latin America, together with Uruguay (ITU, 2017). According to the "ICT Development Index 2017" (IDI), Argentina scores 6.79

out of 10, a figure above the regional (5.21) and the global (5.11) score. The country also surpasses the regional average in terms of availability of computers in households (67.6%) and home connectivity to the Internet (63.8%).

The irruption and development of ICT has also reached the educational sphere. Over the past two decades, investments in technological infrastructures and programs to support the use of ICT in educational institutions have been major items of public policy agendas in Latin America (SITEAL, 2014). Educational systems have made large efforts to provide schools with computers and Internet, and to train pupils and teachers in their basic applications (Sunkel, Trucco and Möller, 2011). In particular, Argentina launched the “Conectar Igualdad” Program in 2010. It attempted to reduce digital and educational gaps by distributing more than four and a half million netbooks to students and teachers at the secondary level (Alderete and Formichella, 2016).

Considering the fast development of ICT and the adoption of policies for promoting ICT in education, it is relevant to evaluate whether the access and use of new technologies in households may improve educational outcomes in Argentina. Although a large number of studies have addressed this issue both for developed and developing countries, the empirical evidence remains inconclusive. On the one hand, several scholars find a positive impact of ICT on some educational outcome (i.e.: Gómez Fernández and Mediavilla, 2018; Formichella and Alderete, 2018; Alderete et al., 2017; Spiezia, 2010; Carrillo, Onofa and Ponce, 2010). On the other hand, some analyses find no effect or even a negative one (i.e.: Malamud et al., 2018; Faber et al., 2016; Torres and Padilla, 2015; Witte and Rogge, 2014; Muñoz and Ortega, 2014; Sprietsma, 2012; Cristia, Ibararán, Cueto, Santiago and Severín, 2012). For the particular case of Argentina, Alderete and Formichella (2016) have examined the impact of the “Conectar Igualdad” Programme on educational performance at secondary level. However, no further studies investigate the influence of new technologies on educational outcomes.

To reduce this gap in the literature, the aim of this paper is to examine whether computers with Internet access at home have a payoff in terms of educational performance. The research tackles the following questions: (i) Do computer and Internet access at home lead to better educational performance?; (ii) If so, what is the payoff in terms of mathematics, reading and science scores?; (iii) How do computer and Internet access at home affects school failure?. To answer these queries a Propensity Score Matching (Rosenbaum and Robin, 1983) is estimated using PISA data from Argentina available for the year 2012. Studies on the impact of ICT on educational performance have used several methodologies. We can distinguish studies based on experimental designs (Carrillo et al., 2010; Banerjee et al., 2007), and others non experimental studies by using simple correlation analysis (Mcalister, Dunn and Quinn, 2005), multivariate regression techniques (Angrist and Lavy, 2002), probit models and regression models (Spiezia, 2010), hierarchical lineal regression model approach (Gomez Fernandez and Mediavilla, 2018), structural equation models (Alderete et al., 2017; Aristizabal et al., 2009), instrumental variables (Machin et al., 2007), and propensity score matching (Alderete and Formichella, 2016). This matching procedure minimizes the selection bias problem in non-experimental data by conditioning on regressors. In this way, it allows comparisons between a control and a treatment group beyond student, household and school characteristics.

The paper is structured as follows. Section 2 reviews the literature on the impact of ICT on educational outcomes. Section 3 discusses the data and methods. Section 4 provides a data description before matching, and section 5 discusses the matching results. Section 6 concludes and suggests some directions for future research.

2. Literature Review

There is a large body of research on the relationship between ICT and educational outcomes. However, the evidence found so far is not conclusive. Some studies claim that ICT may positively affect some educational outcomes while others find no effect. This section reviews this literature by focusing on Latin American countries and, particularly, on Argentina.

Studies claiming that ICT have a positive impact on educational outcomes argue that new technologies enhance performance by increasing students’ flexibility and autonomy, and by improving learning attitudes and experience. Among this research, Gómez Fernández and Mediavilla (2018) have recently examined the impact on academic performance of the use and availability of ICT at school and at home. By using a hierarchical lineal regression model approach with data from PISA 2015 for Spain, they find a positive impact of ICT use on educational outcome if ICT is used for entertainment at home and students are interested in ICT. Furthermore, Alderete et al. (2017) test the hypothesis that the relationship between the ICT access and the educational performance is mediated by the ICT use both at home and at school. By estimating a Structural Equation Model (SEM) for Spain using data from PISA 2012, they obtained that ICT access at home significantly and positively

impact educational performance, while ICT use outside school reinforces this relationship. On the contrary, ICT access and use at school has a significant and negative incidence on the educational performance. Moreover, Castellano and Pantoja (2017) examine a group of primary students from Andalucía, Spain, and find positive results in self-esteem and reading efficiency. Huertas and Pantoja (2016) also analyzes the influence of ICT on academic performance and student motivation. They perform a quasi-experimental method based on a sample of 194 secondary students from Málaga, Spain. The authors conclude that students using ICT achieve better results and are more motivated.

On the other side, Spiezia (2010) analyzes the impact of new technologies on the educational outcomes of secondary school pupils for all countries participating in PISA ICT 2006 questionnaire. The author concludes that ICT-use at home has a larger effect than ICT-use at school. Moreover, Machin et al. (2007) provide evidence of a positive casual effect of ICT investment on educational achievements in British primary schools. Furthermore, Banerjee et al. (2007) find that the use of a computer-assisted learning program has a positive and significant impact on the results of mathematics in urban primary schools in India.

