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Access to ICT at Argentine elementary school children's homes and its impact on school achievements

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Abstract
This article analyzes the relationship between access to Information and Communication Technology (ICT) and school performance. It contributes to the empirical literature in the area since there is no consensus yet. Moreover, the context associated with COVID-19 pandemic also considers the analysis as the most relevant. The goal of this article is to study the impact of ICT on school performance at elementary level. The hypothesis set forth is that having both a computer and connection to Internet at the students' homes, improves their school related achievements. To contrast it, we propose an econometric model using the *Propensity Matching Score (PSM)* methodology with data from the Learning 2018 (Aprender 2018) campaign of students at the last year of elementary school in Argentina and in each of the regions that conform it. Finally, there is evidence in favor of the hypothesis.

Keywords Elementary education · ICT access · School performance · Propensity score matching · Argentina

1 Introduction

In the last decades, Information and Communication Technology (ICT) has gained significance as a determining factor in school results ((Hurwitz & Schmitt, 2020; Formichella et al., 2020). Thus, the United Nations Organization for Education, Science and Culture (2015) establishes that ICT is a priority in the educational context due to

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its favoring inclusion, the possibility of teaching and learning and, at the same time, efficiency in the system management.

Therefore, the unequal distribution of access to ICT in the students' homes and/or at their schools, can give rise to differences in their educational achievements. In the context of isolation linked to the Covid-19 pandemic, this issue has become more significant due to the impossibility of teaching in person. Ziegler et al., (2020) show that, in the middle of the pandemic (November 2020) access to and use of devices with educational purposes was very unequal in Argentina. On the one hand, 58.8% of elementary students in public schools only had access through their mobile phone. On the other hand, 12.5% of students only used a notebook, PC or tablet, while 24.0% combined the mobile phone with some of the other devices mentioned. Finally, 3.9% did not use any. That is to say, almost 4% of elementary school students of public schools remained uncommunicated and lost continuity in their schooling process.

Inequalities at home are associated with diverse social, economic and cultural factors. In the same way, inequalities at school are explained by a variety of features inherent to these organizations. In addition, given that the Argentine educational system is decentralized and each province manages its basic education, the geographical location of the venue matters (Formichella & Rojas, 2009). There is a significant gap between socio-educational indicators of the provinces in Argentina (Buchbinder et al., 2019).

A distinctive aspect among the regions is the distribution of rural population, since it is in the rural sector where the largest proportion of individuals with Unsatisfied Basic Needs lives (*Necesidades Básicas Insatisfechas-NBI*), which turn into disadvantages in the digital gap as well as in the educational results. This situation is heterogeneous all throughout the country, and among the regions that have the largest rural population are NEA -Northeastern Argentina- and NOA -Northwestern Argentina- (a little less than 20%) (CEPAL, 2016).

In the same way there is heterogeneity within the urban sphere. According to data of the Home Permanent Survey –Encuesta Permanente de Hogares (EPH), that provides information related precisely to this sector, in the fourth trimester of 2020 the Patagonia, Northwestern and Great Buenos Aires regions registered the highest home Internet access (92.4%, 91.9% and 90.5% respectively) surpassing the national average. Whereas access to computers, in comparison to Internet, was evinced in smaller proportions in each region, being the Patagonia and GBA-Greater Buenos Aires- the ones that presented the highest percentages with such availability (70.6% and 65.2%, respectively) (INDEC, 2021). In the following Table (1) this can be observed with greater detail:

These differences also have been observed in relation to the educational policies linked to ICT, not only as regards the particular policies of each region, but also the way in which regions implemented the policies enforced at a national level (Bilbao & Rivas, 2011). Therefore, even if in the last few years there has been considerable progress in the use of Internet, broadband connection and particularly mobile broadband, quality and equality with regard to access to these technologies has not yet been achieved. Thus, differences with regard to access to ICT are evinced in both urban and rural regions as well as within the urban sector, particularly among the different quintiles of income distribution (CEPAL, 2016).

Table 1 Percentage of homes with access to ICT per region (urban sector)

Region (according to Internet access)	Percentage of homes with access to Internet	Percentage of homes with computers
Patagonia	92.4	70.6
Northwest (NOA)	91.9	59.2
GBA	90.5	65.2
Cuyo	89.3	59.9
Pampean	88.5	63.6
Northeast (NEA)	88.0	56.6

Note. Source: own elaboration according to the INDEC (2021).

At this moment, the goal of this article is to study the effect access to ICT in the students' homes has on their educational achievement. The article focuses on the educational elementary level. Firstly, because literature shows that younger students or digital natives have been assigned the ability to multitask, that is, to process simultaneously several sources of information. These young people are also developing critical competences that lead to new cognitive and learning processes (Dede, 2005; Oblinger & Oblinger, 2005). As a result of this view, they are treated differently to previous generations. On the contrary, other evidence shows this is a missense since digital natives have never lived in a non-digital world (Kirschner and Bruyckere, 2017; Calvani et al., 2012). Secondly, although some studies have examined the ICT impact on the educational outcome in the secondary level in Argentina (Formichella et al., 2020; Formichella & Alderete, 2020; Llach & Cornejo, 2018; Alderete & Formichella, 2016) research on impact evaluation in the elementary level is scarce to null.

This paper contributes to the empirical literature on impact evaluation, since studies on the impact of ICT at home on educational outcome in the elementary level are scarce. Besides, this paper offers a large-scale and representative sample that includes students from different cultural and socioeconomic backgrounds and collects data at individual, household and school level. The educational system in Argentina is organized into four levels: initial (first 3 years), primary or elementary (6 or 7 years, depending on the region), secondary (5 or 6 years depending on the region), and superior. At the elementary level, which is our research interest, there are public schools, private schools, and mixed schools. Differences in school management, among other reasons, explain the large educational inequality in resources and outcomes. Besides, educational segmentation and segregation are present (Waltemberg et al., 2021). The data utilized for the estimation corresponds to the Learning 2018 campaign at the elementary level in the entire country. In the same way, given the divergences enunciated among the geographical regions, the same technique is applied to subsamples corresponding to each region. The survey evaluates the 95% of elementary level schools and 8 out of 10 students from Argentina in the Language and Maths disciplines.

In this vein, the hypothesis presented is that said access improves school results and, to contrast it, the *Propensity Score Matching* (PSM) matching technique is used. On the other side, it does not estimate PSM based on experimental data (observational data in both groups: treatment and control). On the contrary, it is a quasi-experimental design that does not rely on random assignment (search for White and

Raitzer 2017 for explanation of impact evaluation). Randomized experiments are prospectively designed and executed trials to explore any specific intergroup difference among individuals. Some restrictions of these trails are the need of specific information about what constitutes each of the groups of study (Jupiter, 2017). Moreover, a strict idea and prescription of the protocols in the different groups is required. Since randomization tend to be costly and difficult to design, they become impossible to deal with, they might not be ethical, and they might not be ideal. In this scenario, it is not ethical to provide an educational gain to one group of students.

The article is structured in the following manner: the antecedents on the topic are presented in the next section; the methodology, data and variables are detailed in the one after that; in section four the results are exhibited and in the fifth section are the final considerations that emerge from the investigation.

2 Background

2.1 The relation between ICT access at home and student achievement

The 21st Century confronts society with the challenges of the information society that is plagued with ICT with a significant impact on our daily lives. According to the OCDE, each citizen should have ICT and basic digital capabilities in order to be able to adapt to the new society. Particularly, we should pay attention to the impact ICT has on students and the implementation of educational policies at the technological level. Currently, many policies or educational technology interventions for children have been effective in the world (Hurwitz, 2019), and policy makers promote early access to technology as the first step on the educational path (US Department of Education, 2017).

