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One Laptop per Child at Home: Short-Term Impacts from a Randomized Experiment in Peru[†]

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This paper presents results from a randomized controlled trial whereby approximately 1,000 OLPC XO laptops were provided for home use to children attending primary schools in Lima, Peru. The intervention increased access and use of home computers, with some substitution away from computer use outside the home. Children randomized to receive laptops scored about 0.8 standard deviations higher in a test of XO proficiency but showed lower academic effort as reported by teachers. There were no impacts on academic achievement or cognitive skills as measured by the Raven's Progressive Matrices test. Finally, there was little evidence for spillovers within schools. (*JEL* I21, I28, J13, O15)

The One Laptop per Child (OLPC) program aims to foster self-empowered learning by providing personal laptops to children in developing countries. To date, approximately 2.4 million OLPC XO laptops have been distributed to children in more than 50 countries. Peru alone accounts for over one third of these laptops with purchases of 860,000 laptops at a cost of $188 each. Usually, these laptops have been distributed through schools, and the preponderance of use has occurred in the classroom (Cristia et al. 2012). However, the emphasis on self-empowered learning by the founders of OLPC suggests that these laptops may also be beneficial when used

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outside the structured classroom environment, and at home in particular.[1] This paper presents short-term impacts from the first experimental study of providing OLPC XO laptops for use at home on children's social, educational, and cognitive outcomes.

We designed and implemented a randomized controlled trial (RCT) in which we provided XO laptops to approximately 1,000 students attending public primary schools in Lima, Peru. The RCT incorporated randomization at both the school level and the individual level. We began by randomly selecting 14 treatment schools and 14 control schools from a sample of low-achieving public primary schools and conducting a detailed baseline survey. Within treatment schools, we provided a random sample of participating students with XO laptops for home use through in-class lotteries, while students in control schools did not receive any interventions. The design of this RCT was explicitly intended to account for potential spillovers from treatment by incorporating an approach pioneered by Duflo and Saez (2003) whereby treatment is provided to a random subsample of individuals within a random sample of more aggregate units.[2] We examine short-term impacts using a follow-up survey on third and sixth graders conducted approximately five months after the start of the intervention, focusing first on differences between lottery winners and nonwinners within treatment schools.

We find that our intervention was successful in increasing the exposure of children to XO laptops at home. Compliance with the randomized assignment was extremely high: 93 percent of treatment students received laptops and no student in the control group received a laptop. The intervention increased the likelihood that children had a computer or laptop at home by 40 percentage points, while children in the treatment group were 33 percentage points more likely to use computers at home in the week prior to the follow-up survey. Interestingly, the intervention led to a decline of 11 percentage points in the likelihood of computer use in Internet cafes, suggesting that children who won a laptop substituted computer use at home for use outside the home. Overall, children in the treatment group report using computers at home for about 18 minutes longer each day. The largest effects of computer use were associated with playing computer games, although these are games designed by OLPC affiliates have a strong educational component. In addition, the intervention generated a 0.81 standard deviation increase in scores on an objective test that measured proficiency in using the XO laptop.

Despite increased exposure to XO laptops, the intervention had few impacts on other outcomes. There were no significant differences between treatment and control groups on objective and self-reported skills for using a Windows personal computer (PC) and the Internet. There were no significant impacts on math and reading scores based on results from a national exam that is administered to second grade students. And there were no statistically significant effects on cognitive skills, as measured

[1] Indeed, the OLPC Website (http://laptop.org/faq.en_US.html) explains that "mobility is important, especially with regard to taking the computer home at night...bringing the laptop home engages the family." The OLPC project is not the only program that encourages children to use computers outside the structured environment of the classroom. The "Euro 200" program in Romania and the "Yo Elijo Mi PC" program in Chile are two other examples of government initiatives that provide home computers to low-income children.

[2] Duflo and Saez (2003) use this design to explore information spillovers in retirement decisions within academic departments of a particular university in the United States and find evidence for social network effects.

by the Raven's Progressive Matrices test. The only significant impacts were those reported by teachers who stated that children in the treatment group were significantly less likely to exert effort at school compared with their counterparts in the control group. Finally, there were no significant effects of the intervention on social skills and expectations of future educational attainment as reported by teachers.

Our null impacts on academic and cognitive skills are quite precisely estimated because we randomized within schools at the individual level. However, this introduces the possibility of bias due to potential spillovers. Taking advantage of the two-stage randomization procedure across and within schools, and together with comprehensive data on social networks collected at baseline, we explore the presence of spillovers in three ways. First, we focus on students in treatment schools who participated in the lotteries but did not win laptops, and compare those with and without friends who received XO laptops. Second, we repeat this exercise but analyze spillovers on laptop lottery winners.[3] Third, we compare children who did not receive XO laptops in treatment schools to those in control schools. In general, we do not observe spillovers across students for academic achievement, cognitive skills, or reported effort. The only evidence for spillovers emerges from significantly higher levels of proficiency in using the XO laptop among friends and classmates of children who received XO laptops.

Although there is a large literature exploring the causal impacts of computer use at school (e.g. Angrist and Lavy 2002; Machin, McNally, and Silva 2007; Banerjee et al. 2007), only a few recent studies have provided compelling estimates for the impact of home computers on children's outcomes. Malamud and Pop-Eleches (2011) used a regression discontinuity design to examine a Romanian government program that provided home computers to poor children in families below a particular income threshold. They found that home computers led to lower school grades but higher cognitive skills and computer skills one year after the computers were distributed. Cristia et al. (2012) evaluated the OLPC program by implementing a school-level randomized controlled trial across 319 primary schools in rural Peru. They found no impacts on academic achievement in math and language standardized tests but also observed some positive and significant impacts on cognitive skills. It is important to note, however, that although children were supposed to take their laptops home as part of the program, only 40 percent of laptops were used at home because of concerns from school principals and parents. Mo et al. (2013) conducted a randomized experiment of home computers among 300 third-grade migrant students in Beijing. They find positive impacts on computer skills and marginally significant impacts on math scores in some specifications. Finally, Fairlie and Robinson (2013) conducted an experimental study of home computers within middle and high schools in the United States. They found no impacts of home computers on academic achievement based on standardized tests or grades.[4]

[3] This empirical exercise tests the "digital saturation" hypothesis espoused by proponents of the OLPC program who argue that the effectiveness of the program is enhanced when more children in targeted schools receive laptops.

[4] Several other studies have estimated the impacts of home computers using more demanding identification assumptions. For example, Fairlie, Beltran, and Das (2010) found positive impacts of home computers on a broad range of educational outcomes using nationally representative data (Current Population Survey and National Longitudinal Survey of Youth) for the United States. Vigdor and Ladd (2010) exploited changes in home computer ownership over time as reported by students in North Carolina and found negative impacts on math and reading test scores.

This paper makes several contributions to the existing literature on technology in education. First, this study represents the only randomized evaluation of XO laptops focused on the home environment. To our knowledge, it is also the largest randomized evaluation exploring the effects of expanding home computer access in a developing country. Focusing on this setting is especially policy relevant given that governments and households in the developing world are making significant investments to expand home computer access. Second, we can provide evidence on spillover effects by exploiting the two-stage randomization design (across both schools and individuals) and rich baseline information on social networks. Third, because our individual-level randomization includes more than 2,800 students with follow-up data, we can provide precise estimates of impacts on a variety of outcomes. Finally, our study is the first to collect the entire history of computer use logs providing important evidence on potential mechanisms underlying the observed impacts on outcomes.

The remainder of the paper is structured as follows. Section I describes the design and implementation of the RCT. Section II explains our data collection efforts. Section III presents the basic empirical strategy and discusses the main results. Section IV offers additional results on spillovers and heterogeneous effects by extending the basic empirical strategy. Finally, Section V provides a summary of our findings and draws some policy implications.

