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ABSTRACT

The Effects of Shared School Technology Access on Students Digital Skills in Peru[1]

This paper analyzes the effects of increased shared computer access in secondary schools in Peru. Administrative data are used to identify, through propensity-score matching, two groups of schools with similar observable educational inputs but different intensity in computer access. Extensive primary data collected from the 202 matched schools are used to determine whether increased shared computer access at schools affects digital skills and academic achievement. Results suggest that small increases in shared computer access, one more computer per 40 students, can produce large increases in digital skills (0.3 standard deviations). No effects are found on test scores in Math and Language.

JEL Classification: I21, I28

Keywords: technology, education, digital skills, impact evaluation

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1. Introduction

Governments around the world are making large investments in technology in education programs. There is mounting research on the effects of these programs on learning in core subjects such as Math and Language (for example, Cheung and Slavin, 2013). However, many programs are mainly intended to develop students digital skills, that is, on preparing students to effectively use technology in their lives.[2] Public programs that provide one personal laptop to each student have shown sizable positive effects on digital skills (Malamud and Pop-Eleches, 2011; Mo et al., 2012). However, these programs might be too costly for many countries.[3] Alternatively, providing shared computer access at schools might give students sufficient technology exposure at a fraction of the cost. Yet, there is little evidence of the effects of such less expensive programs on the development of digital skills.

This paper examines whether moderate increases in school computer access affect students' digital skills. Additionally, we assess effects on test scores in Math and Language. The methodology exploits cross-sectional variation in computer access across secondary schools in Peru. This variation might be correlated with a host of important variables, raising the possibility of biased estimates. We tackle this challenge in two steps. First, we focus the analysis on public, urban and large schools. Avoiding comparing dissimilar schools, such as private and public schools, may reduce the expected correlation in computer access and baseline outcomes. Second, we exploit administrative data to generate, through propensity-score matching, two groups of schools with similar educational inputs other than computer access. This matching exercise is implemented within departments to ensure that comparisons are done across students living in the same geographical areas. We proceed to collect extensive data from 202 selected schools on characteristics of students, teachers, and principals, computer access and use, digital skills and test scores in Math and Language. Finally, we estimate effects by comparing average outcomes between schools with high computer access per student (treatment group) and those with low access (comparison group).

[2] For example, Mark Hovatter, chief facilities executive of the Los Angeles Unified School District, said about the district program to provide free iPads to all 640,000 students: "The most important thing is to try to prepare the kids for the technology they are going to face when they are going to graduate."

[3] Low-cost laptops from the One Laptop per Child program cost about 200 dollars, compared with 48 dollars spent per primary student yearly in low-income countries and 555 dollars in middle income countries (Glewwe and Kremer, 2006).

As expected given how schools were selected, results generated from the data collected confirm that schools in the treatment group have more intensive access to technology resources. On average, treatment schools had 12 more computers and were 24 percentage points more likely to have Internet access compared with those in the comparison group. Also, treatment schools had increased availability of computer labs and technology coordinators (20 and 27 percentage points differences, respectively). Results indicate significantly positive effects of increased school computer access on students' digital skills of about 0.3 standard deviations (t-ratio 4.8). There is no evidence of effects on Math and Language. Results are robust to the inclusion of student, teacher and principals controls. Consistent with these estimated effects on outcomes, we show that growth in computer access translated to increases in computer use only for teaching digital skills. Students in the treatment group spent 0.8 more hours per week learning digital skills (t-ratio 3.8) and there were no effects on the time used for Math and Language. This consistency between results on time use and skills suggest that the estimates indeed correspond to causal effects.

The identification assumption of the paper is that the treatment and comparison groups, in the absence of differences in computer access, should be similar in all dimensions. Propensity-score matching techniques should generate treatment and comparison groups balanced in the administrative variables used to predict treatment. However, these sets of schools could differ significantly in other dimensions not measured in administrative records. For example, treatment schools not only have greater access to computers but also cater to more affluent students, have better teachers and more effective principals. This possibility would introduce bias into the estimation of treatment effects. Because we collected rich data on students, teachers and principals, after creating the treatment and comparison groups, we can explore the validity of the identification strategy in depth. We can check balance in dimensions not used in the matching exercise. In short, we use administrative data to generate a suitable comparison group and primary data to check the identification strategy and estimate effects.

Extensive balancing tests provide supportive evidence to the identification strategy followed. Students in the two groups present similar socio-demographic characteristics such as age, sex, parents' education and home assets. For example, 49 percent of treatment students' mothers hold high school degrees compared with 47 percent in the comparison group (66 percent versus 64 percent for students' fathers). Similarly, the mean difference in students' age across groups is only 0.05 years (14.64 versus 14.69). Also reassuringly, teachers and principals present similar socio-demographic characteristics, educational background and experience. Still, it is well established that identifying treatment effects with cross-sectional variation requires strict assumptions that might not hold in practice (LaLonde, 1986). Therefore, the results presented should be interpreted as suggestive, and more robust evidence should be generated to confirm their validity.

This paper mainly contributes to the emerging literature documenting the effects of expanding computer access on digital skills.[4] As noted, the available literature has analyzed the effects of programs that have provided personal computers to students. Fairlie (2012) studies the impact of a program for college students and finds a 17 percentage point increase in self-reported computer mastery. Malamud and Pop-Eleches (2011) estimate that a program that provided vouchers for the purchase of computers in Romania improved digital skills by 0.25 standard deviations. Mo et al. (2012) evaluate the impact of a program in China for primary students and find an impact of 0.33 standard deviations on computer skills. Beuermann et al. (2012) study a program in Peru and find an impact of 0.88 standard deviations on skills specific to the use of the OLPC laptop but no effects on skills associated with Windows or Internet use.

