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Evidence from a Randomized Experiment in Ecuador

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Abstract[1]

This paper studies the effects of information and communication technologies (ICT) in the school environment on educational achievement. To quantify these effects, the impact is evaluated of a project run by the municipality of Guayaquil, Ecuador, which provides computer-aided instruction in mathematics and language to students in primary schools. Using an experimental design, it is found that the program had a positive impact on mathematics test scores (about 0.30 of a standard deviation) and a negative but statistically insignificant effect on language test scores. The impact is heterogeneous and is much larger for those students at the top of the achievement distribution.

JEL Classifications: C93, I21
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1. Introduction

Improving the quality of education is a priority for most developing countries. Policymakers usually agree that such improvements could lead to structural shifts in productivity and boost long-term economic growth. Governments face the challenge of identifying efficient ways to use their scarce resources and raise the quality of education.

The provision of information and communications technology (ICT) to schools and its use for educational purposes can increase student achievement in at least two ways. First, the availability of ICT in the classroom shifts the level of educational inputs and could thus affect students' learning outcomes. Second, exposure to ICT may increase the cognitive abilities of students, allowing them to learn faster. Computer-aided instruction may be more relevant in a context in which teacher quality is poor, which is the case in most developing countries.

Previous studies have shown that programs that provide computer-aided mathematics instruction can positively influence students' test scores.[2] For example, Barrow et al. (2009) found that an instructional computer program for pre-algebra and algebra in the United States had a positive effect on test scores (about 0.17 of a standard deviation). Similarly, Banerjee et al. (2005) found that computer-assisted mathematics instruction raised mathematics scores of fourth-grade students in Vadodara, India (at least in the short run). Other studies have found little or no effect. Using credible identification strategies, Leuven et al. (2007), Goolsbee and Guryan (2006), Angrist and Lavy (2002), and Rouse and Krueger (2004) found no evidence that the use of computers and software had a positive impact on student achievement. Additional research is needed to understand the circumstances under which the provision of ICT can have a positive impact on student learning outcomes.

As the relative prices of computers and other technological devices decline, the use of ICT in the classroom is becoming increasingly popular even in developing countries. Moreover, computer-aided instruction is being used not only to facilitate learning of mathematics but also other core subjects such as language, history, and social sciences. While the empirical evidence

[2] Several studies have analyzed the effects of computer technology in the classroom. For example, some analyze the impact of subsidies to invest in computer technology (Angrist and Lavy, 2002; Goolsbee and Guryan, 2006; and Machin, McNally, and Silva, 2007). Others provide direct evidence of the effectiveness of computer technology as an input in the education production function, providing evidence of existing correlations (Wenglinsky 1998) or results from randomized evaluations (Barrow et al., 2009; Banerjee et al., 2005; Rouse and Krueger, 2004; and Ragosta et al., 1982). Barrow et al. (2009) and Banerjee et al. (2005) provide credible evidence that the effects of ICT use on test scores are positive.

in the literature suggests that computer-aided instruction in mathematics can raise student achievement, it is not clear if similar effects are found when computer-aided instruction is used to facilitate learning of other subjects. Given limited student resources (time and attention), computer-aided instruction may facilitate learning of all subjects equally. Alternatively, ICT may be more effective for teaching certain subjects, such as mathematics, and may not be as effective in other areas (for example, reading). Identifying the type of computer-aided instruction that is most effective should be a priority in designing efficient interventions, particularly in developing countries where resources are heavily constrained.

In this paper, we explore whether computer-aided instruction in both mathematics and language can help increase students' educational achievement in each of these subjects. To analyze this question, we focused on measuring the impact of one particular program in Guayaquil, Ecuador that provides computers and software to facilitate instruction in mathematics and language to primary schools. The project, called *Más Tecnología,* is financed by the Municipality of Guayaquil. It began in April 2005 and targets more than 400 elementary schools (grades three to five). Schools in the program receive basic infrastructure for computer labs and four computers per school. All computers contain software specifically designed to facilitate students' learning of language and mathematics. The software personalizes the curriculum of each student based on the results of an initial assessment, and students are expected to use the software at least three hours per week. Finally, a comprehensive plan of teacher training is implemented. The training includes general computer lessons as well as training to use the software. With the proper instruction, teachers are able to track the academic progress of each student.

To measure the impact of the *Más Tecnología* program on student achievement, we used an experimental design. At the beginning of the 2007-08 school year, we randomly assigned the treatment to eight schools (about 400 students) and randomly assigned a set of eight schools (about 400 students) to the control group. The treatment group received the intervention in April-May 2007, and the control group received the program in January 2009.

The program may have a short or a long-term impact on students' learning achievement. In this study, we focused our efforts on quantifying the effects of the *Más Tecnología* program about two years after the program was initially implemented. Our findings provide robust evidence suggesting that *Más Tecnología* had a positive impact on mathematics test scores (about 0.30 of a standard deviation) and a negative but statistically insignificant effect on language test scores. Moreover, for mathematics the impact is heterogeneous and is much larger for those students at the top of the achievement distribution, suggesting that such programs may increase the performance gap between those students at the top and those at the bottom of the achievement distribution.

The rest of the document is organized as follows. Section 2 provides details about the program and describes educational achievement trends in Ecuador. In Section 3, we describe the experimental design as well as the empirical models. Sections 4 and 5 present the data and results, respectively. Section 6 concludes.

2. Education Quality in Ecuador and the *Más Tecnología* Program

According to the International Commission on Education, Equity, and Economic Competitiveness in Latin America (1998):

> Education is in crisis in Latin America and the Caribbean. While enrollment has increased rapidly and significantly over the past three decades, the quality of education has declined in the same proportion. The teaching of language, mathematics and science is very poor in most countries. Few students develop appropriate skills in the areas of critical thinking, problem solving and decision-making. Only the small number of children attending elite private schools receive adequate education, while the vast majority of children attend failing public schools, which do not have adequate funding, and thus do not acquire the knowledge and skills necessary for economic success or active civic participation. In an era when good schools are increasingly crucial to economic development, Latin America is falling behind.