Although several studies of the impact of ICT on education have been published, studies at the elementary level has been scarce not only in Argentina but in the world. Some exceptions can be found in China, South Korea, Taiwan, and South Africa, among others (Meelissen, 2008; Kim et al. 2014, Wang & Chen 2021). Moreover, only a few has focused on the ICT at home effect. The educational value of the Internet at home has recently been reviewed by Daoud et al. (2020). Research in this area has shown that there is no consensus about such impact. While some research finds a positive effect of ICT at home (Kim et al., 2014; Wong et al., 2015; Wainer et al., 2015; Hurwitz & Schmitt, 2020; Wang & Chen, 2021), other investigations evince a negative effect (Cristia et al., 2017; De Melo et al., 2013; Malamud et al., 2018) or an ambiguous one –that is, they only find effects in some of the variables of access to ICT or in one of the disciplines of educational achievement analyzed (Saez López, 2012; Ryu, 2014). The authors that claim a negative influence hold that ICT can produce problems, especially on children with scarce digital abilities by distracting them from learning or worse even, by demotivating their participation in the activity. According to Hurwitz & Schmitt (2020), the impact on educational performance will depend on the digital abilities little children can acquire while using Internet.

In Argentina, some articles have focused on the analysis of a province or region, while others on the country as a whole. Among the first, Lusquiños (2020) estimates the ICT effects on the performance of elementary students in two jurisdictions of Argentina based on a multilevel model. According to the author, access to computers at home and mobile phones is not associated to better performance. On the other hand, Tagliani (1999) studies educational performance at a group of schools in Rio Negro, Argentina through an Ordinary Least Square model of a transversal cut, with data from their own survey. The author finds that, among other factors, access to certain teaching materials such as computer programs is an explanatory factor of the average students' performance.

Among the second group, Cortelezzi et al., (2018), based on data of Learning 2016 –Aprender 2016-, estimate a multilevel regression model. They find that access to a computer and Internet at home has a positive effect on educational achievements, whereas they do not evince such impact in access to a mobile phone. In the same way, Llach & Cornejo (2018) study the factors associated with school performance with data from Learning 2016 and find similar results. On the other hand, Tuñon & Poy (2016) estimate logistical regression models with data from the Survey of the Argentine Social Debt of 2011. They find that the socioeconomic status (SES), which includes owning a computer at home, is negatively correlated with the probability of a low scholar outcome (qualification below average). Then, SES impacts positively on school achievements. However, these authors cannot distinguish the ICT effect from the rest of SES factors. Finally, Roman & Murillo (2014) estimate multilevel models with data from the Second Explanatory and Comparative Study (Segundo Estudio Comparativo y Explicativo -SERCE) of the UNESCO. They conclude that the availability of a computer at home positively affects educational achievements.

2.2 Covariates associated with student achievement

Among the predictors linked to school performance are personal or individual factors concerning mainly demographic characteristics; family factors and factors related to the school. Some authors show that gender and family income are significantly related to performance (Wang & Chen, 2021; Hurwitz & Schmitt, 2020). In fact, women's academic performance is higher than men's with regard to Internet use and digital skills. However, this result contradicts certain literature (Cristia et al., 2017; Meelisen, 2008). In Argentina, research done at a secondary level has found that boys obtain better results in math and science, whereas women in language (Alderete & Formichella, 2016). In the same way, attending more years at the initial level of education (Pre-K) has been found to be correlated with more favorable school achievements later, just as repeating a grade is associated to lower results (Formichella et al., 2020; Alderete & Formichella, 2016).

There is consensus that factors at the family level, such as the educational level of the parents, predict the development of digital skills at an early age (Hurwitz & Schmitt, 2020; Saçkes et al., 2011) and they have an incidence on school performance. In the same way, there is consensus with regard to the role of the socioeconomic and cultural level of the students' home. Several articles demonstrated that access to ICT at home is associated with SES (González Betancor et al., 2021; Kim et al., 2014). The better the educational atmosphere and occupational status of the parents, the better the school results will be at the elementary level (Lusquiños, 2020;

Alves et al., 2017; Meelissen 2008), just like at the secondary level. On the contrary, other studies have not found a significant relationship with SES (De Melo, 2013). In addition, having more books and/or educational resources which is one of the most leading SES indicators in large-scale studies in education (Gustafsson et al., 2018) also favors performance (Sayans-Jiménez et al., 2018; Serio 2016). In the same line, drinking water (Middel & Kameshwara, 2021; Diaz-Gines et al., 2019; De Melo, 2013) and number of people per room (Tuñon & Poy, 2019; Llach & Cornejo, 2018; Pierse et al., 2016 are related to student achievement. Therefore, child labor would have the opposite effect if is understood as a proxy variable of SES (Llach & Cornejo, 2018).

On the other hand, the type of school students attend by virtue of the availability or not of educational resources and their socioeconomic level is also of interest (Machin et al., 2007). It is worth highlighting the positive relationship between access to ICT at school and the educational achievements (Formichella et al., 2020; Alderete & Formichella, 2016). However, there is no consensus about the role of the type of school management on the educational outcomes. Some studies stress there is no significant effect (Formichella and Kruger, 2013; Formichella 2011; Calero y Escardibul, 2007) while other papers argue there is a significant correlation (Cornejo & Llach, 2018; Kruger, 2018).

Finally, we should mention the relevance of the geographical issue on school performance. Several authors have found evidence regarding the existence of a digital gap that accompany the discrepancies in school achievement among the territories or regions of one country (Reggi & Gil-García, 2021; Cornejo & Llach 2018; Toudert, 2015). Programs aimed at providing schools with technological resources have had an impact in t+he rural sector by minimizing the digital gap between urban and rural contexts (Moral Pérez et al., 2014); even more so in the current pandemic context (Sosa Díaz, 2021).

3 Methodology, data and variables

3.1 Explanation of the Propensity score matching technique

With the aim of determining if access to ICT at home improves the educational performance of students in the last school year, a quasi-experimental investigation design was implemented. This method provides a solution to the non-randomness of ICT availability, since students who have ICT at home could differ qualitatively from the other students. At the same time, this qualitative difference would have a correlation with the educational performance. Then, the relationship between access to ICT at home and educational performance is susceptible to the problem of endogeneity.

In face of this problem of selection bias, a matching technique called *Propensity Score Matching (PSM)* of Rosembaum & Robin (1983) is used. PSM estimates the effect of access to ICT at home by means of comparing the educational results of students with access to ICT at home and those students with similar observable characteristics but without access. This quasi experimental design offers an appropriate technique in face of the lack of control of an individuals' participation assignment process in a group (treatment group, group with access to ICT at home)The matching method consists in a model technique for estimating the causal effects with observational data and has been recommended by Schneider et al., (2007), among others. This article estimates the average effect of the treatment (of accessing to ICT at home) on the educational performance. To this end, the lost potential value for each individual is imputed if it had belonged to the opposite treatment condition, on the basis of comparing the information of similar individuals (Guo & Fraser, 2015; Rosenbaum & Rubin, 1983). The effect of the average treatment is the average effect at population level of moving or displacing an entire population from the untreated condition to the treated condition (Austin, 2011). In this article, it consists of the effect obtained if all the students (comparables) had access to ICT at home. Then, this article seeks to examine what would have been the educational performance of students who have access to ICT at home if these technologies had not been available.

3.2 Description of the PSM process

The design of the PSM can be summarized in four stages: (a) estimation of the probabilistic model (probit), or the probability that the treatment be assigned to a student (accessing ICT at home); (b) the propensity score reckoning (PS); (c) the division of the sample in two sub-samples: the treated (those who receive treatment) and the controls (those who do not receive treatment), and the selection of the region of common support (CS); and (d) the matching of the cases in a non-parametric form. To summarize, each treated individual is assigned a control with a similar score (PS) and matched pairs are constructed (the same control can form a pair with more than one treated individual). Once the assumptions have been validated, estimations are carried out by means of different matching methods (Closest Neighbor, Kernel, and Radius) which allows contrasting and analyzing the significances of the differences between them (Bernal y Peña, 2016). By means of these methods, the difference in the educational performance of each pair of students is estimated (treated/control), in order to estimate the average difference in the entire sample named Average Treatment Effect (ATE).

To contrast the null hypothesis (ATE is null, there are no differences between the treated and controls) a significance "t" test is obtained from the standard error of the difference between each pair. Afterwards, it is concluded that the treatment has a significant effect on school performance if the null hypothesis is rejected.