To benchmark the magnitude of the effects estimated in our study we can compare them to those from the studies of Malamud and Pop-Eleches (2011) and Mo et al. (2012), who measure effects on a similar outcome measure (digital skills in a Windows environment expressed in standard deviations). The estimated effects are similar (around 0.3 standard deviations), suggesting that programs that provide shared access to computers in schools might generate similar effects compared with those that provide personal laptops. However, as mentioned, programs that provide shared access in schools will be significantly less expensive in monetary terms. In this evaluation, treatment schools have, on average, 12 additional computers shared among about 500 students (namely, 1 computer per 40 students), compared with the 1-1 ratio involved in programs distributing personal laptops. However, a

[4] It also contributes to the emerging literature on the effects of increasing computer and internet access in schools in test scores in Math and Language (Angrist and Lavy, 2002; Barrera-Osorio and Linden, 2009; Cristia et al., 2012; Goolsbee and Guryan, 2008; Machin, McNally and Silva, 2007). A related literature has analyzed the effects of specific software on these outcomes (Banerjee et al., 2007; Barrow, Markman and Rouse, 2009; Dynarski et al., 2007; He, Linden and MacLeod, 2008; Linden, 2008; Rouse and Krueger, 2004).

comprehensive analysis should consider all associated costs and that models of shared computer access at the school for acquiring digital skills will demand class time, reducing its potential use for core subjects.

The rest of the paper is organized as follows. Section 2 briefly describes how technology has been introduced into public secondary schools in Peru. Section 3 presents the research design including the administrative and primary data used, the matching procedure and the empirical models estimated. Section 4 reports results on computer time use, digital skills and academic achievement, and Section 5 concludes.

2. Technology in Public Secondary Schools in Peru

Prior to 1996, there had been limited efforts to promote technology access and use in public schools in Peru. Between 1996 and 2001, several small-scale independent programs, mainly targeting secondary schools, were launched. These programs funded some technology resources (hardware, software, training and support) and required some investments from participating schools to be included in the program. These investments were typically funded by parents, private donations or other (non-public) sources of funding. This requirement promoted ownership and sustainability of the investment but at the expense of poor targeting (large public urban schools in more affluent areas received more resources). In this context, computers were mainly used for acquiring digital skills, for browsing the web, and for communication purposes.

In 2001, a highly publicized national technology in education program, *Proyecto Huascarán*, was launched. Its objective was to increase the quality of the education sector by incorporating the use of technology in the learning process. The program mainly targeted secondary schools although some primary schools were also covered. Schools selected into the program received hardware, software (Microsoft Office applications and digital media but not interactive software) and teacher training, and they were prioritized to receive Internet access. In addition, the program funded "innovation room coordinators" assigned to some schools. These individuals, trained in information technology and pedagogy, were responsible for ensuring the effective use of computer labs in subject areas. They were also expected to organize training sessions in the schools to contribute to the development of subject teachers' and principals' digital skills. This structure suggests that the program sought to incorporate the use of computers into core-subject teaching and not just enhance computer skills.

Regarding the procedure employed to select schools into the Huascarán program, interviews with former government officials suggest that there were some guidelines, but no strict protocol. Eligible schools had to be public and they should not have been covered by previous governmental programs (data checks showed that both requirements were always fulfilled). Within eligible schools, three factors were considered to select the final set of schools: i) high enrollment levels, ii) ease of access to schools, iii) commitment by principals, teachers and parents to support and sustain the initiative. Still, other factors may have been considered. Between 2006 and 2008 (the period relevant to this study) there was little policy action on technology in education in secondary schools as the government shifted its efforts to implement the One Laptop per Child program in primary schools in rural areas.

3. Research Design

3.1. Administrative Data

The administrative data used in the study are produced by the Peruvian Ministry of Education from yearly school censuses. Coverage is high, and the yearly non-response rate hovers around 3 percent. Information is available on the following characteristics: location, private or public status, the year the school opened, enrollment per grade, gender and overage status, number of sections per grade, number of teachers and administrative staff, repetition and dropout rates, physical infrastructure, textbooks, number of computers, the presence of a network connection, Internet access and the existence of a computer lab. In the analysis, the data used correspond to the year 2006. A few variables are not available from that year, in which case data from previous years are used.

We construct a measure of computer access for each student at a school (Student ICT Potential Access or SIPA), a linear transformation of the student-computer ratio computed as:

$$SIPA_s = \frac{Computers_s}{Enrollment_s} * 2 * 25$$

where *s* indexes the school. *SIPA* represents the average number of hours per week that students would use computers if they were used continuously during class time and shared between two students (students spend about 25 hours in school per week). Therefore, it expresses technology access in weekly hours that computers could be used. For example, in a school with 10 computers and 500 enrollees, if computers were used continuously by pairs of students, the average student would use them 1 hour per week (10/500*2*25=1). Using this measure of computer access permits the interpretation of changes in computer access as changes in potential hours of computer use per week per student. Furthermore, this measure of potential computer use provides an indication of efficiency when compared with actual computer use. Between 2001 and 2006, SIPA increased from 0.8 to 2.2 hours per week in secondary schools in Peru (Cristia, Czerwornko and Garofalo, 2013).

3.2. Sample Construction

This papers aims to estimate the effects of increased technology access on digital skills and academic achievement. Generating plausible estimates of this causal relationship in a non-experimental setting involves dealing with the fact that computer access may be correlated with other factors affecting the outcome variables. We tackle this problem by collecting data from two groups of schools similar in observed characteristics but different in technology access. The procedure followed to construct the sample is described next.

