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Can One-to-One Computing Narrow the Digital Divide and the Educational Gap in China? The Case of Beijing Migrant Schools

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Summary. — One Laptop Per Child (OLPC) is a high profile initiative to narrow the inequality of access to ICT and improve educational performance. However, there is little empirical evidence on its impacts. In order to assess the effectiveness of OLPC, we conducted a randomized experiment of OLPC with Chinese characteristics involving 300 third-grade students in Beijing migrant schools. Our results show that the program improved student computer skills by 0.33 standard deviations and math scores by 0.17 standard deviations. The program also increased student time spent using educational software and decreased student time spent watching TV. Student self-esteem also improved.

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Key words — One Laptop Per Child, RCT, Asia, China, Beijing migrant school, computer skills, math test scores

1. INTRODUCTION

Access to and facility with Information and Communication Technology (ICT) in the 21st century is increasingly important for individuals. There are direct benefits of having easier and faster access to information through ICT adoption (Jensen, 2007). For instance, only individuals that have accurate information about prices can engage in efficient trading. Individuals with good information can often better utilize social services, such as education and health. Good information is more accessible when an individual is more facile with ICT (Çilan, Bolat, & Coşkun, 2009). ICT has also become an important contributor to growth in productivity and a country's overall economy (World Bank, 2006). As ICT adoption in industries becomes widespread, the demand for workers with computer skills has also increased, generating higher wage rates for ICT-savvy individuals (van Ark, O'Mahony, & Timmer, 2008). As a result, skills associated with ICT are crucial for individuals to be competitive in labor markets and secure higher earnings (Autor, Katz, & Krueger, 1998; Vicente & López, 2011).

Unfortunately, the inequality of access to and expertise in ICT (henceforth, the *digital divide*) is substantial in both developed and developing countries (Norris, 2001). In the United States, 80% of the households with an income over $75,000 have internet at home, while only 25% of the poorest households have internet at home (Dickard & Schneider, 2002). In developing countries, such as India, the rate of access to the internet for urban households in 2008 was 10 times that for rural ones (Singh, 2010). In China, internet penetration was almost four times higher in urban areas than in rural areas (Chinese Internet Network Information Center, 2010). Computer ownership is found to be 14 times higher for urban children than the rural children (Yang *et al.*, 2012). As access to ICT during childhood is a strong predictor of expertise in ICT in adulthood, the school-aged digital divide may be expected to be transformed into future disparities in productivity and earnings (Baouendi & Wilson, 1989). There is a concern that a persistent digital divide in society may contribute to entrenched and long term stratification of wealth, opportunity, and quality of life between peoples of the world (Autor *et al.*, 1998).

The One Laptop Per Child program (henceforth, OLPC) is a high profile initiative that has aimed to narrow the digital divide and educational gap. The OLPC concept was first proposed by MIT professor and investor Nicholas Negroponte, who had a vision to revolutionize education through the development and distribution of low-cost laptops (Buchele & Owusu-Aning, 2007). OLPC was designed to bridge the digital divide by providing inexpensive computers with network capability to poor children around the world who would otherwise not likely have access to them. The laptops were specially designed to cope with low-power supply and the ruggedness of poor urban and rural areas. The software included with the machines consisted of a graphical user interface and programs designed to improve learning by allowing interaction between users and access to information via networking and the

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internet. The OLPC program states that it was set up to provide a more efficient infrastructure for learning and gaining access to information (Trucano, 2011). The program was also expected to generate enthusiasm for learning among students, improve educational performance, and help users overcome the digital divide (Bhatta, 2008).

A number of scholars, however, have disputed the premise that providing laptops to disadvantaged children will either reduce the digital divide or improve educational outcomes. For example, some point out that without certain classroom structure or teacher training, the program is almost certainly going to be ineffective in achieving its goals (Butler, 2007). Furthermore, developing countries typically do not have access to learning-based software and other digital content that sustain the long-term interest of children, a factor that is essential to OLPC's success (Kraemer, Dedrick, & Sharma, 2009). Empirical evidence of the impact of ICTs on student learning is also mixed. There is empirical evidence which shows that computer assisted learning programs have a negative impact on academic performance of students (Angrist & Lavy, 2002). However, laptops/computers used in school instruction were found to improve the learning of students in some cases (Banerjee, Cole, Duflo, & Linden, 2007; Warschauer, 2008). In other cases, it has been found to reduce test scores in the short run due to the complexity of program incorporation (Grimes & Warschauer, 2008).

Given the controversy about ICT's efficacy as a learning aid and the fact that more than two million OLPC laptops have been distributed in more than 40 countries (Verma, 2011), there is surprisingly little empirical evidence on the impacts of the program. Most of OLPC projects did not set up formal evaluations (Nugroho & Lonsdale, 2009). Even if they did, the evaluations were either anecdotal or descriptive (Hourcade, Beitler, Cormenzana, & Flores, 2008). The OLPC project in Sri Lanka is one of the few projects that did incorporate systematic data collection into its design. However, no official report is available so far (Aturupane, 2010). To date, we have only found a descriptive study which states that the OLPC program had a positive impact on math and English test scores based on grading registries in three of the sample schools of the OLPC project (Mozelius, Rahuman, & Wikramanayake, 2011). The other evaluation, a study to evaluate the impact of OLPC in Haiti, was severely interrupted by the earthquake in 2008 (Näslund-Hadley, Kipp, Cruz, Ibarrán, & Steiner-Khamsi, 2009). To the best of our knowledge there has been only one rigorous evaluation of the impacts of the OLPC program using methods that seek to identify true causality between the program and any academic or non-academic outcomes. Recently the OLPC project in Peru has reported the findings from a randomized experiment (Cristia, Ibarrarán, Cueto, Santiago, & Severín, 2012). They have found that the program increased computer use and general cognitive skills. However, in their program, no impact is found on math and language test scores.

This study aims to use rigorous empirical methods to assess the effectiveness of OLPC in narrowing the digital divide between poor and rich children in China and in increasing the human capital of disadvantaged children. In order to meet this goal, we pursue three specific objectives. First, we examine the impacts of our OLPC-like program on the computer skills of children, comparing them against those of children that were not selected to be a part of the program. Second, we assess the program's ability to improve academic performance in math and Chinese language. Finally, we investigate the impacts of the program on a set of non-academic outcomes.

Given the ambitious nature of our goals, we necessarily need to limit the scope of our work. First, our program is not a formal member of the OLPC deployments. We did attempt to mimic some of the essential features of the OLPC program, namely making a laptop a normal part of a student's learning in everyday life. However, there are some aspects that were different. First, self-learning is more emphasized in our project. In order to assist student learning at home, we incorporated the learning/remedial tutoring software package described below (in Section 2(b)). These software packages and their games contained material that is consistent with the official schooling curriculum. Second, in our program connectivity is less emphasized. The formal OLPC projects use laptops that have activated network functions which allow students to share collaborative activities with their classmates. Our laptops were all capable of accessing the internet. However, the access to the internet does require that households obtain a subscription with certain telecom companies. Only about 37% of the treatment students had internet access at home during the intervention.

A second limitation is that our sampling is restricted to migrant children in Beijing. While the external validity of our evaluation is admittedly compromised by focusing on this population (e.g., we are not sure if the results of our study are valid had we given laptops to students in poor, rural areas), we believe the study is valuable for several reasons. First, the number of the rural-to-urban migrants in China has reached 150 million and it is still growing rapidly (ACWF, 2008). There are estimated to be more than 20 million school aged children in China that migrated with their parents and go to school in urban areas. Second, migrant children often lack access to quality education. On account of China's unique household registration system, rural to urban migrants often live in poor communities at the edges of the cities without convenient access to social services (Lai *et al.*, 2011). In particular, many migrant children are not able to easily enroll in urban public schools (due in large part to space limitations). As a result, up to 70% of migrant children (at least in Beijing) have to go to loosely regulated and privately run, for-profit schools that were opened specifically for serving children from poor migrant families (*migrant schools*—Tao & Yang, 2007). The poor quality of facilities and teachers of these schools have been found to seriously undermine the performance of migrant students (Lai, Luo, Zhang, Huang, & Rozelle, 2012). On the positive side, however, school settings like this are typical of schools in other developing countries, which will make the lessons from the study of interest to those who study other resource constrained schooling environments.

The rest of the paper is organized as follows. Section 2 explains the study's design, describes the dataset, and reviews the study's statistical approach. Section 3 presents the results of our analysis. In this section, we examine the impact of our program on student computer skills, math test scores, and Chinese test scores. We also test heterogeneous effects on the three outcomes and investigate if the program affects any other non-academic outcomes. Section 4 concludes.

2. RESEARCH DESIGN, DATA, AND STATISTICAL APPROACH

In this section there are four subsections. The first subsection describes the sampling. The second subsection reviews the experimental design. The third and fourth subsections recount the data collection effort and present the statistical approach.