Analytically, the problem starts with estimating the average effect on the result of a binary treatment. Given a student i, i = 1, ….N. it is determined that (Yi(0), Yi(1)) represents the two potential performances, Yi(0) indicating the educational result of student I if the treatment is not assigned to him/her, that is to say, if he does not have access to ICT at home; and Yi(1) indicates the educational result of student I if the treatment is assigned to him/her or has access to ICT at home. In case both states are observed simultaneously, the effect of access to ICT at home (treatment) on student I would be represented simply by the difference Yi(1)-Yi(0). However, this is not feasible given that only one of the possible states is observable (it is a quasi-experimental not an experimental design).

$$Yi = Yi\,(Wi) = \begin{cases} Yi\,(0)\,if\,Di = 0 \\ Yi\,(1)\,if\,Di = 1 \end{cases}$$

Given Di a variable that indicates whether the student has access to ICT or not at home. It is assumed that the educational results of students reach the following values taking into account the models of Quandt (1972) and Rubin (1974).

$Y_1 = \mu_1(X) + U_1$.

$Y_0 = \mu_0(X) + U_0$.

Where Yi represents the educational outcome in state i (Y1 if he participates, he has access to ICT at home; Y0 if he does not participate), X are the regressors or explanatory variables, observed random variables and U the residuals, unobserved random variables.

In face of this problem, the literature on impact assessment use different versions of variation averages with respect to the population analyzed. The average causal effect obtained from the comparison between average educational results and under the condition of access to ICT at home, is expressed in the following formula.

$$\underbrace{E(Y_i \mid D_i = 1) - E(Y_i \mid D_i = 0)}_{\text{Difference observed in the average educational results}} = \underbrace{[E(Y_{1i} \mid D_i = 1) - E(Y_{0i} \mid D_i = 1)]}_{\text{ATT: average effect of accessing ICT at home in the treated}} + \underbrace{[E(Y_{0i} \mid D_i = 1) - E(Y_{0i} \mid D_i = 0)]}_{\text{Selection bias}}$$

The problem arises in the "average treatment effect of the treated", ATT, since it is not possible to observe cases with educational result Y_0 for students who have access to ICT at home (D = 1); and this explains the presence of a selection bias (Heckman, 1990). The matching method offers a response to the selection bias by substituting the sampling by conditioning the regressors. In this way, a probit or logit model is estimated, such that the maximum authenticity function acquires greater relevance than the estimators' significance level (Heckman et al., 1999).

Given that the PSM is determined starting from the observable characteristics, the omission of relevant variables for the analysis must be mitigated. This problem of omission or of unobservable variables (such as the parents' motivation for ICT) constitutes a problem when there is a correlation of this omitted variable not only with the treatment assignment (accessing ICT at home) but also with the result (educational performance in Learning). Regarding this topic, Chen & Kaplan (2015) affirm that the PSM enables minimizing the bias in the treatment effect in comparison with other estimation techniques of treatment effects that use PS.

3.3 Methods of PSM

There are several methods to estimate the average treatment effect of the treated and each one is based on a different way of defining distance between the treated and the control. The following matching methods are used in the article:

Closest neighbor method that creates the pairs between the treated and controls; a case with closest PS control is sought for each treated. Generally, the reposition method is used in which case a control can be matched with more than one treated. Upon carrying out the matching, the difference between the result obtained by the treated and that of the controls is reckoned.

Method based on Kernel it is based on the weighted average of the results of more than one control j (untreated) (possibly all) where the weight assigned to a control j depends on the closeness of the observables of both treated i and controls j. That is to say that the individuals who received treatment are matched with a weighted average of the individuals that belong to the control group.

Radius or Caliper Method this technique uses all the comparable observations within specified radium of PS or scores (radius or caliper). Starting from it, the maximum distance from the PS is determined (*caliper*) and the pair is sought within its radius. One advantage of the radius method is that it uses as many comparison units as they are available within the radius. Thus, it is possible to use extra units (of fewer units) when good matchings are reached (not reached) (Dehejia & Wahba, 2002).

Finally, it is worth mentioning that the estimates are carried out with the STATA 14 Program and the command psmatch2.

3.4 Data and variables

The data used correspond to the program Learning 2018. They are public in nature, provided by the Ministry of Education of Argentina. The results of the last year of elementary school are examined, for the entire country and for each of the geographical regions that conform it (Pampean, Cuyo, NEA, NOA, Patagonia and CABA). The score obtained by students on the different Learning 2018 tests on language and math is used as a result variable.

The information provided by Learning 2018 is better than other data bases because it is the only one that allows comprehension of educational differences among regions.

For each student, a propensity score (PS) is estimated, which represents his probability of accessing ICT at home as well as a dependent function of a set of observable variables. With regard to the control variables, variables linked to the students, their home and the educational institution they attend are used (Lazear, 2001).

3.4.1 Dependent/Outcome variable

It consists in the educational result; the score obtained in the different tests: Mathematics and Language. It is a continuous numerical variable that can take a value of 0 to 800 (Secretariat of educational assessment, 2018).

3.4.2 Treatment variable

Home ICT access: Indicates availability of computers or notebooks at home with Internet connection. The variable reaches a value 1 if the student has a computer and/or notebook at home and also has Internet connection.

3.4.3 Control variables

Boy: it is a variable that reaches a value 1 if the student is masculine and zero if the opposite is the case.

Repetition: it is a variable that reaches a value 1 if the student ever repeated a grade level and zero in the opposite case.

Pre-K: it is a binary variable that indicates if the student attended the initial level before the corresponding level at 4 years old. It reaches a value 1 if this is the case and zero if the opposite is true.

Parents' education: it is a binary variable that indicates the educational level reached by the parents. It reaches a value 1 if at least one of the parents finished secondary school and 0 if the opposite is the case.

Child labor: it is a binary variable that indicates if the student has helped his/her parents or relatives with work outside the home or if he/she has done work at home, such as taking care of siblings, working on a farm, and/or doing housechores. If the student has dedicated time to such activities the variable adopts a value 1 and zero if the case is the opposite.

People per room: it is a numeric variable that represents the level of overcrowding in the home. It is estimated as the quotient between the number of people that live in the home and the number of rooms available.

Drinking water: it is a binary variable that indicates the presence (it takes a value 1) or absence (it takes a value 0) of drinking water at home.

Number of books: it is a numeric variable regarding the availability of books at home.

Urban: variable that adopts a value 1 if the school the student is registered at is in an urban area and 0 if it is in a rural area.

Public management: it is a binary variable that represents if the school the student attends is a public management institution (it takes value 1) or if on the contrary, it is a private management institution (it takes value 0).

In the Learning 2018 program, as opposed to the one of 2016, there is no data about the vulnerability quartile of the school in spite of being an important sociodemographic factor to explain not only the probability of ICT access at home but also as the educational result of the student (Alderete & Formichella, 2020). It is not possible to use the socioeconomic level index provided by Learning because it includes the ICT indicator, used here as treatment. For those reasons, the type of school management and urban/rural areas were introduced as *proxy* variables of SES. Students of schools with greater vulnerabilities are expected to correspond to public management and rural schools and, therefore, they have less probabilities of accessing ICT than the rest, as well as worse educational performance.

Table 2 Descriptive Statistics

Variable	Observations	Median	SD	Min	Max
ICT	494,469	0,68	0,47	0	1
Repetition	564,961	0,10	0,30	0	1
Parents' education	441,496	0,78	0,42	0	1
Boy	567,711	0,50	0,50	0	1
People per room	564,602	1,59	1,09	0,1	11
Drinking water	524,924	0,93	0,25	0	1
Number of books	563,280	3,48	1,85	1	6
Child Labor	523,111	0,62	0,48	0	1
Kindergarten	544,927	0,52	0,50	0	1
Public Management	585,292	0,70	0,46	0	1
Urban	585,292	0,89	0,32	0	1

Note. Source: own elaboration based on Learning 2018

In the same way, according to what was explained in the background section, students whose parents have an educational level lower than secondary school completed are expected to have fewer chances of accessing ICT and have lower educational results. The same happens to students in homes with more people per room, the absence of drinking water at home, the presence of child labor or the repetition phenomena. While the contrary effect is expected with having more books at home or assistance at the initial level at an early age.

4 Results

In Table 2 the descriptive statistics for the country's total are shared, not only of the result variables, but also of treatment and controls. It is observed that the variables are mostly binary with the exception of number of people per room and number of books that are continuous. The binary variables with highest median are "boy", "kindergarten" and "child labor".