I. Study Design

An RCT employing randomization at both the school level and the individual level forms the basis of the study design. First, we randomly selected 14 treatment schools and 14 control schools from a sample of low-achieving public primary schools. Then, within treatment schools, we conducted lotteries to provide a random set of students with XO laptops. Students in control schools did not receive any intervention. In all schools, children also had occasional access to their school's own computer lab. The timeline of the study is as follows. Baseline data were collected in April/May 2011, and the within-school lottery (and delivery of laptops) was implemented in June/July 2011. Training for students was offered in August/September 2011, and the follow-up data were collected in November 2011. This section describes the selection of schools and the within-school interventions in more detail.

A. *Selection of Schools*

We targeted large low-performing public elementary schools in Lima. Specifically, we selected public elementary schools with morning shifts that enrolled between 400 and 800 students according to the 2010 School Census data. We then ranked these schools according to their average performance on the second grade national standardized examination between 2007 and 2009. We administered a brief phone survey to the 70 lowest performing schools with valid contact information, and collected updated information on enrollment, number of sections, and access to computers and classrooms. We further restricted our sample to schools that had fewer than 25 class sections (namely, a maximum of 4 classes per grade), a ratio of school computers to students lower than 0.15, and a classroom available for a computer lab in the afternoon. This resulted in a target sample of 40 schools.

To assign schools to treatment and control status, we carried out a pair-wise matching procedure based on Bruhn and McKenzie (2009) who implement the "optimal greedy algorithm" suggested by King et al. (2007). We matched on average class size and the ratio of computers to students in each school. The pairs were formed to minimize the Mahalanobis distance between the values of class size and computer-to-student ratios within pairs, and one unit in each pair was randomly assigned to treatment and the other to control. We proceeded to visit the treatment and control schools in each pair and invite each school to participate in the study with official endorsements from the Ministry of Education. Due to concerns about our capacity to implement treatment in all 20 treatment schools, we reduced the study sample to the first 14 school pairs visited.[5] All 28 schools agreed to participate in the study. While these schools are not representative of the overall school population in Lima, the focus on low-performing public schools with relatively low levels of computer penetration is likely to be most relevant for policy.

B. *Within-School Interventions*

The principal intervention for this study involved providing XO laptops to randomly selected students in treatment schools. In June–July 2011, we conducted a public lottery for four XO laptops within each class/section. However, only children whose parents provided written consent were included in the lottery.[6] These procedures were developed in coordination with schools, principals, and teachers. The lotteries were conducted in class and parents were invited to attend in order to assure transparency.[7] We distributed 1,048 laptops provided by the Ministry of Education of Peru, although not all of these laptops were included in our main analysis sample because we focused on children in grades 3–6 for our follow-up survey.

The laptops were specifically designed to be used by primary students in developing countries. These netbook-sized computers are light, sturdy, energy-efficient and portable. The laptops have 512 MB of RAM, 2 GB of flash storage and a battery that lasts for about two to three hours. The operating system is Linux and the graphical interface is known as Sugar.[8] This graphical interface has been designed to be used by children and there are hundreds of applications that can be installed.

Thirty two applications, selected by the Ministry of Education for nationwide use, were installed in the distributed laptops. The applications included: (i) standard

[5] The project was constrained by a hard deadline for the distribution of laptops. Given limited staff capacity for implementing the randomization and the delivery protocol, we prioritized the quality of implementation above the project scale. We have compared pretreatment characteristics of the final 28 schools to the 12 schools not included in the study and found that most were not significantly different.

[6] The original protocol specified that classes would be eligible for the intervention only if more than 60 percent of the children in the class obtained consent from their parents or legal guardians. However, after it emerged that most classes had very high rates of participation, it was decided not to exclude the few classes with participation rates below the original threshold.

[7] We conducted focus groups with parents and teachers from the schools to explore alternative approaches to conduct the randomization and there was fairly broad consensus regarding lotteries.

[8] The laptops do not run Windows, and they are not compatible with software designed for that operating system. However, most files (e.g. images, sound and text documents) are compatible with the Windows environment.

applications such as word processor, drawing software, calculator, and chat; (ii) educational games including Tetris, Sudoku and a variety of puzzles; (iii) applications to create, edit, and play music; (iv) two programming environments; and (v) other applications including sound and video recording and certain sections of Wikipedia. The laptops were also preloaded with age-appropriate e-books selected by the Ministry of Education.[9] While children could download additional applications, the provision of laptops did not come with Internet access, and computer logs indicate that students typically used the preinstalled applications.

To encourage adequate use of the laptops, we provided all beneficiary students with an instruction manual and training sessions. The manual we developed presented general information about how to use the laptop and more in-depth practical instruction for ten prioritized applications. The manual was designed for primary school children and emphasized graphical illustrations and practical assistance on how to use the applications rather than covering technical knowledge. Weekly training sessions took place in each treatment school during a seven-week period in August and September 2011. On each Saturday during the training period, there were three two-hour sessions for students arranged by grade (1–2, 3–4, and 5–6 grades, respectively). Average student attendance was about 50 percent, and approximately 70 percent of students attended at least one session.

II. Data

The primary data used in this study were collected at baseline in April/May 2011 and for a short-term follow-up in November 2011, roughly coinciding with the academic school year that is from March to mid-December.[10] The general format of the baseline and follow-up data collection was extremely similar, consisting of student surveys, teacher surveys, and a battery of tests. However, while we tested all children in grades 1 through 6 at baseline, we only tested students in grades 3 to 6 in the follow-up. In addition, the student surveys were restricted to children in grades 3 to 6 at both baseline and follow-up because of the difficulty in eliciting accurate responses from younger children. Consequently, the analysis in this paper is focused on children in grades 3 to 6. The attrition rate of students between the baseline and follow-up for this sample was just 3 percent, and it was not statistically different between laptop winners and nonwinners in treatment schools, or between students in treatment and control schools.

We developed three different assessments of computer skills: (i) an objective test that measured the proficiency in using an XO laptop, (ii) a multiple-choice test consisting of 5 questions intended to measure practical knowledge about using a Windows PC and Internet, and (iii) a set of 11 (yes/no) subjective questions in which students were asked to report whether they could perform various tasks related

[9] Administrators at the Ministry of Education indicated that they expected these applications would raise children´s achievement through access to information (e.g. Wikipedia), facilitating the processing of tasks (e.g. word processing), or exercises to develop cognitive abilities (e.g. educational games).

[10] We also used administrative data from the Ministry of Education to construct the initial sample of primary schools and implement the pair-wise matching procedure, as described above.

to using a PC and Internet. Note that the objective test was only administered at the follow-up while the other two tests were administered at baseline and follow-up.

We also administered the Colored Raven's Progressive Matrices test that was specifically designed for children ages 5 to 11 and has been widely used to assess nonverbal cognitive ability. In this test, respondents are presented a series of progressively more difficult matching exercises that require choosing the figure that completes a pattern. The test measures "educative ability—the ability to make sense and meaning out of complex or confusing data; the ability to perceive new patterns and relationships, and to forge (largely nonverbal) constructs which make it easy to handle complexity" (Pearson Assessment 2011).

At baseline, we also tested students in grades 1 to 6 in math and reading achievement. These achievement tests were administered in a group setting and were developed separately for each grade using items drawn from previous nationally standardized exams. Although we did not administer these tests in the follow-up due to lack of funding, we do analyze math and reading test scores for second grade students in our sample using administrative data on individual-level standardized tests from the Student Census Evaluation (ECE) of November 2011. These tests have been conducted annually since 2007 and evaluate reading comprehension and mathematics based on the national curriculum.[11] Note that, in the empirical analysis, cognitive and achievement measures are standardized by grade, subtracting the mean and dividing by the standard deviation of students who participated in the laptop lottery but did not win.

