EDUCATION QUALITY AND TEACHING PRACTICES

By

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Abstract

Improving school quality with limited resources is a key issue of policy. It has been suggested that instructing teachers to follow specific practices together with tight monitoring of their activities may help improve outcomes in under-performing schools that usually serve poor populations. This paper uses a RCT to estimate the effectiveness of guided instruction methods as implemented in under-performing schools in Chile. The intervention improved performance substantially and by equal amounts for boys and girls. However, the effect is mainly accounted for by children from relatively higher income backgrounds and not for the most deprived. Based on the CLASS instrument we document that quality of teacher-student interactions is positively correlated with the performance of low income students; however, the intervention did not affect these interactions. Guided instruction can improve outcomes, but it is a challenge to reach the most deprived children.

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1 Introduction

Improving the quality of education for children from lower socioeconomic backgrounds is key to offering equal opportunity and arresting the intergenerational transmission of poverty. However, achieving this can be challenging in practice. For example observational studies as well as studies with randomized assignment of students to teachers have concluded that teachers can have a large impact on performance (Rivkin, Hanushek, and Kain (2005) and Chetty, Friedman, and Rockoff (2014) and for Ecuador Araujo, Carneiro, Cruz-Aguayo, and Schady (2016)). However this literature has been unable to identify what makes a good teacher; and even if it did, turning around the quality of teachers to a sufficient extent will likely prove far too difficult and slow. So the natural question is whether we can improve outcomes by identifying and implementing innovative teaching practices and relying on the existing human resources; solving this problem can have major policy implications for most countries in the world.

An experiment in Chile provides a unique opportunity to address this question. The educational psychology literature focusses on the method of instruction as an approach to improve school performance. The basic principle is that it is possible to compensate for low teacher skills by providing them with specific prepackaged classroom material and directions for teaching to any group of students in standardized ways. These methods can be controversial and there is an active debate on the extent to which prescriptive methods can be successful. While advocates of *minimal instructional guidance* argue that students learn best when they discover concepts by themselves, those who believe in *guided instruction* argue that the cognitive architecture of the human brain is such that students' learning is maximized when teachers directly explain the concepts that students are required to know (Kirschner, Sweller, and Clark, 2006).

Guided instruction methods, in turn, come in many forms. They are distinguished by the degree of discretion that teachers have to adapt instruction according to the characteristics of the particular group of students they are facing (Ganimian and Murnane, 2014). These methods are usually complemented by training teachers to support them in the use of these instruction materials. This method is known in the literature as *scripted instruction* and became very popular ever since the launch of high scale educational programs like Success for All and DISTAR in the United States (Slavin, Lake, Chambers, Cheung, and Davis, 2009).

In this paper we contribute to the understanding of the effectiveness of direct instruction approaches in schools that serve deprived populations, by analyzing the impact of a large-scale guided instruction program in Chile aimed at low performing schools. We focus on the performance of students in the national standardized Math, Language, and Science tests and our results are based on a school-level randomized trial.

The program in question, known as *Plan Apoyo Compartido* (henceforth, PAC), was implemented by the Chilean Ministry of Education in 2011. The main intervention of the program was to support teachers through a modified method of instruction by adopting a more prescriptive model. Teachers in treated schools received detailed classroom guides and scripted material to follow in their lectures. The program was intended to be implemented gradually, so only a group of eligible schools was invited to participate in the first year. Our measure of students' learning is their performance in the Chilean standardized Education Quality Measurement

System evaluations (henceforth SIMCE evaluations, for its name in Spanish). We concentrate the analysis on students who were in their fourth grade of elementary school in years 2011 and 2012 and attended eligible schools.

Our results suggest that the program had positive and significant effects, particularly for kids from the most advantaged backgrounds within treated schools (students in schools with higher socioeconomic status or from higher income families within our lower income population). Overall, the program improves Reading test scores by about 10% of a test score standard deviation the first year of implementation. Program effects increase significantly in the second year: test scores improve in all subjects in between 9% and 13% of a test score standard deviation. All these effects are statistically significant. Moreover, kids in schools with high socioeconomic status participating in the program improved SIMCE scores by 20% of a test score standard deviation with respect to comparable kids in control schools. Finally, students from high-income families see the greatest benefits from the program, their test scores improving by between 10% and 20% of a test score standard deviation. All these results are strongly robust to adjustments in our inference strategy to control for multiple testing.[1]

To better understand the impact of PAC on students' test scores we analyze the effects of the program on the quality of teacher-students interactions based on the CLASS (Classroom Assessment Scoring System; see Pianta, Mashburn, Downer, Hamre, and Justice (2008).[2] A random subsample of treatment and control schools from the PAC program where invited to participate in the CLASS experiment. The experiment involved filming several hours of classroom teaching and coding them to score teachers' interactions with their students based on very specific teachers' behaviors that coders look for. We first show that CLASS scores correlate positively and significantly with students' performance, and particularly for those from lower income background. Then, we show that PAC did not cause significant improvements in CLASS scores, which may explain why low income students were more modestly impacted by the PAC.

Our study offers an important contribution to the literature on understanding and improving education quality. We are specifically testing a program that is easily scalable and which does not make inordinate demands on human resources, but which, according to a well established literature, can offer real improvements in pupil performance. From a methodological point of view the experimental design on a particularly large number of schools offers the power needed to detect even relatively small effect sizes. Second, we provide the first assessment of the interaction between a large scale instruction intervention and the CLASS in producing learning outcomes. The use of CLASS as a tool for understanding the mechanisms through which the intervention works, by implementing it on both treatment and control groups is new in the literature.[3]

The paper is organized as follows. The next section describes the program intervention, the experimental design and the data used in this paper. Section 3 describes the identification and inference strategies. Section

[1] A recent paper by Araujo, Carneiro, Cruz-Aguayo, and Schady (2016) focuses on the relationship between the quality of teacher-students interactions and test scores in Ecuador. Their study finds that one standard deviation increase in the quality teacher-students interaction results in approximately 10% of a standard deviation of higher students' tests scores.

[2] also used in Araujo, Carneiro, Cruz-Aguayo, and Schady (2016) also used the CLASS in their experiment

[3] He, Linden, and MacLeod (2009) also evaluates a scripted Reading preschool program in Mumbai, India and Albornoz, Anauati, Furman, Luzuriaga, Podestá, and Taylor (2017) evaluates the effects of teacher training interventions in Buenos Aires, Argentina. Unlike theirs, our paper focuses on fourth grade primary school students.

4 presents the main results of the paper. Section 5 studies the importance of teacher-students' interactions to improve performance and the impact of PAC on these interactions. Finally, section 6 concludes.

2 Experimental design, data, and randomization check

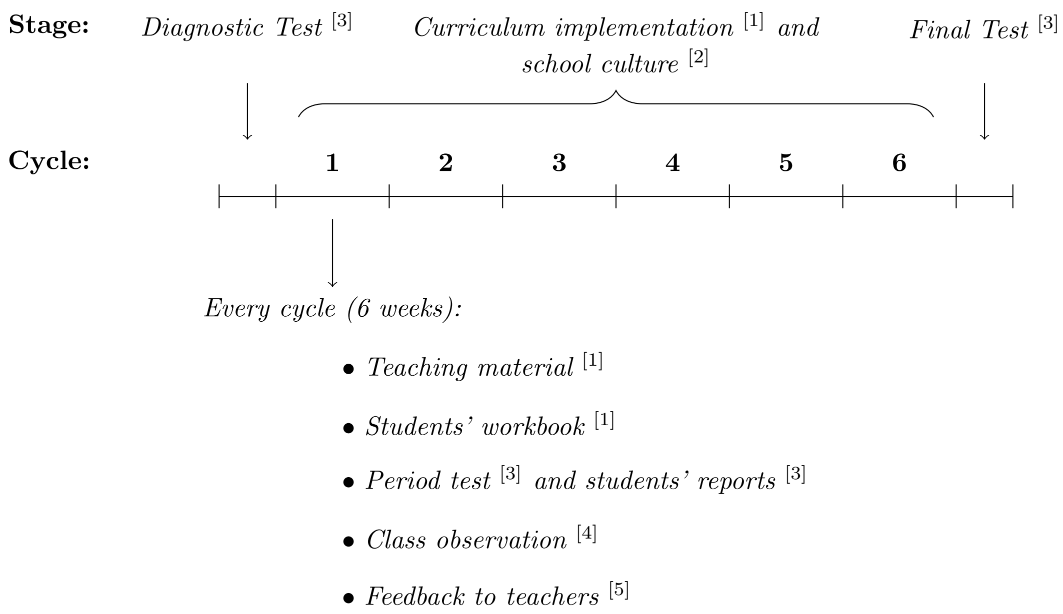
2.1 Plan Apoyo Compartido (PAC)

PAC was implemented by the Chilean Ministry of Education in 2011 as a targeted educational policy providing technical and pedagogical support to schools historically performing below average in the national standardized test, SIMCE. It aimed at improving student' learning outcomes in Math and Language from pre-K to fourth grade (and, additionally, in Natural and Social Sciences for students in third and fourth grades), changing practices inside the classroom and the school. The PAC targeted low performing public and subsidized private schools nationwide.[4] We describe the design and implementation of the PAC next.

PAC design The design of PAC included five components and was implemented in six-week cycles (see Figure 1). The first component, called "effective implementation of the national curriculum"(indicated [1] in the figure), consisted in the development of unified pedagogical material and planning tools distributed to teachers. These tools included an annual curricular programming, a series of teaching materials designed for each six-week cycle, and a set of daily planning activities to be used by teachers in the classroom. The second component (indicated [2] in the figure) consisted of promoting a school culture and environment that encourages learning. A manual was developed and delivered to schools to guide the implementation of the ideas. The third component (indicated [3] in the figure) was the use of student evaluations as a tool for guiding teaching. This component included the development of four types of tests to monitor progress in students learning: a diagnostic test to determine the initial level of academic skills and knowledge administered at the beginning of the school year, intermediate and final tests to determine students' progress, and students' performance reports. Each of these testing instruments was applied in different moments of the semester to help analyze students' performance in Math and Language (MINEDUC, 2013). It is worth noting that unlike the SIMCE tests, these instruments were not standardized tests and could be applied voluntarily by PAC schools. The fourth component (indicated [4] in the figure) was defined as the "optimization of the use of school time for learning in the classroom", and consisted in promoting class planning and frequent class observation in schools to provide feedback to teachers. Finally, the last component known as "promotion of teachers' professional development" (indicated [5] in the figure) aimed at promoting frequent internal school staff meetings to discuss students' progress.