Prior to carrying out the matching, one can observe that the availability of ICT at home generates significant statistical differences in the educational result: an average difference of 33.88 points in the math results and of 37.51 in the language ones are verified. On the other hand, also before the *matching*, it can be seen on Table 3 that the variables chosen as explanatory and conditioning of the matching evince significant statistical discrepancies between those who do not have access to ICT and those that do.

The first results to be presented are those corresponding to the probabilistic estimation model (PROBIT) that is carried out in order to reckon the probability whether a student shall be part of the treatment (access to ICT at home), and later reckon the *Propensity Score Matching* (PSM).

Just as it is observed in Table 4, all the variables considered in order to explain the treatment probability ended up being significant, except two: "boy" and "child labor". In the same way, the signs that accompany the coefficients of the significant variables are the expected ones according to the background: if the student did not repeat a grade and attended Kindergarten before he/she was 4 years old, the greater the probability of having access to ICT at home and of achieving better results at school. Similarly, the better the socioeconomic level (represented by more educated

Table 3 Differences in the explanatory variable medians according to Access to ICT

ICT		Repetition	Parents education	Boy	People per room	Drinking water	Child Labor	Kinder garten	Public Management	Number of books
0	Median	0,15	0,65	0,48	1,94	0,86	0,63	0,41	0,87	1,21
	N	154,747	114,091	155,381	155,448	152,629	144,460	147,753	157,881	117,143
	Typ. Dev.	0,35	0,48	0,50	1,25	0,34	0,48	0,49	0,34	1,21
1	Median	0,06	0,87	0,50	1,34	0,96	0,60	0,60	0,57	2,03
	N	332,269	270,000	332,253	332,848	329,127	314,551	323,826	336,588	250,343
	Typ. Dev.	0,23	0,33	0,50	0,86	0,20	0,49	0,49	0,50	1,35
Total	Median	0,09	0,80	0,50	1,53	0,93	0,61	0,54	0,66	1,76
	N	487,016	384,091	487,634	488,296	481,756	459,011	471,579	494,469	367,486
	Typ. Av.	0,28	0,40	0,50	1,04	0,26	0,49	0,50	0,47	1,36
Sig Av Dif		0	0	0	0	0	0	0	0	0

Note. Source: own elaboration based on Learning 2018

Table 4 PROBIT Model Estimate in Language and Mathematics

	Language			Mathematics		
Variables	Coefficient	Error	p-value	Coefficient	Error	p-value
Repeating	-0,32	0,05	0,00	-0,35	0,05	0,00
Parents' education	0,41	0,03	0,00	0,41	0,03	0,00
Boy	0,02	0,02	0,31	0,02	0,02	0,32
People per room	-0,21	0,01	0,00	-0,21	0,01	0,00
Drinking water	0,56	0,05	0,00	0,55	0,05	0,00
Number of books	0,06	0,01	0,00	0,06	0,01	0,00
Child Labor	0,02	0,02	0,46	0,02	0,02	0,46
Kindergarten	0,18	0,02	0,00	0,84	0,02	0,00
Public Management	-0,48	0,03	0,00	-0,47	0,03	0,00
Urban	0,45	0,04	0,00	0,44	0,04	0,00
_cons	-0,18	0,09	0,04	-0,17	0,09	0,05

Note. Source: own elaboration based on Learning 2018

parents, fewer people per room, having drinking water and a larger number of books), the greater will be the chance that the student shall have access to ICT as well as more favorable educational results. Likewise, if he/she attends a school in an urban area, or if such school is privately managed, the probability of belonging to the treated and of attaining better achievements also increases.

Then, the Propensity Score (PS) is estimated and starting from it the sample is divided into two groups: the treated and the controls. Thus, the common support

Table 5 Common support region. Sample size with PSM according to result variable and region

Region	Educational Results	Treated	Controls	Total
Patagonia	Mathematics	11,392	3709	15,101
	Language	11,501	3756	15,257
NOA	Language	25,004	17,130	42,134
	Mathematics	24,881	16,952	41,833
NEA	Language	15,091	12,372	27,463
	Mathematics	15,005	12,266	27,271
CUYO	Language	17,710	9641	27,351
	Mathematics	17,608	9569	27,177
CABA	Language	15,473	1472	16,945
	Mathematics	15,444	1477	16,921
Pampeana	Language	144,249	45,892	190,141
	Mathematics	143,843	45,464	189,307
Total	Language	229,028	90,263	319,291
	Mathematics	228,173	89,437	317,610

Note. Source: own elaboration based on Learning 2018

region is determined. In the following Table (5) the number of individuals in each group within the common support region can be observed, for each result variable (mathematics score and language score), for the country's total and for each region.

Finally, the results found upon matching the non-parametric cases shall be presented; that is to say, after forming pairs upon selecting a control with similar scores (PSM) for each treated; the same individual being able to be the control for more than one treated. Next the results can be observed according to three different matching methods.

4.1 Matching method: Kernel

According to the Kernel methodology the result obtained is that the ATT of the score, in language as well as in mathematics, of the treated group is higher in all the regions and for the country's total (see column 6 in Table 6); and that the median difference between such groups is statistically significant (see column 8 on Table 6). In the same way, the median difference in percentage terms for each score can be observed, calculating the difference in absolute value in relation to the median result in the treated (column 7 of Table 6).

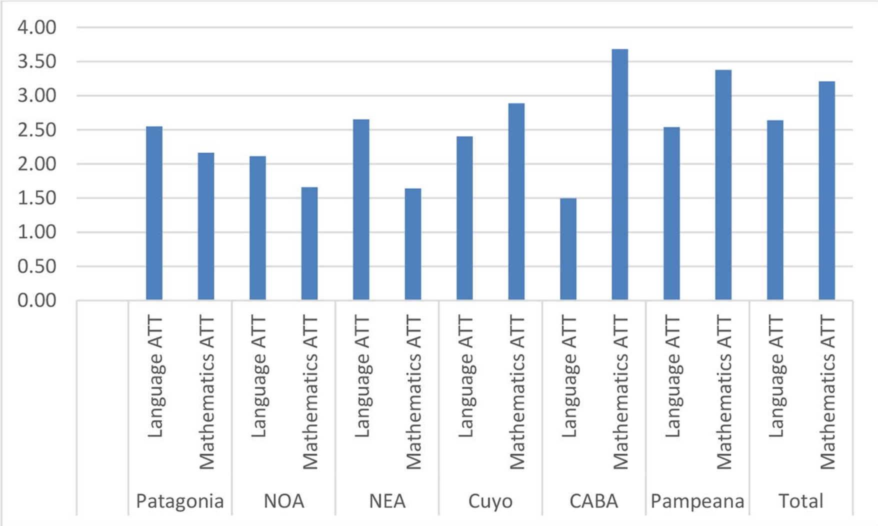
Thus, for the total sample, one can observe that the treated have a score in language that is 2.6% higher than that of the untreated; the same happens in mathematics, but the percentage is higher (3.2%). In other words, the group of students with access to ICT at home has a higher average performance, in language as well as in mathematics (see picture 1).

With respect to the regions, following the proposed reasoning, CABA is the one that evinces the largest difference in percentage terms, between the treated and the untreated in the area of mathematics; and NEA is the one with the smallest discrepancy in those terms. While in the language area the participation of the regions is repeated, in the inverse way, the largest difference is observed in NEA whereas in CABA the smallest (see picture 1).