Student surveys aimed to capture information on socio-demographic characteristics, access, and use of computers and laptops, as well as participation in other activities. The questions on participation were posed for whether a particular activity was completed in the previous day. The questions about computer and Internet use were substantially more detailed. They elicited information about where the computer and Internet use took place and which specific activities were undertaken; in addition, they examined the intensive margin by asking about hours and minutes of use in the prior day. We were also able to extract log files from the XO laptops of about 67 percent of beneficiaries. This provides for a more detailed look at the nature of use and allows for some objective assessments of patterns of use.[12] While not necessarily representative, students whose logs were obtained appear to have mostly similar baseline characteristics to their counterparts without logs.

We collected information on social networks at baseline and in the follow-up by asking children to list their four closest friends and their friends when partaking in other activities.[13] To generate an estimate of the number of friends not constrained by the list, we constructed the number of friends for an individual based on the number of times they were listed by other students in the class. Finally, teachers completed self-administered questionnaires that collected information on background

[11] See http://umc.minedu.gob.pe/ for more information and results from recent years.

[12] These logs recorded the date and time when each session started as well as roughly when every application was closed (parental consent included permission to gather this information). This provides an upper bound for use because we cannot be certain that children are actually using the computer throughout the time that an application is open.

[13] These included the four friends with whom they did homework, the four friends whom they visited at home, and the four friends they listed as those with whom they would share a computer if they would receive one.

characteristics, access and use of computers, attitudes towards computers in education, as well as their perceptions of their students' social popularity, effort at school, and expected educational attainment.

III. Main Results

A. *Empirical Strategy*

The empirical framework for our main analysis uses observations on children who participated in the lottery within the 14 treatment schools to compare children who won a laptop with those who participated in the lottery but did not win. In particular, we estimate the following regression model:

$$Y_{ijk} = \boldsymbol{\beta}'\mathbf{X_{ijk}} + \delta Winner_{ijk} + \mu_j + \varepsilon_{ijk}, \tag{1}$$

where Y_{ijk} denotes the outcome of interest for child i, in class j and school k observed at follow-up, μ_j is a class fixed effect, and $\mathbf{X_{ijk}}$ is a vector of control variables observed at baseline that includes the outcome at baseline, age, sex, number of siblings, number of younger siblings, whether the father lives with the child, whether the father works at home, and whether the mother works at home. $Winner_{ijk}$ is a treatment indicator that takes the value of one if child i in class j and school k won a computer, and zero otherwise. Finally, ε_{ijk} is the error term that is clustered at the school level k in each regression. Accordingly, estimates of δ quantify the differences in means between laptop winners and nonwinners.

The main sample includes 2,851 students attending grades 3 to 6 of treatment schools whose parents provided consents for participating in the study.[14] Among these, 610 were assigned to receive laptops. The attrition rate in this sample is 2 percent for both winners and nonwinners, and not statistically different between them. When we examine effects on math and language achievement using administrative data from the ECE evaluations, we focus on 766 students (including 172 lottery winners) in grade 2 in treatment schools whose parents provided consent for participating. The attrition rate in this sample is 7 percent for both winners and nonwinners, and not significantly different between them. Moreover, for both samples, the baseline characteristics of the attriting and nonattriting students are not significantly different by treatment assignment.

Table 1 provides strong evidence that the within-school randomization was successful in generating balance between treatment and control groups. Among the 16 selected characteristics none are significant. Moreover, among all 40 collected characteristics, only two were significant, and only at the 10 percent level. All our results are based on intent-to-treat (ITT) estimates; that is, we compare laptop winners with nonwinners regardless of whether winners actually received a laptop. Given

[14] In addition, the sample in each specification is restricted to students who have nonmissing information for the relevant outcome and nonmissing information regarding home access to computers/laptops at baseline and follow-up. We also restrict the sample to observations with nonmissing covariates at baseline, although our results are similar without controlling for covariates.

TABLE 1—BALANCE BETWEEN LAPTOP WINNERS AND NONWINNERS IN TREATMENT SCHOOLS

	Winners (1)	Nonwinners (2)	Adjusted difference (3)	Observations (4)
Student characteristics				
Age	10.00	10.05	0.03	2,851
			(0.03)	
Male	0.49	0.48	0.01	2,851
			(0.02)	
Household characteristics				
Number of siblings in household	2.29	2.24	0.02	2,851
			(0.09)	
Father lives at home	0.77	0.77	−0.00	2,851
			(0.03)	
Father works outside home	0.88	0.88	−0.01	2,851
			(0.02)	
Mother works outside home	0.51	0.53	−0.03	2,851
			(0.03)	
Phone	0.45	0.48	−0.03	2,786
			(0.02)	
Electricity	0.90	0.91	−0.01	2,813
			(0.02)	
Car	0.25	0.28	−0.03	2,768
			(0.02)	
Access				
Computer or laptop at home	0.41	0.43	−0.01	2,851
			(0.02)	
Internet at home	0.30	0.34	−0.04	2,812
			(0.02)	
Academic achievement (2nd grade)				
Math	−0.04	0.00	−0.07	766
			(0.12)	
Reading	−0.16	0.00	−0.10	753
			(0.09)	
Digital skills				
Objective PC and Internet test	−0.06	0.00	−0.05	2,851
			(0.04)	
Self-reported PC and Internet skills	−0.01	0.00	0.01	2,851
			(0.05)	
Cognitive skills				
Raven's progressive matrices	0.02	0.00	0.06	2,670
			(0.05)	

Notes: This table presents estimated differences between laptop lottery winners and nonwinners who participated in the laptop lottery within treatment schools. The sample includes students in third to sixth grade except from results for academic achievement that correspond to second graders. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors on an indicator for winning the laptop lottery from OLS regressions with class fixed-effects. Estimated standard errors, reported in parentheses, are clustered at the school level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

the 93 percent take-up rate, the ITT estimates will be similar to the treatment on the treated (TOT) estimates.[15] This take-up rate is not so surprising given that these

[15] Approximate TOT estimates can be obtained by scaling up the ITT estimates by 1/0.93 or 1.075.

families had already agreed to participate in the lottery, and it confirms the successful implementation of our intervention.[16]

B. *Computer Access and Use*

Table 2 presents our findings related to self-reported computer access and use for all winners and nonwinners. The effect of the intervention on the likelihood that children report having a computer at home is 40 percentage points. This represents a large effect on access to home computers but it is somewhat ameliorated, as 50 percent of children in the control group already own a computer.[17] There are also significant differences in computer use, with impacts of 5 and 9 percentage points for using a computer last week and yesterday, respectively. Besides these aggregate measures, we collected several more detailed measures of computer utilization at both the extensive and intensive margins.

First, we examine *where* children use their computers. Consistent with the nature of our intervention, we observe a large increase of 33 percentage points in the likelihood of using computers at home during the previous week. There is no change in the likelihood of using a computer in school. Interestingly, lottery winners are 11 percentage points less likely to use computers in Internet cafes. Therefore, it seems that children who win a laptop are substituting computer use at home for use outside the home. We also measure computer utilization on the intensive margin by asking children about the number of minutes they used a computer during the previous day. We find that children in the treatment group report using computers at home for 18 minutes longer each day. There are small negative effects on the intensive margin of utilization at school, Internet cafes, or friends' houses, although (marginally) significant only for the last category. As a useful check on these self-reported measures of utilization, we also determine actual usage for the treated group from logs that we installed in the laptops. The average daily use based on these logs was 52 minutes over the first six months of the intervention, or 10 minutes lower than the 62 minutes a day reported by the children themselves. Note that students report overall computer use at home, which can occur with the provided XO laptops or with other computers.

Second, we examine *how* children use their computers. Table 2 indicates that lottery winners are 10 percentage points more likely to use computers to play games. They are also 4 percentage points less likely to watch videos on their computers. Lottery winners do not differ from nonwinners in their likelihood of reporting computer use for homework and music. Note that we also measured Internet access and utilization. However, given that our initial intervention did not include any provision for Internet access, it is not surprising that there were no effects on either Internet access or utilization.