We begin with schools that participated in the annual surveys conducted by the Ministry of Education between 2001 and 2006, identifying public urban secondary schools with 20 or more students in their third year. This simple include 2,333 schools. We further restrict the sample to three departments, Lima, Puno and Ancash, to reduce the geographical dispersion of the data collection process and survey costs (*N*=831).[5] Next, we order schools by their *SIPA* in their departments and assign them to the following groups: i) low *SIPA*: below the 50th percentile; ii) medium SIPA: between the 50th and 75th percentile; iii) high SIPA: above the 75th percentile. We dropped schools with medium SIPA and defined those in the high SIPA category as the "treatment group" and those in the low SIPA category as the "comparison group." Discarding schools with intermediate values of computer access allowed starker contrasts in computer access between schools in defined treatment and comparison

[5] There are 25 departments in Peru, similar to states in the United States. Lima accounts for about 30 percent of national enrollment in secondary schools.

groups. Treatment schools have an average SIPA of 2.76 versus 0.43 in the comparison group.[6] This is the "Pre-Matched" sample, which contains 633 schools.

Columns 1 and 2 in Table 1 present means of observable characteristics for schools in the treatment (high SIPA) and comparison (low SIPA) groups in the Pre-Matched sample. Column 3 documents that there are several statistically significant differences among these groups. High SIPA schools tend to have lower enrollment and fewer students per teacher; they are also less likely to have an assistant principal and more likely to have libraries, as well as tend to be older. These differences motivate the use of propensity-score matching techniques to balance observable covariates across groups. Therefore, we proceed to predict treatment (namely, high SIPA) using a logistic regression and including the 20 variables presented in the top panel of Table 1 as controls (linearly and squared), the cross-interactions between four key variables (number of years operating, total enrollment, student-teacher ratio, Internet booth in the town), department dummies and interactions among the four mentioned variables and department indicators. We empirically explored including different sets of covariates, estimating separate regressions for each department, but balancing tests suggested that the chosen specification outperformed the alternatives analyzed.

We matched schools in the treatment and comparison groups by their predicted propensity score using nearest neighbor matching without replacement and applying a caliper of 0.02. As mentioned, we implemented the matching process within departments to ensure that treatment effects were estimated by comparing schools in similar geographical areas. The resulting sample included 282 schools, consisting of 141 pairs of matched schools. We provided this list of schools to a specialized survey firm with the instruction of targeting pairs of matched schools. If it was not possible to survey a school (because of its location or for failure to obtain permission to apply the instruments), the pair was dropped. In addition, the firm was instructed to collect data from about 140 schools in Lima, 30 in Ancash and 30 in Puno. The final sample of matched surveyed schools contains 202 schools, consisting of 101 pairs.[7]

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[6] Alternatively, schools could have been assigned to just two groups of low and high SIPA defined by the median value. However, in this case mean SIPA for the treatment group would have been reduced to 2.05.

[7] There were few instances of refusals to participate in the survey by schools. Therefore, the survey firm tended to target schools clustered geographically to reduce data collection costs. Because the firm had to collect data from complete pairs of matched schools these decisions should not affect the composition of treatment and comparison groups. We document few differences in observable characteristics between the 282 "matched" and

Columns 4 to 6 in Table 1 suggest that the documented differences in the Pre-Matched sample are reduced substantially when focusing on schools in the Matched and Surveyed sample. None of the 20 indicators used in predicting the propensity score present statistically significant differences between the treatment and comparison groups (Panel A). In addition, administrative variables not used in the matching procedure also tend to balance across the two groups (Panel B). The same pattern arises when analyzing the density distribution of the propensity score. Figure 1 shows that the propensity score distribution for treatment observations is shifted to the right versus those from the comparison group when focusing on the Pre-Matched sample. In contrast, Figure 2 shows that both distributions are almost on top of each other for the Matched and Surveyed sample. We complement these figures performing two-sample Kolmogorov-Smirnov tests for equality of the score distribution functions. For the Pre-Matched sample the null of equality is rejected at the 1 percent level, although for the Matched and Surveyed sample there is little evidence against this hypothesis (p-value of 0.949).

3.3 Primary Data

Primary data were collected in the 202 matched schools in November 2008. A third-grade class was randomly selected within each school, and questionnaires were administered to students, teachers, principals, and technology coordinators. A total of 4,897 students were surveyed, 50.3 percent of whom attended treatment schools.

The central outcome for this paper is a measure of students' digital skills. We applied a technology competence test intended to capture students' skills to use computers effectively. The test was developed by experts from the Measurement Center of the Pontifical Catholic University of Chile with strong experience in the design and application of psychometric tests.[8] The test was a paper-based instrument that aimed to simulate the use of a computer presenting screen shots and asking students how to perform certain tasks. Although it would have been desirable to have applied a computer-based exam, this was not feasible because some participating schools did not have the required resources. Therefore, a significant effort was exerted to generate a valid and reliable instrument to measure students' digital skills.

the 202 "matched and surveyed" schools, with the exception that the former tended to have lower average enrollment (459 versus 508, respectively).

[8] http://www.mideuc.cl.

The design of the test involved four steps. First, the areas and competencies to evaluate were determined based on a syllabus used by the International Computer Driving License Foundation (ICDL). This is an internationally recognized institution that certifies basic technology skills in 148 countries and 25 languages.[9] The exam evaluated the following areas: basic skills and file management, word processing, operating spreadsheets, and information and communication.[10] Second, about 210 items were developed that emphasized practical skills in operating computers and the Internet. Third, a pilot application involving about 500 students was implemented in schools in Lima similar to those participating in the study. Fourth, results from the pilot application were analyzed and standard procedures were applied to select those items that satisfy desired psychometric properties. The resulting test included 54 items and students were expected to complete it in one hour.