Table 6 Estimation of ATT (according to Kernel) for each region and for the country's total

(1) Region	(2) Variable	(3) Sample	(4) Treated	(5) Controls	(6) Difference	(7) Difference in % (6)/(4)	(8) T-stat
Patagonia	Language Score	Without match	546,01	514,87	31,13	5,70	20,58
		ATT	546,01	532,09	13,92	2,55	7,22
	Mathematics	Without match	520,84	494,90	25,94	4,98	14,24
	Score	ATT	520,84	509,57	11,27	2,16	4,91
NOA	Language Score	Without match	538,87	506,49	32,38	6,01	39,00
		ATT	538,87	527,48	11,40	2,11	10,27
	Mathematics Score	Without match	516,04	495,56	20,49	3,97	20,58
		ATT	516,04	507,48	8,56	1,66	6,39
NEA	Language Score	Without match	533,85	501,99	31,87	5,97	31,27
		ATT	533,85	519,69	14,16	2,65	10,20
	Mathematics Score	Without match	505,68	494,78	10,90	2,15	9,07
		ATT	505,68	497,38	8,30	1,64	4,95
Cuyo	Language Score	Without match	541,56	504,57	36,99	6,83	35,73
		ATT	541,56	528,54	13,02	2,40	9,78
	Mathematics Score	Without match	523,61	485,75	37,85	7,23	30,96
		ATT	523,61	508,49	15,12	2,89	9,70
CABA	Language Score	Without match	575,88	540,89	34,99	6,08	16,05
		ATT	575,88	567,26	8,61	1,50	2,11
	Mathematics Score	Without match	569,52	524,85	44,66	7,84	16,41
		ATT	569,52	548,55	20,97	3,68	6,25
Pampeana	Language Score	Without match	547,13	511,27	35,86	6,55	79,96
		ATT	547,13	533,25	13,89	2,54	23,31
	Mathematics Score	Without match	531,55	495,00	36,55	6,88	67,93
		ATT	531,55	513,60	17,95	3,38	25,46
Total	Language	Without match	546,81	509,01	37,80	6,91	115,06
	Score	ATT	546,81	532,38	14,43	2,64	31,56
	Mathematics Score	Without match	529,58	494,57	35,00	6,61	88,68
		ATT	529,58	512,58	17,00	3,21	31,16

Note. Source: own elaboration based on Learning 2018



Picture 1 Difference (in %) between treated and controls (according to Kernel). (Source: own elaboration based on Learning 2018)

4.2 Matching method: Radius Caliper

With the Radius Caliper matching method, Table 7 also shows that there is a difference in the score, in language as well as in mathematics, among the treated and the untreated students, and that such difference is statistically significant in every case. That is to say, a positive effect of access to ICT at the students' home on school performance is evinced for the country's total and for each one of the analyzed regions.

In percentage terms, for the country's total the treated have 2.7% higher results than the untreated; whereas in mathematics such percentage is 3.3%. In the same way, observing the regions, the greatest impact is seen in CABA, in both language as in mathematics, the lesser effect in language in the NOA and the lesser effect in mathematics in the NEA (see picture 2).

4.3 Matching method: nearest neighbor

Finally, with the "Nearest neighbor" matching method, it can be observed that the average effect of the treated is statistically significant in every case, with the exception of the mathematics results in the NEA and Patagonian regions (Table 8).

Again, in percentage terms, for the country's total the treated have 2.1% higher results in language than the untreated, whereas in mathematics such percentage is smaller (1.7%). In the same way, observing the regions, the greatest impact on language is verified in the Pampean region and on mathematics in CABA, whereas the lesser effect on language is in Cuyo and the lesser effect in mathematics is in the NOA (see picture 3)

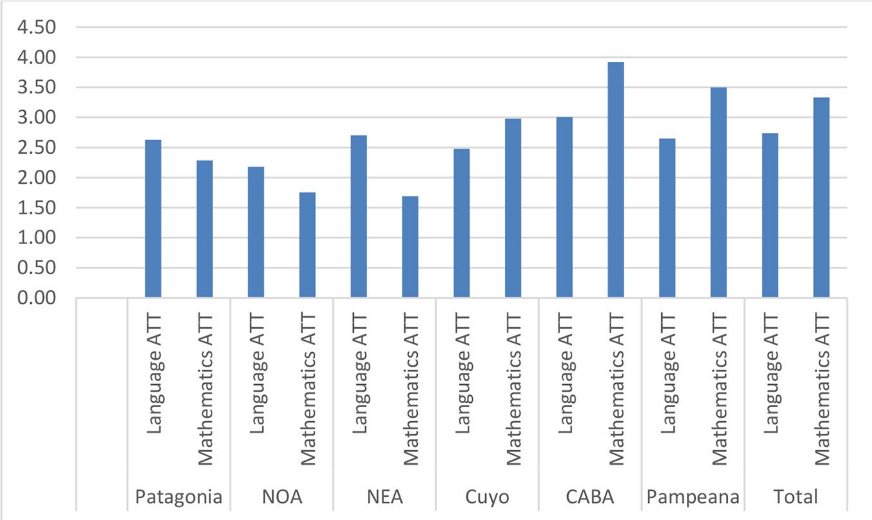
To summarize, from the reading of the econometric results found through the three matching methods, it can be said that access to ICT at the students' homes is

Table 7 ATT estimation (according to Radius Caliper) for each region and for the country's total

(1) Region	(2) Variable	(3) Sample	(4) Treated	(5) Controls	(6) Difference	(7) Difference en % (6)/(4)	(8) T-stat
Patagonia	**Language Score**	Without match	546,01	514,87	31,13	5,7	20,58
		ATT	546,01	531,66	14,35	2,63	7,56
	Mathematics Score	Without match	520,84	494,9	25,94	4,98	14,24
		ATT	520,84	508,94	11,9	2,28	5,26
NOA	**Language S.**	Without match	538,87	506,49	32,38	6,01	39
		ATT	538,87	527,14	11,73	2,18	10,65
	Mathematics S	Without match	516,04	495,56	20,49	3,97	20,58
		ATT	516,04	506,99	9,05	1,75	6,81
NEA	**Language S.**	Without matching	533,85	501,99	31,87	5,97	31,27
		ATT	533,85	519,43	14,42	2,7	10,45
	Mathematics S.	Without match	505,68	494,78	10,9	2,15	9,07
		ATT	505,68	497,14	8,54	1,69	5,13
Cuyo	**Language S.**	Without match	541,56	504,57	36,99	6,83	35,73
		ATT	541,56	528,15	13,41	2,48	10,17
	Mathematics S.	Without match	523,61	485,75	37,85	7,23	30,96
		ATT	523,61	508,01	15,59	2,98	10,1
	Language S.	Without match	575,88	540,89	34,99	6,08	16,05
CABA		ATT	575,88	558,57	17,31	3,01	6,4
	Mathematics S.	Without match	569,52	524,85	44,66	7,84	16,41
		ATT	569,52	547,2	22,32	3,92	6,78
Pampeana	**Language S.**	Without match	547,13	511,27	35,86	6,55	79,96
		ATT	547,13	532,64	14,49	2,65	24,68
	Mathematics S.	Without match	531,55	495	36,55	6,88	67,93
		ATT	531,55	512,96	18,59	3,5	26,76
Country	**Language S.**	Without match	546,81	509,01	37,8	6,91	115,06
total		ATT	546,81	531,84	14,97	2,74	33,21
	Mathematics S.	Without match	529,58	494,57	35	6,61	88,68
		ATT	529,58	511,94	17,63	3,33	32,8

Note.Source: own elaboration based on Learning 2018

associated with a positive effect on the educational achievements in language and mathematics all over the country and in each of the regions that conform it, with the exception of the NEA and Patagonian regions according to the "Nearest neighbor"



Picture 2 Difference (in %) between treated and controls (according to Radius Caliper). (Source: own elaboration based on Learning 2018)

method. The extreme magnitudes about the effect of treatment can be observed in the following summary table (Table 9):

5 Discussion

This paper contributes to the empirical literature on impact evaluation, since studies on the impact of ICT at home on educational outcome in the elementary level are scarce. Besides, this paper offers a large-scale and representative sample that includes students from different cultural and socioeconomic backgrounds and collects data at individual, household and school level. The survey evaluates the 95% of elementary level schools and 8 out of 10 students from Argentina in the Language and Maths disciplines.

As we can see in Table 10 .recent studies do not use quasi experimental methods to evaluate the impact of ICT at home on the educational outcome at elementary school level. While some of them are not very recent studies and based on randomization and experimental design as they are public programs or interventions (with their related ethical concerns)(see Cristia et al., 2017; De Melo et al., 2013), the others utilized less robust tools to control for endogeneity. Among them, the most recent one, Hurwitz (2020) estimate a SEM model but is based on a small-scale sample (N = 101). Besides, the authors examine the ITC usage and digital skills as the variables of interest which are conditioned by unobservable variables such as preferences and ease to use.