The situation in Ecuador is consistent with that of much of the region. By 2001, the country had achieved universal primary education, but academic performance has remained low and has even declined in the past decade (UNESCO, 2005). Figures 1 and 2 outline the changes in national mathematics and language scores between 1996 and 2007 for third, seventh, and tenth-graders. Overall, math scores fell by between 1 and 2 points for each grade, with decreases of 0.1 to 0.4 points between 2000 and 2007. Language scores fared slightly better for third and seventh-graders, with overall increases under one grade point and significant improvement between 2000 and 2007. However, language scores for tenth-graders fell almost 2 points between 1996 and 2007. These scores are on a scale of 20. In percentage terms, as of 2007, third graders on average knew less than 50 percent of the tested material in mathematics, while seventh and tenth-graders knew less than 30 percent. As far as the language material tested, students in all grades knew an average of 60 percent or less (Government of Ecuador, 2007).

The persistence of poor performance despite high enrollment rates signals the need for a greater focus on increased quality in Ecuador's education policies and the search for alternative teaching and learning methods. One alternative that has gained much popularity in recent years is the incorporation of ICT in the classroom. Both the 2000 Regional Framework for Action and Ecuador's 2006 Ten-Year Plan for Education emphasize the provision and use of ICTs in schools in order to improve education quality. The *Más Tecnología* program is an example of such an initiative.

In April 2005, the Department of Social and Educational Action (DASE) in the Municipality of Guayaquil began implementing the *Más Tecnología* program ("More Technology: Quality Education for Guayaquil") as an attempt to boost the quality of public education in Guayaquil.[3] In addition to boosting the quality of public education, *Más Tecnología* aims to narrow the persistent gap in educational quality between private and public institutions by providing ICT tools to the teaching and learning processes in Guayaquil's classrooms. The program was and continues to be managed by *E-dúcate,* a local non-profit organization.

The *Más Tecnología* program (as of its implementation in 2005) aimed to i) provide computer infrastructure and Internet access to at least 300 elementary schools (50 percent of all Guayaquil public schools); ii) install the *Personalized Complementary and Interconnected Learning* software (APCI) as well as other educational tools in each computer lab; iii) train at least 800 teachers and administrators in the use of computers, the Internet and, in particular, the APCI application; and iv) engage parents in the various activities and stages of the project.

The APCI application is a key component of the *Más Tecnología* program. It is a learning platform designed to improve the academic achievement of primary students in language and mathematics. The APCI program enables the customization of the curriculum to the results of an

[3] In 2000, the Municipality of Guayaquil created the Department of Social and Educational Action (DASE). This department was given the challenging task of improving the quality of the public education system and decreasing the persistent gap in education quality between private and public institutions. Despite the absence of official statistics, it is clear that there is a large gap in the quality of education between public and private schools in Ecuador.

initial assessment conducted for each student. Students can learn at their own pace through a program adapted to their specific needs and educational levels. The courses that students receive reinforce the theory behind the practice, reviewing certain concepts before, during, and after the exercises. Because the APCI platform is individualized and does not require teachers, it enables students to continue learning outside of the classroom. APCI is designed to be a guide for the teacher's management of educational activities, because through reports, he or she can determine how a student is progressing and compare the results to the class's progress. APCI also allows for the comparison of academic averages of grades, schools, counties, provinces, and regions. The mathematics and language exercises feature characters and songs created by local artists.

In each school, the program is implemented in four stages. First, the basic infrastructure is delivered: each school is outfitted with a computer lab consisting of four computers connected to the Internet. Second, the APCI and other educational software are installed in the computer lab. While APCI is the focus of the *Más Tecnología* program as a tool to improve students' academic achievement in mathematics and language, other software such as ENCARTA and CD-TODO are installed in computer labs and integrated into classroom activities as well. Third, the principal and at least two teachers from the schools receive training to i) support the management of education through the APCI, ii) manage teaching and learning in environments supported by the APCI, and iii) use the Internet as a tool for research and learning. Finally, students use the APCI platform on a regular basis. Students are expected to use the software at least three hours per week.

As of October 2005, more than 200 school principals and teachers had been trained, and computer labs had been installed in more than 100 schools. By 2008, the program surpassed its initial goals: 1,900 computers had been delivered to 450 schools and nearly 4,000 teachers and directors had been trained.

3. Conceptual Framework and Identification Strategy

Before evaluating the impact of the *Más Tecnología* program, it is important to assess from a conceptual point of view how it can affect educational outcomes. As is standard in the literature (see for example, Hanushek, 1979), we define an education production function of the form

(1) $$Y_{it} = f(B_{it}, P_{it}, S_{it}, A_{it}, I_i),$$

where, for student *i*, Y_{it} is the achievement measured at time *t* (most commonly measured by test scores), B_{it} is a vector of family characteristics, P_{it} is a vector that contains information about the student's peers and S_{it} is a vector of school inputs. I_i and A_{it} are vectors that denote individual academic abilities. Notice that some of these skills may change over time (through training and study) while others may not.

How can the use of ICT in the classroom increase student achievement? We think there are at least two ways in which *Más Tecnología* can have a positive impact on students' learning outcomes. First, the program can increase the vector of school inputs S_{it} by providing infrastructure to schools (computer labs and software), and training to teachers. Presumably, improvements in schools' assets and teacher quality can potentially improve learning outcomes. Secondly, exposure to ICT may shift the cognitive abilities of students, A_{it}, allowing them to learn faster.

To empirically measure the impact of the program, we linearize equation (1) as follows:

(2) $$Y_{.i} = \beta_0 + \beta_1 T_i + X_i \gamma + \varepsilon_i .$$

Here, the dependent variable Y_i is the standardized test score for each student *i* and T_i is a dummy variable that takes the value of 1 if the student attends a school that is part of the treatment group (a school that received the program) and 0 if the student is part of the control group (a school that did not receive the program). X_i is a vector of student, household, teacher and school characteristics and ε_i is an i.i.d. mean zero error term. The parameter of interest, β_1, measures the impact of the program on test scores.