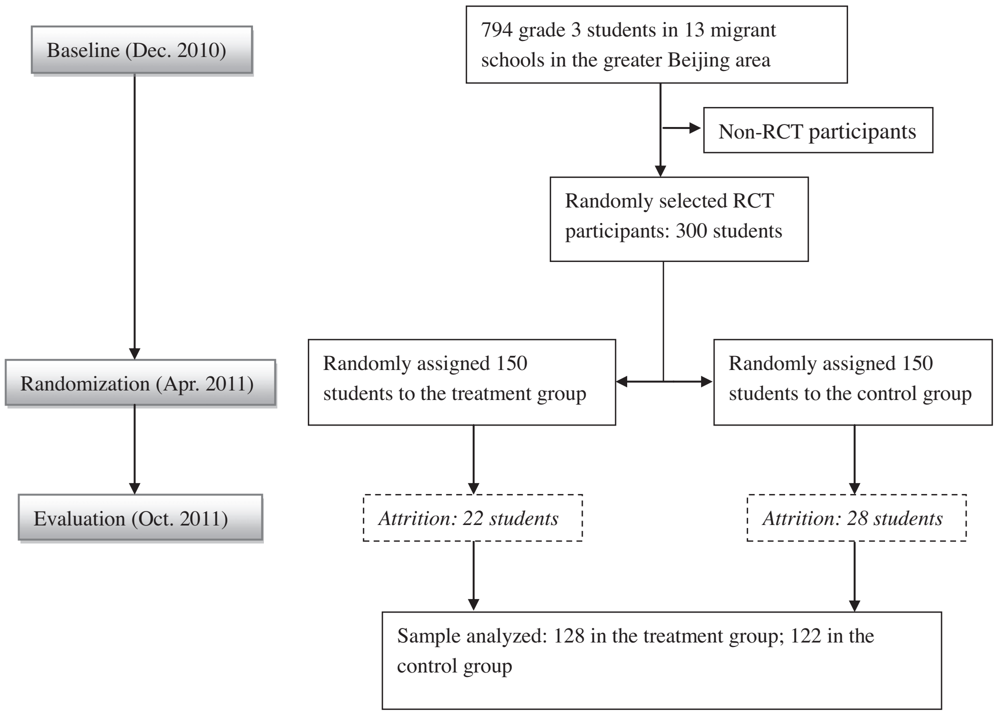

Figure 1. *Experiment profile.*

(a) *Sampling*

We conducted a randomized experiment to assess the effectiveness of an OLPC-like program in narrowing the digital divide between poor and rich children in China and in increasing the human capital of disadvantaged children. A total of 300 grade three students in 25 classes of 13 Beijing migrant schools were involved in our study. We focus on grade three students because our learning assisted software is targeted only at this level.

In choosing our sample we obtained a list of 13 migrant schools located in a total of three different districts of greater Beijing. [1] The three districts have among the highest concentrations of migrant workers and migrant schools in Beijing. In total, there were 69 schools in these districts. From the list of these 69 schools, we randomly chose thirteen schools to form the basis of our experiment sample.

We selected 300 grade three students from the thirteen migrant schools to include in our experiment (Figure 1). Among a total of 794 grade three students in the 13 schools, we randomly chose 300 students. [2] Half of the 300 students were randomly assigned to the treatment group and the other half were assigned to the control group. In a total of 25 classes, there were on average six treatment students and six control students in each class. For this reason we do not consider our study a cluster RCT. In our analysis, however, we do control for class fixed effects. The baseline survey was conducted in December 2010.

By the time of evaluation (November 2011), although we managed to track every student whose contact information was valid and was still attending school in Beijing, we still had an attrition rate of 16.7%. We were able to track 128 students in the treatment group and 122 students in the control group (Figure 1). In other words, 250 out of the initial 300 students were found and participated in the evaluation survey. In fact, this level of attrition (of both treatment and control students) during a period of 9 months is reasonable due to the fact that migrants have a high level of mobility (i.e., they often move from job to job or have to move their living quarters). The schools that migrants often attend (in this case, private migrant schools) also often face sudden closings. In our sample, younger students, students with lower Chinese test scores, and those who had siblings were more likely to attrit (Table 1, column 1). If the mother had a lower education and the father ran a business, the attrition rate of their children was also likely to be higher.

Fortunately (from the viewpoint of the evaluation of our RCT), the attrition of students from the sample seems to be independent of the assignment of the OLPC intervention. The attrition rate is 14.7% for the treatment group (22/150) and 18.7% for the control group (28/150). The difference in the attrition rates between the two groups is not statistically significant. Moreover, when comparing the students that attrited in the treatment group to those of the control group, we found that they had (statistically) similar characteristics, with the exception of gender (difference only weakly significant; Table 1, column 2).

To divide the 300 initial participants into treatment and control groups, we proceeded as follows. First, we randomly selected 150 participants to receive the OLPC intervention. However, the randomization was not done until after we conducted a baseline survey to collect information on the student and family characteristics (data collection described more below). With the aid of our baseline data (all 300 survey forms were valid), the random assignment was done with pre-balancing using fourteen baseline characteristics. In other words, after the pre-balancing/assignment, all fourteen variables were balanced between the students in the control and treatment groups (Table 2, column 6), indicating that the differences in these variables were statistically insignificant.

Table 1. *Comparisons of the student characteristics between the attrited students and those remaining in the sample and the characteristics of attrited students between the treatment and control group in the 13 migrant schools*

		Sample: sample + attrition obs.[d] Dependent variable: attrition (1 = attrited; 0 = remained) [1]	Sample: attrition obs.[e] Dependent variable: treatment (1 = treatment; 0 = control) [2]
[1]	Baseline math score (units of standard deviation)[a]	0.03	−0.08
		(0.03)	(0.22)
[2]	Baseline Chinese score (units of standard deviation)[b]	−0.05*	0.24
		(0.03)	(0.16)
[3]	Baseline computer skills (units of standard deviation)[c]	0.03	0.22
		(0.03)	(0.19)
[4]	Age (number of years)	−0.11***	0.11
		(0.03)	(0.17)
[5]	Male (1 = yes; 0 = no)	−0.05	0.43*
		(0.04)	(0.21)
[6]	Baseline math study efficacy scale (1–4 points)	−0.04	−0.13
		(0.05)	(0.30)
[7]	Student used computer before (1 = yes; 0 = no)	0.12**	−0.16
		(0.05)	(0.30)
[8]	Student had access to internet (1 = yes; 0 = no)	0.01	0.03
		(0.06)	(0.31)
[9]	Student is an only child (1 = yes; 0 = no)	−0.09*	0.22
		(0.05)	(0.69)
[10]	Age of father (number of years)	0.01	0.04
		(0.01)	(0.03)
[11]	Age of mother (number of years)	−0.01	−0.03
		(0.01)	(0.03)
[12]	Father has a junior high school or higher degree (1 = yes; 0 = no)	−0.02	−0.02
		(0.06)	(0.32)
[13]	Mother has a junior high school or higher degree (1 = yes; 0 = no)	−0.10*	−0.02
		(0.05)	(0.24)
[14]	Father runs a business (1 = yes; 0 = no)	0.14*	0.14
		(0.08)	(0.33)
[15]	Mother runs a business (1 = yes; 0 = no)	−0.08	0.33
		(0.09)	(0.36)
[16]	Class dummy variables	Yes	Yes
[17]	Observations	300	50
[18]	*R*-squared	0.223	0.608

Source: Authors' survey.
* Significant at 10%. Robust standard errors in brackets.
** Significant at 5%.
*** Significant at 1%.
a/b The baseline math/Chinese score is the score on the standardized math/Chinese test that was given to all students in the sample before the OLPC program.
c The baseline computer skills scale is the standardized mean score on a set of computer skill questions that was given to all students in the sample before the OLPC program.
d The sample includes both the sample observations (non-attrition) and the attrition observations.
e The sample is limited to the attrited observations.

(b) *Experiment arm/intervention*

The main intervention involved two main activities: (a) the distribution of laptops installed with learning/remedial tutoring software; and (b) a single training session (which was done when the computer was passed out). The first step in the intervention occurred when the treatment students and their parents were informed of their selection into the program. This was done on a one to one basis away from the school environment. Our enumerators contacted each of the treatment students and their families by phone. We explained the program to them. They were told this was a project run by the Chinese Academy of Sciences. We told them that their child would be given a laptop computer for free and asked them to participate in a single training session. There were several parents (about 10 of the 150) that wanted verification from the school principal (perhaps thinking this was a scam or a commercial venture), but, by and large, the parents and the students expressed gratitude and excitement and promised to attend the training session. In other words, the compliance rate was 100%. We contacted the students at home in order to minimize negative (frustration-based) spillover on other students in the class (the control students, who were blind to the treatment).