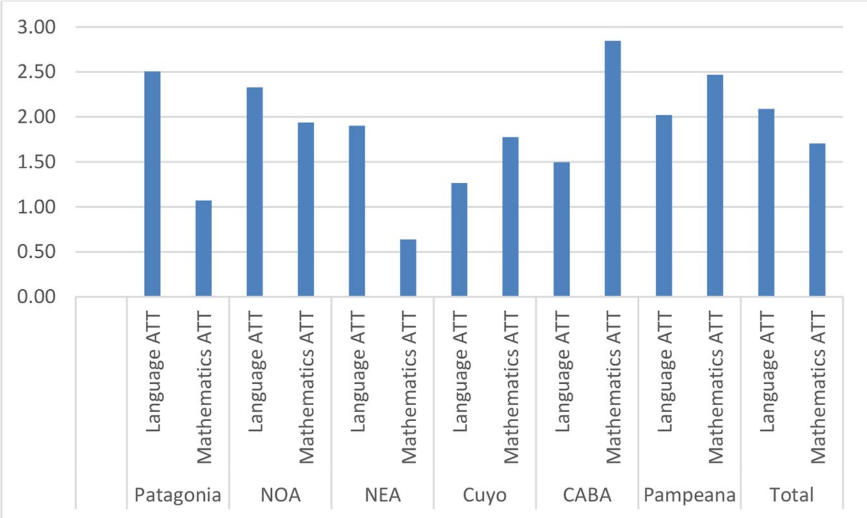
In this way, the results found inclined the scale in favor of international investigations that find access to ICT as a relevant determinant of the educational achievements at elementary level (Meelissen, 2008; Kim et al. 2014; Wang & Chen 2021).

Table 8 ATT estimation (According to Nearest Neighbor) for each region and for the country' total

(1) Region	(2) Variable	(3) Sample	(4) Treated	(5) Controls	(6) Difference	(7) Difference in % (6)/(4)	(8) T-stat
Patagonia	**Language score**	Without match	546,01	514,87	31,13	5,70	20,58
		ATT	546,01	532,33	13,68	2,51	4,97
	Mathematics Score	Without match	520,84	494,90	25,94	4,98	14,24
		ATT	520,84	515,26	5,58	1,07	1,70
NOA	**Language score**	Without match	538,87	506,49	32,38	6,01	39,00
		ATT	538,87	526,32	12,55	2,33	6,86
	Mathematics score	Without match	516,04	495,56	20,49	3,97	20,58
		ATT	516,04	506,05	10,00	1,94	4,62
NEA	**Language score**	Without match	533,85	501,99	31,87	5,97	31,27
		ATT	533,85	523,70	10,15	1,90	4,64
	Mathematics Score	Without match	505,68	494,78	10,90	2,15	9,07
		ATT	505,68	502,46	3,22	0,64	1,28
Cuyo	**Language score**	Without match	541,56	504,57	36,99	6,83	35,73
		ATT	541,56	534,71	6,85	1,27	3,39
	Mathematics score	Without match	523,61	485,75	37,85	7,23	30,96
		ATT	523,61	514,31	9,30	1,78	3,93
CABA	**Language score**	Without match	575,88	540,89	34,99	6,08	16,05
		ATT	575,88	567,26	8,61	1,50	2,11
	Mathematics Score	Without match	569,52	524,85	44,66	7,84	16,41
		ATT	569,52	553,31	16,21	2,85	3,29
Pampeana	**Language score**	Without match	547,13	511,27	35,86	6,55	79,96
		ATT	547,13	536,07	11,06	2,02	6,18
	Mathematics Score	Without match	531,55	495,00	36,55	6,88	67,93
		ATT	531,55	518,43	13,12	2,47	6,18
Total	**Language Score**	Without match	546,81	509,01	37,80	6,91	115,06
		ATT	546,81	535,39	11,42	2,09	6,78
	Mathematics Score	Without match	529,58	494,57	35,00	6,61	88,68
		ATT	529,58	520,56	9,02	1,70	4,51

Note. Source: own elaboration based on Learning 2018

Through the different matching methods, a positive impact of access to ICT at home on school performance in language and mathematics is evinced. In the same way, the variables used to carry out the matching also have the signs mentioned by the litera-



Picture 3 Difference (in %) between treated and controls (according to Nearest Neighbor). (Source: own elaboration based on Learning 2018)

Table 9 Effect of treatment according to method and discipline

Method / Discipline	ATT – Mathematics		ATT- Language	
	Greater impact	Lesser impact	Greater impact	Lesser impact
Kernel	CABA	NEA	NEA	CABA
Radius	CABA	NEA	Pampean	NOA
Closest neighbor	CABA	NOA	CABA	Cuyo

Note. Source: own elaboration

ture in the subject in Argentina (Lusquiños, 2020; Cortelezzi et al., 2018; Cornejo & Llach, 2018; Tuñon & Poy, 2016). The greater the educational level of the parents, the fewer people per room and greater number of books at home, the greater the probability of having access to ICT and of reaching higher educational achievements. Moreover, the absence of drinking water at the student's home, having repeated a grade or not having attendend Kindergarten reduce such chances. Finally, those who attend privately managed schools and belong to the urban environment have greater probabilities of belonging to the treated groups and of reaching greater educational results, which is also consistent with previous literature.

With respect to the impact of treatment in each of the regions, discrepancies are observed, such as it was found in previous investigations (Lusquiños, 2020; Cornejo & Llach, 2018). The greatest effect on mathematical discipline is evinced in CABA according to the three matching methods utilized, which gives consistency to the result. This jurisdiction is, at the same time, the one that represents the greatest computer penetration and the largest percentage of homes with access to Internet. However, the lesser effect of treatment on mathematical achievements is observed in the NEA region, according to the Kernel and Radius methods, and in NOA according to the nearest neighbor method. In this case, NEA and NOA are the regions with the

Table 10 Research about the impact of ICT at home on the educational Outcome

Paper	Country	Data date	Sample size (N student)	Methodology	ICT variable	Age Group (only elementary/children or mixed: children and high school/other)
Cristia et al., (2017)	Peru	2005–2007	20,923	OLS, experimental	OLPC	mixed
De Melo et al., (2013)	Uruguay	2006–2012	7209	Panel, difference in difference (randomization, experimental)	Internet use, Ceibal OLPC	mixed
Hurwitz & Schmitt (2020)	USA	2010	101	SEM structural equation model	Internet use, digital skills	children
Kim et al., (2014)	Korea	2011	11,767	Multilevel	ICT usage time	children
Malamud (2018)	Peru	2011–2013	540	OLS	Internet at home	children
Wainer (2015)	Brazil	2007–2011	7 million	Confidence interval, test	Computer and Internet	children
Wang (2021)	Taiwan	2013	943	Multilevel	ICT use, application	mixed
Wong et al., (2015)	Shangai, China		1500	Mean comparison, test	Internet access	mixed

Note. Source: own elaboration

greatest percentage of rural population and lesser access to ICT. Thus, in the case of mathematics, it seems that treatment is more effective in populations familiarized with ICT.

With regard to language, the results are not so clear, since coincidences between the different matching methods used are not observed. A deeper analysis of this issue can give rise to further research.

6 Conclusions

ICT has modified people's daily lives for a long time and what occurred in the educational context is no exception. In the same way, currently there are digital access and literacy gaps between students, an issue that has acquired greater relevance in face of the lockdown generated by the Covid-19 pandemic. In this scenario, students from less developed countries are expected to be less prepared to engage in online education. This disadvantage position is primarily explained by their weak ICT access.

In this context, throughout this article the impact of ICT on educational results at an elementary level in Argentina has been studied. Such impact has also been analyzed in each of the regions of the said country. The results presented evince a clear stand in favor of the proposed hypothesis: students who have access to a computer with Internet connection at home reach, *ceteris paribus*, higher educational achievements, in the language as well as in the mathematics fields.

Similarly, it has been found that the level of impact differs amongst the regions. For instance, in the mathematics area the effect is greater than in GBA (Greater Buenos Aires), a jurisdiction that has high levels of access to Internet and computers at home. Whereas in the NEA and NOA regions the effect is lesser, precisely where access to the ICT is one of the most limited. However, in the language field it is not possible to establish systematic relationships and could be the object of future research.