[4]The Chilean system of education includes three types of schools: public schools, subsidized private schools, and private schools. Public schools are both financed and administered by the public sector; subsidized private schools are administered by private agencies but receive funding from the State in the form of vouchers per attending student; finally, the third group includes schools that are administered privately and tuition is paid by the students' families.

Figure 1: Design of *Plan Apoyo Compartido*†



† *Source: Chilean Ministry of Education*

A central feature of the Program's design to assist the implementation and monitoring of the PAC activities was the creation of two support teams - one internal and one external to schools - expected to work closely together. The first team, the Education Leadership Team (henceforth ELE, from its name in Spanish), consisted of the school principal, the head of the technical and pedagogic office of the school, and two distinguished teachers. The second group, the Team of Technical and Pedagogic Advisors (henceforth ATP), comprised three representatives of the regional Department of Education (the DEPROV), aimed at providing external support to the ELE teams. Each ATP visited its assigned schools every 6 to 7 weeks to advise the ELE on the use of the teaching material, on the development of a diagnosis of the school's strengths and weaknesses, and on the analysis of the students' tests scores to study progress (MINEDUC, 2013).

Monitoring and assessment of PAC implementation at the school level The Ministry of Education collected information on the ATPs visits to schools and its findings. Still, as part of the effort to assess the impact of the Program (which included this paper's analysis), the Chilean Ministry of Education designed two instruments, mainly focused on gathering evidence on the extent to which teachers and schools used the pedagogic material provided by the Program, implemented PAC components, and received the support of ELEs and ATPs.

The first instrument was a protocol specifically developed to observe and code class videotapes on key aspects of the program.[5] Independent raters were asked to observe the videos and indicate whether the program intervention activity is observed in the classroom or not, establish if teachers in the classroom implemented

[5]The protocol followed to code videos resembles the CLASS protocol described in section 5.

the scripted instruction method, and determine if teachers organized their classroom according to the program guidelines. The key aspects that were observed in both PAC and control schools were class structure, encouragement of critical thinking, norms and schedule, and evaluation of students' performance. In Appendix A we present the correlation between participating in PAC and the average score in these relevant dimensions of the program implementation. The data indicates that PAC schools are observed to perform better in the PAC objectives within the classroom. The difference between treated and control schools is only significant when it comes to the enforcement of norms and schedule. PAC classrooms are 5.8 percentage points more likely to follow the norms and schedule relative to non- PAC schools. Within this dimension, a particularly interesting aspect concerns the use of prepacked material by the teachers. Coders were asked to indicate if they observe teachers in the classroom using special workbooks as a pedagogic resource (the scripted class manuals, or "PAC book" in the case of the treated schools). PAC schools are 23 percentage points more likely to use the scripted workbooks in class relative to non-PAC schools. The difference is significant at the 1% level.

The second instrument to assess the degree of implementation of the PAC at the school level was to interview the head of the technical and pedagogic office of the school (henceforth JUTP, from its name in Spanish) and a set of teachers within the schools that participated in the monitoring evaluation. These surveys gathered information about the key ingredients of the program. For example, authorities were asked if their school utilizes annual planning in class, whether students are periodically evaluated, whether the teachers understand and explain norms of behavior to students, and the frequency with which the school organizes meetings between teachers and authorities to monitor the performance of students (see figure 1).

Table A2 shows the correlation between PAC treatment and the responses of JUTPs. The first three columns are concerned with annual planning activities within the school. 93.38% of JUTPs in the sample respond that the school engages in annual planning of the curriculum and we do not detect differences between PAC and control schools in annual planning. However, columns (1) to (3) evidence that PAC schools are significantly more likely to have the annual planning performed by the PAC authorities or by the ELE team and significantly less likely to leave the curriculum design to teachers. This evidence may be an indication of one of the dimensions in which teachers in PAC schools were supported by the authorities. Columns (4) and (5) provide evidence of two additional dimensions of support to teachers. The evidence presented in column (4) indicates that PAC schools are observed about 34.2% more times by the ELE team relative to control schools. Moreover, column (5) indicates that teachers in PAC schools receive feedback after these observations in about 30.5% more times than control schools. Finally, teachers' responses are consistent with the JUTPs answers, although we do not detect significant differences between PAC and control schools in teachers' responses.[6] For example, consistent with the JUTPs reports, teachers in PAC schools are more likely to having their classrooms observed and to receive feedback after observations.

[6]The vast majority of teachers in the sample respond positively to the questions. It is worth remarking that the fact that all teachers, including PAC teachers, implement the key program instruments is reassuring of the implementation of PAC.

2.2 Eligibility and Randomization

Among public and subsidized private schools in Chile, PAC considered two main eligibility criteria to define the target group of schools: first, the school's baseline average SIMCE score for the years between 2005 and 2009 in Math and Language should be below the national average (252 points out of 500); and second, there should be at least 20 students per level on average from pre-K to fourth grade.[7] 2,286 schools met these criteria and were ranked by their 2005-2009 average SIMCE scores in Language and Math. The bottom 1,000 schools were automatically considered eligible. Since participation in the program was voluntary, refusal to participate was expected, so in order to reach a target of around 1,000 eligible schools in the first year of the program, the Ministry increased the sample within each DEPROV by 50%, going up in the SIMCE ranking.[8] Of the resulting 1,480 eligible schools 632 located in "small" DEPROVs (DEPROVs with 40 schools or less) were allocated to the program automatically and do not form part of the evaluation and analysis. The remaining 848 schools located in "large" DEPROVs were randomly allocated to treatment and control groups. Five schools in the randomization are excluded from the analysis because they show missing information on school and students' characteristics in both the 2011 and 2012 data sets. All in all, of the 843 schools considered in this analysis, 648 were randomly selected to the treatment group and 195 were randomly selected to the control group.[9]

2.3 2012 CLASS intervention

The second part of this paper analyzes the relationship between teacher-students interactions and learning outcomes. To measure the quality of teacher-students interactions, we use the well-known CLASS measurement system Pianta, Mashburn, Downer, Hamre, and Justice (2008). The CLASS is an instrument used in the Education literature to measure the quality of teacher-student interactions, as a proxy to teachers' quality or effectiveness.

To produce the CLASS measures, a randomly selected group of 158 PAC schools (79 from the PAC treatment group and 79 from the PAC control group) were invited to have their fourth grade classrooms videotaped for four full lessons. The CLASS intervention took place in 2012, the second year of implementation of the PAC program. After class observations, thoroughly trained coders watch and analyze the videotapes and assign a score for teacher-students interactions in several dimensions (details will be presented in section 5).

The CLASS experiment had an extremely good compliance: in the end, 137 invited schools agreed to participate in the filming sessions and 185 classrooms within participating schools had lectures filmed. Non-participation is fairly well balanced between the treatment and control schools.[10] The sample of treated and control schools that participated in the CLASS experiment is also well balanced in school pre-treatment char-

[7] The Ministry of Education also required that the schools administrators should have no sanctions related to the voucher subsidies system in the previous three years.

[8] At this point some schools were excluded after consultation with DEPROV authorities either because of bad management or because they were already receiving technical and pedagogical assistance from well-known agencies of pedagogical support in Chile.

[9] Two of the 843 schools in the randomization are missing from our 2011 data set. Therefore, we consider 841 schools in 2011. Four of the 843 schools in the randomization drop out of our sample in 2012. Therefore, our analysis for 2012 is based on 839 schools. We discuss attrition in this section below.

[10] Among these 185 classrooms, 94 were in control PAC schools and 91 were in treatment PAC schools. Among the 91 classrooms in PAC schools, in turn, 78 were participating in the PAC, while 13 were in schools invited to participate in PAC but did not accept.

acteristics. These characteristics include the school income group, the past average SIMCE score of the school, the experience of fourth grade teachers, the experience of the school principal, and the tenure at the school of fourth grade teachers and the principal. For all these baseline characteristics we cannot reject the hypotheses that they are equal among PAC and non PAC schools that participate in the CLASS experiment.

2.4 Data

The analysis in this paper relies on administrative data provided by the Ministry of Education. This data set includes student level information on treatment status, test scores, and baseline demographic characteristics. Table A3 in appendix B shows summary statistics of all the variables used in this paper, namely, test scores and baseline characteristics, for the group of students that took each of the subject tests (post attrition samples).

2.5 Treatment- control balance and attrition

In our empirical results we exclude from the 2012 data those schools that implemented the CLASS observation system because of Hawthorne effects (Landsberger, 1958) - an issue we return to in the results section. As we show there, the CLASS intervention had impacts of its own thus contaminating the control schools that were part of it. CLASS was randomly allocated in both treatment and control schools and thus there is no bias in excluding these schools.

Table A4 in the Appendix shows summary statistics and randomization checks at the school level. The evidence shows that the randomization at the school level was successful: all pre-treatment school characteristics are balanced across PAC and control schools. Moreover, the result of an F-test of joint significance of school baseline characteristics on random assignment indicated that we cannot reject the null hypothesis that no variable jointly predicts treatment.

Table A5 in the Appendix, displays a set of randomization checks for the entire population of fourth grade students (the pre attrition sample) and for the three post attrition samples (Reading, Math, and Science test takers). The table is divided in three panels, corresponding to the 2011 cohort, the 2012 cohort that excludes schools participating in the CLASS intervention, and the whole 2012 sample. Each panel displays the results of a test of differences in means of attrition rates and baseline characteristics across treatment status, and a test of joint significance of the impact of baseline characteristics on treatment status.

In general, attrition rates in our sample are very low and baseline characteristics are balanced in both, the pre attrition and the post attrition samples. In 2011 there is no student that missed all three subject tests in the sample. When analyzing attrition rates by subject for this cohort (not reported in the table), only 2.06% of students missed the Reading test, 2.08% missed the Math test, and 1.97% missed the Science test. Moreover, attrition rates are balanced between the treatment and control groups, as shown in the first three rows of the 2011 panel of Appendix Table A5. There, the statistic reported is the difference in attrition rates between the treatment and control groups. These differences are very small: relative to the control group, there is 0.7% less students missing the Reading test and 0.1% more students missing the Math and Science tests in the treatment group. However, all p-values indicate that these differences are not significant.

The next set of rows show the results of a test of differences in means of baseline characteristics. Most baseline characteristics are balanced even among the students that did not drop out of the data. The exceptions are *low income* and mother and father *incomplete high school*: test takers in the treatment group are less likely to be from a low income family and less likely to have a parent with incomplete high school. Even when the p-value indicates that these differences are individually significant, the magnitude of the economic effect is extremely small, around 2%. Moreover, the last row of the 2011 panel shows that taken together, baseline characteristics do not significantly predict whether a student is in the treatment or the control group, even in the post attrition samples. The statistic reported is the F-statistic of the joint test, and p-values indicate that we cannot reject the null hypothesis that baseline characteristics do not jointly determine the random allocation to the program.