To identify β_1 we use an experimental design where schools are randomly assigned to treatment and control groups.[4] In particular, at the beginning of the 2007-2008 school year (in April 2007), E-dúcate received resources to expand the *Más Tecnología* program in more than 100 schools over the following three years (about 35 schools per academic year). Sixteen of these schools were randomly chosen to be part of our study. Then, we randomly assign eight of these schools to a treatment group, which received the *Más Tecnología* program at the beginning

[4] Experimental evaluations, while generally more difficult to perform, are widely accepted as the most reliable form of impact evaluation. To ensure the validity of the experiment, there must be no selection bias (non-random selection of treatment/control groups) or contamination (exposure of the control group to intervention) during the established experimental time period. We discuss some of these issues later.

of the 2007-2008 school year (in April-May 2007), and eight schools to a control group, which did not receive the program until January 2009. Table 1 shows the name of each school, the group to which it was assigned (treatment or control) and the number of fifth grade students per school who participated in the experiment. When the program was implemented, about 500 students were part of the treatment group and about 500 were part of the control group. At the time of randomization, we had little information about the schools. Besides enrollment, we knew if the school had access to the public sewage network and the number of bathroom facilities. As demonstrated in Table 2, no significant differences were found between the treatment and control schools using the information available at the time the randomization was implemented.

As was discussed in the introduction, ICT programs may have a short and/or long-term impact on students' learning achievements. The focus of our study was to quantify the effects of the *Más Tecnología* program on student performance about two years after its implementation. For this reason, we compared (conditional) mean test scores in mathematics and language between treatment and control groups in December 2008, almost two years after the program was implemented. That is, we estimated equation (2) using the December 2008 survey and interpreted the estimate of β_1 as the causal effect of the program on the variables of interest: mathematics and language test scores. Given the random assignment, differences in outcomes between these groups (captured by the estimate of β_1) can be attributed to the intervention.

Resource constraints at the beginning of the project precluded the administration of a baseline survey before the intervention. Shortly after the project started, however, additional funds were secured and we were able to perform two additional surveys: one in July 2007 and another in December 2007. Information from these surveys allowed us to estimate alternative specifications where differences in outcomes between treatment and control groups are estimated controlling for initial levels and trends in student achievement. In particular, the following models can be estimated:

(3) $$Y_{.i} = \beta_0 + \beta_1 T_i + \alpha_0 N^0{}_i + X_i \gamma + \varepsilon_i ,$$

and

(4) $$Y_{.i} = \beta_0 + \beta_1 T_i + \alpha_0 N^0{}_i + \alpha_1 N^1{}_i + X_i \gamma + \varepsilon_i .$$

Here, N^0_i and N^1_i refer to test scores of student i in the first (July 2007) and second (December 2007) surveys, respectively.

Finally, we analyzed whether the impact of the program was heterogeneous. If *Más Tecnología* had a larger (and positive) effect among those students who are at the left tail of the achievement distribution, such a program could help reduce the large variance in test scores that most public schools in Ecuador experience. If the opposite is true, the program could intensify the achievement differences between those students at the top and those at the bottom of the achievement distribution. To explore these questions, we added an interaction term to equation (3) as follows:

(5) $$Y_{.i} = \beta_0 + \beta_1 T_i + \alpha_0 N^0{}_i + \alpha_1 T_i N^0{}_i + X_i \gamma + \varepsilon_i .$$

Here, a positive (negative) α_1 favors the latter (former) hypothesis.

4. Data and Variables

In July 2007, surveys were administered to students' households, to teachers, and to school administrators. Similarly, students took standardized tests in mathematics and language in July 2007, December 2007, and December 2008. The household survey provides data about the student and her home environment; these include information about her age, gender, whether the father lives in the home, whether the student works outside the home, whether the student receives help from an adult with homework, daily hours of TV watched by each student, whether the student is exposed to violence in the home, years of schooling of the head of household, number of family members under 6 years old, number of family members between 6 and 17 years old, a home infrastructure index,[5] and a household goods index.[6] In the teacher questionnaire, educators were asked about their years of teaching experience, whether they had been granted tenure by the Ministry of Education, whether they had attended training courses in

[5] The home infrastructure index is equivalent to the sum of 10 dummy variables that equal one if the home has an indicated infrastructure characteristic and 0 otherwise. The characteristics include: roof, walls, floor, rooms, cooking fuel, a bathroom, running water, electricity, plumbing, and garbage collection service. Values of 10 indicate the best living conditions and 0 represent the worst conditions.

[6] The household goods index is equivalent to the sum of eight dummy variables that equal one if the household owns a particular durable good and 0 if otherwise. The variables used include: refrigerator, stove, iron, telephone, air conditioning, sound equipment, car and computer. A value of 8 indicates that the home has all of the goods, while a value of 0 would mean that the home has none of the goods.

the last four years, and whether they knew how to use a computer. Finally, the administrators' survey was used to find out the characteristics of the school such as the number of students and whether the school participates in the PAE program,[7] and to compute a school infrastructure index.[8] Once missing observations were eliminated, the total sample is composed of a total of 738 students, 16 schools, and 31 mathematics and language teachers.