In sum, starting from the results found, one can affirm that access to ICT produces a positive impact on school performance, but such impact is not totally homogenous among regions. Thus, the door that enables carrying out an investigation as to the causes of such differences has been opened. In future research we propose to utilize multilevel type models in which one of the levels is the province or region in order to be able to detect which variables have a bearing on the discrepancies presented here.

With respect to political considerations, any initiative that seeks to guarantee access to computers at elementary level student homes, or subsidize the corresponding Internet service would be in tune with enabling the usufruct of the benefits of access to ICT on school achievements. On the other hand, it is worth pointing out that access to ICT is a necessary condition, but in itself is not enough to put it to good use (Alderete & Formichella, 2020). Therefore, policies that favor such access should be complemented with other types of initiatives linked to its use. In fact, the last data of Learning does not collect data on the use of Internet.

Data Availability The datasets analyzed during the current study are available in the Aprender 2018 repository, https://drive.google.com/file/d/18Y0gy0ZsjT4n7e9hlSOtCuvI0DFdhJt6/view.

Conflict of interest None.

References

Alderete, M. V., & Formichella, M. M. (2016). The effect of icts on academic achievement: the Conectar Igualdad programme in Argentina. Organización de las Naciones Unidas. *Cepal Review*, *119*(8); 83–100.

Alderete, M.V & Formichella, M.M (2020). Análisis de la primera brecha digital y su vínculo con el fracaso escolar en la Provincia de Buenos Aires. *Anales de la LV Reunión Anual de la Asociación Argentina de Economía Política*. Regrtieved from www.aaep.org.ar/anales

Austin, P. C. (2011). An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate Behavioral Research*, *46*, 399–424

Bernal, R., & Peña, X. (2016). *Guía Práctica para a Evaluación de Impacto* (4th printed ed.). Bogotá: Ediciones Uniandes

Bilbao, R., & Rival, A. (2011). Las provincias y las TIC: avances y dilemas de política educativa. *Documento de trabajo CIPPEC* 76,1–58. Retrieved from https://www.cippec.org/wp-content/uploads/2017/03/2538.pdf

Buchbinder, N., McCallum, A., & Volman, V. (2019). *El estado de la educación en Argentina. Informe Argentinos por la educación*. Retrieved from https://cms.argentinosporlaeducacion.org/media/reports

Calero, J., & Escardibul, O. (2007). Evaluación de servicios educativos: el rendimiento en los centros públicos y privados medido en PISA-2003. *Hacienda Pública Española / Revista de Economía Pública*, 183-(4/2007): 33 – 6

Calvani, A., Fini, A., Ranieri, M., & Picci, P. (2012). Are young generations in secondary school digitally competent? A study on Italian teenagers. *Computers & Education*, *58*(2), 797–807

Chen, J., & Kaplan, D. (2015). Covariate Balance in Bayesian Propensity Score Approaches for Observational Studies. *Journal of Research on Educational Effectiveness*, *8*, 280–302

Comisión Económica para América Latina y el Caribe (CEPAL) (2016). *Estado de la banda ancha en América Latina y el Caribe* (LC/W.710/Rev.1). Santiago de Chile: CEPAL. Retrieved from http://repositorio.cepal.org/bitstream/handle/11362/40528/

Cornejo, M., & Llach, J. (2018). Factores condicionantes de los aprendizajes en la escuela primaria y media. Evidencias a partir de las pruebas Aprender 2016. *Anales de la LIII Reunión Anual de la Asociación Argentina de Economía Política.* Retrieved from http://www.aaep.org.ar

Cortelezzi, M., Cura, D., Pissinis, A., Valencia, D., & Buchbinder, N. (2018). *Aprender en la era digital. Estudio para Proyecto Educar 2050 y Fundación Telefónica.* Retrieved from https://educar2050.org.ar/wp/wp-content/uploads/2019/01/Aprender-en-la-era-digital-version-web.pdf

Cristia, J. P., Ibarrarán, P., Cueto., S., Santiago, A., & Severín, E. (2017). Technology and child development: evidence from the one laptop per child program. *American Economic Journal: applied economics*, *9*(3), 295–320

Daoud, R., Starkey, L., Eppel, E., Vo, T., & Sylvester, A. (2020). The educational value of internet use in the home for school children: A systematic review of literature. *Journal of Research on Technology in Education*. DOI: https://doi.org/10.1080/15391523.2020.1783402

Dede, C. (2005). Planning for neomillennial learning styles. *EDUCAUSE Quarterly*, *28*(1), 7–12

De Melo, G., Machado, A., Miranda, A., & Viera, M. (2013). Profundizando en los efectos del Plan Ceibal. *Serie Documentos de Trabajo, DT 12/2013*. Instituto de Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República, Uruguay

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for Non-experimental causal studies. *The Review of Economics and Statistics*, *84*(1), 151–161

Díaz-Ginéz, T. A., Sevilla-Excevio, J. C., & Silva-Díaz, H. (2019). Rendimiento académico y factores de salud ambiental asociados en estudiantes de una institución educativa pública de la región Cajamarca, Perú. *Revista Experiencia En Medicina Del Hospital Regional Lambayeque*, *5*(1), 05–12

Formichella, M. M., & Rojas, M. (2009). El proceso de descentralización educativa en la Argentina. Un caso: La provincia de Buenos Aires. In A. M. Goetsche, & Coord (Eds.), *Perspectivas de la educación en América Latina* (pp. 167–188). Editores FLACSO Ecuador y Ministerio de Cultura de Ecuador

Formichella, M., Krüger, N. (2013). El fracaso escolar en el nivel medio argentino: ¿es menos frecuente en las escuelas de gestión privada debido a su administración? *Regional and Sectoral Economic Studies*, *13*(3), 127–144

Formichella, M. M., Alderete, M. V., & Di Meglio, G. A. (2020). New technologies in households: Is there an educational payoff? Evidence from Argentina. *Education in The Knowledge Society (EKS)*, *21*(18), 1–14

Formichella, M. M., & Alderete, M. V. (2020). El efecto de las TIC en comprensión lectora: un modelo de panel de datos. *Revista Semestre Económico*, *23*(54), 181–199

González-Betancor, S. M., López-Puig, A. J., & Cardenal, M. E. (2021). Digital inequality at home. The school as compensatory agent. *Computers & Education*, *168*, 104195

Guo, S., & Fraser, M. W. (2015). *Propensity Score Analysis: Statistical Methods and Applications* (2nd ed.). Thousand Oaks, CA: Sage

Gustafsson, J. E., Nilsen, T., & Hansen, Y. K. (2018). School characteristics moderating the relation between student socioeconomic status and mathematics achievement in grade 8. Evidence from 50 countries in TIMSS 2011. *Studies In Educational Evaluation*, *57*, 16–30

Heckman, J. (1990). Varieties of selection bias. *American Economic Review*, 80 (2). Nashville, Tennessee, American Economic Association

Heckman, J., Lalonde, R., & Smith, J. (1999). *The Economics and Econometrics of Active Labor Market Programs*. In ashenfelter, O. & Card D. (eds.), Handbook of labor economics (pp. 1865–2097), 3A. Amsterdam, North-Holland

Hurwitz, L. B. (2019). Getting a read on ready to learn media: A meta-analytic review of effects on literacy. *Child Development*, *90*, 1754–1771

Hurwitz, L. B., & Schmitt, K. L. (2020). Can children benefit from early internet exposure? Short- and long-term links between internet use, digital skill, and academic performance. *Computers & Education*, *146*, 103750

INDEC (2021). Acceso y uso de tecnologías de la información y la comunicación. EPH. *Informes Técnicos* 5 (89), 1–16. Retrieved from https://www.indec.gob.ar/uploads/informesdeprensa/mautic05213B13B3593A.pdf

Jupiter, D.C. (2017). Propensity Score Matching: Retrospective Randomization?. *The Journal of Foot and Ankle Surgery*, *56*(2), 417–420

Kim, H. S., Kil, H. J., & Shin, A. (2014). An analysis of variables affecting the ICT literacy level of Korean elementary school students. *Computers & Education*, *77*, 29–38

Kirschner, P., Bruyckere, P., & De (2017). The myths of the digital native and the multitasker. *Teaching and Teacher Education*, *67*, 135–142

Krüger, N. (2018). An evaluation of the intensity and impacts of socioeconomic school segregation in Argentina. In X. Bonal & C. Bellei (Eds.), *Understanding school segregation: Patterns, Causes and consequences of spatial inequalities in education* (pp. 210–243). Bloomsbury Academic.