To conduct the training, we obtained approval from the schools to provide us with a classroom on a chosen weekend for holding the training session and distributing the laptops. The choice of the weekend also was done to minimize the dis-

Table 2. *Comparison of student and family characteristic between the treatment and control groups in the 13 migrant schools*

		Treatment (128 obs.)		Control (122 obs.)		Difference = Treatment − Control	
		Mean [1]	SD [2]	Mean [3]	SD [4]	Mean [5]	*P*-value [6]
[1]	Baseline math score (units of standard deviation)[a]	0.16	0.97	−0.01	0.96	0.17	0.17
[2]	Baseline Chinese score (units of standard deviation)[b]	0.12	0.87	0.01	0.96	0.11	0.34
[3]	Baseline computer skills score (units of standard deviation)[c]	0.04	0.99	−0.06	1.05	0.10	0.44
[4]	Age (number of years)	10.01	0.83	10.10	0.99	−0.09	0.43
[5]	Male (1 = yes; 0 = no)	0.56	0.50	0.57	0.50	−0.01	0.86
[6]	Student had transferred to a different school (1 = yes; 0 = no)	0.14	0.35	0.20	0.40	0.06	0.24
[7]	Baseline math study efficacy scale (1–4 points)	3.34	0.46	3.31	0.51	0.03	0.58
[8]	Student used computer before (1 = yes; 0 = no)	0.70	0.46	0.65	0.48	0.05	0.42
[9]	Student had access to internet (1 = yes; 0 = no)	0.34	0.48	0.37	0.48	−0.02	0.68
[10]	Student is an only child (1 = yes; 0 = no)	0.19	0.39	0.22	0.42	−0.03	0.51
[11]	Age of father (number of years)	37.41	4.97	36.94	4.82	0.47	0.45
[12]	Age of mother (number of years)	35.52	3.96	35.59	4.65	−0.07	0.90
[13]	Father has a junior high school or higher degree (1 = yes; 0 = no)	0.79	0.41	0.78	0.42	0.01	0.84
[14]	Mother has a junior high school or higher degree (1 = yes; 0 = no)	0.65	0.48	0.66	0.48	−0.01	0.90
[15]	Father runs a business (1 = yes; 0 = no)	0.23	0.43	0.27	0.45	−0.04	0.51
[16]	Mother runs a business (1 = yes; 0 = no)	0.18	0.39	0.21	0.41	−0.03	0.51

Source: Authors' survey.
[a/b] The baseline math/Chinese score is the score on the standardized math/Chinese test that was given to all students in the sample before the OLPC program.
[c] The baseline computer skills scale is the standardized mean score on a set of computer skill questions that was given to all students in the sample before the OLPC program.

ruption to the daily schedule of the students and to keep information about the program from the control students. The school principals also were asked not to announce our event in public or treat the treatment students differently from the control students.[3] On the chosen weekend day, we held a 2 h training session during which students practiced how to use their laptop and access and use the learning/remedial tutoring software. At the end of the session, the students and parents were allowed to take home the laptops after signing a formal receipt. They were not charged anything and were told the laptop was their own.

Our research team took great care in preparing the necessary hardware, software, and user manuals in a way that would facilitate the implementation of the program. As the first step of these efforts, we acquired 150 identical laptop computers. All the laptops were donated from a single manufacturer. On these full-fledged computers, we installed three sets of learning/remedial tutoring software. The first set of software consists of a commercial, game-based math-learning program that was obtained via donation. The software provided remedial tutoring material (both animated reviews and remedial questions) for math for grade three students. The designers of the program also made sure it could be used in conjunction with the material that students were learning in their math class. The second set of software was a similar program that contained materials on Chinese language for grade three students. The third set of software was a program developed by our own team. In choosing the math questions to be included in the software, we consulted experienced elementary school math teachers in both public and migrant schools, as well as experts who were committee members at the Center for Examination of Beijing, an institute that designs city-wide uniform tests for elementary schools in Beijing. Volunteers from the Tsinghua University's Department of Computer Science and Graphics Design, one of the top computer science departments in China, were recruited to design the animation/picture-based game interface so that the games would be attractive to students.[4]

We also produced and included in the software package audio-enhanced PowerPoint tutorials to demonstrate to the students in a step-by-step fashion the basic computer operations and how to use each of the software programs. We also exerted great effort to draft the tutorial in a way that third grade students with relatively low levels of literacy could understand. The words were simple with extensive graphic illustrations. An audio file of the same content was also inserted into each PowerPoint slide so that any student with a low level of reading comprehension could still understand the material being taught in the tutorial. Complementary to the tutorials, we included for each piece of software a user manual with more instructions on the materials in the software.

During the training session, students practiced both basic computer operations and used the learning/remedial tutoring software. Students and their parents were asked to sit side by side while the student was using the laptop. In this way, it was possible for the parents to also understand the software and offer aid to their children at home. During the session the students first watched the animated tutorials on basic computer operations. They were then shown the tutorials and manuals for each set of software. Finally, they were given around 15 min to use the software. The timing of all of the training sessions was carefully orchestrated to be the same.

(c) *Data collection*

The research group conducted a total of two rounds of surveys to all grade three students in the thirteen schools.[5] The first round of survey (the baseline) was conducted in late December 2010. It was at the end of the fall semester and before our intervention had begun. The second round of survey (the evaluation) was conducted in October, 1 month after the students matriculated into grade 4 and 6 months after the intervention had started.

In each round of the survey, the enumeration team visited each school and conducted a three-block survey. In the first block students were given a standardized math test and a standardized Chinese language test. The math test included about 20 questions selected from the TIMSS test data bank (slightly different numbers of questions were included in different rounds).[6] The Chinese language test included about 30 questions. The questions for the Chinese language tests were selected from official examination books and exercise books with aid from the Center for Examination of Beijing Municipality. Students were required to finish the tests in each subject in 20 min. All the students took the math test first and then they took the Chinese test. Our enumeration team monitored the test (and put a lot of effort to minimize cheating) and strictly enforced the time limits. The scores of the students on the math and Chinese tests were normalized and used as our measures of student academic performance.

In the second block enumerators collected data on student computer skills. In order to create our main measure of student computer skills, we asked the students a set of eight questions on basic computer operations, such as whether the student knew how to turn on/switch off the computer, use the keyboard, use the mouse, *etc.* (see Table 8 for the full list). We used these questions to generate eight dummy variables and took the normalized mean to create the indicator of student computer competency (*standardized computer skill scale*).

In the third block of the survey we collected information on the demographic and socioeconomic characteristics of the students. From this part of the survey we were able to create a number of control variables. The dataset includes measures of each student's *age* (measured in years), gender (described by an indicator *male*, which is equal to one for boys, and zero for girls), and whether the *student is an only child* (which is equal to one for only child, and zero for students that have sibling(s)). A set of questions on parents were also included to generate variables of the age of parents (*age of father* and *age of mother*), education level of parents (*father has a junior high school or higher degree* and *mother has a junior high school or higher degree*), and the job of parents (*father runs a business* and *mother runs a business*). Additionally, a variable measuring *math study efficacy* (or ability to solve math problems) was created using a seven-item psychological scale for math efficacy. To create an indicator of whether a student had switched schools (or transferred) during the period of our project, we compared the name of the school during the baseline and the name of the school during the evaluation survey and created the variable *student had transferred to a different school* (which equals one if their current school is different from original school, and it equals zero if they stayed in the same school).

Importantly, in the third block students were also asked to answer questions that help us measure some of the non-academic outcomes. From the block we created a variable to indicate student *learning activity using computers* (the variable equals one if the student stated that he/she used any computer software for learning, such as doing extra exercises and homework, and it equals zero if the student did not use any computer software for learning purposes). A variable was created to indicate if the *student had access to internet* at home (the variable equals one if the student had access to internet, and it equals zero if the student did not have access). An indicator of self-esteem was created from the responses of students in a ten-item psychological scale measuring self-esteem (*student self-esteem scale*) based on the Rosenberg Self-esteem Scale. We also documented the activities that the student was engaged in the day (or 24 h period) before the survey and created a variable *TV watching* (the variable is equal to one if the student watched TV 1 day before the survey, and it is equal to zero if the student did not watch TV).

(d) *Statistical methods*

We used both unadjusted and adjusted Ordinary Least Squares (OLS) regression analysis to estimate how the academic and non-academic outcomes were changed by the intervention. Our unadjusted analysis regressed changes in the outcome variables (i.e., post-program outcome value minus pre-program outcome value) on a dummy variable of the treatment (intervention) status. We used adjusted analysis as well to improve precision and test for heterogeneous treatment effects. In all regressions, we used heteroskedasticity-robust standard errors. The models are presented in order of increasing comprehensiveness.

First, the unadjusted model is:

$$\Delta y_i = \beta_0 + \beta_1 T_i + \varepsilon_i \qquad (1)$$

where Δy_i is the change in the outcome variable during the program period for child i. T_i is a dummy variable for the student receiving treatment (equals one for the treatment group and zero for the control group), and ε_i is a random disturbance term.

We used several variables (measured in changes over time) to measure changes in several different student academic and non-academic outcomes (Δy_i). The first primary outcome variable of our analysis is the level of student computer skills which is measured by the student standardized computer skill scale. The second set of primary outcome variables are the two academic outcomes which are measured by the standardized math test score and the standardized Chinese language test scores. Besides the primary outcome variables, we also included four additional non-academic outcomes, namely, the learning activity while using computers; the time students spent watching TV; and the measure of student self-esteem.[7]

To improve the efficiency of the estimation, we built on the unadjusted model in Eqn. (1) by including a set of control variables and class fixed effects:

$$\Delta y_{ic} = \beta_0 + \beta_1 T_i + \theta' y_{0ic} + \delta' X_{0i} + \Phi_c + \varepsilon_{ic} \qquad (2)$$

where all the variables and parameters are the same as those in Eqn. (1), except that we added the vector of class fixed effects (Φ_c) and a set of control variables. Specifically, we controlled for y_{0ic}, the pre-program outcome value for student i in class c, and a vector of additional control variables (X_{0i}). The variables in X_{0i} contained student and family characteristics (age, male, student had transferred to a different school, baseline math study efficacy scale, student used computer before, student is an only child, age of father/mother, father/mother has a junior high school or higher degree and father/mother runs a business).