Table 3 shows means and standard deviations of all variables for the July 2007 survey. The first and second columns report statistics for control and treatment groups, respectively, while the third column computes differences between them. While there are no statistically significant differences between the characteristics of students in the treatment and control groups, households in the treatment group appear to have higher levels of schooling and have more durable goods. Similarly, schools that received the program have more experienced teachers and are less likely to participate in PAE. Hence, it appears that the treatment group may have certain advantages, like higher average incomes or teaching inputs (in the form of years of experience), which could be reflected in test scores. Because there are statistically significant differences between the treatment and control groups, equation (3) may not be ideal for measuring the impact of the program. We return to these points later.[9]

5. Results

5.1 Baseline Results

In an ideal randomized trial, one could estimate the impact of a program or intervention by simply comparing the mean differences between outcomes in the treatment and control groups. In this section, we compare conditional mean differences in test scores using the December 2008 survey. That is, we estimate equation (2) and analyze the determinants of mathematics and language test scores; results are shown in Table 4 and Table 5, respectively. For robustness, five different specifications are estimated. In the first column, the only covariate added to the model

[7] PAE (Programa de Alimentación Escolar) is a school nutrition program initiated by the Ecuadorian government in 2005 that provides lunch to students free of charge.
[8] The school infrastructure index is constructed of 10 dummy variables that equal one if the building does have the indicated infrastructure characteristic and 0 otherwise. The variables used include: running water, plumbing, electricity, bathrooms, library, medical clinic, classrooms in good condition, computer laboratory and playground. Values of or close to 10 indicate the best conditions and at or near 0 represent the worst conditions.
[9] Notice that given the small sample of schools (16) it is not unlikely that in a randomized assignment statistically significant differences between treatment and control groups are found.

is *T*, the treatment status of the student school. In columns (2) to (5), student, household, teacher, and school variables are added to the model, respectively.

Table 4 shows the determinants of mathematics test scores. The estimate of β_1 (0.38) shows that the (unconditional) mean mathematics test score in those schools that received the program is about 0.4 standard deviations higher than those schools who did not. This result is notably robust once student, household, teacher, and school characteristics are added. In all specifications, the difference is statistically significant at conventional levels using standard errors that are clustered at the school level (16 clusters).

When the number of clusters is small, cluster-robust standard errors are biased downwards. While bias corrections have been proposed in the literature (Kauermann and Carroll, 2001; Bell and McCaffrey, 2002; for example), Angrist and Lavy (2002) show that adjustment of cluster-robust standard errors can lead to significant differences. In a recent study, Cameron et al. (2008) advised computing standard cluster-robust standard errors but used a t-distribution to perform statistical tests about the statistical significance of coefficients; the degrees of freedom should be equal to the number of groups minus two. In our application, we have 16 schools, which imply critical values of 3.49, 2.36 and 1.89 for the 1 percent, 5 percent and 10 percent significance level, respectively. In the tables, we report significance levels using a conventional normal distribution. Notice, however, that our results remain significant at the 10 percent level when the test suggested by Cameron et al. (2008) is used.

Table 5 focuses on language test scores. Results displayed in this table suggest that the program had no impact on language test scores. While on average language test scores from the treatment group are about 0.2 standard deviations higher than those from the control group, these differences are not statistically significant.

Other coefficients in Tables 4 and 5 provide interesting insights about the determinants of student achievement in Guayaquil's public schools and deserve some discussion. For instance, we find evidence of a clear gender achievement gap: female students on average have higher mathematics and language test scores than males. Language test scores decrease with age. For instance, the language test score of a 17 year-old sixth grader is about one standard deviation lower than the median 12 year-old sixth grader in our sample. We also find a negative correlation between test scores and receiving homework help at home. Interestingly, we find that students of teachers who have been granted tenure by the Ministry of Education have higher test scores.

5.2 Alternative "Robust" Specifications

The evidence above suggests that *Más Teconología* had a positive impact on mathematics test scores but no effect on language test scores. It is possible, however, that differences in test scores in December 2008 could reflect differences that existed before the program was implemented, say in April 2007. This is a valid concern given the small number of schools assigned to treatment and control groups. Moreover, notice from Table 3 and our discussion at the end of the data section that the July 2007 survey shows some statistically significant differences between treatment and control groups. In particular, it seems that households and schools that received the program had higher levels of educational inputs. Thus, higher test scores in the schools that received the program could be attributed to better educational inputs rather than to the intervention. To measure the conditional mean differences between treatment and control at the "baseline," we estimate equation (2) using the July 2007 (Test #1) survey. In particular, we estimate separate linear regression models that explain the determinants of mathematics and language test scores using the same five specifications shown in Tables 4 and 5. We report the coefficient on the treatment variable in the first and fourth column of Table 6. These results suggest that in July 2007 there were no statistically significant differences in mathematics test scores but large and important ones, about 0.4 standard deviations, in language. Most likely, this gap can be explained by the differences in the student environment between treatment and control groups. Alternatively, one cannot rule out that the program may have had a very large short-term effect on language test scores, but no short-term impact on mathematics. Given our previous discussion, we think this is unlikely explanation. Equation (2) is also estimated using data from the intermediate survey taken in December 2007 (Test #2) and results are shown on the second and fifth column of Table 6. Findings show a slight increase in average mathematics test scores in the schools that received the program by December 2007.

Given our concerns about potential differences in educational inputs between treatment and control groups, ideally we would like to use a baseline survey performed before the intervention to control for students' initial test score levels. Unfortunately, for the reasons discussed in the previous sections, such data are unavailable. Instead, we use the July 2007 survey as a proxy for a baseline survey even though the program was already implemented. We think this is not a bad strategy considering that it took between three to six months after the software was installed before students regularly used the APCI platform.

We then estimate equation (3) and show results in Tables 7 and 9. Table 7 and Table 9 display results from an OLS regression where the dependent variable is the December 2008 standardized mathematics and language test score (Test #3), respectively. Besides the treatment indicator and the July 2007 test score, covariates include the same set of variables used to estimate equation (2) and vary for each of the five specifications shown on these tables. Parameter estimates suggest that, controlling for test score levels in July 2007, the program had a large and statistically significant effect on mathematics test scores (about 0.3 standard deviations) but no statistically significant effect on language. It is striking, however, that the differences in language test scores between those students in the program and those in the control group decrease over time (see Table 6). This is evidenced by the negative coefficient (though not statistically significant) on the treatment variable in Table 9.