[16] The few cases of noncompliance occurred because of children whose parents did not follow the procedure to receive the assigned laptop.

[17] Note that only 43 percent of students in the control group report having a home computer at baseline, suggesting that many of them acquired a computer after (and, perhaps, because of) our intervention. Although we did not collect information about the nature of other computers in the household, these are unlikely to be XO computers.

Table 2—Effects on Laptop Winners in Treatment Schools: Computer and Internet Access and Use

	Winners (1)	Nonwinners (2)	Adjusted difference (3)	Observations (4)
Access				
Computer or laptop at home	0.89	0.50	0.40	2,851
			(0.03)***	
Use				
Last week	0.95	0.90	0.05	2,791
			(0.01)***	
Yesterday	0.81	0.73	0.09	2,851
			(0.03)***	
Use by place (*last week*)				
School	0.53	0.54	0.01	2,641
			(0.03)	
Home	0.82	0.50	0.33	2,641
			(0.02)***	
Internet café	0.43	0.54	−0.11	2,631
			(0.02)***	
Friend's house	0.20	0.23	−0.02	2,561
			(0.02)	
Use by place (*minutes yesterday*)				
School	19.41	23.01	−1.36	2,851
			(2.19)	
Home	61.85	44.99	18.20	2,851
			(4.93)***	
Internet café	30.75	34.25	−3.23	2,851
			(3.67)	
Friend's house	11.30	15.44	−3.78	2,851
			(2.06)*	
Type of use (*last week*)				
Homework	0.74	0.74	0.01	2,692
			(0.02)	
Games	0.79	0.70	0.10	2,659
			(0.03)**	
Music	0.67	0.64	0.04	2,638
			(0.03)	
Videos	0.38	0.43	−0.04	2,612
			(0.02)*	
Internet Access				
Internet at home	0.38	0.37	0.03	2,812
			(0.02)	
Used Internet last week	0.80	0.81	0.00	2,851
			(0.02)	

Notes: This table presents estimated differences between laptop lottery winners and nonwinners who participated in the laptop lottery within treatment schools. The sample includes students in third to sixth grade. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors on an indicator for winning the laptop lottery from OLS regressions. Controls include the baseline value of the outcome, class fixed-effects, and demographic characteristics as detailed in the text. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

We also explored the data from the computer logs in more detail (see Table A1 in the Appendix). There is a clear decline in utilization over time by gender, grade, and prior home computer access. There is also some evidence that boys use computers more intensively than girls (an average of 55 versus 47 minutes daily). Furthermore, children that report having no previous access to home computers display a significantly higher utilization than children with previous access (an average of 58 versus 44 minutes daily). In terms of the particular software applications used, we observe that boys are more likely to listen to music than girls, and that younger children in third and fourth grade are less likely to use the music applications than their older counterparts.

C. *Skills and Teacher Perceptions*

The main outcomes for this intervention were children's computer skills, academic achievement, cognitive skills, as well as teacher perceptions of social skills, effort, and educational potential. Table 3 reveals an extremely large positive effect of the intervention on the items testing XO-specific laptop knowledge. This effect equals 0.81 of a standard deviation. While this result confirms that children learned how to use the XO laptop, it does not necessarily imply broader impacts. Indeed, there are no significant differences between treatment and control students in both tests aimed at measuring skills related to using a PC and Internet, although the small number of items may also limit our ability to discern sizeable effects.[18]

We did not administer a test of academic achievement in the follow-up, but we were able to use administrative data from the ECE to examine impacts on math and reading test scores for second grade students in our sample. The estimated effects in this subsample are positive but insignificant for both math and reading scores. We also administered the Raven's Progressive Matrices test, which aims to measure nonverbal abstract reasoning. Previous findings in Malamud and Pop-Eleches (2011) and Cristia et al. (2012) found significant effects of exposure to computers on this measure of cognitive skills. However, while the estimated effect of the current intervention is positive as in earlier studies, it is small and insignificant. One possible explanation for the absence of any effects here is the short period of exposure to the laptops. Another is that children in urban areas already have a relatively high base level of cognitive skills that is not as easily improved through technology. Their scores on this test are far higher than those of their counterparts in rural Peru. Finally, children in urban areas have generally had more prior exposure to computers at school and elsewhere.

In addition, we collected information on teacher's perceptions of their students' social popularity, effort at school, and expected educational attainment.[19] For the first two dimensions, we asked teachers how they evaluate each pupil within his classroom: below average, average, or above average. Regarding educational expectations, the options reported by teachers consisted of whether the child was expected

[18] We do find some small positive significant effects on a couple of the test items related to general computer skills that are useful for either an XO or a PC.

[19] It is important to note that, although the intervention occurred at home, teachers were probably aware of which students in their class had received the OLPC XO computers.

Table 3—Effects on Laptop Winners in Treatment Schools: Skills and Teacher's Perceptions

	Winners (1)	Nonwinners (2)	Adjusted difference (3)	Observations (4)
Digital skills				
Objective OLPC test	0.79	0.00	0.81	2,737
			(0.06)***	
Objective PC and Internet test	0.01	0.00	0.06	2,851
			(0.04)	
Self-reported PC and Internet skills	0.00	0.00	0.02	2,851
			(0.05)	
Academic achievement (2nd grade)				
Math	0.07	0.00	0.07	766
			(0.08)	
Reading	0.05	0.00	0.07	753
			(0.09)	
Cognitive skills				
Raven's progressive matrices	0.04	0.00	0.05	2,670
			(0.04)	
Teacher's perceptions				
High skills in making friends	0.52	0.54	−0.02	2,786
			(0.02)	
High academic effort in class	0.42	0.47	−0.05	2,787
			(0.02)**	
Expected to complete university	0.62	0.64	−0.02	2,781
			(0.02)	

Notes: This table presents estimated differences between laptop lottery winners and nonwinners who participated in the laptop lottery within treatment schools. The sample includes students in third to sixth grade except from results for academic achievement that correspond to second graders. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors on an indicator for winning the laptop lottery from OLS regressions. Controls include the baseline value of the outcome (except when estimating effects on the OLPC test), class fixed-effects, and demographic characteristics as detailed in the text. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

to attain primary, secondary, or postsecondary education. We then constructed summary indicators that take the value of one if the teacher reported the highest possible outcome for the pupil and zero otherwise. We did not observe any effect of treatment on the teacher's perception of social popularity or educational expectations. However, there is some evidence that effort at school was negatively affected; children who won a lottery were 5 percentage points less likely to provide high levels of effort at school as compared to nonwinners. Again, this finding is in line with the evidence on negative effects of home computer access on school grades in Romania reported by Malamud and Pop-Eleches (2011).