For the case of Latin America, a few published studies evaluate the impact of ICT on educational performance. Alderete and Formichella (2016) examine the effects of a public program in Argentina named “Conectar Igualdad” that provides one computer to each secondary student in order to guarantee ICT access. By using the propensity score matching method (henceforth, PSM) and PISA 2012 information, the authors find statistically significant differences in average academic achievement associated with participation in the program. Moreover, Pacheco Olea (2015) analyzes a group of students from an industrial technical college in Ecuador and finds that ICT have a positive effect on academic performance. The author recommends teachers to become aware of their proper use and to incorporate them in the classroom. Besides, Muñoz and Ortega (2014) examine some programs in Chile and argue that ICT use at school should be complemented with other variables for a better educational performance. Besides, Román and Murillo (2014) estimate the impact of computer access and use on math and reading achievement among 6th grade students from Latin America. Based on information from the Second Comparative and Explanatory Study (UNESCO) and using a multilevel econometric model, they find out a positive effect of both ICT access and use on performance. Cristia et al. (2012) reach a similar conclusion for the case of the “Laptop per Child” program in Peru. The authors suggest that ICT is a necessary but not sufficient condition for increasing educational attainment. This also requires that teachers have digital skills for a proper ICT use in their practices (Córdoba and Herrera, 2013). Moreover, based on an experiment with primary schools in Ecuador, Carrillo et al. (2010) conclude that new technologies have a positive impact on mathematics results. Barrera and Linden (2009) also employ a matching methodology to evaluate the results of the “Computers for Education” Program in Colombia. They conclude computer access at school does not change learning outcomes if it is not complemented by a proper ICT use. Also, Aristizabal et al. (2009) employ a structural equation model to examine the impact of ICT use at home (Internet use and devices such as video games consoles) and at school (computers and educational software) on the educational achievements in Colombia. By using PISA ICT 2006 and 2009 data, they find that ICT variables have a positive effect with ICT use at school showing the largest impact.

In contrast, studies that do not find a positive relationship between ICT use and educational outcomes argue that the adoption of technological resources does not increase educational performance *per se*. A successful ICT adoption requires complementary actions and resources in order to generate a real educational innovation and ensure a proper, efficient and effective use of technologies (Selwyn, 2004). This means that human and organizational resources are also needed to complement and fully exploit the potential of ICT. Within this group of studies, Malamud et al (2018) offers experimental evidence for the impact of internet access at home on a broad range of child outcomes in Peru. The authors find no significant effects of internet access on math and reading achievement, cognitive skills, self-esteem, teacher perceptions, or school grades when compared to either group. Torres and Padilla (2015) reject the finding of a positive effect of ICT on educational outcomes in Colombia. Moreover, Witte and Rogge (2014) apply a matching technique by using the 2011 “Trends in International Mathematics and Science Study” (TIMSS) data from The Netherlands. Their results report no significant differences in the test outcomes after controlling for teacher, school, and regional characteristics. In an estimate of how access to and the use of computers and the Internet influence the educational outcomes of Brazilian pupils. Besides, Beuermann et al. (2015) show that the provision of portable computers for the home does not improve academic performance. Similarly, Agasisti et al. (2017) analysis the use of ICT at home and show that in most OECD countries there is an association between using computers intensely at home for homework and achieving a worse academic performance. Sprietsma (2012) even finds a negative impact of ICT on mathematics and reading tests. According to the author, schools face a trade-off between investing in technological infrastructure versus other more effective pedagogical means.

Besides, Leuven, Lindahl, Oosterbeek and Webbink (2007) find negative effects of subsidies for computers and software on student performance. Similarly, Goolsbee and Guryan (2006) find no significant effects of the E-Rate Program on student performance in California schools. More generally, Fuchs and Woessman (2004) analyze PISA 2000 results for a set of 31 countries and find that –after controlling for student, family and school characteristics– access to computers at home negatively affects educational outcomes while access at school is not significant. Lastly, Angrist and Lavy (2002) examine a public policy program in Israel aimed at increasing the availability of computers in schools and conclude that ICT use in the teaching-learning process has no significant impact on school performance.

3. Methodological issues

3.1 Data

This research is based on the PISA database that is compiled triennially by the OECD¹. PISA assesses the mathematics, science, and reading skills of 15-year-old students in various countries. It also collects information on the students' socioeconomic context and the schools attended (OECD, 2009). Argentina participated in this program in 2000, 2006, 2009 and 2012. This paper uses data from 2012, the most recent database available.

PISA outcome results range from 0 to 800 with a mean of 500 and a standard deviation of 100. The evaluation outcomes are shown as “plausible values” (PV) to represent a student's set of skills. Since the objective of PISA is to assess the skills of a population rather than individuals, every student responds to a set number of items. Based on these responses, estimation is made of the responses to the full questionnaire. On the basis of the information obtained, PISA assigns five plausible values for each skill (OECD, 2009). Performing separate calculations for each of these values, and obtaining an average is an appropriate procedure to make a consistent estimate of any statistical value and, hence, of any model's parameters (OECD, 2009). This is the procedure followed in the present research.

3.2. The Propensity Score Matching Technique

The relationship between availability of computers with an Internet connection at home and students' educational attainment may suffer from endogeneity since households with ICT are most likely different from those without, and these differences may be correlated with academic achievement. Therefore, a raw comparison of average test scores between the groups of pupils with and without ICT at home would be biased due to the presence of other (observable and non-observable) factors affecting this relationship. Ideally, if we were able to construct a random experiment where access to personal computers with Internet (henceforth, PCI) was independent from certain intrinsic household characteristics we could make unbiased comparisons. Unfortunately, this is not feasible in this research.

As a result, a quasi-experimental experiment design appears as the most appropriate methodology. Dehejia and Wahba (1999, 2002) argue about the auspicious performance of propensity-score matching estimators in observational studies. PSM estimates are closer to the experimental benchmark than those emerging from traditional evaluation methods. Our aim is to determine what would be the educational achievement of secondary school students with PCI at home, if they had not access to this technology. The PSM methodology developed by Rosenbaum and Robin (1983) is appropriate for such an analysis. The technique constructs an artificial “clone” or a “match” for every student being evaluated with identical (personal, family, and school) characteristics apart from PCI access at home (i.e., the treatment). Every treated student is then matched to another similar non-treated student to enable unbiased comparison of their educational performance. The average impact of PCI access at home is estimated by the mean difference in the outcomes of the matched pairs.