In order to test for heterogeneous program effects, we also include in the multivariate regression models specified in Eqn. (2) an interaction term between the treatment dummy variable and one or more pre-program outcome variables. For example, we test whether the change in computer skills differs for students who were more skilled in computer at the time of the baseline relative to students who were less skilled. This is done by including in the regression an interaction term between the treatment dummy variable and the baseline computer skill scale. We also test if internet access at home made students benefit differently from the program by including the interaction term between treatment dummy variable and the variable of internet access. Heterogeneous effects of standardized math test scores and Chinese test scores are tested in a similar way.

3. RESULTS

(a) *Impact on computer skills*

The results in Figure 2 show that students in the treatment group improved significantly in their computer skills when compared to students in the control group. The pre-program standardized computer skill scales were similar between the treatment and control groups (Figure 2, panel A, bars labeled with "Before"). After the intervention, the students in the treatment group improved significantly more in the test of computer skills than did the students in the control group (Figure 2, panel A, bars labeled with "After"). The difference in improvement in standardized computer skill scales between the two groups is 0.32 standard deviations (Figure 2, panel B). Considering that the program only ran for only a little more than half a year, the size of the program effect can be counted as significant.

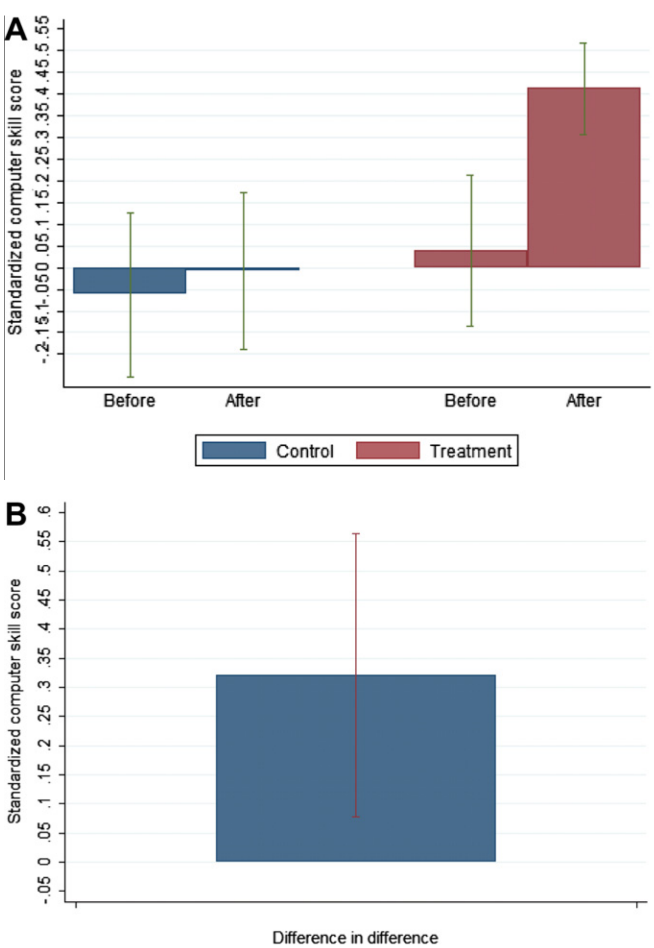

Figure 2. *Change in the standardized computer skill scale before and after the OLPC program. (Panel A) Standardized computer skill scale before and after OLPC: the treatment and control group. (Panel B) Difference in difference in the standardized computer skill scale before and after the OLPC program between the treatment and control group.*

The multivariate regression analyses (adjusted and unadjusted) are consistent with our graphical descriptive analysis. As expected (in fact, by construction), the estimated treatment effect on computer skills is also equal to 0.32 standard deviations when using Eqn. (1), the unadjusted model (Table 3, row 1, column 1). When control variables are added as in Eqn. (2), the estimate of program effect slightly rises to 0.33 standard deviations (Table 3, row 1, column 2). The coefficient measuring the effect on computer skills is significant at the 0.01 level. Clearly, and perhaps unsurprisingly (but, also reassuringly), when students have a laptop at home, they become more facile with computers. Such a result means at the very least the program in some (even small) way helps narrow the digital divide.

(b) *Impact on academic outcomes*

Perhaps more surprising, given some of the skeptical discussion in the literature (e.g., Butler, 2007; Kraemer *et al.*, 2009), our analysis demonstrates that the one-to-one computer program appears to lead to improvements in math test scores, albeit the effect is smaller. After the program, the point estimate of the standardized math test scores increased more for the treatment group relative to those of the control group (Figure 3, panel A). The difference in improvement between the two groups is 0.07 standard deviations (Figure 3, panel B). The multivariate regressions analysis is also consistent with the graphical analysis. Although, the results of the unadjusted regression show that students in the treatment group improved more in their standardized math test scores (by 0.07 standard deviations) than the students in the control group, the estimated coefficient is not significant (Table 4, row 1, column 1). When controlling for student, family characteristics and class fixed effects (as in Eqn. (2)), the estimate of program effect rises to 0.17 standard deviations (Table 4, row 1, column 2). Perhaps more importantly, the estimated coefficient of the program effect is significant at 0.1 level.[8] This positive impact of the program on math scores is consistent with the preliminary results reported in Mozelius *et al.* (2011) in the Sri Lanka OLPC project. The impact from our analysis is also similar with what is reported in the findings of another field experiment (in which computers were given to students that were attending community college in the United States—Fairlie & London, 2011). Although targeting an older group of students than did our study, the estimated level of the impact on a measure of educational outcome is 0.14 standard deviations.

The program, however, does not seem to affect Chinese language test scores. Using the descriptive statistics, the changes in standardized Chinese language test scores before and after the intervention are small for both the treatment and control groups (Figure 4, panel A). The difference in the changes between the two groups is less than −0.03 standard deviations (Figure 4, panel B). The regression results also are consistent with the graphical analysis. The estimated program effect on standardized Chinese test scores is −0.03 standard deviations when using the unadjusted model (Table 5, row 1, column 1). When using the adjusted model, the estimated effect is 0.01 standard deviations (Table 5, row 1, column 2). However, their estimated effects in both of the models are not statistically significant.

(c) *Heterogeneous effects of the OLPC intervention*

The estimation results using Eqn. (2), but including interaction terms between the treatment dummy variable and pre-program outcomes, demonstrate that the OLPC intervention

Table 3. *Ordinary least squares estimators of the impacts of OLPC program on student computer skills in the 13 migrant schools*

		Dependent variable: standardized post-OLPC computer skill scale − standardized baseline computer skill scale	
		(1)	(2)
[1]	Treatment (1 = treatment; 0 = control)	0.32** (0.12)	0.33*** (0.10)
[2]	Baseline math score (units of standard deviation)[a]		0.09 (0.08)
[3]	Baseline Chinese score (units of standard deviation)[b]		−0.07 (0.07)
[4]	Baseline computer skills score (units of standard deviation)[c]		−0.67*** (0.07)
[5]	Age (number of years)		−0.06 (0.06)
[6]	Male (1 = yes; 0 = no)		0.23** (0.11)
[7]	Student had transferred to a different school (1 = yes; 0 = no)		−0.19 (0.16)
[8]	Baseline math study efficacy scale (1–4 points)		0.05 (0.11)
[9]	Student used computer before (1 = yes; 0 = no)		0.28*** (0.11)
[10]	Student had access to internet (1 = yes; 0 = no)		−0.09 (0.14)
[11]	Student is an only child (1 = yes; 0 = no)		−0.01 (0.02)
[12]	Age of father (number of years)		0.01 (0.01)
[13]	Age of mother (number of years)		−0.05 (0.13)
[14]	Father has a junior high school or higher degree (1 = yes; 0 = no)		0.01 (0.12)
[15]	Mother has a junior high school or higher degree (1 = yes; 0 = no)		0.27* (0.14)
[16]	Father runs a business (1 = yes; 0 = no)		−0.17 (0.17)
[17]	Mother runs a business (1 = yes; 0 = no)		0.33*** (0.10)
[18]	Class dummy variables	No	Yes
[19]	Observations	250	250
[20]	R-squared	0.026	0.545

Source: Authors' survey.
* Significant at 10%. Robust standard errors in brackets.
** Significant at 5%.
*** Significant at 1%.
[a/b] The baseline math/Chinese score is the score on the standardized math/Chinese test that was given to all students in the sample before the OLPC program.
[c] The baseline computer skills scale is the standardized mean score on a set of computer skill questions that was given to all students in the sample before the OLPC program.

had heterogeneous program effects on the standardized computer skill scales of students who entered the OLPC program with different levels of computer skills (Table 6, columns 1 and 2). Compared with the students in the control group, students in the treatment group who were less skilled in computers (e.g., by one standard deviation) improved 0.26 standard deviations more in their computer skill scales than those who were more skilled at the baseline survey (row 2, column 1).

Similarly, students who had never used a computer before the OLPC program and the ones who did not have access to internet at home improved even more. According to our results, the students that had never touched a computer before the program raised their computer skill scales by 0.78 standard deviations more than the ones who had used a computer before the OLPC program (row 2, column 2). The students that did not have access to internet at home improved computer skills by 0.41 standard deviations more than the ones who had access at home (row 2, column 3). This result is important because one of the goals of the OLPC program is to reduce the digital divide. At least among these students, it appears to be doing just that.