To shed light on the validity and reliability of the test, a field validation exercise was performed in November 2008. In this exercise, 210 third-grade secondary students in Santiago, Chile answered the developed paper-based test and completed the computer-based test administered by the ICDL Foundation. The results indicate that the paper-based test is valid and reliable. Regarding validity, scores in the paper-based test presented a correlation of 0.76 with those generated from the computer-based exam. In terms of reliability, the paper-based test presented a value of 0.94 in the Cronbach's Alpha.

Students were also evaluated in Math and Spanish. These tests were designed for the study using public items developed by the office in charge of designing and applying standardized achievement tests in the Ministry of Education of Peru (*Unidad de Medicion de la Calidad*). Additionally, students completed a self-administered questionnaire that collected demographic data, computer access and use at home, and information on computer availability and general use at school. In each class, students were randomly assigned to one of three groups. One group of students had to complete an additional section that collected information about the extent and type of computer use in Math. The second and third group had to complete similar sections on the use of computers in their Language and technology classes.

Math, Spanish, and technology teachers of the selected students were also surveyed. Information collected included demographic characteristics, technology access, use, training,

[9] http://www.ecdl.com.

[10] The test is intended to measure basic computer skills. As such, it might be considered as a "low-order" digital skills test.

and skills self-perception. Data were also collected on the actual use of computers in the third-grade class. School principals reported information on demographic characteristics, technology access, use, training, and skills self-perception and school inputs, focusing particularly on those related to technology. Finally, technology coordinators, when available, were surveyed to collect data on technology school inputs, extent, and type of use.

3.4 Empirical Models

Using the sample of matched and surveyed schools, we run OLS regressions to estimate mean differences in the treatment and comparison groups across relevant variables. These variables include the following: i) technology-related inputs at schools (for example, computer and Internet access); ii) student, teacher and principal characteristics; iii) computer time use by place (at school and out of school) and by subject (Technology, Math, Language); iv) test scores in digital skills, Math and Language. Regressions are run under the following specification:

$$(1) \quad y_{is} = \alpha + Treatment_s \beta + \varepsilon_{is}$$

where y_{is} represents the outcome variable, $Treatment_s$ is a dummy variable for treatment assignment status, ε_{is} represents the error term and *i* and *s* are student and school indices. The coefficient β is the parameter of interest and corresponds to an estimate of the average difference. Standard errors are clustered at the school level in all regressions.

4. Results

4.1. Checking the Identification Strategy

The empirical strategy, if successful, should have generated two sets of schools with different levels of access to technology but that are similar in several dimensions correlated with educational outcomes. In this subsection we test these two conditions.

We start by examining differences in technology access between treatment and comparison schools using the data collected for the study (Table 2). Panel A documents that treatment schools have significantly higher access to technology inputs. SIPA in treatment schools is 2.9 versus 1.3 in comparison schools. Similarly, treatment schools are, on average, 24 percentage points more likely to have internet access and 27 percentage points more likely to have a technology coordinator. This is not surprising given how the treatment and comparison groups were constructed. Nonetheless, it is important to document these differences considering that the groups were constructed using 2006 administrative data, which might have some measurement error, and that the primary data reported here were collected in November 2008.

Panel B explores whether there are also differences in principals' and teachers' technology skills. Results indicate that principals and teachers in treatment schools are significantly more likely to report that they learned to use computers at school (15 and 9 percentage points, respectively). This is consistent with treatment schools' increased likelihood of having technology coordinators and the expectation that these specialists provide training to principals and subject teachers. However, there is little evidence suggesting that principals and teachers in treatment schools had acquired more skills than their counterparts at comparison schools. In addition, there are no statistically significant differences in teachers' self-reported skills in general and pedagogical computer use, or in directors' general and administrative computer use. Additionally, results suggest that, in general, principals and teachers have low confidence in their abilities to operate computers effectively. For example, the average teacher reports being able to do 3.5 tasks among 8 listed tasks (2.9 tasks for principals).[11] Summing up, treatment schools have better access to technology-related resources (computer, internet and technology coordinators) but teachers and principals have low levels of digital skills, similar across treatment and comparison schools.

We now turn to the second condition required for our empirical strategy: for schools in the treatment group to be similar to those in the comparison group in relevant dimensions. To provide evidence of this issue, we examine a range of characteristics of students, teachers and principals. Table 3 shows that treatment and comparison students have similar demographic characteristics and home assets. In terms of technology access, students in the treatment schools are slightly more likely to have a computer at home (33 percent versus 28 percent, t-ratio 1.93). However, there is not a significant difference in computer access when finishing primary school, which suggests that having greater access in secondary schools might have

[11] Regarding general computer skills, teachers and principals answer whether they could do the following 8 tasks: produce a letter, send an attachment, take pictures and show them in the computer, save documents in folders, create a budget or student list in a spreadsheet, participate in Internet discussions, produce a simple presentation and use the Internet to buy online.

caused some families to invest in computers at home. Note that because of the large sample size (4,897 students in 202 schools) we can estimate mean characteristics and differences across groups precisely.

Table 4 documents few differences in subject teacher characteristics between treatment and comparison schools, regarding demographics, work experience or home assets. Teachers in treatment schools are slightly less likely to have computers at home (76 percent versus 82 percent, t-ratio 1.45). Table 5 shows that principals in treatment schools present similar characteristics to those in comparison schools. The only statistically significant difference is found for home computer access, though in this case principals in treatment schools are less likely to have this resource (87 percent versus 98 percent, t-ratio 3.03). The combined evidence from Tables 3 to 5 indicates that treatment students, teachers and principals are similar to their counterparts in comparison schools. This provides further validity to the empirical strategy adopted and suggests limited potential bias in estimates of causal effects on outcomes presented next. Therefore, we tentatively interpret differences in outcomes across groups as evidence of the effects of greater technology access.