The PSM comprises various steps. First, the likelihood that the student receives the treatment (i.e., PCI access at home) is estimated conditional on certain characteristics, by means of a probit model. From this step, the predicted probability or propensity score for each student is obtained. Next, the sample is split into two

1. Learning standardized tests such as PISA, have been criticized (Llach, Montoya and Roldan, 1999). However, at present, there is no alternative source of statistical information that could be used as a proxy of educational outcomes.

sub-samples: treated and control (i.e., without PCI access at home), and arranged in descending order. An area of common support where the distribution of the propensity scores for the treated and the controls overlaps is defined. Then, a control with a similar propensity score or probability is found for each treated student in order to form pairs². The difference in educational performance is estimated for each pair and the average difference is calculated for the whole sample. This is known as the “Average Treatment Effect on the Treated” (ATT), and represents the payoff in terms of educational performance for those students with new technologies in their homes. If the hypothesis of null ATT is rejected by a “t” test, we can confirm that ATT is significantly different from zero. Finally, a sensitivity analysis of the results is performed by simulating the capacity of an unobserved variable to cause bias.

Becker and Ichino (2002) offer several commands that accomplish different propensity-score matching estimators of the Average Treatment effect on the Treated (ATT). In particular, matching relies on the assumption of conditional independence of potential outcomes and treatment assignment given observables, i.e., on the fact that selection into treatment is only driven by factors that the researcher can observe.

Matching estimators can reduce conventionally measured bias if two conditions are carry out (Heckman, Ichimura and Todd, 1997): 1) both the treated and control units use the same questionnaire or survey form, 2) the non-experimental control group and the treated group come from the same population. If these conditions are encountered and the Conditional Independence Assumption is likely, matching can be a better strategy to control for observables than regression modelling (assuming that there is no credible source of exogenous variation).

The implication of these assumptions is that systematic (for example, average or distributional) differences in outcomes between treated and control units with the same values for the covariates are attributable to the treatment. Recent analysis has considered estimation and inference for average treatment effects under weaker assumptions than typical of the earlier literature (Imbens, 2004).

In analytical terms, we estimate the average effect of a binary treatment on a continuous scalar product. For a student i , with $i = 1, \dots, N$, with interchangeable units we define (Y_{i0}, Y_{i1}) as the potential outcomes so that Y_{i0} is the educational performance of a student i that does not receive the treatment, and Y_{i1} is the educational performance of a student receiving the treatment. This achievement can be measured by the scores obtained by the pupils in standardized learning tests such as PISA. If D_i denotes the treatment, i.e. PCI access at home, this means:

$$Y_i = Y_i(D_i) = \begin{cases} Y_{i0} & \text{if } D_i = 0 \\ Y_{i1} & \text{if } D_i = 1 \end{cases}$$

The objective is to determine the reward or payoff in terms of educational performance for the treated students. If the academic performance of a student with and without PCI at home were both observable, then the payoff for that student would be simply $(\Delta = Y_{i1} - Y_{i0})$. However, it is not common to observe both outcomes simultaneously for the same student. One solution would be to run a random experiment where potential outcomes were independent of treatment. However, this is unfeasible in our case so we artificially build a counterfactual group using the PSM technique.

An assessment of average educational achievement provides information on potential outcomes but does not necessarily explain the phenomenon. Comparison of average educational achievement conditioned on PCI access is formally related to the average causal effect given by the following equation:

$$E(Y_{i1} | D_i = 1) - E(Y_{i0} | D_i = 0) = [E(Y_{i1} | D_i = 1) - E(Y_{i0} | D_i = 1)] + [E(Y_{i0} | D_i = 1) - E(Y_{i0} | D_i = 0)]$$

Observed difference in average educational outcomes

ATT: average effect of PCI access at home on the treated

Selection bias

Only if the treatment among students with equal propensity scores is purely random will the selection bias be removed. The PSM methodology solves the selection bias problem in non-experimental data by replacing the randomization of the experiment with the conditioning on regressors (Heckman, 1990). To this end, we estimate a logit or probit model where the maximum likelihood function will be more relevant than the statistical significance of the parameters (Heckman, Lalonde, and Smith, 1999).

2. Since perform a PSM with replacement is employed, a control can be matched with more than one treated student.

There are different matching algorithms that can be used to calculate the impact on the ATT based on the propensity score. They mainly differ in the way the distance between the treated and the control is measured. In this research we use the following matching methods:

Nearest Neighbor - matches treated and control students on the basis of the closest propensity score. An untreated student j with propensity score P_j is chosen to be the match or control of a treated student i with propensity score P_i ($C(P_i)$) if:

$$C(P_i) = \min_j \|P_i - P_j\|$$

This method uses one control student to compare with every treated student.

Kernel - matches treated students with a weighted average of all control students. Weights are inversely proportional to the distance between the propensity scores of treated and untreated students.

Stratification - allows matching based on a variable that contains the layer number in the area of common support. Students used in the ATT estimation belong to the minimum maximum range of the propensity scores of the treated group. Thus, the defined area includes positive density values for both treated and control students (Smith and Todd, 2005).

3.3. The probit model

The probit model allows us to estimate the propensity of a given pupil to access PCI at home, conditioned on student, family and school characteristics. Only variables that simultaneously affect the decision to participate in the treatment, and the outcome variable, should be included in the estimation (Bernal and Peña, 2011).

The treatment is assigned to secondary students living in households with PCI access at home in 2012. Therefore, the dependent variable (Y) is "Computers at home with Internet access". This is a dummy variable equal to 1 if the student lives in a house with PCI and zero otherwise. It is built on two binary variables available in PISA:

- a) Computers at home.
- b) Internet access.