At the same time, we find no significant evidence of heterogeneous program effects of OLPC on standardized math test scores (row 2, columns 4 and 5). Students who scored relatively high and relatively low on the standardized math test did equally well. There were also no heterogeneous effects on

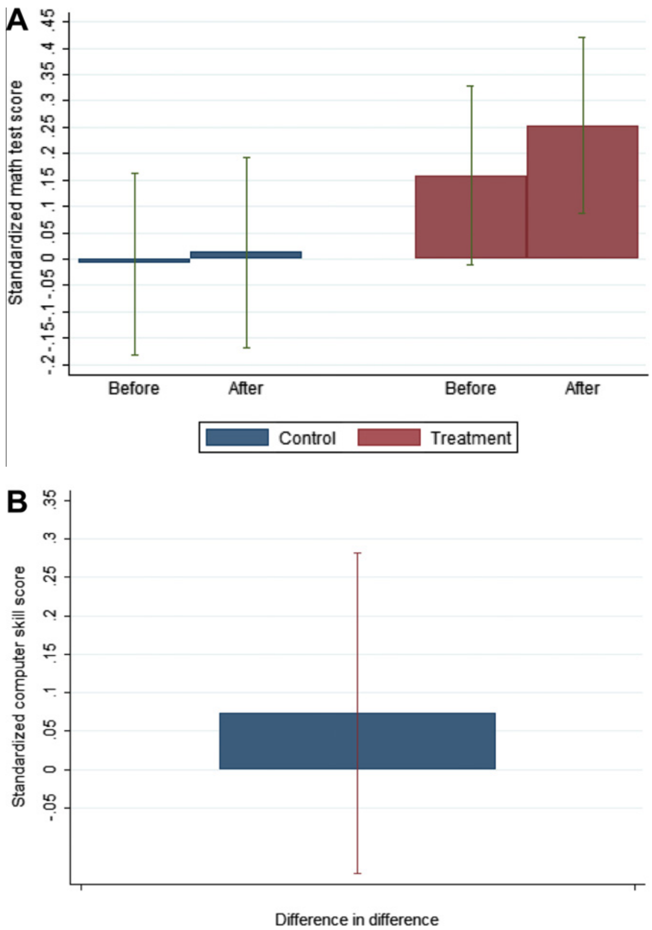

Figure 3. *Change in the standardized math test scores before and after the OLPC program. (Panel A) Standardized math test scores before and after OLPC: the treatment and control group. (Panel B) Difference in difference in the standardized math test scores before and after the OLPC program between the treatment and control group.*

standardized Chinese language test scores (row 2, columns 6 and 7).

(d) *Impact on additional non-academic outcomes*

Our OLPC intervention not only improved student computer skills and academic performance in math, but also non-academic traits for students in the treatment group (Table 7). At baseline, there were only 7% of students in the treatment group and 9% of students in the control group who had ever used a computer for learning purposes, such as doing exercises and homework. After the program, students in the treatment group were more likely to conduct learning activities using computer software by 14% relative to the control group.

Interestingly, after the OLPC program, students in the treatment group were 12% less likely to watch television (as measured by their recall of activities performed 1 day before the survey) than the students in the control group (column 3). Studies have suggested that computer use can serve as a distraction from schooling for students (Oppenheimer, 1997). However, there might be an offsetting effect because computer use tends to be more interactive than television watching, and students substitute television time by computer time (Fiorini, 2010). If watching television is a relatively inefficient way of learning, as is pointed out by many scholars (Anderson & Pempik, 2005; Pool, Koolstra, & van der Voort, 2003), substituting time in front of the television with time on the computer could have improved the students' academic results after our OLPC program.

On a scale of one to four, students in the treatment group also scored 0.12 points higher in a self-esteem assessment than the students in the control group (column 4). As Heckman and Rubinstein (2001) and Heckman, Stixrud, and Urzua (2006) have suggested, non-cognitive traits are not only crucial in educational attainment and accumulation of human capital, they also play an important role in one's competitiveness in the labor market and in leading a successful life. Our results are consistent with Lai, Luo, *et al.* (2012) who has also found that a computer-assisted learning program boosts self-confidence among treated children in addition to academic outcomes. Although the causality might go in both directions, our results are important for understanding the link between academic outcomes and self-esteem.

4. CONCLUSION

In this paper we present the results from a randomized field experiment of a One Laptop Per Child (OLPC) program involving 300 third-grade students in thirteen migrant schools in the suburban areas of Beijing. The main intervention involved the distribution of laptops installed with learning/remedial tutoring software and a single training session. In order to assist student learning at home, the installed learning/remedial tutoring software was tailored to the regular school curriculum and provided the students with many drills and exercises that were related to the material they were learning in class.

Our results indicate that the OLPC program has significant beneficial effects on student computer skills around 6 months after the program began. The students in the treatment group improved significantly in computer skills relative to the control group, by 0.30 standard deviations on standardized computer skill scales, with even greater impacts for those students who started with lower computer skills or no experience with computers. In this way, our results suggest that OLPC may be able to reduce the digital divide.

The OLPC program is also shown to improve student academic outcomes (at least in math) and has an impact on a set of non-academic traits. Student standardized math scores were increased by 0.17 standard deviations by comparing the score changes between the treatment group and the control group. Although a positive impact on math test scores is found, the result's relatively low level of statistical significance (10%) warrants cautious interpretation. In order to check for the robustness of such an effect as well as to better understand the full nature of our study's external validity, more replications and continued evaluation of a scaled-up version of the program are needed.

Although it is not clear from our results why the program only influenced math test scores and had no impact on Chinese test scores, the reason is unlikely due to the differences in the effectiveness of the software we installed. The computer-assisted learning programs using the same set of software have been shown to improve both math and Chinese test scores in rural school in China (Lai, Zhang, *et al.*, 2012; Zhang, Lai, Pang, Yi, & Rozelle, 2012). The difference in impacts of our program could be a result of how the students used the software at home. It could be that without teacher instruction, it is easier to do math exercises on one's own. It could also be that the games in the math software suite are more fun to play than the Chinese ones, and as a result, students, on their own, spent more time practicing with the math software.

Table 4. *Ordinary least squares estimators of the impacts of OLPC program on student standardized math test scores in the 13 migrant schools*

		Dependent variable: standardized post-OLPC math test score − standardized baseline math test score	
		(1)	(2)
[1]	Treatment (1 = treatment; 0 = control)	0.07	0.17*
		(0.11)	(0.10)
[2]	Baseline math score (units of standard deviation)[a]		−0.39***
			(0.07)
[3]	Baseline Chinese score (units of standard deviation)[b]		0.11
			(0.07)
[4]	Baseline computer skills score (units of standard deviation)[c]		−0.02
			(0.07)
[5]	Age (number of years)		−0.01
			(0.07)
[6]	Male (1 = yes; 0 = no)		0.21**
			(0.10)
[7]	Student had transferred to a different school (1 = yes; 0 = no)		0.23
			(0.22)
[8]	Baseline math study efficacy scale (1–4 points)		0.09
			(0.12)
[9]	Student used computer before (1 = yes; 0 = no)		0.05
			(0.14)
[10]	Student had access to internet (1 = yes; 0 = no)		0.08
			(0.12)
[11]	Student is an only child (1 = yes; 0 = no)		0.08
			(0.13)
[12]	Age of father (number of years)		−0.00
			(0.02)
[13]	Age of mother (number of years)		0.01
			(0.02)
[14]	Father has a junior high school or higher degree (1 = yes; 0 = no)		0.06
			(0.13)
[15]	Mother has a junior high school or higher degree (1 = yes; 0 = no)		−0.10
			(0.12)
[16]	Father runs a business (1 = yes; 0 = no)		0.11
			(0.18)
[17]	Mother runs a business (1 = yes; 0 = no)		−0.17
			(0.21)
[18]	Class dummy variables	No	Yes
[19]	Observations	250	250
[20]	*R*-squared	0.002	0.358

Source: Authors' survey.
* Significant at 10%. Robust standard errors in brackets.
** Significant at 5%.
*** Significant at 1%.
[a/b] The baseline math/Chinese score is the score on the standardized math/Chinese test that was given to all students in the sample before the OLPC program.
[c] The baseline computer skills scale is the standardized mean score on a set of computer skill questions that was given to all students in the sample before the OLPC program.

For such a single dimension intervention, the impact is not small. Other more prominent education experiments (e.g., the Tennessee Star Program and the Computer Assisted Learning Program) improved test scores by similar levels and were considered successes (Banerjee *et al.*, 2007; Mosteller, 1995). Our estimated effect is slightly higher than that of the Nutrition Program in China (Luo *et al.*, 2012; 0.1 standard deviations of improvement after 5-month nutritional treatment). The effect size is approximately that of the Computer Assisted Learning Program in migrant communities in China (Lai, Luo, *et al.*, 2012 found 0.14 standard deviations of improvement in math scores after one-semester, in class treatment).