D. *Time Use and Social Networks*

Table 4 shows the impact of the intervention on a broad set of activities. These measures are based on binary variables indicating that the child reported being

Table 4—Effects on Laptop Winners in Treatment Schools: Time Use and Social Networks

	Winners (1)	Nonwinners (2)	Adjusted difference (3)	Observations (4)
Activities performed yesterday				
Completing domestic chore	0.56	0.52	0.04	2,734
			(0.02)*	
Caring for household members	0.47	0.51	−0.03	2,729
			(0.03)	
Shopping	0.37	0.41	−0.04	2,734
			(0.02)*	
Working in the streets	0.03	0.03	0.00	2,731
			(0.01)	
Working at a store	0.15	0.15	−0.01	2,723
			(0.02)	
Doing homework	0.94	0.95	−0.01	2,733
			(0.01)	
Playing	0.79	0.83	−0.03	2,738
			(0.02)	
Watching TV	0.88	0.88	0.00	2,735
			(0.01)	
Reading	0.59	0.65	−0.05	2,730
			(0.03)*	
Social networks				
Friends	3.40	3.44	−0.02	2,851
			(0.07)	
Visiting other classmates' homes	1.86	1.87	0.02	2,851
			(0.10)	
Homework partners	1.95	1.97	−0.03	2,851
			(0.09)	
Total contacts	4.88	4.93	−0.05	2,851
			(0.09)	

Notes: This table presents estimated differences between laptop lottery winners and nonwinners who participated in the laptop lottery within treatment schools. The sample includes students in third to sixth grade. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors on an indicator for winning the laptop lottery from OLS regressions. Controls include the baseline value of the outcome, class fixed-effects, and demographic characteristics as detailed in the text. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

engaged in each activity in the previous day. Interestingly, there is a small positive and marginally significant effect on the likelihood of completing domestic chores such as cooking, cleaning, and washing clothes and dishes. However, for the most part, the increased likelihood of using the computer seems to crowd out other activities even if they are not individually significant. For example, children who won the lottery report a significantly lower likelihood of reading books, stories, or magazines equivalent to 5 percentage points. This result is consistent with Malamud and Pop-Eleches (2011) who found that home computers were associated with lower daily reading. Finally, we find no evidence that winning an XO laptop affects the number of children who report themselves as friends or the frequency of visits from these friends.

IV. Further Results

A. *Spillovers across Friendship Networks*

Inherent in the nature of within-school randomization is the possibility for spillovers across students. This represents a potential concern for estimating treatment effects within schools because the comparison group of students may have also been affected by the treatment. In addition, the existence of spillovers across students is also a question of substantial interest in the education literature. We begin by exploring the potential for spillover effects by taking advantage of social network data reported by all students in treatment schools at baseline, and looking at spillovers on children who did not win the lottery.

That is, we restrict the sample to students in treatment schools whose parents provided consent and that did not win the lottery (2,241 students in third to sixth grade). Then, we split these students into two subgroups: children reported as close friends of at least one child who did win a lottery, and those not mentioned as a close friend of any child who won the lottery. Specifically, we run the following OLS regression model (with some abuse of notation by repeating some of the coefficients for the sake of clarity):

$$Y_{ijk} = \boldsymbol{\beta}'\mathbf{X_{ijk}} + \gamma Friend_{ijk} + \lambda N_{ijk} + \mu_j + \varepsilon_{ijk}, \tag{2}$$

where $Friend_{ijk}$ takes the value of one if child i in class j and school k was reported as a close friend by at least one lottery winner, and zero otherwise. N_{ijk} is the number of participating children who report child i as a close friend. All other variables are defined as in equation (1). It is important to control for N_{ijk} because children with more participating friends are also more likely to have a lottery winner among their friends. However, conditioning on the number of friends, whether a child has a friend who won a laptop should be random. We find that, once we condition on the number of participating friends, baseline characteristics are well balanced between students whose friends won laptops and those who did not (see Table A2 in the Appendix).

In equation (2), γ quantifies the difference between nonwinners *with* friends among the lottery winners and nonwinners *without* friends among any lottery winners. Under the assumption that children who were not close friends with the lottery winners experienced little or no spillovers from the intervention, we can interpret γ as a measure of the spillover effect. Insofar as the intervention involved home computers that were used outside of school, we believe that this assumption is a reasonable one.[20]

We do not observe strong spillover effects on children who did not win their own computers through the lottery. Table 5 indicates no significant differences in computer access and use. However, although not shown here, children within the direct social network of laptop winners did report a significant increase of 3.1 minutes of daily computer use at a friend's house. This is a small effect, but it does suggest that

[20] Nevertheless, it is possible that the effect of computer use at home leads to differences in behavior at school that influence children outside the immediate social network of lottery winners.

Table 5—Spillovers on Friends: Effects of Laptop Winners on Nonwinners

	Nonwinners with winner friends (1)	Nonwinners without winner friends (2)	Adjusted difference (3)	Observations (4)
Access				
Computer or laptop at home	0.52	0.48	0.01	2,241
			(0.02)	
Use				
Last week	0.91	0.90	0.02	2,193
			(0.02)	
Yesterday	0.73	0.73	−0.00	2,241
			(0.02)	
Digital skills				
Objective OLPC test	0.07	−0.09	0.08	2,153
			(0.04)*	
Objective PC and Internet test	0.07	−0.09	0.07	2,241
			(0.04)	
Self-reported PC and Internet skills	0.03	−0.04	0.01	2,241
			(0.04)	
Cognitive skills				
Raven's progressive matrices	0.03	−0.04	−0.02	2,101
			(0.04)	
Teachers' perceptions				
High skills in making friends	0.61	0.47	0.03	2,194
			(0.03)	
High academic effort in class	0.52	0.40	−0.00	2,194
			(0.03)	
Expected to complete university	0.69	0.57	−0.01	2,190
			(0.02)	

Notes: This table presents estimated differences between nonwinners with laptop lottery winner friends and nonwinners without laptop winner friends, all of whom participated in the laptop lottery within treatment schools. The sample includes students in third to sixth grade. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors on an indicator for having at least one laptop winner friend from OLS regressions. Controls include the baseline value of the outcome (except when estimating effects on the OLPC test), class fixed-effects, number of friends that participated in the lottery, and demographic characteristics as detailed in the text. Friends are defined using baseline data on social networks. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

some nonwinners were able to increase their utilization of computers through their social networks. Indeed, there was also a small significant spillover effect of 0.08 standard deviations in XO-specific computer skills. But more importantly, there were no significant spillover impacts on other computer skills, or on cognitive skills and teacher perceptions.[21] Consequently, the possibility that spillovers from friendship networks would bias our main findings appears to be minimal.

[21] There was also no evidence for spillover effects in time-use or number of friends.

B. *Spillovers across Winners: Testing the "Saturation Hypothesis"*

The availability of information on friendship networks also enables us to test for spillovers of treatment on other children who won XO computers through the lottery. This is related to the principle of "digital saturation" espoused by the OLPC initiate whereby the effectiveness of an XO laptop is affected by the presence of having more XO laptops in the network.[22] We explore this in an analogous fashion, as in the previous section, by focusing on spillovers for children who won the lottery.

We split children who won the lottery into two subgroups: children reported as close friends of at least one other child who did win a lottery, and those not mentioned as a close friend of any child who won the lottery. We run the same regression model (2) as before, but restricted to the sample of winners.

Thus, γ would the difference in means between winners *with* friends among the lottery winners and winners *without* friends among any lottery winners. Under the assumption that children who were not close friends with other lottery winners experienced little or no spillovers from the intervention, we can interpret estimates of γ as a measure of the spillover effect on winners. Moreover, once we condition on the number of participating friends, we find that baseline characteristics are well balanced between winners whose friends also won laptops and those whose friends did not (see Table A3 in the Appendix).

We do not observe strong spillover effects on children who won the lottery, although our estimates are not as precise because we have a smaller sample of winners. Table 6 indicates no significant differences in computer access and use. There are also no significant differences in computer skills, although there is a positive effect of 0.23 standard deviations in OLPC XO-specific computer skills and negative effects in other types of computer skills. Perhaps more importantly, the magnitudes of differences in cognitive skills and teacher perceptions are much smaller and insignificant. Given these findings, the effectiveness of an XO laptop at home does not appear to be affected in the presence of more friends who have XO laptops themselves.

C. *Spillovers across Classmates*

To the extent that spillover effects are transmitted entirely through social networks, the aforementioned strategy will be effective in identifying spillover effects. But if some spillovers also occur outside of social networks, then such strategy would underestimate these effects. Accordingly, our third strategy for estimating spillover effects considers all winners' classmates by comparing all nonwinner children (i.e., lottery participants and nonparticipants) within the 14 treatment schools to children in the 14 control schools. However, because the treatment schools and control schools do not seem to be well balanced at baseline (see Table A4 in the Appendix), we use a difference-in-differences specification.[23] This approach eliminates any

[22] The OLPC initiative aims to provide every child with a laptop but they also draw an analogy with vaccinations suggesting that the effectiveness of these laptops may increase with scale.