The model can be expressed in terms of an unobservable latent variable (Y^*) which represents the propensity of a given student to access PCI at home. Indicators to assess the availability and/or the use of ICT at home are computer use at home (Spiezia, 2010). Several studies based on PISA data use the possession of a computer at home as an ICT indicator (Schmitt and Wadsworth, 2006; Fairlie, et al., 2010; Notten and Kraaykamp, 2009). Other indicators are ICT available at Home Index (Gomez Fernandez and Mediavilla, 2018; Alderete et al., 2017), Internet use at home (Aristizabal et al., 2009).

In this model, Computers at home with Internet access is explained by a set of observable independent variables:

The relationship between the observed dummy variable (Y) and the latent variable (Y^*) is shown in the following equation:

$$Y_i^* = X_i \beta + \epsilon_i \quad i = 1, \dots, N$$

$$Y = 1 \text{ if } Y_i^* > 0$$

$$Y = 0 \text{ if } Y_i^* \leq 0$$

Studies of ICT and educational outcomes, discussed in Section 2, provide information on the factors influencing the treatment. Consequently, our model includes the following set of independent variables to account for student, family, and school characteristics.

Student and family level variables

- Repeater: a dummy variable that takes the value 1 if the student has failed a grade at primary or secondary education level;
- Secondary studies: a dummy variable that equals 1 if the parents' highest level of education is secondary;
- Tertiary studies: a dummy variable that equals 1 if the parents' highest level of education is higher (university) degree;

- HISEI (Highest International Social and Economic Index): a continuous variable referring to the parents' occupational status. It represents the maximum occupational hierarchy between both parents and captures the occupational attributes that translate into family revenue.

School level variables

- TCSHORT: index on teacher shortage at school. This index has an average of zero and a standard deviation of 1 for the OECD countries;
- RATCMP15: index of computer availability. It is the ratio of the number of available computers for educational purposes to the number of students attending the grade for 15 years old;
- ESCS average: a continuous variable reflecting the school average index of Economic, Social and Cultural Status (ESCS). PISA produces an ESCS index for each student in order to build a broad measure of socioeconomic status including information on parents' occupational status and education, and household's material and cultural attributes (OECD, 2010);
- Private: a dummy variable equal to 1 if the school is private (e.g. a private entity has the power to make decisions concerning its affairs) and zero otherwise.

PISA surveys contain several variables that can be used as a proxy for the characteristics of the students, their families and their schools. We used the above indicators to explain the determinants of computer use with internet access at home. We did not consider computer use at school since PISA data is not available on this topic for Argentina. Neither have we had to study ICT use in other place because this data is less available than the others in Argentina, and because this type of use is likely to be less related to education.

4. Descriptive results before matching

A total of 5,908 observations are available from PISA 2012 for the case of Argentina, 93% of which have information on ICT. Among this 93%, 75% of students live in households with PCI and the remaining 25% do not.

The raw data statistics before matching are provided in Table 1 that shows the differences among groups for educational performance. Scores are higher for the group of students with PCI at home for all three competences assessed by PISA. Those pupils with PCI at home, on average achieve 56.9 more points for mathematics, 70.4 more for reading, and 62.9 more for science. The ANOVA F test shows that the average differences between groups are statistically significant. This means academic performance for the group of students with PCI at home is between 7% and 9% higher than for the group without PCI at home. However, as previously discussed, this simple comparison of educational performance means between groups is biased by endogeneity. Differences in performance may be due to household characteristics that result in the presence of a computer and Internet access at home, and not by ICT access per se. By applying the PSM methodology we minimize this bias.

| Skills | With PCI at home | Without PCI at home | F ANOVA |
|---------|------------------|---------------------|-------------|
| Math | 412.72 | 355.84 | 762.195 *** |
| Reading | 424.73 | 354.38 | 753.29*** |
| Science | 429.37 | 366.49 | 761.088*** |

Table 1. Average differences in educational achievement. Source: Based on PISA 2012 data. Note: *** p-value \leq 1%.

Table 2 shows the main characteristics of both groups of students before matching. On average, students from households with new technologies have fewer repeaters; a lower share of parents with secondary education; a higher share of parents with tertiary education; and have parents with higher occupational status. They also attend schools where teacher shortage is less acute; where there is a higher ratio of computers per pupil; and where pupils are from families with higher socioeconomic status. All these average differences between groups are statistically significant according to the ANOVA F test.

| Variable | Group | N | Mean | Min | Max | F ANOVA |
|--------------------|-------------|------|----------|--------|-------|-----------|
| Repeater | With PCI | 3521 | 0.18347 | 0 | 1 | 84.86*** |
| | Without PCI | 1002 | 0.35728 | 0 | 1 | |
| Secondary_ Studies | With PCI | 3997 | 0.21315 | 0 | 1 | 0.089*** |
| | Without PCI | 1294 | 0.22024 | 0 | 1 | |
| Tertiary_ studies | With PCI | 3997 | 0.57167 | 0 | 1 | 408.25*** |
| | Without PCI | 1294 | 0.26429 | 0 | 1 | |
| HISEI | With PCI | 3777 | 49.58 | 11.56 | 88.96 | 500.39*** |
| | Without PCI | 1154 | 33.33 | 11.01 | 88.96 | |
| TCSHORT | With PCI | 4027 | 0.03387 | -10.91 | 35.96 | 14.007*** |
| | Without PCI | 1304 | -0.09816 | -10.91 | 35.96 | |
| RATCMP15 | With PCI | 3735 | 0.81753 | 0 | 27.5 | 17.021*** |
| | Without PCI | 1251 | 0.60262 | 0 | 27.5 | |
| ESCS_ average | With PCI | 4133 | -0.42816 | -18.63 | 1.07 | 46.993*** |
| | Without PCI | 1355 | -1.152 | -2.69 | 1.07 | |
| Private | With PCI | 4061 | 0.18000 | 0 | 1 | 10.539*** |
| | Without PCI | 1313 | 0.14166 | 0 | 1 | |

Table 2. Average differences in the explanatory variables. Source: Based on PISA 2012 data.
PCI = Computer with Internet access.