Lazear, P. (2001). Educational production. *The Quarterly Journal of Economics*, *116*(3), 777–803

Llach, J. J., & Cornejo, M. (2018). Factores condicionantes de los aprendizajes. Primaria y secundaria. *Serie de informes de investigación 3*. Secretaría de Evaluación Educativa del Ministerio de Educación, Cultura, Ciencia y Tecnología de la Nación. Retrieved from https://www.argentina.gob.ar/sites/default/files/factores_condicionantes_de_los_aprendizajes.pdf

Lusquiños, C. (2020). Acceso a TIC, Habitualidad en el Uso y Desempeño Escolar en Contextos Diferenciados. ¿Una Alternativa para el Aprendizaje en Escuelas Primarias?. *Revista Internacional de Educación para la Justicia Social*, 2020, 9(3e), 1–15

Machin, S., McNally, S., & Silva, O. (2007). New Technology in Schools: Is There a Payoff? *Economic Journal*, *117*, 1145–1167. https://doi.org/10.1111/j.1468-0297.2007.02070.x

Malamud, O., Cueto, S., Cristia, J. P., & Beuermann, D. (2018). Do children benefit from internet access? Experimental evidence from a developing country. *BID working paper*. In https://doi.org/10.18235/0001392

Meelissen, M. (2008). Computer Attitudes and Competencies among Primary and Secondary Students. In J. Voogt, & G. Knezek (Eds.), *International Handbook of Information Technology in Primary and Secondary Education* (pp. 381–395). New York: Springer. https://doi.org/10.1007/978-0-387-73315-9

Middel, A., & Kameshwara, K. K. (2021). *Does access to services have a causal impact on children's education in Peru? Evidence from panel data analysis*. Paper presented at Comparative and International Education Society, Seattle, USA United States

del Moral Pérez, M. E., Martínez, L. V., & Piñeiro, M. D. R. N. (2014). Oportunidades de las TIC para la innovación educativa en las escuelas rurales de Asturias. *Aula abierta*, *42*(1), 61–67

Oblinger, D. G., & Oblinger, J. L. (2005). Educating the net generation Boulder, CO:EDUCAUSE

Pierse, N., Carter, K., Bierre, S., Law, D., & Howden-Chapman, P. (2016). Examining the role of tenure, household crowding and housing affordability on psychological distress, using longitudinal data. *Journal of Epidemiology and Community Health*, *70*(10), 961–966

Quandt, R. (1972). A new approach to estimating switching regressions. *Journal of the American Statistical Association*, *67*(338), 306–310

Reggi, L., & Gil-Garcia, J. R. (2021). Addressing territorial digital divides through ICT strategies: Are investment decisions consistent with local needs? *Government Information Quarterly*, *38*(2), 101–562

Roman, M. (2014). Disponibilidad y uso de TIC en escuelas latinoamericanas: incidencia en el rendimiento escolar. *Educ Pesqui*, *40*(4), 869–895. https://doi.org/10.1590/s1517-97022014121528

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, *70*, 41–55

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies'. *Journal of Educational Psychology*, *66*(5), 688–701

Ryu, J. (2014). *ICT and Educational Outcomes*. Tesis de maestría en economía. Alto University School of Business, Finlandia

Saçkes, M., Trundle, K. C., & Bell, R. L. (2011). Young children's computer skills development from kindergarten to third grade. *Computers & Education*, *57*, 1698–1704. 10.1016

Saez López, J. M. (2012). Valoración del impacto que tienen las TIC en educación primaria en los procesos de aprendizaje y en los resultados a través de una triangulación de datos.Revista Latinoamericana de Tecnología Educativa11 (2). http://campusvirtual.unex.es/revistas

Sayans-Jiménez, P., Vázquez-Cano, E., & Bernal-Bravo, C. (2018). Influencia de la riqueza familiar en el rendimiento lector del alumnado en PISA. *Revista de Educación*, *380*, 129–155. Influencia de la riqueza familiar en el rendimiento lector del alumnado en PISA

Schneider, B., Carnoy, M., Kilpatrick, J., Schmidt, W. H., & Shavelson, R. J. (2007). *Estimating Causal Effects Using Experimental and Observational Designs*. Washington, DC: American Educational Research Association

Secretariat of educational assesment [Secretaría de evaluación educativa]. (2018). Aprender 2018. Informe nacional de resultados. 6to año nivel primario. In https://www.argentina.gob.ar/sites/default/files/aprender2018_primaria.pdf

Serio, M. (2016). *Desigualdad de oportunidades educativas en Argentina.* Tesis de Doctorado en Economía, Universidad Nacional de la Plata

Sosa Díaz, M. J. (2021). Emergency Remote Education, Family Support and the Digital Divide in the Context of the COVID-19 Lockdown. *International Journal of Environmental Research and Public Health*, *18*(15), 7956

Tagliani, P. (1999). Análisis de factores que explican el rendimiento de las escuelas de nivel primario. El caso de Río Negro. Económica, 45(3),401–422. https://revistas.unlp.edu.ar/Economica/article/view/8584

Toudert, D. E. (2015). Brecha digital y perfiles de uso de las TIC en México: Un estudio exploratorio con microdatos. *Culturales*, *3*(1), 167–200

Tuñón, I., & Poy, S. (2016). Factores asociados a las calificaciones escolares como *proxy* del rendimiento educativo. *Revista Electrónica de Investigación Educativa*, *18*(1), 98–111. http://redie.uabc.mx/redie/article/view/615

Tuñón, I., Poy, S. Resultados educativos en lengua: el aporte diferencia de factores individuales, familiares e institucionales en contextos sociales dispares [en línea]. En:, Tuñón, I., Domínguez i Amorós, M., & Fernández Aguerre, T. (2019). (comps.). *Viejos y nuevos clivajes de la desigualdad educativa en Iberoamérica.* Ciudad Autónoma de Buenos Aires: CLACSO ; Barcelona : INCASI, International Network for Comparative Analysis of Social Inequalities ; Europa : European Commission. Disponible en: https://repositorio.uca.edu.ar/handle/123456789/9300U.S. Department of Education - Office of Educational Technology (2017). Reimagining the role of technology in education: 2017 national education technology plan update. U.S. Department of Education, Washington, DC

U.S. Department of Education. (2017). *Reimagining the Role of Technology in Education*, Office of Educational Technology. https://tech.ed.gov/files/2017/01/NETP17.pdf

UNESCO. (2015). *Qingdao Declaration*. Ed. UNESCO.

Wainer, J., Vieira, P., & Melguizo, T. (2015). The association between having access to computers and Internet and educational achievement for primary students in Brazil. *Computers & Education*, *80*, 68–76

Waltemberg, F., Britto, A., & Krüger, N. (2021). *La educación básica en Argentina y Brasil en el siglo XXI: políticas innovadoras, avances y desafíos, en: Políticas públicas na Argentina e no Brasil (2003–2020): diferenças, convergencias e desafíos*. Editorial: EDUFF-HUCITEC.Niteroi, Brasil

Wang, Y., & Chen, H. (2021). A Multilevel Study: Factors Influencing Taiwan Primary School Students' ICT Literacy.International Journal of Information and Education Technology, 11 (1)

Wong, Y. C., Ho, K. M., Chen, H., Gu, D., & Zeng, Q. (2015). Digital divide challenges of children in low-income families: The case of Shanghai. *Journal of Technology in Human Services*, *33*(1), 53–71

Ziegler, S., Volman, V., & Braga, F. (2020). Los cambios en la educación argentina durante la pandemia de COVID-19. *Informe Argentinos por la Educación*. https://cms.argentinosporlaeducacion.org/media/reports/ArgxEdu_Conectividad_Dispositivos.pdf

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