The conclusions from the 2012 cohort are similar. First, attrition rates are higher than in the 2011 cohort, but still low. In this cohort 15% of students missed the Reading test, 15.26% missed the Math test, and 15.36% missed the Science test (statistics not reported in the table). However, differences in attrition rates between treatment and control groups for 2012 are small and insignificant. Being in the treatment group is associated with about 1% lower probability of sitting for the Reading, Math, and Science tests relative to the control group, but these differences are not significantly different from zero, which suggests that the higher overall attrition in 2012 does not bias our results of the impact of PAC on SIMCE.

As further corroborative evidence panel B in Table A5 shows that the 2012 subsample excluding schools contaminated by the CLASS intervention is also balanced: all baseline characteristics are jointly insignificant in explain treatment status, as evidenced by the F-test. Individually, all baseline characteristics are balanced between treatment and control groups, with the exception of *Nbr years failed* (the number of grades a student had to retake prior to the fourth grade), which difference is economically negligible in magnitude and statistically only marginally significant.

In sum, we find no evidence that the experimental design was compromised in any way. In both cohorts the difference in the proportion of attritors is negligible in magnitude and not significant and the randomization was successful in balancing baseline characteristics, even for the post attrition samples.

3 Estimation and inference

Our results explore overall effects as well as heterogeneous treatment effects by school and students' demographic characteristics. In our heterogeneity analysis we first analyze results by school socio-economic status. Second, we define four groups of students based on the interaction between the gender of the student and her household income (*Female- Low income*, *Female- Medium-High income*, *Male- Low income*, and *Male- Medium-High income*).

The focus on income is mainly motivated by the need to understand whether such programs are particularly helpful for the most deprived, or by contrast they reinforce resources provided by parents. In general there is ample evidence showing an association between income and wealth with child outcomes. Whether such association extends to responses to interventions is an open and important question. Gender is also important; girls tend to perform better than boys in Reading and worse than boys in Math and Science (OECD, 2015). These outcomes may be related to teachers' practices. Using the same sample of fourth grade teachers in Chile as this paper, Bassi, Mateo Díaz, Blumberg, and Reynoso (2018) show that teachers in fact pay more attention to boys than girls, and those differentiated behaviors are correlated with worse performance in SIMCE in Math and Science among the girls. It is thus important to understand whether there are substantial differences in the response to interventions.

The results we present are obtained by a regression at the individual student level

$$SIMCE_{ijgk} = \beta_{gk} + \gamma_{gk} T_{ij} + X_{ijg}\delta_{gk} + \epsilon_{ijgk} \tag{1}$$

where $SIMCE_{ijgk}$ is the test score of student i, in school j, in demographic group g, and in subject $k = \{Math, Language, Science\}$. This is measured in units of a standard deviation of the control group (which we will refer to as SD units henceforth). T_{ij} is is a dummy indicating whether the student attended a school j that was randomized into the program (PAC); X_{ijg} is a vector of student-school characteristics that includes baseline characteristics;[11] and ϵ_{ijgk} is a random error term, which because of randomization is uncorrelated with treatment assignment.

Not all schools assigned to the program actually implemented it: there is non-compliance in both the 2011 and the 2012 cohorts. Table 1 shows take up rates of schools considered eligible to the program, for both years 2011 and 2012 and for the total schools that were ever considered eligible.

Table 1: Randomization and implementation, school level

		All schools		2011 sample		2012 sample	
		Implemented PAC					
		No	Yes	No	Yes	No	Yes
Randomized into PAC	No	185	10	194	0	115	10
	Yes	150	498	155	492	164	413

Notes: PAC stands for *Plan Apoyo Compartido*. *All schools* refers to the 843 schools that were considered eligible by the program and considered in the program evaluation at some point. The *2011 sample* consists of the 841 schools that were originally included in the program evaluation sample. The *2012 sample* consists of the 702 schools that remained in the program evaluation sample in the second year and were randomly excluded from the CLASS intervention (that is, 839 schools that continued in 2012 minus 137 schools that participated in CLASS). *Implemented PAC* is a dummy variable that takes value one if the school participated in PAC and zero otherwise. *Randomized into PAC* is a dummy variable that takes value one if the school that randomly assigned to the treatment group and zero otherwise.

In 2011 about 23% of schools randomized into the program did not implement it. In this case if we replace the randomization indicator T_{ij} with whether treatment actually took place and then use the randomization indicator as an instrument we will identify the effect of treatment on the treated because noncompliance is only one sided. In 2012 however, we have two sided noncompliance, with 8% of schools not assigned to the program

[11] The covariates include, whether the student lives in a household with at least one parent and/or siblings; whether the student lives in a household with members of the extended family; the number of times the student failed a school year; mother's education: dummies for "no education", "incomplete primary", "primary", "incomplete high school", "high school", "some college", "college +"; father's education (same dummies as mother education).

by the randomization actually getting it.[12] IV in this case identifies the LATE parameter under the additional monotonicity assumption that randomization either does not change treatment status or induces the school to adopt the program but never the reverse.[13] In all cases using as treatment variable the original randomization (T_{ij}) provides an unbiased estimate of the intention to treat parameter (ITT), namely the effect of having been offered the program.

At the student level Table 2 shows that for the 2011 cohort 76% of students were exposed to it as a result of the school being assigned to receive PAC. No student in the control group was exposed. The percentage varies slightly by demographic groups because the composition of the schools is not uniform. For the 2012 cohort the percent of exposed students as a result of being randomized into the program is 63%; some student in the control group did however receive the treatment. Table A9 in the appendix shows similar conclusions for the whole sample of 2012 schools.

Table 2: First stage. Dependent variable: Implemented PAC.

	2011				
	All	**Girls**		**Boys**	
		Low Income	**High Income**	**Low Income**	**High Income**
Randomized into PAC	0.761***	0.775***	0.721***	0.769***	0.745***
	[.734;.788]	[.746;.803]	[.68;.761]	[.707;.782]	[.74;.797]
Observations	31384	10938	2330	11492	2581
	2012				
	All	**Girls**		**Boys**	
		Low Income	**High Income**	**Low Income**	**High Income**
Randomized into PAC	0.6321***	0.6528***	0.6226***	0.6509***	0.6455***
	[.575; .683]	[.596; .704]	[.561; .682]	[.589; .697]	[.591; .706]
Observations	29905	8740	2225	8894	2622

Notes: PAC stands for *Plan Apoyo Compartido*. The dependent variable is *Implemented PAC*, a dummy variable that takes value one if the student attends a school that participated in PAC and zero otherwise. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *All* refers to all students pooled together. *Low Income* is a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country. *High Income* is a dummy that takes value one if *Low Income*= 0. 95% bootstrapped confidence intervals are shown in brackets. ***Variable significant at the 1% level. Clustering at the school level. The 2012 sample excludes schools that implemented CLASS.

In deriving standard errors and carrying out inference we cluster at the school level, which is the randomization unit. Since we will be splitting the sample by demographic characteristics and testing families of hypotheses we adjust the p-values for multiple testing using the step-down procedure of Romano and Wolf (2005). The resulting p-value is the Family wise error rate (FWE), namely the probability that we incorrectly identify one coefficient as significant in the entire group of hypotheses being tested. We use 1000 bootstrap replications to compute all standard errors and confidence intervals.

[12]Table A8 in the appendix shows a similar picture when all 2012 schools are considered.
[13]See Imbens and Angrist (1994).

4 Main Results

4.1 CLASS, Hawthorne Effects and the 2012 sample

As mentioned earlier, in order to better understand how PAC works and how it may affect teacher practices it was decided to implement the CLASS observation system in a random subset of 137 PAC treatment and PAC control schools. The CLASS was effectively another intervention consisting of videotaping lectures in full knowledge of the teachers within randomly selected PAC control and PAC treated schools. The question is whether CLASS had an effect in itself, thus contaminating the control group. Exploiting the fact that CLASS was randomly allocated, we estimate the treatment effect of receiving CLASS by comparing the outcomes for children in whose schools CLASS was implemented to those in which it was not, among the schools that did not implement the PAC (PAC controls). The mere implementation of CLASS significantly improved SIMCE scores by 23%, 18% and 21% of a standard deviation for Reading, Math and Science respectively. However, CLASS had no additional effect on learning outcomes for children in the PAC treatment group.[14] This is a characteristic example of the so called *Hawthorne effects* (Landsberger, 1958; Levitt and List, 2011) which lead to productivity increases when people feel they are being monitored.[15] The implication is that by including schools that received CLASS in our evaluation sample we would blunt the estimated effects of the PAC; hence we exclude all 2012 schools in treatment and control that implemented CLASS. Importantly since CLASS was randomly allocated, this causes no bias, but instead produces results that correctly reflect the PAC intervention. The estimates that include the CLASS sample are presented in Appendix E for completeness.

4.2 Overall effects

Table 3: Impact of PAC on SIMCE

	Intention to treat effect (ITT)		
	Reading	Math	Science
Randomized into PAC	.108	.087	.055
	[.06;.15]	[.03;.14]	[.01;.1]
	(.01)	(.02)	(.06)
Control Group Mean	243.83	236.12	235.18
Control Group SD	50.38	47.17	44.83
Number of Clusters	842	843	843
Observations	56193	56116	56104

Notes: PAC stands for *Plan Apoyo Compartido*. *Implemented PAC* is a dummy variable that takes value one if the student attends a school that participated in PAC and zero otherwise. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. The effects shown are in units of the control group standard deviation. 95% bootstrapped confidence intervals are shown in brackets. Romano-Wolf step down p-values from the two sided test accounting for all3 hypotheses are shown in parenthesis. All regressions include cohort fixed effects. Clustering at the school level. The 2012 sample excludes schools that implemented CLASS.

We start by showing in Table 3 the overall Intention to Treat (ITT) effects of the experiment pooling the data from the two cohorts together and controlling for cohort fixed effects. In all Tables that follow we report results without covariates (other than cohort effects when we pool them). Appendix F reports the results when we

[14] Detailed results in Table A10 in appendix D.

[15] In other contexts observation has been shown to reduce teacher absentees, which can also have an impact on performance (Duflo, Hanna, and Ryan, 2012).

include covariates. In this and all Tables that follow we report 95% confidence intervals (CI) in square brackets and RW stepdown p-values in parentheses, both computed using the bootstrap.

The impacts on Reading and Math are both large, and significant even controlling for multiple testing. The results for Science are smaller and the Romano Wolf (RW) stepdown p-value is 0.06. Overall the conclusion from this table is that the intervention was successful in improving learning standards. In what follows we first consider how the program worked for separate cohorts and we then proceed with heterogeneity analysis.