Did *Más Tecnología* divert students from reading and other activities that reinforce language towards other activities that make them more successful at mathematics? These are important questions that require further research.

Finally, we compute an alternative specification where differences in outcomes between treatment and control groups are estimated controlling for trends in students' achievement. In particular, we estimate equation (4) controlling for students' test scores taken in the first (July 2007) and second (December 2007) surveys. Results for mathematics and language test scores are shown on Tables 8 and 10. As shown in these tables, once we control for trends in the test scores, our main results remain unchanged: the *Más Tecnología* program seems to have had a large and statistically significant impact on mathematics and a negative but statistically insignificant effect on language test scores.

Notice that the sample size used to estimate equations (3) and (4) is much smaller than the sample used to estimate equation (2). The "loss" of observations between the first and third tests is explained by dropout and absenteeism rates. To verify that attrition rates are not introducing biases into our results, we checked to see if students without grades for the second and third tests are equally distributed between the treatment and control groups.

The results of our attrition analysis appear in Tables 11 and 12. In Table 11 (12), the dependent variable equals one if the student took the mathematics (language) test in the first survey but not on the third. Explanatory variables include the same set of covariates used in the previous models as well as the treatment indicator. Across all specifications, we did not find any evidence that attrition was correlated with treatment.

5.3 Heterogeneous Effects

In this section we investigate if the impact of the program depends upon students' initial performance (in July 2007). To achieve this purpose, we estimate equation (5) and show the results in Tables 13 and 14. The results shown in Table 13 suggest that the positive effect of *Más Tecnología* on mathematics test scores is significantly larger for those students who performed better on the initial test. For instance, the program raises mathematics scores of students who achieved a score 1.5 standard deviations above the mean in the first test by about 0.6 standard deviations (0.3 + 0.21*1.5). Meanwhile, the impact for students who performed poorly on the initial test, say 1.5 standard deviations below the mean, is non-existent (0.3 – 0.21*1.5). These results suggest that the program increases the performance gap between those students at the top and those at the bottom of the achievement distribution. Table 14 displays the same set of results for language test scores. While the positive coefficient on the interaction term suggests that the program may have a positive impact for those students with higher than average performance on language tests, these estimates are not statistically significant.

6. Conclusion

This paper provides robust evidence that a program that introduced computer-aided instruction in mathematics and language in Guayaquil public primary schools succeeded in raising children's mathematics test scores but failed to increase language test scores. The effects are large: students who receive the program increased on average about 0.30 standard deviations on their mathematics test scores but lowered their scores in standardized language tests (although the latter finding is not statistically different than zero).

Our results suggest that the provision of ICT can increase educational achievement. Why did the program succeeded in raising children's mathematics achievement? We think that the delicate combination of hardware (provision of computers and a computer lab), software (APCI Platform) and teacher training made this program a success story. Provision of hardware without software or without teacher training may not yield the same positive results. Thus, one must be careful to consider these points when generalizing our findings.

The lack of positive effects of the program on language test scores is both puzzling and interesting. On the one hand, one may argue that the software used to teach language to the children was ineffective. On the other hand, it is also possible that the use of ICT for mathematics diverted students from reading and other activities that reinforce language towards other activities that make them more successful at mathematics. Understanding how the use of ICT in the classroom crowds out the attention of the children from one subject to another is a topic that deserves further research.

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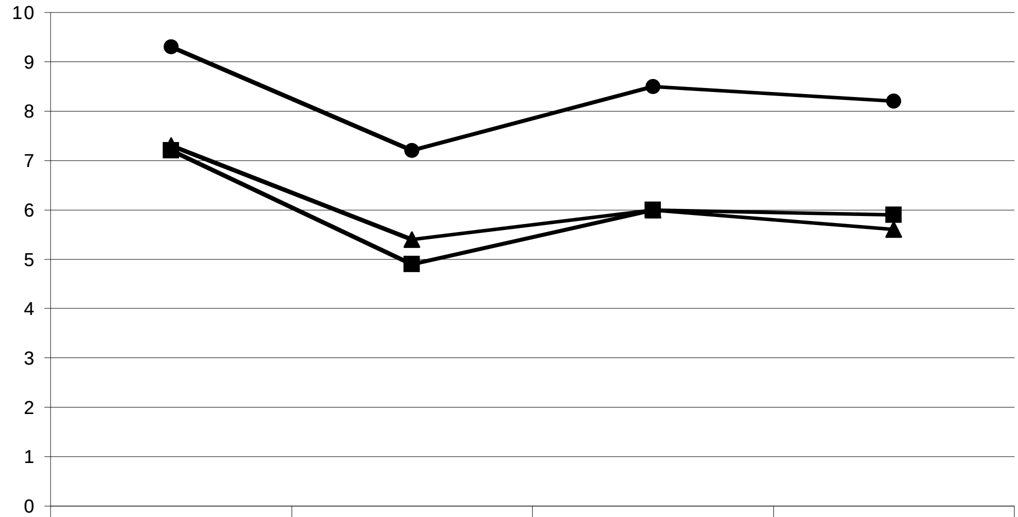
Figure 1. National Mathematics Test Scores in Ecuador (Public Schools), 1996-2007