4.2 Effects on Computer Use

This subsection explores whether increased technology access in treatment schools has translated into higher use, and, specifically, for what subjects. Table 6 shows the number of weekly hours of computer time use reported by students, both at school and outside school. Results indicate large effects of computer access on total use at school, though the increase is concentrated on teaching digital skills. Treatment students spend about 2.1 hours per week using computers at school compared with 1.0 hours for comparison students (t-ratio 5.15). However, there are no differences in computer time use in Math or Language classes across groups. The average time spent using computers to learn Math or Language is low and virtually identical in treatment and control schools (0.3 hours per week). In contrast, the time devoted to teaching digital skills is significantly higher in treatment schools versus comparison schools (1.6 versus 0.8, respectively). Consistent with the few differences in students' characteristics documented earlier, particularly for home technology access, there is no difference in the time spent using computers outside school.

Combining the estimates about total computer time use in school with information about SIPA, we can get a rough estimation about the fraction of time that computers are actually used. For treatment schools, computers seem to be used about 72 percent of the time (2.1 hours used / 2.9 hours of potential use). The corresponding estimate for comparison schools is 77 percent (1.0 / 1.3). These estimates should be interpreted with caution, as there are strong assumptions underlying these estimates including that computers are always shared by two students, that information reported by students about time use is accurate and that use by third-graders is representative for all students in the school.

Table 7 complements these results by presenting estimates of average hours per week that teachers report spending using computers in the Math, Language and technology classes. Again, we document no statistically significant effects in time spent on Math and Language using computers. However, subject teachers report much higher levels of computer use in their classes compared with students (0.8 hours versus 0.3 hours).[12] Regarding time spent teaching digital skills, there are no statistically significant differences across treatment and comparison groups in the average time reported by technology coordinators in these activities. However, note that this information was provided only by technology coordinators in schools that have them. Table 2 documents that treatment schools are significantly more likely to have technology coordinators. Therefore, combining these two factors (more technology coordinators and the same average time that they are teaching when present), we expect that students in treatment schools would have spent more time learning digital skills than those in comparison schools.

In short, increased access to technology resources in treatment schools has led to more time spent using computers to learn digital skills, with no effects on the time used to learn Math or Language. These findings are consistent with experimental evidence from Colombia. The evaluation of the "*Computadoras para Educar*" program showed that increased school computer access produced an increase in the time devoted to learning digital skills with no effects on computer use in Math or Language (Barrera-Osorio and Linden, 2009).

[12] No objective data can be used to determine whether students or teachers are reporting this information accurately. It is plausible that subject teachers might over-report computer time use if intensively using technology resources is expected from them. However, there is ample evidence documenting that respondents tend to over-report time spent in socially desirable activities and under-report those considered undesirable (United Nations, 2005).

One potential explanation for these results is that subject teachers, on average unprepared to effectively incorporate technology into instruction, decide not to increase the time spent using computers when facing an expansion of computer access. In fact, in comparison schools less than 30 percent of computer time was spent in teaching Math and Language. This suggests that subject teachers in comparison schools may not have been constrained in their use of computers because of low access levels. In economic terms, possibly, the binding constraint for the use of technology in core subjects would be low demand by teachers rather than limited supply. If so, to achieve increased technology use in core subjects, more guidance to teachers about how to effectively use these resources might be needed rather than expansion in computer access. Additionally, investments in digital content can be expected to contribute to increasing demand for and effectiveness of computer use.

4.3 Effects on Digital Skills and Academic Achievement

This subsection explores whether the differential access to technology inputs generates effects in digital skills and academic achievement. In theory, schools with higher levels of technology inputs could have higher learning in Math and Spanish through two channels. First, if instruction time when using computers generates more learning than traditional instruction, we would expect schools with increased access to computers to generate more learning, provided there is an increased use of computers for the particular subject. Treatment schools have more available instruction time with computers but, as documented above, it does not translate into increased use in Math and Spanish lessons. Therefore, we do not expect that treatment schools will enjoy higher learning in these subjects through this channel. Second, even if the time used in treatment and comparison schools were equal, there could be effects generated through higher "computer use productivity" in the treatment group. The instructional time using computers could be similar, but learning might be faster in treatment schools because of a better use of the available technology resources. However, we do not expect impacts through this channel because we have already documented that teachers in the treatment group seem similarly prepared (or unprepared) to integrate technology in the classroom. Additionally, computer time spent in core subjects is so low that the difference in productivity would have to be implausibly large to generate measurable impacts.

Given that we have documented that increased technology access translates into increased use in teaching digital skills, we would expect to document positive impacts on digital skills in treatment schools. However, note that the increase in average total time devoted to computer use, inside and outside schools, seems to have moderately increased (8.5 versus 7.0 weekly hours for treatment and comparison students, respectively). The additional use that students enjoy at school might not generate increased digital skills if there are decreasing returns of computer use to digital skills partially because the software used in school and outside school are similar. Therefore, whether increased access to computers in schools for the treatment group translates into better digital skills is an empirical question.

We test these hypotheses by estimating OLS regressions of test scores in Math, Spanish, and digital skills on a treatment indicator. Column 1 in Table 8 presents the results without controls. As expected, we find no impacts in Math and Language. However, we do find statistically significant positive impacts on digital skills. Students in the treatment group outperformed those in comparison schools by 0.31 standard deviations. Columns 2, 3 and 4 report estimated effects when progressively controlling for student, subject teacher and principal characteristics.[13] Adding these controls greatly reduces the standard errors, though there are limited changes in estimated coefficients. Focusing on effects on digital skills, the regression that includes all controls yields a virtually identical coefficient (0.31 standard deviations,) though the standard error decreases to 0.06 (t-ratio 4.8). The robustness of results across specifications provides further evidence for the validity of the empirical strategy followed.