While we do not know the exact mechanism through which the program had influenced students, our results hint at several impact pathways. For example, the improved scores may be a result of the fact that the students used more learning/remedial tutoring software at home than did students in the control group. Of course, this was a direct part of the intervention (remember, the laptop that was given to each student was preinstalled with remedial/learning software). [9] However, there may have been other effects. Students in the treatment

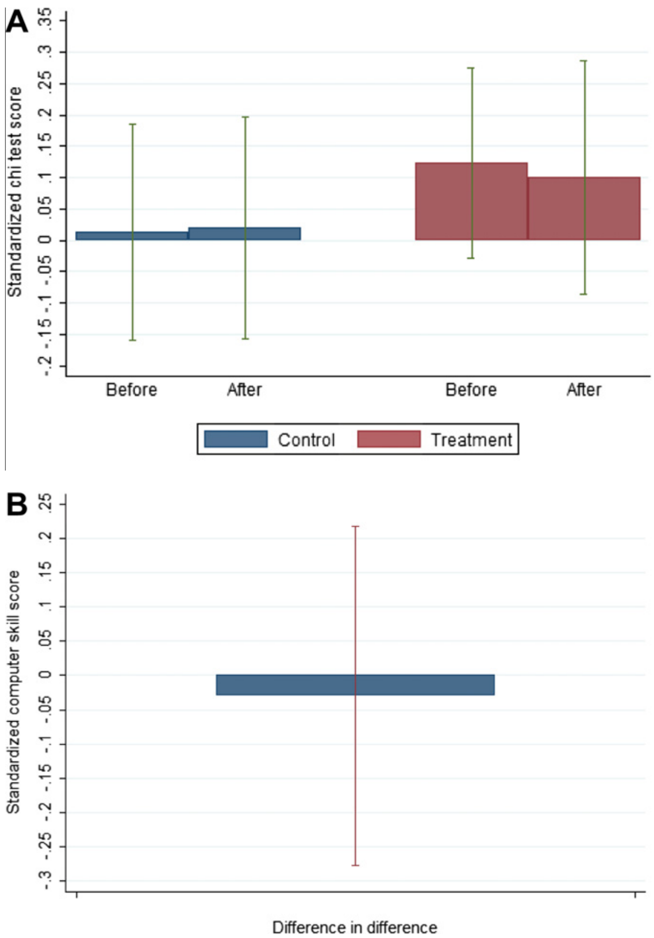

Figure 4. *Change in the standardized Chinese test scores before and after the OLPC program. (Panel A) Standardized Chinese test scores before and after OLPC: the treatment and control group. (Panel B) Difference in difference in the standardized Chinese test scores before and after the OLPC program between the treatment and control group.*

group spent relatively more time using their computer (with the learning software and other uses) and spent relatively less time watching television. Student self-esteem was also significantly improved after the OLPC program.

The heterogeneous effects on the impact of our = program on students that had internet at home and those that did not may help provide evidence of the ways that our project in China are affecting students versus the ways that the traditional OLPC (in other countries) are in theory supposed to affect students. A large part of the impact of the traditional OLPC program is supposed to come through the student's access to the internet. We find that having access to the internet does not enhance a treatment student's math learning (relative to a treatment student without access to internet) as measured by the standardized math tests. At least in our program, then, we do not find that access to the internet gives the students any extra edge. We do find, however, that when students do not have access to the internet, giving them a computer enhances their computer skills more than when a student already has access to the internet. This perhaps is not surprising seeing that the student without access to the internet will surely have less experience with computers prior to the intervention. To the extent that increasing the knowledge of students about computers is an important goal in and of itself, however, the results suggest that the act of getting hold of a computer—with or without internet access—is useful. This is an important result if there was any thought of pushing OLPC in rural schools, since according to Yang *et al.* (2012) less than 5% of students in poor areas of rural China have access to the internet at home.

As among the first rigorous impact evaluations of an OLPC-like program, our study contributes to the understanding on whether or not an OLPC program can reduce the digital divide and benefit learning of disadvantaged children. In our case the disadvantaged children are among the 20 million school aged migrant children whose parents are not able to provide enough instruction, as they have low education levels and they are constantly on the run for work. Inferior to the some of the poorest rural schools in China, migrant schools typically do not have the capacity to help students who fall behind (due either their own low level of instruction or due to the fact that migrant children often are in and out of schools and have many learning problems—Lai *et al.*, 2011). One way to help such students is to provide them with a carefully designed package, including software and hardware, that can help them continue to learn (and learn effectively) at home. Although our package does not feature complete internet access and learning from wider sources of information (as is typically part of the standard OLPC package), the students were apparently affected by either having a computer at home or by having access to the game-based tutoring software we offered (or both). As shown in our results, such a package is effective in improving both the academic and non-academic outcomes of underprivileged children.

Our study also provides important information for policy makers who are interested in using ICT to make education more efficient and more equitable. On one hand, it is an encouraging piece of evidence for policy makers in both developed and developing countries that are incorporating individual PCs into the classroom and for self-study at home. In addition to the 40 countries that are implementing OLPC around the world, developed countries, such as South Korea, are committed to making computers one of the main learning tools for students (and to make them free for students from poor families (Saenz, 2011).

As an increasing number of countries are adopting programs that incorporate individual computers in the classroom and at home, it is important to assess the cost effectiveness of our OLPC program compared to other alternatives. Although the laptops came at no cost to our OLPC program, if the government is going to scale up the program, we calculate the average cost per tenth of a standard deviation of improvement in the student test scores to be US$4.9.[10] The cost is similar with the computer-assisted learning program in China (Lai, Zhang, *et al.*, 2012, US$5.2 to US$5.8/tenth of a standard deviation) and the computer-assisted learning program in India (US$4.2/tenth of a standard deviation). However, as we are using our own measure of computer skills, it is not possible to compare cost effectiveness in terms of computer skill improvement. It is also important to keep in mind that the one-dimensional benefit that we incorporated in our calculation of cost effectiveness does not reflect on the program impact on students' future returns in the labor market (which is shown to be closely related with ICT skills). Moreover, our program demands less enforcement and implementation effort than computer-assisted learning programs, since teacher training and the enforcement of the protocols of computer classes are not necessary in our program.

Table 5. *Ordinary least squares estimators of the impacts of OLPC program on student standardized Chinese test scores in the 13 migrant schools*

		Dependent variable: standardized post-OLPC Chinese test score − standardized baseline Chinese test score	
		(1)	(2)
[1]	Treatment (1 = treatment; 0 = control)	−0.03 (0.13)	0.01 (0.12)
[2]	Baseline math score (units of standard deviation)[a]		0.31*** (0.08)
[3]	Baseline Chinese score (units of standard deviation)[b]		−0.65*** (0.08)
[4]	Baseline computer skills score (units of standard deviation)[c]		−0.09 (0.07)
[5]	Age (number of years)		0.05 (0.07)
[6]	Male (1 = yes; 0 = no)		−0.14 (0.12)
[7]	Student had transferred to a different school (1 = yes; 0 = no)		−0.10 (0.21)
[8]	Baseline math study efficacy scale (1–4 points)		0.19 (0.13)
[9]	Student used computer before (1 = yes; 0 = no)		−0.03 (0.15)
[10]	Student had access to internet (1 = yes; 0 = no)		0.02 (0.14)
[11]	Student is an only child (1 = yes; 0 = no)		0.29** (0.12)
[12]	Age of father (number of years)		0.00 (0.02)
[13]	Age of mother (number of years)		0.01 (0.02)
[14]	Father has a junior high school or higher degree (1 = yes; 0 = no)		−0.21 (0.15)
[15]	Mother has a junior high school or higher degree (1 = yes; 0 = no)		0.36*** (0.13)
[16]	Father runs a business (1 = yes; 0 = no)		0.30 (0.20)
[17]	Mother runs a business (1 = yes; 0 = no)		−0.28 (0.22)
[18]	Class dummy variables	No	Yes
[19]	Observations	250	250
[20]	*R*-squared	0.000	0.447

Source: Authors' survey.
*Significant at 10%. Robust standard errors in brackets.
**Significant at 5%.
***Significant at 1%.
[a/b] The baseline math/Chinese score is the score on the standardized math/Chinese test that was given to all students in the sample before the OLPC program.
[c] The baseline computer skills scale is the standardized mean score on a set of computer skill questions that was given to all students in the sample before the OLPC program.

On the other hand, our study also suggests that more program evaluations should be conducted before large investments are made by governments and schools in OLPC programs. As ICT continues to develop rapidly and as more learning-based software becomes readily available, more research is required to evaluate variations of the OLPC program that incorporate these systems and software. In this way, government policies may be better tailored to more effectively and cost-efficiently promote the education of the poor. Do we need to provide students with a computer? Would providing hardware be less effective if there was no software? Or could we just provide the software? In the current study, it is not possible for us to separately evaluate the impact of the giving a student a free laptop (without software). This is because both the software and the hardware (the laptop) were integral parts of the whole package of our program. However, such a program would be an interesting topic for future study.

It would also be interesting and informative in the future to evaluate a comprehensive set of interventions combining a number of different programs that (together) might have large and significant effects on students in a number of different dimensions (e.g., emotional stability; physical strength and stature; and intellectual ability). Such a study could include, in addition to an OLPC component, a number of different treatments, including the provision of nutrition to students, teacher training, and better facilities at school.