4.3 Effects by Cohort

Table 4 shows the effects of the program on SIMCE test scores for students in the 2011 and the 2012 cohorts separately. The top panel of the Table shows the ITT estimate while the bottom panel reports the corresponding instrumental variables (IV) results where the explanatory variable is actually receiving PAC and the instrument is being randomized into PAC; the parameter is interpreted as the effect of treatment on the treated for the 2011 cohort where all those randomized out were actually excluded from the program (one sided noncompliance), while for the 2012 cohort it is interpreted as the Local Average Treatment Effect (LATE) under the additional assumption of monotonicity, since there is two sided noncompliance. The RW stepdown p-values allows for all 6 hypotheses (Reading, Math and Science in each of the two years).

Table 4: Impact of PAC on SIMCE by cohort

	Intention to treat effect (ITT)					
	2011			**2012**		
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.095	.068	.033	.127	.117	.089
	[.04;.15]	[.01;.13]	[-.03;.09]	[.07;.19]	[.04;.19]	[.03;.15]
	(.02)	(.22)	(.56)	(.01)	(.03)	(.04)
	Instrumental Variables (IV)					
Implemented PAC	.125	.089	.044	.2	.184	.139
	[.05;.2]	[.01;.17]	[-.04;.12]	[.11;.3]	[.06;.31]	[.06;.24]
	(.02)	(.22)	(.56)	(.01)	(.05)	(.05)
Control Group Mean	244.79	235.76	236.84	242.42	236.65	232.72
Control Group SD	49.97	47.10	44.09	50.94	47.26	45.80
Number of Clusters	840	841	841	702	702	702
Observations	30736	30731	30765	25457	25385	25339

Notes: PAC stands for *Plan Apoyo Compartido*. *Implemented PAC* is a dummy variable that takes value one if the student attends a school that participated in PAC and zero otherwise. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. The effects shown are in units of the control group standard deviation. 95% bootstrapped confidence intervals are shown in brackets. Romano-Wolf step down p-values from the two sided test accounting for all 6 hypotheses in each panel (ITT and IV) are shown in parenthesis. Clustering at the school level. In the second panel the instrument is *Randomized into PAC*. The 2012 sample excludes schools that implemented CLASS.

Considering the results for the ITT and the corresponding ones for IV we find that Reading improved by about 0.10 of a SD in 2011, giving an IV coefficient of 0.125 (RW pva;ue 0.02), revealing a large impact in the schools that actually received the PAC. There is also a 0.07 improvement in Math in the same year, that is individually significant (see CI) but not so once we account for multiple testing (see RW p-value). The remaining effects for 2011 are not significant.

The effects in the 2012 sample are strong: test scores in all subjects improve between 0.09 and 0.13 of SD units relative to control schools, and the effects are all significant, even accounting for multiple testing. The effects are larger than those in 2011, which is consistent with the program maturing and being better embedded in the implementing schools. Indeed, the fraction of classrooms with teachers who are hired in 2012 or who are substitute teachers in the school is only 13.37%, implying improved experience levels with PAC implementation in the second year. So these results point to the persistent and even improving success for the program overall. Table A14 in appendix F shows that these results are robust to including covariates in the specification.[16]

4.4 Heterogeneity Analysis

Given the overall impacts of the program we now investigate whether these differ across gender and socioeconomic status, which are sources of disparities in performance. We will be focussing on three groups: Boys and Girls; children from low Income households versus higher income; and low versus Higher SES schools. We define low income background as children from families with a monthly income less than 300,000 Chilean pesos (US$ 600 in 2011), which is the minimum wage. The SES status of the school is defined by the government based on an index of parental education and income and a vulnerability index.[17] In our sample of PAC eligible schools Lower SES schools are overrepresented, reflecting the fact that underperforming schools tend to serve lower SES students. Our *Low SES* group includes the schools classified by the government as belonging to the Low and medium-Low groups.

The heterogeneity analysis is important for targeting, program improvement and understanding how to reduce important educational deficits: there are large disparities among the groups and a key question is whether the program reduces such inequalities and more generally how it affects the outcomes of each category. Table 5 shows the difference in the SIMCE scores, in standard deviation units, for the control group in both cohorts between boys and girls and between children from lower and higher income families. We also show differences between children in low and higher SES schools.

Girls perform better in Reading and worse in Math and Science while children from higher income groups are performing uniformly better than lower ones. We also find differences between low and higher SES schools, although these are not significant. Nevertheless, it is still interesting to consider the impact of the program across types of school because policy makers often target policies based on overall school composition and because the peer structure is different. We start by considering how the program affected different SES type schools and then we move to gender and family background differences.

[16] The 2012 results including the CLASS subsample are shown in Table A11 in appendix E. These show a decline in the impact of the program. However, this is fully explained by the fact that CLASS raised the performance of the control schools (non PAC) in which it was implemented, as we documented earlier. For further corroboration we also show in section 2 that the PAC intervention was well implemented in 2012.

[17] The Education Quality Assurance Agency, responsible for the SIMCE, classifies schools into socioeconomic categories based on four variables: mothers' years of education, fathers' years of education, monthly income reported by parents, and a vulnerability index developed by the Ministry of Education. The first three variables are obtained from SIMCE parents questionnaires. The average value among parents of the corresponding students grade is calculated for each of these variables. A cluster methodology is applied with these four variables to classify schools (for each grade level in which SIMCE is applied) into five socioeconomic categories: low, medium-low, medium, medium-high, high. Appendix Table A7 shows the distribution of Chilean schools according to their SES along with the distribution in the PAC sample of eligible schools.

Table 5: Differences in performance in the control group, by demographic characteristics and school SES

	Reading	Math	Science
Girls - Boys	.219	-.07	-.094
	[.19;.25]	[-.11;-.03]	[-.13;-.05]
Low Income - Higher Income student	-.109	-.145	-.217
	[-.16;-.06]	[-.21;-.08]	[-.28;-.16]
Low SES - Higher SES School	-.054	-.011	-.069
	[-.15;.05]	[-.13;.1]	[-.17;.03]
Number of Clusters (Control Schools)	194	194	194

Notes: Table shows pairwise differences in performance for students in the control group by demographic characteristics. *SES* variables refer to the school Socio Economic Status as described in this section 4. *Low Income* is a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country. 95% bootstrapped confidence intervals are shown in brackets.

Heterogeneity analysis can be particularly susceptible to false positives (i.e. finding significant results when there are none) because the number of hypotheses being tested is multiplied. Thus for each case we compute RW stepdown p-values for the entire set of hypotheses involved as specified below. Moreover, for this analysis we pool the 2011 and the 2012 data (allowing for cohort effects) so as to increase statistical power.

4.4.1 Effects by School Socio-Economic status

Table 6: Impact of PAC on SIMCE by school socio economic status, with cohort fixed effects

	Low SES			**Medium SES**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.079	.051	.015	.197	.223	.191
	[.03;.13]	[-.01;.11]	[-.04;.07]	[.1;.3]	[.11;.34]	[.09;.29]
	(.02)	(.24)	(.67)	(.01)	(.01)	(.01)
Control Group Mean	243.04	235.82	234.50	248.37	237.84	239.14
Control Group SD	50.12	47.29	44.85	51.61	46.43	44.54
Number of Clusters	706	707	707	194	194	194
Observations	43637	43544	43537	12480	12497	12492

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *SES* variables refer to the school Socio Economic Status as described in section 4. The effects shown are in units of the control group standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. RW step down p-values allowing for all 6 hypotheses from the two sided tests are shown in parenthesis. All regressions include cohort fixed effects. Clustering at the school level. Schools that implemented CLASS are excluded from the 2012 sample.

Table 6 shows the effects of the PAC program on test scores in each of the two SES school groups. The main conclusion from this table is that the program was most successful in schools with higher socioeconomic status among eligible schools: in the Medium SES group the program increased test scores in Reading and Science by about 0.20 of SD units and in Math by over 0.22 of SD units. All effects for the Medium SES schools are highly significant with stepdown p-values of at most 0.01 adjusting for all six hypotheses being considered. These are remarkable improvements. But even more remarkable from a policy perspective is the fact that the program did not increase the performance in the Low SES schools by nearly as much, despite the fact that the baseline performance is similar as shown above. In fact, we reject the hypothesis that the impact of PAC on SIMCE scores are equal for kids in Low SES schools vs kids in Medium SES schools. We aggregate the test scores of different subjects by obtaining the first principal component of test scores within each group and we reject the hypothesis that PAC effects on aggregate test scores are equal for the Low and High SES groups (p-value of 0.015). We also reject equality of coefficients when we compare each SIMCE subject separately instead of taking the principal component (p-values of 0.056 for Reading, 0.022 for Math, and 0.006 for Science).[18]

4.4.2 Effects by gender and family income

We now turn to differences by gender and household income, both sources of disparities in performance. We are particularly interested in how impacts vary between children of different SES backgrounds because it has been a challenge to improve outcomes for the most deprived populations. In addition, gender disparities in educational performance may partly explain male/female differences in labor market outcomes, including in wages and informality rates.

Appendix Tables A17 and A18 show differences between boys and girls and low and higher income background students respectively. We find that overall there are no significant differences in impacts between boys and girls and the estimates are almost the same. However, we find that the impacts for students from higher income backgrounds are approximately twice those of the students from low income families: the reading score improved by 0.167 SD units (p-value 0.01) for the higher income group and only 0.089 SD units (p-value 0.01) for the lower group. The Math score improvements were 0.143 (p-value 0.01) and 0.074 (p-value 0.08) respectively.[19] We now look at this in greater detail by considering gender and income background differences jointly.

The results are shown in Table 7 that pools the two years together and includes cohort fixed effects in the regression.[20] The table presents 12 impacts and the RW stepdown p-values provide significance levels accounting for the fact we are considering these multiple hypotheses. We also report 95% confidence intervals.

The main conclusion from Table 7 is that the program produced significant impacts for the Reading scores for boys from both income groups as well as for girls from a higher income backround. It also improved significantly the Math performance of boys from the higher income group. Specifically, Reading scores for higher income children improve by 0.135 SD units for boys (RW p-value 0.02) and 0.203 SD units for girls (RW p-value 0.01) relative to kids in control schools. The Reading scores for boys in the lower income families improved by 0.10 SD units (RW p-value 0.01). We also find that a 0.18 SD units improvement in the Math scores for boys from the higher income group (RW p-value 0.01). Given the adjustment for multiple hypotheses testing these are particularly strong results. If we were using the conventional single hypothesis p-values many more of these 12 effects would have been classified as significant - for example see the individually significant improvements, implied by the 95% confidence intervals, in Math for lower income boys and girls; however the chance that these are false positives is quite high given the adjusted p-values.[21]

All in all, these results suggest that the PAC had a large and significant effect on the performance of fourth grade boys and girls from relatively higher income backgrounds. This is clear evidence that the structured

[18] See Table A15 in appendix F for results including covariates in the specification.