The results presented suggest that increased technology inputs in schools can be used successfully to reduce differences in digital skills that might exist in the population. Such differences could be associated with differential access to and use of computers by individuals of different socioeconomic status (the so-called "digital divide"). From a policy perspective it is relevant to know whether there is heterogeneity of impacts across different individuals to maximize effects through optimal program targeting. Hence, we next explore whether there are heterogeneous effects on digital skills across groups.

[13] Controls for students, teachers and principals characteristics included in the regressions are presented in Tables 3, 4 and 5, respectively. Access to computers and Internet at home are not included as controls in regressions because they may be affected by computer access at school.

Table 9 presents evidence regarding differential impacts by three dimensions: access to home computers before entering secondary school, gender and mother's education. We do not find statistically significant evidence of differential impacts. However, the results document the extent of the digital divide in this context. Students with computers at home before entering secondary school outperformed those without computers by 0.27 standard deviations. Additionally, results indicate that being male is associated with a 0.12 standard deviation advantage, while having a mother with a high school diploma is associated with a 0.22 standard deviation increase. These results can be used to benchmark the estimated effects on digital skills. The small increases in shared computer access documented in treatment schools produced a positive effect of 0.31 standard deviations, larger than the documented differences across students different baseline computer access, gender and mother's education.

5. Conclusions

This paper studies whether increases in technology inputs in secondary schools in Peru translate into more hours of use of these resources in Math, Language and technology and into learning in these areas. To this end, we applied matching techniques to rich administrative census data for public urban schools to generate two sets of schools that are different in technology access but similar on observable educational inputs. Next, we collected primary data on these schools and verified that the empirical strategy followed achieved both stated objectives. Schools in the treatment group have more than double the number of computers than the comparison group (23 versus 11), increased Internet access (24 percentage points) and increased availability of computer labs and technology coordinators (20 and 27 percentage points, respectively). We also document that important characteristics at the student, teacher and principal levels are well balanced across groups.

We found that increased access to computers in the treatment group translated into increases in time used to teach digital skills, but no increases are found in computer time devoted to Math and Language. Consistent with the findings on use, we find no impacts for Math and Spanish but large effects on digital skills. The estimated impacts are sufficiently large to more than compensate for reductions in test scores in technology associated with not having a computer at home before entering secondary school, being female or having a mother with less than high school.

These results should be interpreted as suggestive rather than conclusive. We have provided several pieces of evidence that suggest the validity of the empirical strategy followed. However, it is important to recognize that this paper exploits only existing cross-sectional variation in computer access, which might be associated with other (not observable) determinants of educational outcomes. Further evidence, from randomized experiments, is warranted before providing prescriptive policy recommendations to countries desiring to use technology to improve educational outcomes.

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Table 1. School Characteristics by Treatment Status

	Pre-Matched			Matched and Surveyed		
	Treatment	Comparison	|t|	Treatment	Comparison	|t|
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Variables used to predict treatment						
Enrollment	449.6	715.6	7.29	515.9	498.9	0.36
Enrollment 3rd year	91.5	145.5	7.15	103.8	103.2	0.06
Students/teachers	18.3	21.2	7.56	19.7	19.6	0.24
% Students in social programs	0.550	0.570	0.68	0.569	0.571	0.05
% Has principal	0.934	0.908	1.17	0.911	0.950	1.11
Number of assistant principal	0.611	0.860	3.05	0.683	0.545	1.10
Administrative staff	6.2	6.4	0.35	5.7	5.5	0.35
% Teachers with teaching degree	0.817	0.851	3.13	0.860	0.841	1.53
% Tenured teachers	0.790	0.814	1.50	0.804	0.824	0.77
Classrooms	21.8	21.0	0.61	20.5	20.4	0.05
% Has teacher lounge	0.526	0.476	1.18	0.495	0.495	0.00
% Has library	0.810	0.723	2.52	0.752	0.713	0.63
Language textbooks	34.9	32.4	0.27	33.7	32.7	0.09
Math textbooks	39.7	32.8	0.76	47.0	36.3	0.76
% Has water supply	0.934	0.943	0.46	0.980	0.950	1.15
% Has electricity	0.976	0.983	0.58	0.980	0.970	0.45
% Has sewage	0.872	0.867	0.17	0.911	0.891	0.47
Year school was established	1976.6	1979.6	2.12	1978.8	1978.9	0.03
% With Social Sciences focus	0.782	0.754	0.80	0.752	0.733	0.32
% Has Internet café in the city	0.645	0.668	0.59	0.703	0.663	0.60
Panel B: Variables not used to predict treatment						
% Student that speak Quechua	0.133	0.159	0.89	0.129	0.119	0.21
% Students that speak Aymara	0.057	0.050	0.37	0.059	0.040	0.65
% Has administrative office	0.844	0.815	0.91	0.832	0.812	0.37
% Has subject labs	0.360	0.386	0.64	0.277	0.406	1.94
% Has gym	0.427	0.346	1.95	0.356	0.317	0.59
N	*211*	*422*		*101*	*101*	

Notes: Data from the 2006 school census are used. The Pre-Matched sample includes secondary public, urban schools in the departments of Lima, Ancash and Puno (N=633). The Treatment group includes schools with high SIPA (computers/student) and the Comparison group those with low SIPA. The Matched and Surveyed sample is a subset of schools from the Pre-Matched sample. Schools in the Treatment group were matched to those in the Comparison group using nearest neighbor matching without replacement and a caliper of 0.02 (N=282). Primary data were collected from pairs of matched schools that were accessible and that agreed to be surveyed (N=202). See Subsection 3.2 for details. Panel A reports statistics for variables used to predict treatment whereas Panel B presents statistics for those not included. Columns (1), (2), (4) and (5) presents means. Columns (3) and (6) presents t-ratios from regressions of the variable on a treatment dummy. Significance at the one and five percent levels is indicated by ** and *, respectively.