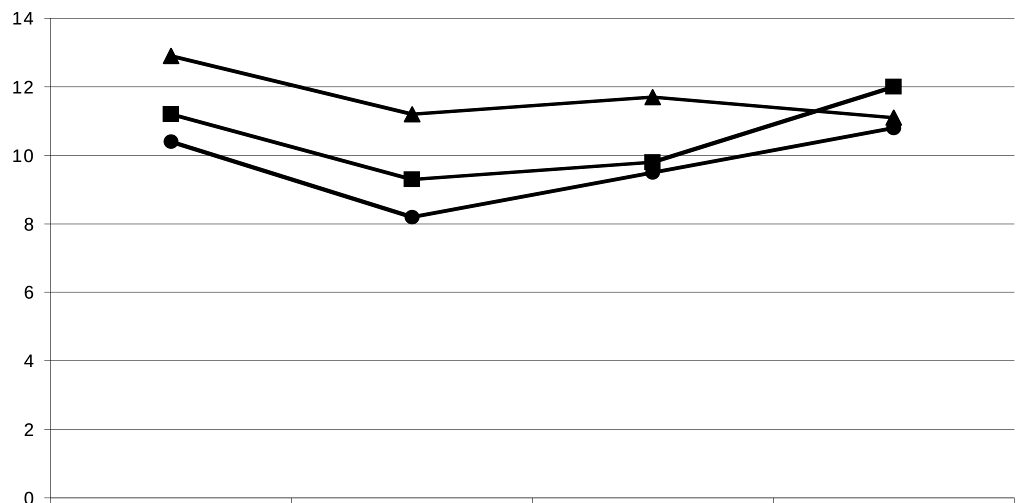


	1996	1997	2000	2007
3rd Grade	9.3	7.2	8.5	8.2
7th Grade	7.2	4.9	6	5.9
10th Grade	7.3	5.4	6	5.6

Year

Source: Authors' compilation based on national records.

Figure 2. National Language Test Scores in Ecuador (Public Schools), 1996-2007



	1996	1997	2000	2007
3rd Grade	10.4	8.2	9.5	10.8
7th Grade	11.2	9.3	9.8	12
10th Grade	12.9	11.2	11.7	11.1

Year

Source: Authors' compilation based on national records.

Table 1. Schools Assigned to Treatment and Control Groups

	School name	Group	# 5th Grade Students (Registered)
1	Ecuador Antártico	C	109
2	Luis Poveda Orellana	C	41
3	Dr. Teodoro Alvarado Olea	C	34
4	Clara Bruno de Piana	C	124
5	Luz del Guayas	C	32
6	Aída León de Rodríguez Lara	C	86
7	Homero Espinoza	C	28
8	José Rodolfo Ugarte Rivera	C	76
9	Francisco Morán Márquez	T	63
10	Alfredo Barandearán	T	54
11	María Piedad Castillo de Levi	T	47
12	Magdalena Cabezas	T	67
13	Néstor Pérez	T	70
14	Atahualpa	T	48
15	Dr. Néstor Cervantes	T	102
16	Luis Enrique Mosquera	T	80
	TOTAL		**1,061**

Source: Authors' compilation.

Table 2. Differences Between Treatment and Control Groups (Primary Schools) before Program Was Implemented

Variable	Control	Treatment	Difference
Mean number of students enrolled	537.143	442.375	94.768
			(105.953)
Share of schools with public sewage system	0.5	0.5	0
			(0.260)
Share of schools with bathroom facilities	0.5	0.375	0.125
			(0.27)
Number of observations	8	8	

Source: Authors' calculations.

Table 3. Descriptive Statistics

Characteristics of the Student	**Control**	**Treatment**	**Difference**
Gender (1 = male)	0.472	0.523	-0.051
			(0.037)
Age	10.297	10.183	0.114
			(0.076)
Father lives in the home (1=yes)	0.663	0.687	-0.024
			(0.035)
Student works outside the home (1=yes)	0.243	0.286	-0.044
			(0.032)
Student receives help with homework (1=yes)	0.666	0.711	-0.045
			(0.034)
Hours of TV watched daily	1.815	1.824	-0.009
			(0.076)
Child lives in violent home environment (1=yes)	0.040	0.046	-0.006
			(0.015)
Number of observations			738
Characteristics of the household	**Control**	**Treatment**	**Difference**
Schooling level of the head of household	8.711	9.814	-1.103
			(0.293)***
Number of members under 6 years old	0.106	0.085	0.022
			(0.023)
Number of members between 6-17 years old	2.583	2.380	0.202
			(0.081)**
Home infrastrucutre index (maximum 10)	5.574	5.515	0.059
			(0.119)
Household goods index (maximum 8)	4.207	4.476	-0.269
			(0.082)***
Number of observations			712

Table 3., continued

Characteristics of the school	Control	Treatment	Difference
Number of students	537.143	442.375	94.768
			(105.953)
Schools participates in PAE program (1=yes)	1.000	0.625	0.375
			(0.196)*
School infrastructure index (maximum 10)	4.286	4.375	-0.089
			(0.852)
Number of observations			16
Characteristics of the teacher	**Control**	**Treatment**	**Difference**
Years of service	21.266	26.625	-5.359
			(2.714)*
Granted tenure by Ministry of Education (1=yes)	0.867	1.000	-0.133
			(0.087)
Has had training courses in last 4 years (1=yes)	8.000	13.375	-5.375
			(3.381)
Knows how to use a computer (1 = yes)	0.733	0.875	-0.142
			(0.144)
Number of observations			31

Source: Authors' calculations.