[19] p-values reported are RW stepdown for 6 hypotheses.

[20] Once again, the 2012 sample exclude the contaminated CLASS sample. Table A13 in appendix E shows the 2012 results that include the sample contaminated by the CLASS intervention.

[21] Results from the estimation of the model with covariates are shown in tables A15 in the appendix and are very similar.

Table 7: Impact of PAC on SIMCE by students' gender and income, with cohort fixed effects

	Girls					
	Low Income			High Income		
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.075	.067	.043	.203	.102	.065
	[.02;.13]	[0;.13]	[-.01;.1]	[.11;.3]	[0;.2]	[-.03;.15]
	(.10)	(.32)	(.38)	(.01)	(.32)	(.38)
Control Group Mean	250.34	233.87	232.23	253.93	242.73	242.24
Control Group SD	48.33	45.62	43.01	49.22	46.44	45.88
Number of Clusters	835	835	835	761	761	760
Observations	19222	19245	19201	4494	4484	4493
	Boys					
	Low Income			High Income		
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.101	.081	.048	.135	.179	.087
	[.05;.15]	[.02;.14]	[-.01;.1]	[.06;.21]	[.1;.26]	[.01;.17]
	(.01)	(.18)	(.38)	(.02)	(.01)	(.32)
Control Group Mean	239.1	238.10	237.45	246.75	243.96	246.09
Control Group SD	51.18	48.04	45.42	52.93	48.68	46.59
Number of Clusters	836	836	836	780	781	781
Observations	19895	19873	19888	5098	5102	5083

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *Low Income* is a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country. *High Income* is a dummy that takes value one if *Low Income*= 0. The effects shown are in units of the control group standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets.RW step down p-values allowing for all 6 hypotheses from the two sided tests are shown in parenthesis. All regressions include cohort fixed effects. Clustering at the school level. Schools that implemented CLASS are excluded from the 2012 sample.

teaching intervention holds real promise. However, the effects on the lower income children are much smaller and when we break them down by gender, the only significant effect is confined to Reading and to boys only. Thus the program, improved quality of education overall and improved the performance of boys and girls by the same amount, but did not reduce the disparities between socioeconomic groups. Thus, we need further understanding on how to improve the performance of children from lower SES backgrounds. Noting that lower parental income is associated with lower baseline achievement (as shown in Table 5), the difficulty of intervening successfully for the most disadvantaged is consistent with much of the literature that shows complementarities between investments in children and earlier achievement (Cunha, Heckman, and Schennach, 2010; Attanasio, Meghir, and Nix, 2019b). It is also consistent with the results of other school interventions: for example Machin, McNally, and Meghir (2010) show that an inner city school intervention in England improved most the performance of the children with higher achievement, although they also showed that the largest effects were observed in under resourced schools, which is not surprising. This raises the urgency of how to design interventions for the most deprived populations and is likely to involve programs specifically targeted to address developmental deficits of children in deprived populations from a very early age (Attanasio et al., 2014, 2019a; Gertler et al., 2014).

In the next section we use the *Classroom Assessment Scoring System* (CLASS) to see whether the program affected the way teachers and students interact.

5 The 2012 CLASS experiment and students' learning

The small and growing literature that studies what characteristics of teachers matter the most for students' learning has recently started to focus on the quality of within classroom teacher-students interactions (Araujo, Carneiro, Cruz-Aguayo, and Schady, 2016). In this section we study how important are teacher-students interactions to improve students' learning in our context, and whether the PAC had any positive impact on the quality of teacher-students interactions. As a preview of our results, we find that higher quality of teacher-students interactions are associated with better test scores of low income students but are not correlated with test scores of high income students. Moreover, we find that the PAC was not successful in improving teacher-students interactions by this measure.

5.1 Measuring the quality of teacher-student interactions

The main instrument used in this paper to measure teacher-student interactions is the CLASS in its Upper Elementary version (fourth to sixth grade, see Pianta, Mashburn, Downer, Hamre, and Justice (2008)). The CLASS is an instrument used in the Education literature to measure the quality of teacher-student interactions, as a proxy to teachers' quality or effectiveness. To produce the CLASS measures, thoroughly trained coders watch and analyze videotaped classes and assign a score for teacher-students interactions in 11 dimensions. These dimensions can be grouped into three main domains: Emotional Support, Classroom Organization, and Instructional Support.[22] Coders look for very specific teachers' behaviors in each dimension, which are well described in the CLASS protocol that guides coders for their scoring.

There are several studies that link better student outcomes (both in learning and in the development of socioemotional skills) with teachers' scores in CLASS. Araujo, Carneiro, Cruz-Aguayo, and Schady (2016) present a brief review of this literature for the US and perform a study for Kindergarten children in Ecuador. However, to the best of our knowledge, no study in the literature analyses the effect of CLASS on test scores for elementary school kids in developing countries.

In 2012, fourth grade teachers in participating schools were videotaped for four full lessons (see section 2.3 for details on the random selection of PAC schools to participate in the CLASS intervention). A total of 185 teachers were filmed following the CLASS protocol.[23]

The coding was done by 10 coders and a supervisor carefully trained and selected.[24] Each of the four school hours filmed per teacher was divided into 15-minute segments and one segment per hour was coded (for a total

[22] Emotional support includes the dimensions of Positive Climate, Negative Climate, Regard for Student Perspectives, and Teacher Sensitivity; Classroom Organization includes the dimensions of Effective Behavior Management, Instructional Learning Formats, and Productivity; and Instructional Climate includes the dimensions of Language Modeling, Concept Development, Analysis and Inquiry, and Quality of Feedback.

[23] The fieldwork and coding according to CLASS was coordinated and implemented by a team of the Centro de Politicas Comparadas de Educacion from the Universidad Diego Portales, which had already applied CLASS for the evaluation of another program in Chile, Un buen Comienzo (Yoshikawa, et al. 2013).

[24] The coders had to take a two-day training course provided by a Teachstone certified trainer, who also had the experience of applying CLASS to the Chilean context. After the course, coders took a four-hour online test (developed by Teachstone), that asks the candidate to watch and code five segments of model videos. The candidate is approved when achieving a reliability rate of at least 80% in all videos and at least in two of the videos the same reliability in all CLASS dimensions. Only the candidates that passed the test were certified to be CLASS coders in this evaluation. In addition, before starting the coding of the videos for the PAC evaluation, coders participated in another training course to adapt their knowledge of CLASS to the Chilean context. The training included watching and coding videos of Chilean teachers, which were previously coded by experienced CLASS coders.

of 760 segments) in each of the CLASS dimensions. Following the CLASS protocol, the score on each dimension was based on a 1 to 7 scale (”low” for scores 1-2, “medium” for scores 3-5, and “high” for scores 6-7). The final CLASS scores for each domain consisted of the average across dimensions within the corresponding domain. For the coding, videos were randomly assigned to the 10 certified coders. The coding process lasted five weeks. During the first week of coding, 100% of the videos were double coded. The double-coding was expected to be gradually reduced in the following weeks if reliability rates remained above 80%.[25] Overall, 52% of the videos were double coded, with an average reliability rate of 84.2%.[26] This inter-coder reliability is comparable to that found in other studies. For example, Araujo, Carneiro, Cruz-Aguayo, and Schady (2016), Brown, Jones, LaRusso, and Aber (2010) report an inter-coder reliability rate of 83% for the 12% of the classroom observations which were double-coded.[27]

5.2 CLASS, Teacher Performance and program effects

Table 8: Association between CLASS and SIMCE 2012, by school socio economic status

	Low SES			**Medium SES**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
CLASS first principal component	.085	.085	.083	.029	.011	.029
	[.06;.11]	[.06;.11]	[.06;.11]	[-.03;.08]	[-.09;.09]	[-.05;.09]
	(.01)	(.01)	(.01)	(.53)	(.83)	(.60)
SIMCE Score Mean	247.934	241.684	236.145	260.803	252.08	250.099
SIMCE Score SD	51.984	48.961	47.098	48.858	45.899	44.11
Number of Clusters	114	114	114	22	22	22
Observations	3608	3572	3582	720	713	713

Notes: *SES* variables refer to the school Socio Economic Status as described in section 4. The effects shown are in units of the corresponding SIMCE test score standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. All outcomes in this table are tested jointly to control for the Familywise Error Rate using the Romano-Wolf step down method. Step down p-values from the two sided test are shown in parenthesis. Clustering at the school level.

In Tables 8 and 9 we report the association between CLASS and SIMCE scores for the 2012 cohort by school SES and in Table 9 by gender and student family icome. The effects reported are in SD units of the SIMCE score for the corresponding demographic group and subject.

Table 8 shows that performance in CLASS is significantly and positively associated with the test scores of students in the most disadvantage schools. Consistently, the most striking result from table 9 is the association between better student-teacher interactions (reflected in a higher CLASS score) and the performance of low income students. In effect, one additional standard deviation in the principal component of CLASS scores is associated with a higher SIMCE test score for low income students of between 0.15 and 0.20 of SD units. For higher income students, effects are smaller and in some cases insignificant. These results are potentially important and consistent with the finding that teachers have a large causal impact on student performance (see

[25] Coding is considered reliable if the difference between the two coders' score is less than 2 points for each CLASS dimension.
[26] When a coding was not considered not reliable, a supervisor did a third coding, which was the final score attributed to that teacher.
[27] Araujo, Carneiro, Cruz-Aguayo, and Schady (2016) get a higher inter-coder reliability rate (93%) double-coding 100% of the videos.

Table 9: Association between CLASS and SIMCE 2012, by students' gender and income

	Girls					
	Low Income			**High Income**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
CLASS first principal component	.158	.161	.143	.159	.028	.066
	[.09; .24]	[.09;.24]	[.06;.21]	[.08;.23]	[-.08;.13]	[-.02;.15]
	(.01)	(.01)	(.01)	(.01)	(.69)	(.33)
SIMCE Score Mean	253.862	239.124	234.441	265.009	252.042	246.767
SIMCE Score SD	49.475	47.855	44.145	47.939	49.585	45.668
Number of Clusters	128	128	128	102	102	102
Observations	1415	1404	1403	297	296	298
	Boys					
	Low Income			**High Income**		
	(7)	(8)	(9)	(10)	(11)	(12)
	Reading	Math	Science	Reading	Math	Science
CLASS first principal component	.187	.201	.194	.126	.105	.198
	[.13;.24]	[.13;.26]	[.13;.26]	[.02;.24]	[0;.22]	[.09;.33]
	(.01)	(.01)	(.01)	(.2)	(.33)	(.02)
SIMCE Score Mean	244.621	245.274	239.259	254.037	252.437	250.899
SIMCE Score SD	53.15	48.746	49.304	50.999	49.422	46.764
Number of Clusters	129	129	129	109	109	109
Observations	1472	1461	1461	365	360	361

Notes: *Low Income* is a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country. *High Income* is a dummy that takes value one if *Low Income*= 0. The effects shown are in units of the corresponding SIMCE test score standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. All outcomes in this table are tested jointly to control for the Familywise Error Rate using the Romano-Wolf step down method. Step down p-values from the two sided test are shown in parenthesis. Clustering at the school level.