Table 2. School Technology Inputs and Staff Skills by Treatment Status

	Treatment	Comparison	Difference
Panel A: Technology inputs			
Computer and internet access			
Has computers	1.000	0.743	0.257**
			[0.044]
Computers	23.485	11.287	12.198**
			[1.753]
SIPA (computers/students x 2 x 25)	2.894	1.269	1.619**
			[0.225]
Has Internet	0.644	0.406	0.238**
			[0.069]
Facilities			
Computer lab	0.624	0.426	0.198**
			[0.069]
Innovation room	0.673	0.426	0.248**
			[0.068]
Computer lab and innovation room	0.307	0.119	0.188**
			[0.056]
Technology coordinator			
Has computer lab or innovation room coordinator	0.594	0.327	0.267**
			[0.068]
Panel B: Principal and teachers technology skills			
Math and language teachers			
Learned to use computers at school	0.471	0.383	0.088*
			[0.044]
General use [0-8]	3.697	3.370	0.327
			[0.247]
Pedagogical use [0-5]	2.192	1.864	0.328
			[0.169]
Principals			
Learned to use computers at school	0.465	0.317	0.149*
			[0.068]
General use [0-8]	3.069	2.762	0.307
			[0.356]
Administrative use [0-5]	1.356	1.168	0.188
			[0.222]
N	*101*	*101*	

Notes: Means and standard errors in brackets. Primary data collected in November 2008 were used. The self-reported technology skills variables for teachers and directors are constructed adding the number of activities that the person reports to be able to do from a pre-specified list. For example, for general computer use it includes the ability to open a file and create a folder. Significance at the one and five percent levels is indicated by ** and *, respectively.

Table 3. Students' Characteristics by Treatment Status

	Treatment	Comparison	Difference
Demographic characteristics			
Age	14.639	14.692	-0.053
			[0.056]
Male	0.482	0.502	-0.020
			[0.024]
Household size	5.950	6.172	-0.222*
			[0.105]
Mother has high school degree	0.491	0.469	0.022
			[0.033]
Father has high school degree	0.663	0.641	0.021
			[0.026]
Native tongue Spanish	0.905	0.919	-0.014
			[0.024]
Home assets			
Washing machine	0.317	0.301	0.016
			[0.029]
TV	0.914	0.925	-0.011
			[0.015]
Cable television	0.475	0.486	-0.011
			[0.037]
Refrigerator	0.628	0.624	0.004
			[0.042]
Phone	0.488	0.486	0.002
			[0.037]
Car	0.173	0.151	0.022
			[0.014]
Motorcycle	0.102	0.140	-0.038*
			[0.016]
Home technology access			
Computer	0.329	0.277	0.052
			[0.027]
Internet	0.163	0.142	0.021
			[0.021]
Had a computer in the last year of primary education	0.202	0.186	0.015
			[0.022]
N	*2,463*	*2,434*	

Notes: This table presents statistics and estimated differences between the treatment and comparison groups at the student level. Primary data collected in November 2008 were used. Standard errors, reported in brackets, are clustered at the school level. Significance at the one and five percent levels is indicated by ** and *, respectively.

Table 4. Math and Language Teachers' Characteristics by Treatment Status

	Treatment	Comparison	Difference
Demographic characteristics			
Age	44.512	43.059	1.453
			[0.816]
Male	0.532	0.485	0.047
			[0.049]
University degree	0.572	0.624	-0.052
			[0.052]
Graduate studies, Master's degree or Ph.D.	0.239	0.257	-0.019
			[0.043]
Background			
Experience as a teacher (years)	17.448	16.089	1.359
			[0.742]
Experience as a teacher in the school (years)	10.831	9.515	1.316
			[0.794]
Experience on the subject (years)	15.020	13.213	1.807*
			[0.727]
Took a specialization course on the subject	0.264	0.248	0.016
			[0.045]
Home assets			
Washing machine	0.468	0.450	0.017
			[0.054]
TV	0.940	0.965	-0.025
			[0.021]
Cable television	0.413	0.500	-0.087
			[0.054]
Refrigerator	0.731	0.772	-0.041
			[0.049]
Phone	0.672	0.708	-0.036
			[0.050]
Car	0.114	0.104	0.010
			[0.030]
Motorcycle	0.015	0.035	-0.020
			[0.017]
Home technology access			
Computer	0.761	0.822	-0.061
			[0.042]
Internet	0.303	0.396	-0.093
			[0.050]
N	*201*	*202*	

Notes: This table presents statistics and estimated differences between the treatment and comparison groups. Primary data collected in November 2008 were used. Standard errors, reported in brackets, are clustered at the school level. Significance at the one and five percent levels is indicated by ** and *, respectively.

Table 5. Principals' Characteristics by Treatment Status

	Treatment	Comparison	Difference
Demographic characteristics			
Age	50.020	50.703	-0.683
			[1.016]
Male	0.723	0.733	-0.010
			[0.063]
University	0.792	0.870	-0.078
			[0.053]
Background			
Teaching studies (years)	5.277	5.089	0.188
			[0.099]
Experience as teacher (years)	14.366	14.931	-0.564
			[0.905]
Experience as principal (years)	8.683	8.614	0.069
			[0.892]
Experience as principal in the school (years)	5.198	5.287	-0.089
			[0.646]
Number of schools that has worked as principal	3.178	2.713	0.465
			[0.355]
Number of schools that has worked as teacher	4.079	3.822	0.257
			[0.487]
Process followed to become principal			
Selection process	0.535	0.525	0.010
			[0.071]
Promotion	0.158	0.158	0.000
			[0.052]
Decree	0.178	0.188	-0.010
			[0.055]
Direct election	0.129	0.129	0.000
			[0.047]
Home technology access			
Computer	0.871	0.980	-0.109**
			[0.036]
Internet	0.495	0.564	-0.069
			[0.070]
N	*101*	*101*	

Notes: This table presents statistics and estimated differences between the treatment and comparison groups. Primary data collected in November 2008 were used. Standard errors, reported in brackets, are clustered at the school level. Significance at the one and five percent levels is indicated by ** and *, respectively.