5. Discussion of results after matching

First, we estimated PSM by means of a probit model. Table 3 presents the determinants of participation in the treatment group. The goodness of fit is adequate according to the likelihood ratio (Prob> chi2 = 0.0000) and pseudo R² statistics. Results show that the probability of PCI access at home is significantly lower among students who had to repeat grades. However, this probability is significantly higher if their parents achieved secondary or tertiary education and are of higher occupational status. Moreover, students attending private schools, schools with a higher ratio of computers per student, and with students of higher socioeconomic status have higher propensity to have PCI at home.

| Variable | Coefficient | Standard error | Significance level |
|--------------------|-------------|----------------|--------------------|
| Repeater | -0.1434337 | .0602816 | ** |
| Secondary_ studies | 0.1330218 | .0716943 | ** |
| Tertiary_ studies | 0.1982314 | .0695756 | *** |
| HISEI | 0.0089865 | .0015486 | *** |
| TCSHORT | -0.0344055 | .0257496 | ns |
| RATCMP15 | 0.0349274 | .0135544 | ** |
| ESCS_ average | 0.87288 | .0531839 | *** |
| Private | 0.1637362 | .0701982 | ** |
| Constant | 0.9260808 | .0951029 | *** |
| N | 3555 | | |
| LR chi2(8) | 784.97 | | |
| Prob>chi2 | 0.0000 | | |
| Pseudo R2 | 0.2140 | | |

Table 3. Determinants of the participation in the treatment. Source: Based on PISA 2012 data.
***p-value ≤ 1%; **p-value ≤ 5%, ns=not significant.

Second, we define a common support area where the distribution of the estimated propensity scores of the treated and the controls overlaps. Figure 1 depicts the kernel density estimates of the propensity scores and the selected region [0.28967; 0.99815].

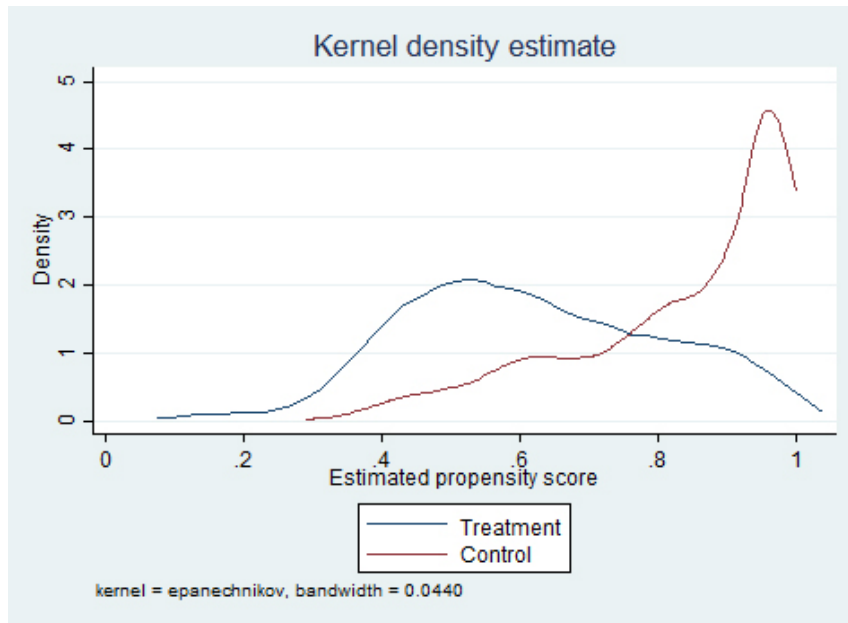


Figure 1. Kernel density estimation

The matching analysis is restricted to this common area which includes 3313 students, of which 2803 are treated and 510 are controls (see Table 4). Students in the different groups are matched using the previously described methods (nearest neighbor, kernel, and stratification).

| Students | N | % | Accumulated % |
|----------|------|-------|---------------|
| Treated | 2803 | 84.60 | 84.60 |
| Controls | 510 | 15.40 | 100 |
| Total | 3313 | 100 | |

Table 4. Distribution of cases. Source: Based on PISA 2012 data.

The results for the estimated ATT are presented in Table 5. There are differences in the average educational performance among the treated and control students for all the skills considered. These differences are statistically significant according to the different matching techniques. Therefore, we can reject the hypothesis of null ATT. Those students with PCI at home, on average, achieve between 20 and 23 more points for mathematics; 25 to 26 additional points for reading, and 26 to 28 more points for science (depending on the matching method employed). Therefore, we find the largest effect of the treatment in the science competence, followed by reading and mathematics.

These differences in educational outcomes are relevant because they represent almost one-quarter of the PISA standard deviation. However, they are almost three times lower than those obtained from a simple mean comparison between groups. Conditioning the experiment on the observed explanatory variables, the performance of students with PCI at home is between 2.5% and 3.5% higher than the performance of students without PCI at home (depending on the skill considered and the matching method applied). Our results support earlier works finding a positive and significant effect of ICT on educational performance in Argentina (Alderete and Formichella, 2016, Alderete et al., 2017).

| Skills | Matching method | Treated | Controls | ATT | t |
|---------|-------------------|---------|----------|---------|--------|
| Math | Stratification | 2803 | 890 | 23.3908 | 4.9348 |
| | Kernel | 2803 | 736 | 20.7214 | 5.5948 |
| | Nearest Neighbour | 2803 | 510 | 22.6212 | 4.3274 |
| Reading | Stratification | 2803 | 890 | 25.4988 | 4.08 |
| | Kernel | 2803 | 736 | 25.5602 | 5.4154 |
| | Nearest Neighbour | 2803 | 510 | 26.7218 | 3.674 |
| Science | Stratification | 2803 | 890 | 27.495 | 4.2802 |
| | Kernel | 2803 | 736 | 26.7 | 4.6602 |
| | Nearest Neighbour | 2803 | 510 | 27.8758 | 3.4058 |

Table 5. Average Treatment Effect on the Treated (ATT): educational achievement. Source: Based on PISA 2012 data.