Table 6. *The ordinary least squares estimators of the heterogeneous program effect on student computer skills, standardized math scores, and standardized Chinese scores with different characteristics in the 13 migrant schools*

	Dependent variable						
	Standardized post-OLPC computer skill scale − standardized baseline computer skill scale			Standardized post-OLPC math test score − standardized baseline math test score		Standardized post-OLPC Chinese test score − standardized baseline Chinese test score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[1] Treatment (1 = treatment; 0 = control)	0.31***	0.85***	0.45***	0.18*	0.12	−0.00	−0.03
	(0.10)	(0.21)	(0.13)	(0.11)	(0.13)	(0.12)	(0.14)
[2] Interactions: Treatment*	Baseline computer skill scale (units of standard deviation)	Student used computer before (1 = yes; 0 = no)	Student had access to internet (1 = yes; 0 = no)	Baseline math score (units of standard deviation)[a]	Student had access to internet (1 = yes; 0 = no)	Baseline Chinese score (units of standard deviation)[b]	Student had access to internet (1 = yes; 0 = no)
	−0.26***	−0.78***	−0.41**	−0.02	0.14	0.18	0.11
	(0.09)	(0.22)	(0.18)	(0.10)	(0.21)	(0.13)	(0.23)
[3] Control variables[c]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
[4] Class dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
[5] Observations	250	250	250	250	250	250	250
[6] *R*-squared	0.594	0.608	0.605	0.355	0.359	0.456	0.447

The baseline computer skills scale is the standardized mean score on a set of computer skill questions that was given to all students in the sample before the OLPC program.
* Significant at 10%. Robust standard errors in brackets.
** Significant at 5%.
*** Significant at 1%.
a/b The baseline math/Chinese score is the score on the standardized math/Chinese test that was given to all students in the sample before the OLPC program.
c Control variables include all the variables that are included in Table 1.

NOTES

1. Greater Beijing includes Beijing's urban districts and the outlying suburban/rural counties and districts.

2. We chose 300 students to be in the study (150 in the treatment group and 150 in control group) based on our power calculations. We calculated that we needed 150 students per experimental arm to detect a standardized effect size of 0.25 with 80% power at a 5% significance level. We assumed an intra-cluster correlation of 0.05, a pre- and post-intervention correlation of 0.5 and 15% loss to follow-up.

3. At the time of the evaluation/endline survey, only 10% of the students in the control group stated that they were aware that some of their classmates got laptops through a Chinese Academy of Science project. Importantly, no one in the treatment or control group were informed that the there would be an evaluation/endline survey after the distribution of the laptops (or at any time). The purpose of the evaluation/endline survey was also kept blind from students, parents and teachers. The enumerators that visited the classes for the evaluation/endline survey were told that this was a study of migrant education run by universities in China (since all of the enumerators were university students).

4. The commercial software we installed in the laptops was *Dian Dian Le*. This software is produced by a domestic company, headquartered in Hebei Province, called *Tianhua Shidai*. A third set of software was developed by the authors. It has a pool of math questions that were put together by experienced primary school math teachers and experts who designed Beijing's uniform tests for elementary schools. We hired animation/computer/software experts from a local university to design the graphics and the simple games that were used to be the interface between the learning material and the students. When the students were using the software, they had to accomplish different tasks by giving the right answers to the math questions. In order to increase the interest of students, the tasks also incorporated folk stories that the kids were often familiar with.

5. We surveyed every grade three student to keep blind the purpose of the survey from the students and teachers. The students that are not included in our experiments are not used in the analysis.

6. The test questions for the standardized math exam were chosen from the TIMSS test data bank. The TIMSS test is one of most common instruments for measuring academic performance for math for primary school students in the world (Mullis *et al.*, 2012). Users (like our team) have access to a pool of questions that have been developed by international experts. TIMMS tests have been used in numerous other studies in the world (e.g., Eklöf, 2010; Leung, 2002; Wößmann & West 2005) and in China (e.g., Cai, Lin, & Fan, 2004; Tsui, 2007). In contrast, the software contains exercise questions that match the math curriculum for China's rural schools. Such questions (drawn from sources that are readily available in education book stores across China) were developed by domestic education experts. Therefore, the source of questions in the standardized exams was different from the source of questions in the software. We also purposely made sure that "by chance" there was no overlap. Hence, it is not possible that the math test was primarily repeating the questions in the software. We believe that scores on the standardized test represents true learning.

7. The test we use is the Rosenberg Self-Esteem Scale (SES) (see Table 8). The test reflects an individual's sense of his or her value or worth, or the extent to which a person values, approves of, appreciates, prizes, or likes him or herself. It has been widely used to proxy individual self-esteem levels (Blascovich & Tomaka, 1991).

Table 7. *The ordinary least squares estimators of the program effect on additional outcome variables in the 13 migrant schools*

		Dependent variables		
		Learning activity using computers (1 = used any computer software for learning; 0 = did not use computer software for learning) (1)	TV watching (1 = watched TV 1day before the survey; 0 = did not watch TV 1 day before the survey) (3)	Student self-esteem scale (1–4 points) (4)
[1]	Treatment (1 = treatment; 0 = control)	0.14**	−0.12*	0.12**
		(0.07)	(0.06)	(0.05)
[2]	Control variables[a]	Yes	Yes	Yes
[3]	Class dummy variables	Yes	Yes	Yes
[4]	Observations	250	250	250
[5]	R-squared	0.267	0.200	0.256

* Significant at 10%. Robust standard errors in brackets.
** Significant at 5%.
*** Significant at 1%.
[a] Control variables include all the variables that are included in Table 1.

8. There is an additional concern that needs addressing. If the control group learned about the program and then took actions (e.g., purchasing their own computers), there might be an effect on the estimated impact. In the case of such a "positive spillover," there would be downward bias to our results and our program might actually have a larger impact. We recognized the potential for such spillovers and tried to do a careful job in implementation to minimize them. For example, we contacted the treatment students at home. We did not announce the program publically. We asked the principals, teachers, parents, and students to keep a low-profile when discussing the program. Of course, it is possible that despite these precautions there were still spillovers. In order to try to assess the nature of any spillover, we conducted an additional set of regression exercises to see if having a relatively large number of treated students in the class had any impact (positive or negative) on the probability of students in the control group using a computer (between the baseline and endline surveys). In the regression analysis, the dependent variable is whether the student used a computer during the treatment period. The main independent variable included the treatment variable, a new variable measuring the "number of treated students in the same class" (or *class-level intensity of the treatment*) and an interaction between treatment and class-level intensity of the treatment. The results (not shown for brevity, but, available as an online supplement) demonstrate that the class-level intensity of the treatment does not change the probability that students in the control group used a computer during the treatment period. The coefficient on the interaction term is insignificant and small in magnitude.

9. An alternative explanation for the results could be that the outcome is driven by curiosity for new equipment/computer. While we do not believe this is the case (since there was improvement in real skills, both computer competencies and math skills), we decided to examine this idea. To do so, we conducted an exercise to test the heterogeneous effects of the OLPC program on students with higher and lower computer skills (which were measured at baseline). The idea is that if there was an excitement effect, the OLPC program would affect students more if they had less computer experience. According to our findings (after adding two variables, one variable measuring the baseline levels of computer experience and an interaction term—treatment times computer experience—to Eqn. (2)), the OLPC program impact on student math test scores does not differ by the level of a student's computer skills before the program (results available from authors upon request). The coefficient on the interaction (that is, treatment times computer experience) is not significant. The point estimate of the interaction effect is also small. In other words, students who were less skilled in computers did not appear to gain more in math learning. Therefore, using this method we do not find evidence to suggest that the math learning is mainly driven by the excitement associated with a new technology.

10. The calculation is based on the approach proposed by Banerjee *et al.* (2007) by assuming a 5-year depreciation cycle of laptops. We then divided the annual treatment cost by the tenth of standard deviations of 1-year treatment effect.

REFERENCES

All-China Women's Federation (ACWF). (2008). Quan Guo Nong Cun Liu Shou Er Tong Zhuang Kuang Yan Jiu Bao Gao (Report of the status of rural left-behind children in China, in Chinese). Retrieved from http://www.women.org.cn/allnews/02/1985.html.

Anderson, D. R., & Pempik, T. A. (2005). Television and very young children. *American Behavioral Scientist, 48*, 505.

Angrist, J., & Lavy, V. (2002). New evidence on classroom computers and pupil learning. *The Economic Journal, 112*, 735–765.

Aturupane, H. (2010). Evaluating the one laptop per child initiative in Sri Lanka. Retrieved from http://blogs.worldbank.org/edutech/blogs/harsha-aturupane.

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market. *Quarterly Journal of Economics, 113*(4), 1169–1213.

Banerjee, A., Cole, S., Duflo, E., & Linden, L. (2007). Remedying education: Evidence from two randomized experiments in India. *Quarterly Journal of Economics, 122*(3), 1235–1264.

Baouendi, H. P., & Wilson, J. D. (1989). Computer education in the primary and middle schools in the People's Republic of China: The late 1980's. *Education and Computing, 5*(4), 275–286.

Bhatta, S. D. (2008). Tackling the problems of quality and disparity in Nepal's school education: The OLPC model. *Studies in Nepali History and Society, 11*(1).