[23] The lack of balance is likely due to the small number of treatment and control schools. Note that the groups are balanced on the characteristics selected for the pair-wise matching procedure but not on all other characteristics. The rates of attrition are not statistically different between treatment and control schools.

TABLE 6—SPILLOVERS ON FRIENDS:
EFFECTS OF LAPTOP WINNERS ON OTHER WINNERS

	Winners with winner friends (1)	Winners without winner friends (2)	Adjusted difference (3)	Observations (4)
Access				
Computer or laptop at home	0.90	0.89	0.00	610
			(0.04)	
Use				
Last week	0.95	0.96	−0.03	598
			(0.03)	
Yesterday	0.81	0.81	−0.01	610
			(0.07)	
Digital skills				
Objective OLPC test	0.83	0.74	0.23	584
			(0.15)	
Objective PC and Internet test	0.01	0.02	−0.15	610
			(0.12)	
Self-reported PC and Internet skills	−0.02	0.02	−0.06	610
			(0.09)	
Cognitive skills				
Raven's progressive matrices	0.11	−0.03	0.08	569
			(0.10)	
Teachers' perceptions				
High skills in making friends	0.54	0.50	0.06	592
			(0.06)	
High academic effort in class	0.46	0.38	0.03	593
			(0.08)	
Expected to complete university	0.63	0.61	−0.01	591
			(0.06)	

Notes: This table presents estimated differences between lottery winners with friends among the other laptop lottery winners and lottery winners without friends among the other laptop winners, all of whom participated in the laptop lottery within treatment schools. The sample includes students in third to sixth grade. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors on an indicator for having at least one laptop winner friend from OLS regressions. Controls include the baseline value of the outcome (except when estimating effects on the OLPC test), class fixed-effects, number of friends that participated in the lottery, and demographic characteristics as detailed in the text. Friends are defined using baseline data on social networks. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

bias from time-invariant differences between treatment and control schools. Still, due to the possibility of differential time trends, results from this approach are more tentative than conclusive. Formally, we run the following regression model (again with some abuse of notation):

$$Y_{ikpt} = \beta + \tau Treat_{pk} + \pi Post_t + \eta Treat_{pk} Post_t + \mu_p + \varepsilon_{ikpt}, \tag{3}$$

where Y_{ikpt} denotes the outcome of interest for child i, in school k, belonging to school pair p, observed at time t. μ_p is a school pair fixed effect, $Treat_{pk}$ takes the value of one if lotteries were conducted in school k of pair p, and zero otherwise. *Pos* t_t takes the value of one for observations collected in the follow-up data collection, and zero otherwise. In equation (3), estimates of η quantify spillover effects operating from laptop winners on their classmates.

There are two additional issues associated with estimating spillover across classmates. First, because the lottery in treatment schools was only performed among students whose parents provided an informed consent, nonwinners are not a random sample of students within treatment schools. In particular, because winners are drawn only from those students who participated in the lottery, nonparticipants are overrepresented in the sample of nonwinners compared to the sample of all students. We deal with this issue by reweighting observations among nonwinners to give more weight to those participating in the lottery. Specifically, we divide students in treatment school classes between those who participated in the lottery and those who did not participate: for the first group we have a random sample (i.e., the nonwinners among lottery participants); for the second group we have the complete sample. Hence, reweighting those who participated in the lottery but did not win by $(N_L + N_w)/N_L$ (where N_L corresponds to the number of lottery participants that lost and N_w to those that won) yields a sample of nonwinners that is representative of the population of students in each school.

The second issue relates to the small number of clusters when making direct comparisons across just 28 schools. It is well-known that standard approaches to estimating regression equations with a small number of clusters can introduce biases in the estimation of standard errors (Bertrand, Duflo, and Mullainathan 2004). Cameron, Gelbach, and Miller (2008) suggest a bootstrapping procedure called wild bootstrap-t to produce an empirical t-distribution that can be used to derive p-values. We implement this bootstrapping procedure and derive critical values for t-stats which are used to determine the appropriate significance levels.

The results pertaining to computer access use and main outcomes are presented in Table 7. Interestingly, we observe that nonwinners in treatment schools had a 4 percentage point higher probability of having a computer at home than children in our control schools. This might suggest a small increase in demand for a home computer for children who did not win a computer. We do not find other effects in computer use and changes in time use. We do observe a significant positive effect on skills for using an XO laptop. This suggests even larger effects of the intervention on XO-specific skills than documented when simply comparing winners and nonwinners within treatment schools.[24] However, we do not find evidence of spillover effects on cognitive abilities, academic achievement, teachers' assessments, or PC and Internet skills. Thus, it does not appear likely that our main findings are affected by bias from spillovers across classmates more generally.

D. *Heterogeneous Effects*

In addition to showing the average impacts of the intervention on the full sample, we also explored for heterogeneous effects by individual characteristics. We focused on differences by gender, grade, age, baseline computer access, and baseline academic

[24] However, it is important to note that we do not have baseline measures of the XO-specific test so these estimates are potentially confounded with the level differences between treatment and control schools.

Table 7—Spillovers on Classmates

	All nonwinners in treatment schools		Students in control schools			
	Baseline (1)	Follow-up (2)	Baseline (3)	Follow-up (4)	Difference-in-differences (5)	Observations (6)
Access						
Computer or laptop at home	0.44	0.49	0.52	0.54	0.04 (0.02)*	9,700
Use						
Last week	0.87	0.91	0.87	0.93	−0.03 (0.03)	9,530
Yesterday	0.69	0.73	0.66	0.71	0.00 (0.03)	9,700
Digital skills						
Objective OLPC test	—	−0.06	—	−0.33	0.24 (0.11)**	4,488
Objective PC and Internet test	−0.02	−0.03	0.04	0.13	−0.10 (0.07)	9,700
Self-reported PC and Internet skills	−0.02	−0.01	0.02	0.03	−0.01 (0.08)	9,700
Academic achievement (*2nd grade*)						
Math	−0.09	−0.05	0.11	0.29	−0.16 (0.17)	2,470
Reading	−0.13	−0.09	0.22	0.23	0.02 (0.10)	2,436
Cognitive skills						
Raven's progressive matrices	−0.08	−0.06	0.14	0.06	0.09 (0.06)	8,938
Teachers' perceptions						
High skills in making friends	0.51	0.52	0.60	0.65	−0.05 (0.04)	9,526
High academic effort in class	0.42	0.42	0.47	0.51	−0.04 (0.03)	9,524
Expected to complete university	0.59	0.58	0.68	0.68	−0.01 (0.03)	9,510

Notes: This table presents estimated impacts between laptop nonwinners in treatment schools (including both lottery participants and nonparticipants) and students in control schools. The sample includes students in third to sixth grade except from results for academic achievement that correspond to second graders. Columns 1 to 4 present means. Column 5 presents estimated coefficients and standard errors from difference-in-differences estimators that control for school pair fixed-effects and have been weighted as discussed in the text. OLS regressions are run to estimate effects on the OLPC test because of the lack of baseline data. Estimated standard errors, reported in parentheses, are clustered at the school level. Given the small number of clusters (28), the critical values for *t*-tests were drawn from a bootstrapped-*t* distribution following the procedure suggested by Cameron, Gelbach, and Miller (2008).

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

achievement, which represent key factors that may be important in mediating the outcomes of a computer-based intervention. These results are shown in Table 8.