Rivkin, Hanushek, and Kain (2005)). Taken at face value the results imply that moving a lower income student from a bottom 2% of teachers to the top 2% can improve outcomes of low income students by close to one standard deviation. There is no causality implied or presumed by these results, which may be entirely due to sorting of better low-income students to better teachers (say because of more pro-active parents). However, it does pose an interesting question as to whether improving interactions could actually lead to better performance for low income students. We thus examine whether the CLASS score was affected by the program.

The impact of PAC on CLASS Table 10 shows the result of regressing CLASS scores on treatment allocation and covariates. The results consistently suggest that the program has no significant effect on teacher-classroom interactions in 2012. Given that CLASS is ranked based on interactions that may somehow be discouraged by the PAC intervention, it may well be that CLASS is not a particularly good way of understanding the mechanisms through which the PAC operated. It may also be that the improvements we observed relate to practices not captured by CLASS, namely the more structured approach to lesson planning and the monitoring of students. On the other hand the loss in sample size has meant that these estimates are not as precise as we would desire. However, the association of CLASS scores with better performance of low income students suggests that improving outcomes for deprived populations should focus more on how teachers interact with low income students, as well as improving practices tested with this intervention. It is important to remember that, after all, the scripted instruction intervention was successful; moreover, while the impacts are concentrated among

Table 10: Impact of PAC on CLASS, classroom level

	Dependent variable: CLASS first principal component			
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Randomized into PAC	-0.5274		-0.2361	
	[-1.128;.093]		[-1.318;.107]	
Implemented PAC		-0.6153		-0.2697
		[-.878;.338]		[-.992;.38]
Covariates	No	No	Yes	Yes
Observations	185	185	184	184

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the school was randomly assigned to the treatment group and zero otherwise. *Implemented PAC* is a dummy variable that takes value one if the school participated in PAC and zero otherwise. In columns (2) and (4) we instrument actual participation in PAC with the random assignment to PAC. Covariates include an indicator of the income group the classroom belongs to, the type of administration of the school (private or public), average SIMCE scores of the school for the period 2005-2009, general experience of the teacher and the school principal, and tenure of the teacher and the principal in the school. 95% bootstrapped confidence intervals are shown in brackets. Clustering at the School level.

the relatively better off, the population we are studying is already lower-income and attending underperforming schools.

6 Discussion and Conclusions

Improving quality of education has proved to be a major policy challenge. While the quality of teachers seems to be of central importance the policy question remains, particularly because it is not clear what constitutes a priori a good teacher. One possibility is to consider more structured teaching methods, that define carefully what teachers are supposed to do and monitor the progress of students throughout the year. This is the idea underlying PAC (Plan Apoyo Compartido) the program we are analyzing in this paper and which was launched in 2011 in Chile. Through standardized teaching material (class preparation) and through the support of internal and external pedagogic teams, the program aimed at reducing the gap, as measured by the standardized test SIMCE, between the poorest student population and the national average. The program was designed with a gradual implementation, which implied that only half of eligible schools could be offered the program. These were selected randomly, which forms the basis of our evaluation.

The results for the first 2011 cohort of implementation were encouraging implying overall improvements in Reading. In the second year of the program, the effects increase for all subjects and become significant also for Math and Science. When we break down the impacts by school socioeconomic status (SES) we find that the positive effects of the program are concentrated among children in schools with higher SES. Moreover, heterogeneous effects by students' gender and family income reveal positive and significant effects particularly for students originating from relatively higher income families. Importantly the effects are the same for boys and girls. Overall, it seems that the program can improve outcomes, but it mainly improves results for the relatively better off.[28]

In order to begin understanding what lies behind these results we used the CLASS system to record classroom

[28]PAC was discontinued in 2014 by the entering administration of the Ministry of Education.

sessions and score teacher-student interactions. CLASS is a well-documented instrument in the education literature that uses a very rigorous protocol to score the ways students and teachers interact along various dimensions (class organization, instructional support and emotional support, measured in 11 different sub-dimensions). We find that CLASS scores are correlated with SIMCE results: a better CLASS score is associated with better performing students, particularly among those from lower income backgrounds. No causality should of course be attributed since it may well be the case that teachers interact better when they are interacting with better performing students. We then examine whether the program shifted the CLASS score, by improving teacher-student interactions and we find no effect at all. However, since CLASS altered the performance of the control group it is hard to interpret this result: in other words the group that was observed via CLASS is not comparable to the one that was not.

Despite the overall success of the program, the urgent question of how to improve outcomes of children from the most deprived backgrounds remains. As much research seems to show the answer may lie in Early Childhood Development Programs, which attempt to ensure that children from the most deprived backgrounds have better cognitive development and access to improved opportunities from the earliest possible age, making them potentially better placed to benefit from schooling.

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Appendix A Evidence on implementation of PAC

Table A1: Correlation between participation in PAC and PAC dimensions, classroom level analysis

	(1)	(2)	(3)	(4)	(5)
	Class structure	Reflective thinking	Norms and schedule	Evaluation	Use of manual
Implemented PAC	0.0129	0.0369	0.0582**	0.0279	0.2300***
	(0.0238)	(0.0291)	(0.0225)	(0.0281)	(0.0733)
Constant	0.4589***	0.5397***	0.7390***	0.8730***	0.1619***
	(0.0171)	(0.0175)	(0.0153)	(0.0200)	(0.0354)
Observations	179	179	179	179	179

Notes: PAC stands for *Plan Apoyo Compartido*. *Implemented PAC* is a dummy variable that takes value one if the school participated in PAC and zero otherwise. **Variable significant at the 5% level. ***Variable significant at the 1% level. Clustering at the School level.

Table A2: Correlation between participation in PAC and PAC components, school level analysis

	(1)	(2)	(3)	(4)	(5)
	Annual planning performed by			Support to teachers	
	PAC team	ELE team	Teachers	ELE classroom observations	Feedback to teachers
Implemented PAC	0.2546***	0.1888**	-0.1830**	1.1593***	1.1176***
	(0.0641)	(0.0858)	(0.0810)	(0.3991)	(0.3826)
Constant	0.0385*	0.3974***	0.7692***	3.3924***	3.6582***
	(0.0219)	(0.0558)	(0.0481)	(0.2442)	(0.2439)
Observations	136	136	136	137	137

Notes: PAC stands for *Plan Apoyo Compartido*. ELE refers to the Education Leadership Team (consisting of the school principal, the head of the technical and pedagogic office of the school, and two distinguished teachers, as described in section 2). *Implemented PAC* is a dummy variable that takes value one if the school participated in PAC and zero otherwise. *Variable significant at the 10% level. **Variable significant at the 5% level. ***Variable significant at the 1% level. Robust standard errors in parenthesis.

Appendix B Summary Statistics

The names of columns indicate the set of students over which summary statistics are calculated.

Columns labeled *Reading*, *Math*, and *Science test takers* indicate the pool of students that took each of the corresponding subject tests. This corresponds to the *post attrition* sample, since for each test, there is a small set of students that did not take the test (we discuss the section 2.5).

Sub-columns labeled *PAC=0* and *PAC=1* refer to treatment status. *PAC* is a dummy variable that takes value one if the student goes to a school that was invited to participate in the program through the randomization, and zero otherwise. In what follows, we refer to the set of students such that *PAC=0* as the *control group* and to the set of students such that *PAC=1* as the *treatment group*.

In turn, the table is divided in three panels, *2011*, *2012-excluding CLASS sample*, and *2012*, indicating the fourth grade cohorts considered in this paper.

The names of rows indicate the variable for which we show summary statistics.

SIMCE scores (Reading, Math, and Science) refer to the grade obtained by students in the SIMCE subject tests.

Baseline characteristics indicate characteristics of the students that do not change because of treatment. They include student demographic characteristics and education of parents. Student demographics are *Female* (a dummy variable that takes value one if the student is a female and zero otherwise), *Low income* (a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, or around 600 dollars at that time),[29] *Nuclear, Extended,* and *Other* family (three dummies that indicate the family structure of the student), and *Nbr years failed* (a count variable that captures the number of primary school years the student had to retake previous to the forth grade). Mother's and father's education refer to the highest education level reached by the student's mother and father. These include *No education*, *Incomplete primary*, *Primary*, *Incomplete high school*, *High school*, *Incomplete college*, and *college*.

[29]SIMCE includes a 1 to 9 scale for the income reported by the parents in the questionnaire that they complete. We consider "low-income" those reporting in categories 1 to 4. It is important to note, tough, that students in our sample belong mainly to low-middle income families in Chile.