Table 4. Conditional Mean Differences in Mathematics Test Score, Test #3

Variable	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	0.38 *	0.38 **	0.38 **	0.41 **	0.37 *
	(0.19)	(0.19)	(0.19)	(0.18)	(0.19)
Equals one if student is male		-0.15 *	-0.15 *	-0.15 *	-0.17 **
		(0.08)	(0.08)	(0.08)	(0.08)
Student Age		-0.08	-0.08	-0.08	-0.07
		(0.06)	(0.06)	(0.06)	(0.06)
Equals one if father lives in the home		-0.11	-0.09	-0.10	-0.11
		(0.08)	(0.07)	(0.07)	(0.08)
Equals one if student works		0.02	0.02	0.02	0.03
		(0.09)	(0.09)	(0.08)	(0.08)
Equals one if student receives homework help at home		-0.14 **	-0.13 *	-0.15 **	-0.14 ***
		(0.07)	(0.07)	(0.07)	(0.07)
Equals one if student lives in a violent home environment		-0.03	-0.05	-0.04	-0.02
		(0.17)	(0.16)	(0.16)	(0.18)
Hours of TV watched daily		0.00	-0.01	0.00	0.00
		(0.04)	(0.04)	(0.04)	(0.04)
Schooling level of the head of the household			0.01	0.01	0.01
			(0.01)	(0.01)	(0.01)
Number of family members under the age of 5			0.21	0.20	0.18
			(0.15)	(0.14)	(0.13)
Number of family members between 6 and 17 years old			0.01	0.01	0.01
			(0.05)	(0.05)	(0.04)
Home infrastructure index (out of 10)			0.03	0.03	0.01
			(0.03)	(0.03)	(0.03)
Household goods index (out of 8)			-0.02	-0.01	-0.02
			(0.05)	(0.05)	(0.05)
Years of teaching experience				-0.01	0.00
				(0.01)	(0.01)
Equals one if granted tenure by the Ministry of Education				0.23	0.20
				(0.19)	(0.26)
Equals one if teacher knows how to use a computer				-0.14	-0.24
				(0.17)	(0.19)
Equals one if school participates in PAE food program					-0.22
					(0.32)
School infrastructure index (scale of 10)					0.12
					(0.06)
Constant term	-0.15 **	0.95	0.65	0.70	0.33
	(0.06)	(0.65)	(0.63)	(0.73)	(0.95)
R square	0.04	0.06	0.06	0.07	0.09
Number of valid observations	644	644	644	644	644

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. The dependent variable is the standardized mathematics test score. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 5. Conditional Mean Differences in Language Test Score, Test #3

Variable	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	0.19	0.20	0.18	0.16	0.16
	(0.22)	(0.22)	(0.21)	(0.20)	(0.21)
Equals one if student is male		-0.29 ***	-0.30 ***	-0.30 ***	-0.33 ***
		(0.07)	(0.07)	(0.07)	(0.07)
Student age		-0.18 ***	-0.16 ***	-0.16 ***	-0.15 **
		(0.06)	(0.06)	(0.06)	(0.06)
Equals one if father lives in the home		-0.05	-0.05	-0.06	-0.07
		(0.07)	(0.07)	(0.07)	(0.07)
Equals one if student works		-0.11	-0.11	-0.11	-0.09
		(0.07)	(0.08)	(0.08)	(0.09)
Equals one if student receives homework help at home		-0.24 ***	-0.25 **	-0.25 ***	-0.24 ***
		(0.09)	(0.10)	(0.09)	(0.09)
Equals one if student lives in a violent home environment		-0.24	-0.26	-0.23	-0.21
		(0.22)	(0.22)	(0.23)	(0.24)
Hours of TV watched daily			0.00	0.02	0.02
			(0.04)	(0.04)	(0.04)
Schooling level of the head of the household			0.02	0.02	0.02
			(0.01)	(0.01)	(0.01)
Number of family members under the age of 5			0.09	0.09	0.06
			(0.15)	(0.15)	(0.14)
Number of family members between 6 and 17 years old			-0.04	-0.04	-0.04
			(0.03)	(0.03)	(0.03)
Home infrastructure index (out of 10)			0.03	0.03	0.02
			(0.04)	(0.04)	(0.03)
Household goods index (out of 8)			0.01	0.02	0.01
			(0.04)	(0.05)	(0.05)
Years of teaching experience				0.00	0.01
				(0.01)	(0.01)
Equals one if granted tenure by the Ministry of Education				0.49 **	0.50 **
				(0.21)	(0.23)
Equals one if teacher knows how to use a computer				-0.16	-0.24
				(0.20)	(0.21)
Equals one if school participates in PAE food program					-0.07
					(0.31)
School infrastructure index (scale of 10)					0.11
					(0.08)
Constant	-0.06	2.10 ***	1.68 ***	1.39 **	0.79
	(0.12)	(0.61)	(0.59)	(0.66)	(0.88)
R square	0.01	0.08	0.09	0.10	0.12
Number of observations	644	644	644	644	644

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. The dependent variable is the standardized language test score. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 6. Conditional Mean Difference in Test Scores between Treatment and Control Groups

	Dependent Variable					
	Standardized Mathematics Test Score			Standardized Language Test Score		
Covariates	**Test #1**	**Test #2**	**Test #3**	**Test #1**	**Test #2**	**Test #3**
(1) Constant	0.20	0.35	0.38 *	0.47 **	0.44 *	0.19
	(0.29)	(0.24)	(0.19)	(0.22)	(0.24)	(0.22)
(2) Constant and student characteristics	0.20	0.35	0.38 **	0.49 **	0.44 *	0.20
	(0.29)	(0.23)	(0.19)	(0.22)	(0.24)	(0.22)
(3) Constant, student and household characteristics	0.17	0.32	0.38 **	0.45 **	0.41 **	0.18
	(0.27)	(0.20)	(0.19)	(0.21)	(0.20)	(0.21)
(4) Constant, student, household and teacher characteristics	0.17	0.32	0.41 **	0.46 **	0.40 **	0.16
	(0.22)	(0.20)	(0.18)	(0.19)	(0.16)	(0.20)
(5) Constant, student, household, teacher and school characteristics	0.04	0.25	0.37 *	0.38 **	0.35 **	0.16
	(0.20)	(0.22)	(0.19)	(0.15)	(0.17)	(0.21)
Observations	718	724	644	720	720	644

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. For each of the dependent variables, we estimate linear regression models using the same five specifications shown in Table 4 and report the coefficient on the treatment variable only. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 7. Determinants of Standardized Mathematics Test Score, Test #3, Controlling for Levels of Past Tests

Description	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	0.24 *	0.25 *	0.26 **	0.30 **	0.32 **
	(0.13)	(0.13)	(0.13)	(0.14)	(0.16)
Standardized Mathematics Test Score, Test #1	0.46 ***	0.46 ***	0.46 ***	0.46 ***	0.46 ***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Student covariates	No	Yes	Yes	Yes	Yes
Household covariates	No	No	Yes	Yes	Yes
Teacher covariates	No	No	No	Yes	Yes
School covariates	No	No	No	No	Yes
R square	0.25	0.26	0.26	0.26	0.26
Observations	546	546	546	546	546