The impact of the intervention on access to home computers by gender is similar, with only slightly higher rates for girls than boys, which are not significantly different from one another. However, there are some differences in our measures of computer use: girls had higher impacts than boys on the extensive margin for the previous week (7 versus 4 percentage points) and the previous day (10 versus

Table 8—Effects on Winners in Treatment Schools by Selected Sub-Groups

	Gender		Grade	
	Males (1)	Females (2)	3rd–4th (3)	5th–6th (4)
Access				
Computer or laptop at home	0.39	0.41	0.42	0.38
	(0.03)***	(0.04)***	(0.03)***	(0.04)***
Use				
Last week	0.04	0.07	0.06	0.05
	(0.01)**	(0.02)***	(0.03)**	(0.02)**
Yesterday	0.08	0.10	0.08	0.10
	(0.04)*	(0.02)***	(0.03)**	(0.02)***
Digital skills				
Objective OLPC test	0.90	0.73	0.76	0.87
	(0.07)***	(0.09)***	(0.08)***	(0.07)***
Objective PC and Internet test	0.11	0.01	0.09	0.02
	(0.05)**	(0.07)	(0.07)	(0.05)
Self-reported PC and Internet skills	0.03	0.00	0.04	−0.01
	(0.07)	(0.06)	(0.07)	(0.05)
Cognitive skills				
Raven's progressive matrices	0.08	0.04	0.03	0.08
	(0.06)	(0.05)	(0.05)	(0.06)
Teachers' perceptions				
High skills in making friends	−0.03	−0.01	−0.03	−0.00
	(0.02)	(0.03)	(0.02)	(0.03)
High academic effort in class	−0.04	−0.06	−0.07	−0.03
	(0.02)*	(0.03)*	(0.02)***	(0.04)
Expected to complete university	−0.00	−0.03	−0.06	0.02
	(0.03)	(0.03)	(0.03)*	(0.03)

(*Continued*)

8 percentage points). Despite the slightly lower impacts of computer access and use, the impact of the intervention on computer skills is higher for boys as there is evidence that boys did obtain some general computer skills from exposure to the XO laptop, and boys scored significantly higher on the XO-specific test as compared to girls (0.90 versus 0.73 of a standard deviation). Teachers' perceptions of academic effort were also lower for girls than boys (6 versus 4 percentage points), but these were not significantly different from one another.

The impact of the intervention on access to home computers by grade is somewhat higher for younger (42 percentage points) than older children (38 percentage points). In part, this is because households with older children were more likely to own a home computer before the intervention. This difference in access is not reflected in any clear difference of use in the previous week or the previous day. The impacts on computer and cognitive skills are larger in magnitude for older children, but they are not significantly different from those of younger children. However, among younger children, the intervention is associated with reports of lower effort by teachers.

The differential impacts of the intervention by prior ownership of computers are quite substantial. Not surprisingly, the impact on access to a home computer at follow-up are considerably larger for children that reported no previous availability of a computer at home as compared to their counterparts who did report having

TABLE 8—EFFECTS ON WINNERS IN TREATMENT SCHOOLS BY SELECTED SUB-GROUPS (*Continued*)

	Baseline computer access		Baseline academic achievement	
	Access (5)	No access (6)	Below median (7)	Above median (8)
Access				
Computer or laptop at home	0.18	0.56	0.41	0.40
	(0.03)***	(0.02)***	(0.03)***	(0.04)***
Use				
Last week	0.02	0.08	0.05	0.06
	(0.01)	(0.02)***	(0.02)**	(0.02)***
Yesterday	0.03	0.13	0.10	0.07
	(0.03)	(0.04)***	(0.03)***	(0.03)*
Digital skills				
Objective OLPC test	0.78	0.84	0.70	0.95
	(0.07)***	(0.09)***	(0.06)***	(0.08)***
Objective PC and Internet test	0.06	0.06	0.01	0.13
	(0.07)	(0.06)	(0.07)	(0.10)
Self-reported PC and Internet skills	−0.02	0.05	−0.01	0.03
	(0.07)	(0.06)	(0.06)	(0.07)
Cognitive skills				
Raven's progressive matrices	0.05	0.06	0.14	−0.01
	(0.07)	(0.04)	(0.05)**	(0.05)
Teachers' perceptions				
High skills in making friends	−0.01	−0.02	0.00	−0.05
	(0.03)	(0.03)	(0.03)	(0.03)
High academic effort in class	−0.04	−0.06	−0.05	−0.06
	(0.03)	(0.03)**	(0.02)*	(0.03)*
Expected to complete university	0.00	−0.03	−0.01	−0.03
	(0.02)	(0.03)	(0.05)	(0.02)

Notes: This table presents evidence on heterogeneous impacts on laptop winners. The sample includes students in third to sixth grade. Each cell in columns 1 to 8 corresponds to the coefficient and standard error on an indicator for winning the laptop lottery from an OLS regression for certain sub-sample in treatment schools. Controls include the baseline value of the outcome (except when estimating effects on the OLPC test), class fixed-effects, and demographic characteristics as detailed in the text. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

access to a computer at home (56 versus 18 percentage points). This differential access is also reflected in patterns of extensive and intensive computer use in almost all categories. Despite the differential in access and use, lottery winners with and without prior access to home computers experienced fairly similar increases in XO skills. There are also no differences in impacts on the Raven's Progressive Matrices tests. The negative impacts on teacher's reports of perceived school effort are also concentrated in the group of lottery winners without previous access.

Finally, the impact of the intervention on access and use of home computers by baseline academic achievement is similar, with just slightly higher rates for children with lower baseline academic achievement.[25] Nevertheless, the impacts on XO-specific skills were significantly larger for children with higher baseline academic achievement

[25] Our measure of baseline academic achievement is the average of standardized math and reading tests implemented by the research team.

(0.95 versus 0.70 of a standard deviation). In contrast, the impacts on cognitive skills were larger for children with lower baseline academic achievement. These were positive and significant at 0.14 of a standard deviation. We did not observe any significant differences in teachers' perceptions by baseline academic achievement.

V. Summary and Policy Implications

This paper presents findings from a five-month follow-up of a randomized experiment in which XO laptops were provided for home use to students attending public primary schools in Lima, Peru. The intervention was successful at increasing children's exposure to computers by raising the likelihood that children had access to a computer at home and increasing the likelihood of home computer use at both the extensive and intensive margin. Although receiving an XO laptop led to a large impact on an objective test of XO proficiency, we find no evidence that the intervention translated into improvements in academic achievement or in skills related to using a Windows PC or Internet. The effect of the intervention on cognitive skills, as measured by the Raven's Progressive Matrices test, was also insignificant. Moreover, based on reports by teachers, children who received laptops were significantly less likely to exert effort at school. There were some differences in impacts by gender and grade, with larger positive effects in computer access and use for children who reported not having a home computer prior to the intervention, and significantly positive impacts on cognitive skills for children below the median level of baseline academic achievement. Finally, we did not detect much evidence for spillovers in impacts within schools, although close friends and classmates of children who received laptops did show significantly higher levels of proficiency with the XO computer.

While this study is not necessarily a full impact evaluation of the OLPC program, it does evaluate several key features of this initiative.[26] Most importantly, the OLPC initiative aims to foster self-empowered learning that can be beneficial outside of the structured classroom environment and at home in particular. Estimating the effects of providing XO laptops for home use is therefore extremely useful for understanding this aspect of the program. Another important principle of the OLPC initiative is "digital saturation" whereby all children have access to a laptop.[27] Although this condition was not fulfilled in our study, we explored whether the effectiveness of the treatment was impacted by the presence of close friends who also received XO laptops. Our estimates were somewhat imprecise but there was no evidence of significant interactions.[28] The OLPC initiative also emphasizes the importance of connectivity, or access to the Internet. The extent

[26] As mentioned earlier, an impact evaluation of the OLPC rollout in rural schools in Peru was conducted by Cristia et al. (2012). However, there was virtually no Internet access in these rural areas, children in these schools did not receive any instruction or training, and only about 40 percent of them regularly took their laptops home.

[27] OLPC principles are laid out in http://wiki.laptop.org/go/OLPC:Five_principles (accessed November 22, 2011). The other principles are child ownership, low ages, and free and open source software. These were all satisfied in our intervention.