Table A3: Summary statistics - post attrition samples

	Reading test takers						Math test takers						Science test takers					
	PAC=0			PAC=1			PAC=0			PAC=1			PAC=0			PAC=1		
	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD
Panel A: 2011																		
<u>SIMCE scores:</u>																		
Reading	6886	245	50	23850	248	50												
Math							6903	236	47	23828	238	48						
Science													6911	237	44	23854	238	44
<u>Baseline characteristics:</u>																		
<u>*Students demographics*</u>																		
Female	6554	.472	.499	22861	.484	.5	6653	.473	.499	23152	.484	.5	6660	.473	.499	23162	.484	.5
Low income	6219	.841	.366	21470	.813	.39	6235	.841	.366	21490	.813	.39	6244	.841	.366	21502	.813	.39
Nuclear family	6886	.613	.487	23850	.617	.486	6903	.613	.487	23828	.619	.486	6911	.613	.487	23854	.617	.486
Extended family	6886	.244	.43	23850	.239	.426	6903	.244	.43	23828	.239	.426	6911	.244	.43	23854	.239	.427
Other family	6886	.143	.35	23850	.144	.352	6903	.143	.35	23828	.143	.35	6911	.143	.35	23854	.143	.35
Nbr years failed	6187	.238	.527	21353	.232	.531	6202	.239	.528	21367	.232	.531	6211	.239	.528	21387	.232	.531
<u>*Mother's education*</u>																		
No education	6201	.007	.086	21352	.006	.078	6215	.007	.086	21374	.006	.077	6225	.008	.087	21387	.006	.078
Inc. primary	6201	.179	.383	21352	.174	.379	6215	.178	.383	21374	.174	.379	6225	.178	.383	21387	.174	.379
Primary	6201	.17	.375	21352	.164	.37	6215	.17	.375	21374	.164	.37	6225	.169	.375	21387	.164	.37
Inc. high school	6201	.235	.424	21352	.218	.413	6215	.235	.424	21374	.218	.413	6225	.236	.425	21387	.219	.413
High school	6201	.324	.468	21352	.341	.474	6215	.324	.468	21374	.341	.474	6225	.324	.468	21387	.341	.474
Inc. college	6201	.034	.182	21352	.038	.191	6215	.034	.182	21374	.038	.191	6225	.034	.181	21387	.037	.19
College	6201	.051	.22	21352	.059	.235	6215	.051	.22	21374	.059	.235	6225	.051	.22	21387	.059	.235
<u>*Father's education*</u>																		
No education	5992	.008	.089	20577	.008	.089	6006	.008	.09	20597	.008	.089	6013	.008	.089	20611	.008	.09
Inc. primary	5992	.17	.376	20577	.158	.364	6006	.17	.376	20597	.157	.364	6013	.17	.376	20611	.157	.364
Inc. primary	5992	.16	.366	20577	.162	.368	6006	.16	.367	20597	.161	.368	6013	.16	.366	20611	.162	.368
Inc. high school	5992	.248	.432	20577	.23	.421	6006	.248	.432	20597	.23	.421	6013	.247	.431	20611	.23	.421
High school	5992	.329	.47	20577	.345	.475	6006	.328	.469	20597	.344	.475	6013	.328	.47	20611	.344	.475
Inc. college	5992	.036	.187	20577	.043	.202	6006	.036	.187	20597	.043	.203	6013	.036	.187	20611	.043	.203
College	5992	.05	.217	20577	.056	.229	6006	.05	.219	20597	.056	.23	6013	.05	.218	20611	.056	.229
Panel B: 2012-excluding CLASS sample																		
<u>SIMCE scores:</u>																		
Reading	4685	242	51	20772	249	52												
Math							4658	237	47	20727	242	49						
Science													4654	233	46	20685	237	46
<u>Baseline characteristics:</u>																		

Table A3: Summary statistics - post attrition samples (continued)

	Reading test takers						Math test takers						Science test takers					
	PAC=0			PAC=1			PAC=0			PAC=1			PAC=0			PAC=1		
	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD
Students demographics																		
Female	4412	.481	.5	20342	.481	.5	4293	.484	.5	19900	.483	.5	4290	.483	.5	19848	.482	.5
Low income	3946	.792	.406	18045	.779	.415	3960	.793	.405	18119	.779	.415	3954	.793	.405	18067	.78	.415
Nuclear family	4685	.563	.496	20772	.572	.495	4658	.569	.495	20727	.576	.494	4654	.569	.495	20685	.576	.494
Extended family	4685	.234	.423	20772	.25	.433	4658	.237	.425	20727	.252	.434	4654	.236	.425	20685	.252	.434
Other family	4685	.203	.402	20772	.177	.382	4658	.195	.396	20727	.172	.377	4654	.195	.396	20685	.172	.378
Nbr years failed	3947	1.25	.592	18055	1.217	.561	3962	1.253	.595	18129	1.218	.561	3956	1.251	.593	18076	1.218	.56
Mother's education																		
No education	3836	.007	.08	17474	.006	.075	3852	.007	.082	17554	.006	.075	3847	.006	.08	17505	.006	.075
Inc. primary	3836	.178	.383	17474	.163	.37	3852	.179	.384	17554	.164	.37	3847	.179	.383	17505	.163	.369
Primary	3836	.173	.379	17474	.169	.374	3852	.175	.38	17554	.168	.374	3847	.174	.379	17505	.169	.375
Inc. high school	3836	.217	.412	17474	.212	.408	3852	.217	.412	17554	.211	.408	3847	.217	.412	17505	.211	.408
High school	3836	.333	.471	17474	.351	.477	3852	.331	.471	17554	.35	.477	3847	.332	.471	17505	.35	.477
Inc. college	3836	.038	.191	17474	.04	.197	3852	.038	.192	17554	.04	.197	3847	.038	.192	17505	.04	.196
College	3836	.054	.225	17474	.06	.237	3852	.054	.226	17554	.06	.238	3847	.054	.225	17505	.061	.239
Father's education																		
No education	3675	.01	.097	16720	.007	.083	3686	.009	.097	16804	.007	.083	3682	.01	.097	16756	.007	.083
Inc. primary	3675	.155	.362	16720	.158	.364	3686	.155	.362	16804	.158	.364	3682	.155	.362	16756	.157	.364
Primary	3675	.176	.381	16720	.162	.368	3686	.176	.381	16804	.162	.369	3682	.174	.379	16756	.162	.369
Inc. high school	3675	.221	.415	16720	.218	.413	3686	.221	.415	16804	.218	.413	3682	.221	.415	16756	.219	.414
High school	3675	.351	.477	16720	.352	.478	3686	.35	.477	16804	.351	.477	3682	.351	.477	16756	.35	.477
Inc. college	3675	.037	.189	16720	.044	.206	3686	.037	.189	16804	.045	.206	3682	.037	.189	16756	.045	.207
College	3675	.051	.22	16720	.06	.237	3686	.051	.221	16804	.059	.236	3682	.051	.22	16756	.06	.237
Panel C: 2012																		
SIMCE scores:																		
Reading	7141	246	51	23353	248	52												
Math							7095	239	47	23273	242	49						
Social Science													7105	235	47	23226	237	46
Baseline characteristics:																		
Students demographics																		
Female	6773	.481	.5	22810	.481	.5	6572	.483	.5	22303	.482	.5	6580	.483	.5	22245	.482	.5
Low income	6048	.8	.4	20229	.783	.412	6065	.801	.399	20292	.783	.412	6063	.801	.399	20236	.783	.412
Nuclear family	7141	.566	.496	23353	.572	.495	7095	.572	.495	23273	.576	.494	7105	.571	.495	23226	.575	.494
Extended family	7141	.235	.424	23353	.248	.432	7095	.237	.425	23273	.25	.433	7105	.236	.425	23226	.249	.433
Other family	7141	.2	.4	23353	.18	.385	7095	.191	.393	23273	.175	.38	7105	.193	.395	23226	.175	.38

Table A3: Summary statistics - post attrition samples (continued)

	Reading test takers						Math test takers						Science test takers					
	PAC=0			PAC=1			PAC=0			PAC=1			PAC=0			PAC=1		
	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD
Nbr years failed	6050	1.243	.588	20242	1.219	.565	6068	1.245	.593	20305	1.22	.564	6066	1.243	.592	20248	1.219	.564
Mother's education																		
No education	5873	.006	.076	19580	.006	.075	5894	.006	.077	19648	.006	.075	5891	.006	.076	19594	.006	.075
Inc. primary	5873	.178	.383	19580	.166	.372	5894	.18	.384	19648	.167	.373	5891	.179	.384	19594	.166	.372
Primary	5873	.173	.378	19580	.169	.375	5894	.173	.378	19648	.169	.375	5891	.172	.378	19594	.17	.376
Inc. high school	5873	.214	.41	19580	.213	.409	5894	.214	.41	19648	.213	.41	5891	.214	.41	19594	.213	.409
High school	5873	.338	.473	19580	.348	.476	5894	.336	.472	19648	.348	.476	5891	.337	.473	19594	.348	.476
Inc. college	5873	.036	.187	19580	.039	.193	5894	.036	.187	19648	.039	.193	5891	.036	.187	19594	.039	.192
College	5873	.055	.228	19580	.058	.235	5894	.055	.228	19648	.059	.235	5891	.055	.228	19594	.059	.236
Father's education																		
No education	5630	.009	.092	18745	.007	.085	5647	.009	.092	18820	.007	.085	5644	.009	.092	18768	.007	.085
Inc. primary	5630	.153	.36	18745	.158	.365	5647	.153	.36	18820	.158	.365	5644	.154	.361	18768	.158	.364
Inc. primary	5630	.172	.377	18745	.165	.371	5647	.172	.377	18820	.165	.371	5644	.17	.376	18768	.165	.372
Inc. high school	5630	.222	.416	18745	.217	.412	5647	.222	.416	18820	.217	.412	5644	.222	.416	18768	.218	.413
High school	5630	.357	.479	18745	.351	.477	5647	.356	.479	18820	.35	.477	5644	.357	.479	18768	.35	.477
Inc. college	5630	.035	.183	18745	.043	.203	5647	.035	.184	18820	.043	.204	5644	.035	.184	18768	.043	.204
College	5630	.054	.225	18745	.058	.234	5647	.054	.226	18820	.058	.234	5644	.054	.225	18768	.059	.235

Table A4: Randomization check, school level

	PAC=1			PAC=0			Diff. in means	
	Obs	Mean	SD	Obs	Mean	SD	Stat.	p-val
Low SES	651	.158	.365	197	.162	.37	-.004	.888
Medium-Low SES	651	.631	.483	197	.675	.47	-.044	.254
Medium SES	651	.21	.408	197	.162	.37	.048	.119
Public	648	.645	.479	194	.67	.471	-.025	.518
Avg SIMCE 2005-2009	651	228.37	11.418	197	227.406	11.573	.964	.304
Avg SIMCE Reading 2010	648	249.552	18.435	195	248.872	17.933	.681	.644
Avg SIMCE Math 2010	648	227.755	19.303	195	226.174	17.069	1.58	.272
Joint F-test p-value: 0.657								

Notes: PAC=1 and PAC=0 denote the treatment and control groups, respectively. *SES* variables refer to the school Socio Economic Status as described in section 4; *Public* is a dummy variable that takes value 1 if the school depends upon the municipality; *Avg. SIMCE* refers to the average score in the SIMCE tests.