Blascovich, J., & Tomaka, J. (1991). Measures of self-esteem. In J. P. Robinson, P. R. Shaver, & L. S. Wrightsman (Eds.). *Measures of personality and social psychological attitudes* (Vol. 1). San Diego, CA: Academic Press.

Buchele, S. F., & Owusu-Aning, R. (2007). The one laptop per child (OLPC) project and its applicability to Ghana. In *Proceedings of the international conference on adaptive science & technology (ICAST'07)*, December 10–12, Accra, Ghana.

Butler, D. (2007). The race to wire up the poor. *Nature, 447*, 6–7.

Cai, J., Lin, F., & Fan, L. (2004). How do Chinese learn mathematics? Some evidence based insights and needed directions. In L. Fan, N. Y.

Wong, J. Cai, & S. Li (Eds.), *How Chinese learn mathematics: Perspectives from insiders* (pp. 535–554). Singapore: World Scientific.

Chinese Internet Network Information Center. (2010). Twenty-fifth statistical survey report on the internet development in China. Retrieved from http://www.apira.org/data/upload/The29thStatistical-ReportonInternetDevelopmentinChina_P9G97q.pdf.

Çilan, Ç. A., Bolat, B. A., & Coşkun, E. (2009). Analyzing digital divide within and between member and candidate countries of European Union. *Government Information Quarterly, 26*, 98–105.

Cristia, J. P., Ibarrarán, P., Cueto, S., Santiago, A., & Severín, E. (2012). Technology and child development: Evidence from the one laptop per child program. IDB Working Paper Series No. IDB-WP-304.

Dickard, N., & Schneider, D. (2002). The digital divide: Where we are. Retrieved from http://www.edutopia.org/digital-divide-where-we-are-today.

Eklöf, H. (2010). Skill and will: Test-taking motivation and assessment quality. *Assessment in Education, 17*(4), 345–356.

Fairlie, R. W., & London, R. A. (2011). The effects of home computers on educational outcomes: Evidence from a field experiment with community college students. *The Economic Journal, 122*(561), 727–753.

Fiorini, M. (2010). The effect of home computer use on children's cognitive and non-cognitive skills. *Economics of Education Review, 29*, 55–72.

Grimes, D., & Warschauer, M. (2008). Learning with laptop: A multi-method case study. *Journal of Educational Computing Research, 38*(3), 305–332.

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. NBER Working Papers 12006, National Bureau of Economic Research, Inc.

Heckman, J. J., & Rubinstein, Y. (2001). The importance of noncognitive skills: Lessons from the GED testing program. *The American Economic Review, 91*(2), 145–149.

Hourcade, J. P., Beitler, D., Cormenzana, F., & Flores, P. (2008). Early OLPC experiences in a rural Uruguayan school. In: *CHI 2008 proceedings*, Florence, Italy.

Jensen, R. (2007). The digital provide: Information (technology), market performance and welfare in the South Indian fisheries sector. *Quarterly Journal of Economics, 122*(3), 879–924.

Kraemer, K. L., Dedrick, J., & Sharma, P. (2009). One laptop per child: Vision vs. reality. *Communications of the ACM, 52*(6), 62–73.

Lai, F., Luo, R., Zhang, L., Huang, X., & Rozelle, S. (2012). Does computer-assisted learning improve learning outcomes? Evidence from a randomized experiment in migrant schools in Beijing. REAP Working Paper 228.

Lai, F., Zhang, L., Qu, Q., Hu, X., Shi, Y., Boswell, M., & Rozelle, S. (2012). Does computer-assisted learning improve learning outcomes? evidence from a randomized experiment in public schools in rural minority areas in Qinghai, China. REAP Working Paper 237.

Lai, F., Liu, C., Luo, R., Zhang, L., Ma, X., Bai, Y., Sharbono, B., & Rozelle, S. (2012). Private migrant schools or rural/urban public schools: where should China educate its migrant children? REAP Working Paper 224.

Leung, F. K. S. (2002). Behind the high achievement of east Asian students. *Educational Research and Evaluation, 8*(1), 87–108.

Luo, R., Shi, Y., Zhang, L., Liu, C., Rozelle, S., Sharbono, B., *et al.* (2012). Nutrition and educational performance in rural China's elementary schools: Results of a randomized control trial in Shaanxi Province. *Economic Development and Cultural Change, 60*(4), 735–772.

Mosteller, F. (1995). The Tennessee study of class size in the early school grades. *The Future of Children, 5*(2), 113–127.

Mozelius, P., Rahuman, K., & Wikramanayake, G. N. (2011). One year of one-to-one computing in Sri Lanka—The impact on formal learning in primary school education. World Education Summit, New Delhi, India, July 13–15.

Mullis, I. V. S., Martin, M. O., Minnich, C. A., Stanco, G. M., Arora, A., Centurino, V. A. S., *et al.* (2012). *TIMSS 2011 encyclopedia: Education policy and curriculum in mathematics and science* Vols. 1 and 2. Chestnut Hill, MA: TIMSS & PIRLS International Study Center, Boston College.

Näslund-Hadley, E., Kipp, S., Cruz, J., Ibarrán, P., & Steiner-Khamsi, G. (2009). OLPC pre-pilot evaluation report Haiti. Education Division Working Paper 2, Inter-American Development Bank, Washington, DC.

Norris, P. (2001). *Digital divide civic engagement, information poverty, and the internet worldwide*. Cambridge, UK: Cambridge University Press.

Nugroho, D., & Lonsdale, M. (2009). Evaluation of OLPC programs globally: A literature review. Australian Council for Educational Research. Retrieved from wiki.laptop.org/images/a/a5/OLPC_Lit_Review_v4_Aug2010.pdf.

Oppenheimer, T. (1997). The computer delusion. *The Atlantic Monthly*, July 1997.

Pool, M. M., Koolstra, C. M. T., & van der Voort, H. A. (2003). The impact of background radio and television on high school students' homework performance. *Journal of Communication, 8*(7), 705–711.

Saenz, A. (2011). South Korea: We're spending $2 billion to put our textbooks on Tablet PCs by 2015. What are you doing? Retrieved from http://singularityhub.com/2011/07/06/south-korea-were-spending-2-billion-to-put-our-textbooks-on-tablet-pcs-by-2015-what-are-you-doing/.

Singh, S. (2010). Digital divide in India: Measurement, determinants and policy for addressing the challenges in bridging the digital divide. *International Journal of Innovation in the Digital Economy, 1*(2), 1–24.

Tao, H., & Yang, D. (2007). Problems of "moving children" of Beijing city in education and its countermeasures (in Chinese). *Jiangxi Educational Research, 1*, 105–110.

Trucano, M. (2011). What's next for plan Ceibal in Uruguay? Retrieved from http://blogs.worldbank.org/edutech/planceibal2.

Tsui, M. (2007). Gender and mathematics achievement in China and the United States. *Gender Issues, 24*(3), 1–11.

van Ark, B., O'Mahony, M., & Timmer, M. (2008). The productivity gap between Europe and the U.S.: Trends and causes. *Journal of Economic Perspectives, 22*(1), 25–44.

Verma, S. (2011). OLPC: Are we there yet?. *Linux Journal, 211*, 98–118.

Vicente, M. R., & López, A. J. (2011). Assessing the regional digital divide across the European Union-27. *Telecommunications Policy, 35*, 220–237.

Warschauer, M. (2008). Laptops and literacy: A multi-site case study. *Technology and Literacy, 3*(1), 52–67.

World Bank (2006). *Information and communications for development global trends and policies*. Washington, DC: The World Bank.

Wößmann, L., & West, M. (2005). Class-size effects in school systems around the world: Evidence from between-grade variation in TIMSS. *European Economic Review, 50*(3), 695–736.

Yang, Y., Zhang, L., Hu, X., Qu, Q., Lai, F., Shi, Y., *et al.* (2012). The roots of tomorrow's digital divide: Documenting computer use and internet access in China's elementary schools today. REAP Working Paper.

Zhang, L., Lai, F., Pang, X., Yi, H., & Rozelle, S. (2012). Computer assisted learning as extracurricular tutor? Evidence from a randomized experiment in rural boarding schools in Shaanxi Province. REAP Working Paper.

APPENDIX A

See Tables 8 and 9.

Table 8. *The basic computer skills that were asked in the student survey*

1	Do you know how to turn on/switch off the computer?
2	Do you know how to use the keyboard?
3	Do you know how to use the mouse?
4	Do you know how to type Chinese?
5	Do you know how to cut/copy/paste/delete?
6	Do you know how to paint?
7	Do you know how to open/close files?
8	Do you know basic knowledge about hardware and software?

Table 9. *Rosenberg Self-Esteem Scale (SES) that was used to test student self-esteem level*

1	I feel that I'm a person of worth, at least on an equal plane with others
2	I feel that I have a number of good qualities
3	All in all, I am inclined to feel that I am a failure
4	I am able to do things as well as most other people
5	I feel I do not have much to be proud of
6	I take a positive attitude toward myself
7	On the whole, I am satisfied with myself
8	I wish I could have more respect for myself
9	I certainly feel useless at times
10	At times I think I am no good at all

The test we use is the Rosenberg Self-Esteem Scale (SES). The test reflects an individual's sense of his or her value or worth, or the extent to which a person values, approves of, appreciates, prizes, or likes him or herself. It has been widely used to proxy individual self-esteem levels (Blascovich & Tomaka, 1991).

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