[28] Separately, we also tested for differential impacts associated with nonexperimental variation in the fraction of students in a class who receive laptops. However, this variation was driven entirely by differences in class-size.

to which Internet access improves the effectiveness of computers is an important question but we were not able to answer it in the present study.[29]

In terms of policy, the results above suggest that providing students with an XO laptop access at home (together with some training) improves their skills in using this specific technology, even after only several months of use. To the extent that improving children's skills in using computers is a relevant goal for an educational system, providing access to them at home may be one way to achieve this. Obviously, the provision of home computers to all students in public schools would be quite expensive. But perhaps other options may be explored, such as increasing the time after school when they can use the computers freely and rotating the times when students can take computers home. More importantly, however, the provision of XO laptops at home does not appear to improve academic achievement and cognitive skills for this population, which are arguably the more important goals of educational systems.

Appendix

Table A1—Average Daily Minutes of OLPC Laptop Use from Logs

		Gender		Grade		Baseline computer access	
	All (1)	Male (2)	Female (3)	3rd–4th (4)	5th–6th (5)	Access (6)	No access (7)
Use							
Overall	52	55*	47	50	53	44***	58
By month							
July	62	63	57	62	61	49***	73
August	54	58	50	54	53	48*	60
September	50	56*	45	47	53	44*	56
October	40	42	37	36	45	35*	43
By type of application							
Music	14	16***	11	12***	16	11**	16
Cognitive games	11	11	12	12	11	11	12
Utilities	11	11	11	11	11	10**	12
Reading	9	10*	8	9	9	8**	10
Programming	6	7	6	6	7	6	7
Others	6	6*	4	6	6	5	6
Math	5	5	4	5	4	4	5
Measurement	2	2*	1	1	2	2	1
Observations	489	207	245	240	234	195	271

Notes: This table presents statistics on patterns of use by groups. It also indicates the statistical significance of differences across subgroups within dimensions analyzed. The sample includes students in third to sixth grade. Column 1 represents overall average. Within each dimension, columns 3, 5, and 7 represent comparison groups. XO applications were grouped in eight types: Cognitive, Reading, Math, Measurement, Music, Programming, Utilities, and Others. Statistics are computed based on logs extracted from laptops for sessions lasting at most 12 hours. We present statistics for July to October to focus on months where all students had laptops for the entire period.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

[29] We tried examining whether the effectiveness of treatment was affected by children's baseline Internet access, but this variation was clearly nonrandom and the results coincide closely with those that distinguish by whether children have prior access to a computer at home.

Table A2—Balance between Laptop Nonwinners with and without Winner Friends

	Nonwinners with winner friends (1)	Nonwinners without winner friends (2)	Adjusted difference (3)	Observations (4)
Student characteristics				
Age	10.02	10.08	0.07	2,241
			(0.04)*	
Male	0.47	0.49	−0.01	2,241
			(0.03)	
Household characteristics				
Number of siblings in household	2.19	2.31	−0.08	2,241
			(0.07)	
Father lives at home	0.78	0.77	−0.01	2,241
			(0.02)	
Father works outside home	0.89	0.88	−0.02	2,241
			(0.02)	
Mother works outside home	0.52	0.54	−0.02	2,241
			(0.03)	
Phone	0.48	0.48	0.00	2,199
			(0.02)	
Electricity	0.92	0.91	−0.02	2,215
			(0.02)	
Car	0.26	0.30	−0.04	2,179
			(0.03)	
Access				
Computer or laptop at home	0.44	0.42	−0.00	2,241
			(0.03)	
Internet at home	0.35	0.33	0.01	2,209
			(0.03)	
Digital skills				
Objective PC and Internet test	0.08	−0.10	0.08	2,241
			(0.06)	
Self-reported PC and Internet skills	0.03	−0.03	−0.01	2,241
			(0.08)	
Cognitive skills				
Raven's progressive matrices	0.04	−0.05	0.01	2,101
			(0.06)	

Notes: This table presents statistics and estimated differences between nonwinners with friends among laptop lottery winners and nonwinners without friends among the laptop winners, all of whom participated in the laptop lottery within treatment schools. The sample includes students in third to sixth grade. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors from OLS regressions. Controls include class fixed-effects and the total number of friends who participated in lottery. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A3–Balance between Laptop Winners with and without Winner Friends

	Winners with winner friends (1)	Winners without winner friends (2)	Adjusted difference (3)	Observations (4)
Student characteristics				
Age	9.93	10.08	−0.06	610
			(0.12)	
Male	0.47	0.51	−0.00	610
			(0.06)	
Household characteristics				
Number of siblings in household	2.29	2.29	−0.35	610
			(0.21)	
Father lives at home	0.77	0.77	−0.01	610
			(0.05)	
Father works outside home	0.86	0.89	0.02	610
			(0.03)	
Mother works outside home	0.51	0.51	−0.01	610
			(0.07)	
Phone	0.48	0.42	0.04	587
			(0.06)	
Electricity	0.91	0.90	−0.02	598
			(0.04)	
Car	0.23	0.27	−0.06	589
			(0.05)	
Access				
Computer or laptop at home	0.44	0.39	0.04	610
			(0.06)	
Internet at home	0.30	0.31	0.04	603
			(0.05)	
Digital skills				
Objective PC and Internet test	−0.04	−0.08	0.05	610
			(0.06)	
Self-reported PC and Internet skills	0.06	−0.08	0.17	610
			(0.13)	
Cognitive skills				
Raven's progressive matrices	0.07	−0.04	0.28	569
			(0.12)**	

Notes: This table presents statistics and estimated differences between lottery winners with friends among the laptop lottery winners and winners without friends among the laptop winners, all of whom participated in the laptop lottery within treatment schools. The sample includes students in third to sixth grade. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors from OLS regressions. Controls include class fixed-effects and the total number of friends who participated in lottery. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4—School Randomization Balance

	Treatment schools (1)	Control schools (2)	Adjusted difference (3)	Observations (4)
Student characteristics				
Age	10.07	10.02	0.04	4,722
			(0.06)	
Male	0.50	0.47	0.03	4,724
			(0.02)*	
Household characteristics				
Number of siblings in household	2.33	2.11	0.21	4,721
			(0.07)***	
Father lives at home	0.77	0.77	0.00	4,708
			(0.01)	
Father works outside home	0.88	0.88	0.00	4,707
			(0.01)	
Mother works outside home	0.55	0.51	0.03	4,718
			(0.02)*	
Phone	0.48	0.53	−0.04	4,628
			(0.02)*	
Electricity	0.91	0.95	−0.05	4,662
			(0.01)***	
Car	0.28	0.28	0.01	4,568
			(0.02)	
Access				
Computer or laptop at home	0.44	0.52	−0.08	4,850
			(0.02)***	
Internet at home	0.34	0.40	−0.05	4,783
			(0.02)**	
Academic achievement (2nd grade)				
Math	−0.09	0.11	−0.13	1,235
			(0.12)	
Reading	−0.13	0.22	−0.33	1,218
			(0.09)***	
Digital skills				
Objective PC and Internet test	−0.02	0.04	−0.06	4,850
			(0.05)	
Self-reported PC and Internet skills	−0.02	0.02	−0.04	4,850
			(0.06)	
Cognitive skills				
Raven's progressive matrices	−0.06	0.14	−0.22	4,469
			(0.04)***	

Notes: This table presents statistics and estimated differences between laptop nonwinners in treatment schools (including both lottery participants and nonparticipants) and students in control schools. The sample includes students in third to sixth grade except from results for academic achievement that correspond to second graders. Columns 1 and 2 present means. Column 3 presents estimated coefficients and standard errors from OLS regressions with school pair fixed-effects and have been weighted as discussed in the text. Estimated standard errors, reported in parentheses, are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

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