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. The dependent variable is the standardized mathematics test score. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 8. Determinants of Standardized Mathematics Test Score, Test #3, Controlling for Levels and Trends of Past Tests

Description	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	0.22	0.22	0.23 *	0.27 *	0.30 *
	(0.14)	(0.14)	(0.14)	(0.15)	(0.17)
Standardized Mathematics Test Score, Test #1	0.34 ***	0.34 ***	0.34 ***	0.34 ***	0.33 ***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)
Standardized Mathematics Test Score, Test #2	0.22 ***	0.21 ***	0.22 ***	0.22 ***	0.23 ***
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Student covariates	No	Yes	Yes	Yes	Yes
Household covariates	No	No	Yes	Yes	Yes
Teacher covariates	No	No	No	Yes	Yes
School covariates	No	No	No	No	Yes
R square	0.28	0.28	0.29	0.29	0.29
Number of valid observations	546	546	546	546	546

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. The dependent variable is the standardized mathematics test score. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 9. Determinants of Standardized Language Test Score, Test #3, Controlling for Levels of Past Tests

Description	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	-0.16	-0.14	-0.15	-0.17	-0.15
	(0.17)	(0.17)	(0.17)	(0.16)	(0.18)
Standardized Language Test Score, Test #1	0.58 ***	0.56 ***	0.56 ***	0.55 ***	0.56 ***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Student covariates	No	Yes	Yes	Yes	Yes
Household covariates	No	No	Yes	Yes	Yes
Teacher covariates	No	No	No	Yes	Yes
School covariates	No	No	No	No	Yes
R square	0.35	0.37	0.37	0.38	0.40
Number of observations	546	546	546	546	546

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. The dependent variable is the standardized language test score. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 10. Determinants of Standardized Language Test Score, Test #3, Controlling for Levels and Trends of Past Tests

Description	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	-0.19	-0.17	-0.18	-0.20	-0.17
	(0.13)	(0.14)	(0.14)	(0.14)	(0.16)
Standardized Language Test Score, Test #1	0.42 ***	0.41 ***	0.41 ***	0.41 ***	0.43 ***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Standardized Language Test Score, Test #2	0.31 ***	0.29 ***	0.28 ***	0.28 ***	0.26 ***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Student covariates	No	Yes	Yes	Yes	Yes
Household covariates	No	No	Yes	Yes	Yes
Teacher covariates	No	No	No	Yes	Yes
School covariates	No	No	No	No	Yes
R square	0.41	0.42	0.42	0.42	0.44
Number of observations	546	546	546	546	546

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. The dependent variable is the standardized language test score. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 11. Attrition in Mathematics Test Scores

Description	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	-0.03	-0.03	-0.04	-0.01	0.00
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
Student covariates	No	Yes	Yes	Yes	Yes
Household covariates	No	No	Yes	Yes	Yes
Teacher covariates	No	No	No	Yes	Yes
School covariates	No	No	No	No	Yes
R square	0.00	0.03	0.04	0.04	0.07
Number of observations	718	718	718	718	718

Note: Table shows results form a linear probability model. Dependent variable equals one if a student is part of the first survey but not part of the third survey. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 12. Attrition in Language Test Scores

Description	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	-0.03	-0.04	-0.04	-0.02	-0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
Student covariates	No	Yes	Yes	Yes	Yes
Household covariates	No	No	Yes	Yes	Yes
Teacher covariates	No	No	No	Yes	Yes
School covariates	No	No	No	No	Yes
R square	0.00	0.03	0.03	0.04	0.07
Number of observations	720	720	720	720	720

Note: Table shows results form a linear probability model. Dependent variable equals one if a student is part of the first survey but not part of the third survey. Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 13. Heterogeneous Effects of the Program on Mathematics Test Scores

Description	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	0.21 *	0.22 *	0.23 *	0.27 **	0.30 **
	(0.12)	(0.12)	(0.12)	(0.13)	(0.15)
Standardized Mathematics Test Score, Test #1	0.36 ***	0.36 ***	0.36 ***	0.35 ***	0.35 ***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
Interaction term (treatment and Test #1)	0.19 ***	0.19 ***	0.19 ***	0.20 ***	0.21 ***
	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
Student covariates	No	Yes	Yes	Yes	Yes
Household covariates	No	No	Yes	Yes	Yes
Teacher covariates	No	No	No	Yes	Yes
School covariates	No	No	No	No	Yes
R square	0.26	0.26	0.27	0.27	0.27
Number of observations	546	546	546	546	546

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. The dependent variable is the standardized mathematics test score (Test #3). Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.

Table 14. Heterogeneous Effects of the Program on Language Test Scores

Description	(1)	(2)	(3)	(4)	(5)
Equals one if school received treatment	-0.17	-0.16	-0.16	-0.18	-0.15
	(0.16)	(0.16)	(0.16)	(0.15)	(0.18)
Standardized LanguageTest Score, Test #1	0.54 ***	0.50 ***	0.51 ***	0.50 ***	0.53 ***
	(0.05)	(0.06)	(0.06)	(0.07)	(0.08)
Interaction term (treatment and Test #1)	0.10	0.12	0.10	0.12	0.07
	(0.08)	(0.09)	(0.10)	(0.10)	(0.10)
Student covariates	No	Yes	Yes	Yes	Yes
Household covariates	No	No	Yes	Yes	Yes
Teacher covariates	No	No	No	Yes	Yes
School covariates	No	No	No	No	Yes
R square	0.35	0.37	0.38	0.38	0.40
Number of observations	546	546	546	546	546

Note: Table shows OLS estimates for the conditional mean difference between schools who received the program and those in the control group. The dependent variable is the standardized language test score (Test #3). Standard errors clustered at the school level (16 clusters) and robust to heteroskedasticity are shown in parenthesis. *, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.
Source: Authors' calculations.