Table 6. Students' Reported Computer Time Use by Treatment Status

	Treatment	Comparison	Difference
In school			
Total time	2.062	1.033	1.028**
			[0.197]
Math class	0.140	0.120	0.020
			[0.053]
Language class	0.156	0.175	-0.018
			[0.071]
Technology class	1.584	0.760	0.824**
			[0.215]
Outside school			
At home	2.549	2.038	0.512
			[0.286]
At Internet cafés	3.424	3.591	-0.166
			[0.221]
At other places	0.429	0.321	0.108
			[0.088]
N	*2,463*	*2,434*	

Notes: This table presents statistics and estimated differences between the treatment and comparison groups. Primary data collected in November 2008 were used. Time use is measured as hours per week. Standard errors, reported in brackets, are clustered at the school level. Significance at the one and five percent levels is indicated by ** and *, respectively.

Table 7. Teachers' Reported Computer Time Use in Class by Treatment Status

	Treatment	**Comparison**	**Difference**
Math	0.538	0.621	-0.083
			[0.199]
N	*101*	*101*	
Language	0.302	0.217	0.085
			[0.087]
N	*100*	*101*	
Technology	3.063	3.727	-0.665
			[0.844]
N	*60*	*33*	

Notes: This table presents statistics and estimated differences between the treatment and comparison groups. Primary data collected in November 2008 were used. Standard errors, reported in brackets, are clustered at the school level. Significance at the one and five percent levels is indicated by ** and *, respectively.

Table 8. Effects of Technology Access on Digital Skills and Academic Achievement

	[1]	[2]	[3]	[4]
Digital skills	0.314**	0.293**	0.312**	0.308**
	[0.100]	[0.071]	[0.063]	[0.064]
Math	0.108	0.095	0.080	0.069
	[0.075]	[0.058]	[0.054]	[0.056]
Language	0.062	0.043	0.058	0.057
	[0.065]	[0.046]	[0.047]	[0.048]
Students' characteristics	N	Y	Y	Y
Teachers' characteristics	N	N	Y	Y
Principals' characteristics	N	N	N	Y

Notes: This table presents estimates of the effects of school shared technology access on test scores in digital skills, Math and Language. The unit of observation is a student. Each cell corresponds to one OLS regression. Labels in rows correspond to dependent variables. Regressions for digital skills, Math and Language include 4,583, 4,541 and 4,763 observations, respectively. Different sets of controls are included in each column. Controls for students', teachers' and principals' characteristics included in the regressions are those presented in Tables 3, 4 and 5, respectively. Access to computers and Internet at home are not included as controls in regressions because they may be affected by computer access at school. All tests have been normalized subtracting the mean and dividing by the standard deviation of the comparison group. Standard errors, reported in brackets, are clustered at the school level. Significance at the five and ten percent levels is indicated by ** and *, respectively.

Table 9. Heterogeneous Effects of Technology Access on Digital Skills

	[1]	[2]	[3]
Treatment	0.327**	0.322**	0.320**
	[0.068]	[0.072]	[0.072]
Computer at home in last year of primary school	0.277**		
	[0.050]		
Computer at home in last year of primary school x Treatment	-0.104		
	[0.086]		
Male		0.124**	
		[0.040]	
Male x Treatment		-0.028	
		[0.057]	
Mother has high school degree			0.218**
			[0.044]
Mother has high school degree x Treatment			-0.028
			[0.070]
N	*4,583*	*4,583*	*4,583*

Notes: This table presents estimates of the heterogeneous effects of school shared technology access on test scores in digital skills, Math and Language. The unit of observation is a student. Each column corresponds to a separate regression. All regressions include controls for students', teachers' and principals' characteristics. The variables included are those presented in Tables 3, 4 and 5. Access to computers and Internet at home are not included as controls in regressions because they may be affected by computer access at school. All tests have been normalized subtracting the mean and dividing by the standard deviation of the comparison group. Standard errors, reported in brackets, are clustered at the school level. Significance at the five and ten percent levels is indicated by ** and *, respectively.

Figure 1
Propensity Score Density - Unmatched Sample

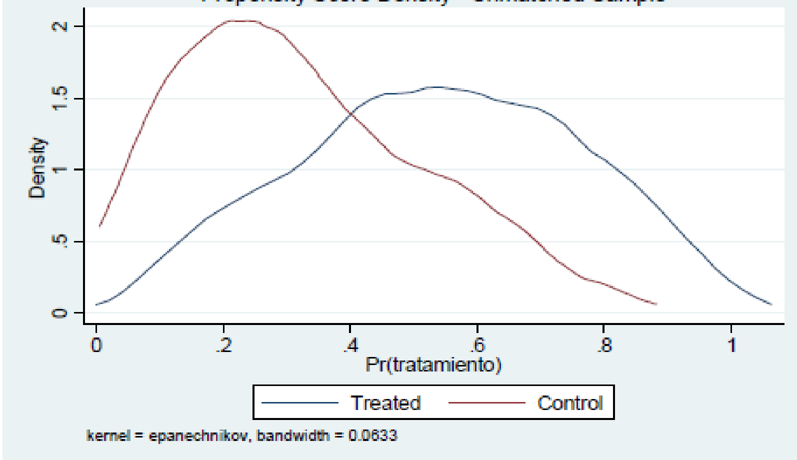

Figure 2
Propensity Score Density - Matched Sample