This research also explores the influence of ICT at home on school failure. PISA scores are broken down into six levels; those students below the second level are deemed as failing to achieve the minimum skills necessary to function in modern society in relation to mathematics, science and reading. Accordingly, we define school failure as incapacity to achieve this threshold³. In this case, the outcome variable is a dummy equal to 1 if the student exceeds the second level of PISA scores and zero otherwise⁴.

The ATT in Table 6 compares the proportions of school failure in the treated and the control groups. The proportion of failures in the treated group is significantly lower than in the control group (ATT negative) for all the skills analyzed, and regardless of the matching method employed. The ratio of treated students not achieving the threshold in mathematics is between 8 and 12 percentage points lower than the ratio in the control group depending on the matching technique employed. Similarly, the range is between 12 and 15 percentage points for reading, and between 13 and 18 percentage points for science. Again, science shows the largest effect of the treatment.

| Skills | Matching method | Treated | Controls | ATT | t |
|---------|-------------------|---------|----------|---------|---------|
| Math | Stratification | 2803 | 890 | -0.1076 | -4.7928 |
| | Kernel | 2803 | 736 | -0.0882 | -3.9226 |
| | Nearest Neighbour | 2803 | 510 | -0.125 | -5.6198 |
| Reading | Stratification | 2803 | 890 | -0.1404 | -4.0698 |
| | Kernel | 2803 | 736 | -0.1266 | -4.758 |
| | Nearest Neighbour | 2803 | 510 | -0.1494 | -4.2528 |
| Science | Stratification | 2803 | 890 | -0.155 | -4.9086 |
| | Kernel | 2803 | 736 | -0.134 | -5.1946 |
| | Nearest Neighbour | 2803 | 510 | -0.188 | -6.509 |

Table 6. Average Treatment Effect on the Treated (ATT): school failure. Source: Based on PISA 2012 data.

The PSM is valid if the observed independent variables determine participation in the treatment, i.e. if there is no bias due to unobservable variables, or if the unobservable variables are not a fundamental determinant of the treatment and the potential outcome variables (Bernal and Peña, 2011). Therefore, based on Nannincini (2007), the robustness of the model was confirmed for both educational outcomes and school failure. ATT estimations were performed under different possible scenarios of deviation from the assumption of conditional

3. The threshold for reading is 480, for mathematics is 482, and for science is 484.

4. The variable has five PV for each student and skill, and we performed separate estimations for each and then calculated the average.

independence. This means that the capacity of an unobservable variable (not included in the probability estimation) to generate bias has been simulated. The results showed no differences in the ATT obtained with the model. We also found no differences between the original impact and the impact on educational performance and on school failure when we included additional variables.

6. Final remarks

This paper examines the influence of ICT access at home on educational performance in Argentina. It is a special case to study because that country, together with Uruguay, is leading the expansion of ICT in Latin America, as it was mentioned in the introduction. Specially, in Argentina there are more houses with personal computers and Internet connectivity than the Latin America average. However, empirical evidence on the relationship between ICT access at home and the educational achievements in Argentina is scarce yet. For this reason, this research aims at contributing to the current state of knowledge by using a specific but well-known quantitative methodology as the Propensity Score Matching. In this sense, this study is part of the first attempts to quantitatively assess whether computer with internet access at home pays off in terms of school attainment. This study complements earlier works and contributes to a better understanding of the impact of ICT in the teaching-learning process and the ICT role in education.

By applying the Propensity Score Matching methodology to PISA 2012 data, we confirm that students with ICT access at home (treated) achieve higher average educational performance. Conditioning the experiment on student-, family-, and school- level characteristics, those students with ICT at home score between 2.5% and 3.5% higher depending on the skill considered and the matching technique employed. This effect is not negligible and accounts for nearly a quarter of the PISA standard deviation.

The availability of new technologies at home not only increases students' educational performance, it also allows many individuals to achieve higher than the school failure threshold. This means that the effect is able to reduce the proportion of students not reaching the minimum level of skills required to function in modern society in adult life. We found that the ratio of failures in the group of students from households with computers and Internet access declines by between 8% and 18% (depending on the skill analyzed, and the matching method employed).

Our research confirms that ICT may play a significant role in education. This finding should be taken into account when designing policies aimed at improving school performance and decreasing failure. Our results also support recent public policies in Argentina and the Latin American region aimed at increasing the spread of ICT.

In the Latin American context, research on the influence of ICT in education is still under development, and more studies are needed in this area. The impact of new technologies could be undervalued if their access is not complemented by a proper use. However, the PISA 2012 database does not provide data on ICT use for Argentina. This is an issue that should be analyzed in future research.

Even though the results obtained in this paper contribute to the empirical literature in the region, they should be interpreted with some caution. First of all, by using a matching approach this paper builds a control group. However, it does not account for all characteristics that may impact the return of ICT. For instance, a missing variable could be the teachers' role play in the use of ICT in teaching. Although we have performed a sensitivity analysis to control for unobservable factors, pedagogical practices and digital skills of teachers could explain differences in educational outcomes.

Acknowledgements

Gisela Di Meglio gratefully acknowledges funding through Fundación Ramón Areces.

References

Agasisti, T., Gil-Izquierdo, M., and Han, S. (2017). ICT use at home for school-related tasks: What is the effect on a student's achievement? Empirical evidence from OECD PISA data. Munich Personal RePEc Archive (MPRA) Paper, no. 81343.

- Alderete, M. V., and Formichella, M. M. (2016). The effect of ICTs on academic achievement: the Conectar Igualdad programme in Argentina. *Cepal Review*, 19, 83-100. doi:<https://doi.org/10.18356/f23c6662-en>
- Alderete, M. V., Di Meglio, G., and Formichella, M. M. (2017). Acceso a las TIC y rendimiento educativo: ¿Una relación potenciada por su uso? Un análisis para España. *Revista de educación* 377, 54-81.
- Angrist J., and Lavy, V. (2002). New evidence on classroom computers and pupil learning. *The Economic Journal*, 112, 735-765. doi:<https://doi.org/10.1111/1468-0297.00068>
- Aristizabal, G., Caicedo, M., and Escandón D. (2009). Las Tecnologías de la Información y Comunicación como determinante en el rendimiento académico escolar, Colombia 2006-2009. Available at: <http://2012.economicsofeducation.com>
- Banerjee, A., Cole, S., Duflo, E., and Linden, L. (2007). Remedying education: Evidence from two randomized experiments in India. *Quarterly Journal of Economics*, 122, 1235-64. doi:<https://doi.org/10.1162/qjec.122.3.1235>
- Barrera-Osorio, F. and Linden, L. (2009). The Use and Misuse of Computers in Education. Evidence from a Randomized Experiment in Colombia. *Policy Research Working Paper* N° 4836, World Bank, Washington D.C. doi:<https://doi.org/10.1596/1813-9450-4836>
- Becker S., and Ichino A. (2002). Estimation of average treatment effects based on Propensity Scores. *The Stata Journal*, 2(4), 358-377. doi:<https://doi.org/10.1177/1536867X0200200403>
- BECTA (2007). Inclusive Learning: An Essential Guide. Available at: <https://bit.ly/2NyIgLv>.
- Bernal, R., and Peña, X. (2011). *Practical Guide for Impact Evaluation*. Bogotá: Ediciones Uniandes.
- Beuermann, D. W., Cristia, J., Cueto, S., Malamud, O., and Cruz-Aguayo, Y. (2015). One Laptop per Child at home: Short-term impacts from a randomized experiment in Peru. *American Economic Journal: Applied Economics*, 7(2), 53-80. doi:<https://doi.org/10.1257/app.20130267>
- Carrillo, P., Onofá, M., and Ponce, J. (2010). Information Technology and Student Achievement: Evidence from a Randomized Experiment in Ecuador. IDB Working Paper N° 78. Available at: <https://bit.ly/2BIJFMT>. doi:<https://doi.org/10.2139/ssrn.1818756>
- Castellano Luque, E. A., and Pantoja Vallejo, A. (2017). Eficacia de un programa de intervención basado en el uso de las TIC en la tutoría. *Revista de Investigación Educativa*, 35(1), 215-233. doi:<https://doi.org/10.6018/rie.35.1.248831>
- Castells, M. (1999). *La Era de la Información. Economía, sociedad y cultura*. Madrid: Siglo XXI.
- Claro, M. (2011). *El papel de las tecnologías de la información y las comunicaciones en la educación inclusiva*. Santiago de Chile: ECLAC.
- Córdoba Gómez, F., and Herrera Mejía, H. (2013). Impacto del uso de objetos de aprendizaje en el desempeño en matemáticas de estudiantes de grado noveno. *Revista Virtual Universidad Católica del Norte*, 39, 47-58.
- Cristia, J., Ibarrarán, P., Cueto, S., Santiago, A., and Severín, E. (2012). Technology and Child Development: Evidence from the One Laptop per Child Program. *IDB Working Paper* N° 304. Available at: <https://bit.ly/2Zeq2UZ>. doi: <https://doi.org/10.2139/ssrn.2032444>
- Dehejia R. H., and Wahba S. (1999). Causal Effects in Non-Experimental Studies: Re-Evaluating the Evaluation of Training Programs. *Journal of the American Statistical Association*, 94(448), 1053-62. doi:<https://doi.org/10.2307/2669919>
- Dehejia R. H., and Wahba S. (2002). Propensity Score-Matching Methods for Nonexperimental Causal Studies. *The Review of Economics and Statistics*, 84(1), 151-161. doi:<https://doi.org/10.1162/003465302317331982>
- Formichella, M. M., and Alderete, M. V. (2018). TIC en la escuela y rendimiento educativo: el efecto mediador del uso de las TIC en el hogar. *Investigaciones educativas de Uruguay*, 9(1), 75-93. doi:<https://doi.org/10.18861/cied.2018.9.1.2822>
- Fuchs, T., and Woessmann, L. (2005). Computers and Student Learning: Bivariate and Multivariate Evidence on the Availability and Use of Computers at Home and at School. ifo Working Paper N°8. Munich: CESifo Group. Available at: <https://bit.ly/2ZfHokd>
- Gomez Fernandez, N., and Mediavilla, M. (2018). Do information and communication technologies (ICT) improve educational outcomes? Evidence for Spain in PISA 2015. Working paper IEB 2018/20, Institut d'Economia de Barcelona. Available at: <https://bit.ly/2ClcglK>
- Goolsbee, A., and Guryan, J. (2006). The impact of internet subsidies in public schools. *The Review of Economics and Statistics*, 88(2), 336-347. doi:<https://doi.org/10.1162/rest.88.2.336>
- Heckman J. J., Ichimura H., and Todd P. (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies*, 64, 605-654. doi:<https://doi.org/10.2307/2971733>
- Heckman J. J., Ichimura H., and Todd P. (1998). Matching as an Econometric Evaluation Estimator. *The Review of Economic Studies*, 65, 261-294. doi:<https://doi.org/10.1111/1467-937X.00044>

- Heckman, J. (1990). Varieties of selection bias. *American Economic Review*, 80, 313-318. Available at: <https://bit.ly/3ia1Ylt>
- Heckman, J., Lalonde, R., and Smith, J. (1999). The Economics and Econometrics of Active Labor Market Programs. In O. Ashenfelter and D. Card (Eds), *Handbook of labor economics*, Vol. 3A (pp. 1865-2097). Amsterdam: North-Holland. doi:[https://doi.org/10.1016/S1573-4463\(99\)03012-6](https://doi.org/10.1016/S1573-4463(99)03012-6)
- Huertas, A., and Pantoja, A. (2016). Efectos de un programa educativo basado en el uso de las TIC sobre el rendimiento académico y la motivación del alumnado en la asignatura de tecnología de educación secundaria. *Educación XXI*, 19(2), 229-250. doi:<https://doi.org/10.5944/educxx1.16464>
- Imbens, G. (2004). Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. *The Review of Economics and Statistics*, 86(1), 4-29. doi: <https://doi.org/10.1162/003465304323023651>
- International Telecommunication Union (2017). *Measuring the Information Society Report, Volume 1*. Geneva: Switzerland.
- Leuven, E., Lindahl, M., Oosterbeek, H., and Webbink, D. (2007). The effect of extra funding for disadvantaged pupils on achievement. *The Review of Economics and Statistics*, 89(4), 721-736. doi:<https://doi.org/10.1162/rest.89.4.721>
- Llach, J., Montoya, S., and Roldan, F. (1999). *Educación para todos*. Buenos Aires: IERAL.
- Mcalister, M., Dunn, J., and Quinn, L. (2005). Student teachers' attitudes to and use of computers to teach mathematics in the primary classroom. *Technology, Pedagogy and Education*, 14(1), 77-105. doi:<https://doi.org/10.1080/14759390500200194>
- Machin, S., Mcnally, S., and Silva, O. (2007). New technology in schools: is there a payoff? *Economic Journal*, 117, 1145-67. doi:<https://doi.org/10.1111/j.1468-0297.2007.02070.x>
- Malamud, O., Cueto, S., Cristia, J. P., and Beuermann, D. (2018). Do children benefit from internet access? Experimental evidence from a developing country. BID working paper. doi:<https://doi.org/10.18235/0001392>
- Muñoz, R., and Ortega, J. (2014). ¿Tiene la Banda Ancha y las TICs un Impacto Positivo sobre el Rendimiento Escolar? Evidencia para Chile. *El Trimestre Económico*, 82(325), 53-87. doi:<https://doi.org/10.20430/ete.v82i325.140>
- Nannincini, T. (2007). A Simulation-Based Sensitivity Analysis for Matching Estimators. *Stata Journal*, 7(3), 334-50. doi:<https://doi.org/10.1177/1536867X0700700303>
- OCDE. (2009). *PISA Data Analysis Manual. SPSS*. (2nded.). Paris: OECD Publishing.
- Pacheco Olea, F. (2015). Las TIC como herramientas en el proceso de enseñanza- aprendizaje para optimizar el rendimiento académico. *Revista Ciencias Pedagógicas e Innovación*, 3(1), 56-62. doi:<https://doi.org/10.26423/rcpi.v3i1.13>
- Pagani, L., Argentin, G., Gui, M., and Stanca, L. (2016). The impact of digital skills on educational outcomes: evidence from performance tests. *Educational Studies*, 42(2), 137-162. doi:<https://doi.org/10.1080/03055698.2016.1148588>
- Román, M., and Murillo, F. J. (2014). Disponibilidad y uso de TIC en escuelas latinoamericanas: incidencia en el rendimiento escolar. *Educação e Pesquisa*, 40(4), 879-895. doi:<https://doi.org/10.1590/s1517-97022014121528>
- Rosenbaum, P. R., and Rubin, D. B. (1983). The central role of the propensity scores in observational studies for causal effects. *Biometrika*, 70(1), 41-55. doi:<https://doi.org/10.1093/biomet/70.1.41>
- Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *New Media and Society*, 6(3), 341-362. doi:<https://doi.org/10.1177/1461444804042519>
- SITEAL. (2014). *Informe sobre tendencias sociales y educativas en América Latina 2014. Políticas TIC en los sistemas educativos de América Latina*. UNESCO, OEI. Available at: <https://bit.ly/2BPkTuA>
- Smith, J. A., and TODD P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125, 305-353. doi:<https://doi.org/10.1016/j.jeconom.2004.04.011>
- Spiezia V. (2010). Does Computer Use Increase Educational Achievements? Student-level Evidence from PISA. *OECD Journal: Economic Studies*. doi:https://doi.org/10.1787/eco_studies-2010-5km33scwlvkf
- Sprietsma, M. (2012). Computers as Pedagogical Tools in Brazil: A Pseudo-panel Analysis. *Education Economics*, 20(1), 19-32. doi:<https://doi.org/10.1080/09645290903546496>
- Sunkel, G., and Trucco, D. (2011). New information and communications technologies for education in Latin America: risks and opportunities. *ECLAC Social Policy Series*, 167, United Nations. Available at: <https://bit.ly/2NEbqZs>
- Sunkel, G., Trucco, D., and Möller, S. (2011). Aprender y enseñar con tecnologías de la información y la comunicación (TIC) en América Latina. Potenciales beneficios. *ECLAC Social Policy Series* Nº 169, United Nations. Available at: <https://bit.ly/3i66Uky>

- Tinio, V. L. (2002). ICT in Education. UNDP Bureau for Development Policy. Available at: <http://www.eprimers.org>
- Torres Tovio, J., and Padilla Velásquez, A. (2015). Las Tecnologías de Información y Comunicación y su efecto en el rendimiento académico de los estudiantes en las escuelas Secundarias del departamento de Córdoba – Colombia. *Revista Electrónica Ingeniería al día*, 1(1), 15-23.
- UNESCO (2014). *Reading in the mobile era. A study of mobile reading in developing countries*. France: United Nations Educational, Scientific and Cultural Organization.
- Van Deursen, A., and Van Dijk, J. (2009). Using the Internet: Skill Related Problems in Users' Online Behavior. *Interacting with Computers*, 21(5-6), 393-402. doi:<https://doi.org/10.1016/j.intcom.2009.06.005>
- Witte, K., and Rogge, N. (2014). Does ICT matter for effectiveness and efficiency in mathematics education? *Computers and Education*, 75, 173-184. doi:<https://doi.org/10.1016/j.compedu.2014.02.012>