Table A5: Randomization check, student level

	Pre attrition sample		Post attrition samples					
			Reading test takers		Math test takers		Science test takers	
	Stat.	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*
Panel A: 2011								
Balancing of attrition rates and baseline characteristics (E(PAC=1) - E(PAC=0))								
Proportion of attritors								
Reading	-.007	.258	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Math	.001	.67	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Science	.001	.784	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Baseline characteristics:								
Students demographics								
Female	.003	.758	.004	.688	.003	.709	.003	.728
Low income	-.02	.048	-.019	.052	-.019	.052	-.019	.052
Nuclear family	.012	.324	.01	.383	.013	.269	.011	.355
Extended family	-.009	.284	-.012	.182	-.01	.241	-.009	.273
Other family	-.003	.786	.001	.88	-.003	.737	-.002	.851
Nbr years failed	-.01	.497	-.009	.539	-.01	.473	-.011	.464
Mother's education								
No education	-.001	.578	-.001	.582	-.001	.575	-.001	.553
Inc. primary	.005	.567	.006	.518	.005	.604	.005	.596
Primary	-.004	.597	-.004	.559	-.004	.559	-.004	.597
Inc. high school	-.022	.007	-.022	.006	-.022	.008	-.022	.007
High school	.017	.131	.017	.127	.018	.12	.017	.129
Inc. college	0	.923	0	.922	0	.891	.001	.858
College	.004	.363	.004	.375	.004	.372	.004	.358
Father's education								
No education	-.001	.661	-.001	.774	-.001	.582	-.001	.694
Inc. primary	-.001	.92	0	.973	-.001	.901	-.001	.887
Inc. primary	.006	.446	.006	.437	.006	.462	.007	.414
Inc. high school	-.02	.015	-.02	.012	-.021	.012	-.02	.016
High school	.009	.372	.009	.38	.011	.307	.009	.376
Inc. college	.005	.186	.005	.237	.005	.188	.005	.19
College	.001	.854	.001	.831	.001	.865	.001	.904
Test of joint significance of baseline characteristics: F-statistic (p-val)								
	1.18 (0.277)		1.18 (0.272)		1.17 (0.282)		1.15 (0.305)	
Panel B: 2012-excluding CLASS sample								
Balancing of attrition rates and baseline characteristics (E(PAC=1) - E(PAC=0))								
Proportion of attritors								
Reading	-.01	.309	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Math	-.014	.172	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Science	-.013	.201	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Table A5: Randomization check, student level (continued)

	Pre attrition sample		Post attrition samples					
			Reading test takers		Math test takers		Science test takers	
	Stat.	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*
Baseline characteristics:								
Students demographics								
Female	-.006	.565	-.005	.603	-.01	.371	-.008	.456
Low income	-.001	.935	-.002	.854	-.003	.831	-.003	.796
Nuclear family	.016	.298	.013	.424	.01	.531	.01	.519
Extended family	.006	.567	.004	.703	.005	.694	.004	.75
Other family	-.022	.215	-.017	.315	-.014	.394	-.014	.414
Nbr years failed	-.036	.076	-.032	.102	-.034	.082	-.032	.098
Mother's education								
No education	0	.908	-.001	.638	-.001	.604	-.001	.71
Inc. primary	-.006	.561	-.008	.453	-.009	.434	-.008	.45
Primary	-.002	.807	0	.995	-.002	.837	0	.999
Inc. high school	-.004	.671	-.005	.648	-.005	.647	-.006	.584
High school	.012	.347	.011	.387	.014	.296	.012	.372
Inc. college	-.003	.494	-.002	.699	-.002	.706	-.002	.665
College	.004	.478	.004	.498	.004	.516	.005	.424
Father's education								
No education	-.003	.155	-.003	.173	-.003	.181	-.003	.184
Inc. primary	.011	.282	.008	.427	.008	.416	.007	.49
Inc. primary	-.014	.146	-.017	.076	-.017	.083	-.015	.125
Inc. high school	-.005	.636	-.001	.923	-.001	.919	0	.965
High school	.001	.927	.001	.912	.002	.898	0	.989
Inc. college	.005	.272	.005	.226	.005	.267	.005	.265
College	.005	.36	.006	.288	.006	.31	.006	.29
Test of joint significance of baseline characteristics: F-statistic (p-val)								
	0.98 (0.483)		0.97 (0.496)		0.94 (0.523)		0.9 (0.575)	
Panel C: 2012								
Balancing of attrition rates and baseline characteristics (E(PAC=1) - E(PAC=0))								
Proportion of attritors								
Reading	-.01	.213	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Math	-.012	.125	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Science	-.01	.231	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Baseline characteristics:								
Students demographics								
Female	-.001	.909	0	.987	-.003	.771	-.002	.827
Low income	-.005	.652	-.006	.552	-.007	.492	-.007	.515
Nuclear family	.014	.299	.011	.405	.009	.515	.009	.498
Extended family	.003	.687	.001	.925	.002	.87	.001	.886
Other family	-.017	.251	-.012	.41	-.01	.481	-.01	.476
Nbr years failed	-.024	.123	-.019	.216	-.022	.155	-.02	.186
Mother's education								
No education	.001	.441	0	.771	0	.798	.001	.695
Inc. primary	-.003	.783	-.004	.655	-.005	.579	-.005	.591
Primary	.001	.844	.003	.658	.003	.722	.004	.621
Inc. high school	-.001	.934	0	.973	0	.977	-.001	.95
High school	.004	.675	.003	.8	.005	.66	.003	.777
Inc. college	-.004	.3	-.003	.439	-.003	.456	-.003	.44
College	.001	.922	.001	.908	.001	.897	.001	.783
Father's education								
No education	-.002	.338	-.002	.351	-.002	.327	-.002	.361
Inc. primary	.015	.061	.013	.122	.012	.138	.011	.172
Inc. primary	-.003	.692	-.005	.512	-.005	.55	-.003	.67
Inc. high school	-.006	.447	-.003	.707	-.002	.777	-.002	.81
High school	-.009	.355	-.01	.334	-.01	.339	-.011	.284
Inc. college	.005	.21	.006	.104	.005	.136	.006	.129
College	0	.945	.001	.83	.001	.886	.001	.836

Table A5: Randomization check, student level (continued)

	Pre attrition sample		Post attrition samples					
			Reading test takers		Math test takers		Science test takers	
	Stat.	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*
Test of joint significance of baseline characteristics: F-statistic (p-val)								
	1.19 (0.268)		1.17 (0.282)		1.15 (0.300)		1.12 (0.332)	

Notes: Pre attrition sample refers to the universe of students in the fourth grade. Post attrition sample refers to the sub sample of students that took each of the subject SIMCE tests. The statistic (*Stat.*) reported in the balancing exercises is E(PAC=1) - E(PAC=0), that is, the difference in means between the treatment and the control groups. The statistic (*Stat.*) reported in the test of joint significance exercises is the F-test. Baseline characteristics include student demographics and Mother's and father's education. Student demographics are *Female* (a dummy variable that takes value one if the student is a female and zero otherwise), *Low income* (a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country), *Nuclear, Extended,* and *Other* family (three dummies that indicate the family structure of the student), and *Nbr years failed* (a count variable that captures the number of primary school years the student had to retake previous to the forth grade). Mother's and father's education refer to the highest education level reached by the student's mother and father. These include *No education*, *Incomplete primary*, *Primary*, *Incomplete high school*, *High school*, *Incomplete college*, and *college*.

Table A6: Balancing of pre-treatment characteristics by gender, sample of test takers

	Girls						Boys					
	Reading		Math		Science		Reading		Math		Science	
	Stat.	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*
Panel A: 2011												
Students demographics												
Low income	-.025	.028	-.024	.034	-.024	.03	-.012	.326	-.012	.298	-.012	.313
Nuclear family	.005	.701	.013	.365	.011	.424	.009	.545	.008	.604	.006	.688
Extended family	-.005	.666	-.005	.665	-.003	.799	-.02	.091	-.017	.138	-.017	.142
Other family	-.001	.958	-.008	.467	-.008	.442	.011	.219	.01	.361	.011	.278
Nbr years failed	.005	.757	.005	.765	.004	.789	-.026	.167	-.029	.136	-.029	.131
Mother's education												
No education	.002	.384	.002	.326	.002	.377	-.004	.122	-.004	.1	-.004	.106
Inc. primary	.008	.505	.008	.471	.008	.474	0	.99	-.003	.796	-.003	.812
Primary	-.007	.498	-.007	.498	-.007	.484	0	.988	0	.987	.001	.889
Inc. high school	-.029	.009	-.028	.013	-.03	.008	-.015	.198	-.014	.202	-.014	.227
High school	.022	.096	.02	.134	.021	.116	.014	.338	.017	.244	.015	.298
Inc. college	0	.96	0	.98	.001	.779	0	.98	0	.978	-.001	.912
College	.005	.488	.004	.512	.005	.487	.004	.495	.004	.474	.004	.462
Father's education												
No education	0	.902	0	.926	0	.877	-.002	.443	-.003	.315	-.003	.381
Inc. primary	.001	.941	.001	.927	.001	.96	-.001	.945	-.002	.859	-.002	.858
Inc. primary	.013	.247	.013	.234	.014	.214	-.001	.96	-.001	.899	-.001	.945
Inc. high school	-.028	.009	-.028	.008	-.029	.008	-.011	.324	-.011	.316	-.009	.418
High school	.007	.626	.007	.638	.007	.624	.01	.436	.013	.312	.01	.424
Inc. college	-.001	.853	-.001	.908	-.001	.925	.009	.063	.009	.05	.009	.053
College	.008	.124	.008	.138	.008	.143	-.005	.528	-.005	.524	-.005	.489
Panel B: 2012												
Students demographics												
Low income	0	.991	-.001	.968	0	.983	-.004	.784	-.005	.774	-.006	.699
Nuclear family	.02	.275	.021	.25	.02	.253	-.005	.784	-.011	.499	-.009	.597
Extended family	-.019	.174	-.021	.149	-.021	.155	.017	.218	.018	.213	.016	.267
Other family	0	.99	0	.997	0	.977	-.013	.441	-.007	.655	-.007	.641
Nbr years failed	-.037	.084	-.037	.088	-.035	.099	-.03	.233	-.032	.206	-.03	.228
Mother's education												
No education	.001	.782	.001	.748	.001	.791	-.002	.538	-.002	.517	-.001	.66
Inc. primary	-.011	.467	-.011	.492	-.01	.541	-.004	.738	-.005	.697	-.004	.732
Primary	.001	.942	-.001	.917	0	.97	-.008	.511	-.008	.498	-.007	.579
Inc. high school	-.016	.255	-.014	.293	-.017	.225	.002	.906	0	.997	0	.976

Table A6: Balancing of pre-treatment characteristics by gender, sample of test takers (continued)

	Girls						Boys					
	Reading		Math		Science		Reading		Math		Science	
	Stat.	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*	*Stat.*	*p-val*
High school	.021	.213	.022	.204	.021	.221	.007	.642	.01	.527	.007	.664
Inc. college	0	.976	0	.963	0	.973	-.002	.73	-.002	.728	-.003	.658
College	.004	.599	.004	.618	.005	.499	.007	.363	.007	.376	.008	.328
Father's education												
No education	-.004	.253	-.004	.254	-.004	.255	-.002	.518	-.002	.505	-.002	.511
Inc. primary	.005	.715	.005	.693	.004	.772	.013	.306	.013	.318	.012	.351
Inc. primary	-.023	.075	-.023	.069	-.022	.088	-.017	.153	-.017	.167	-.015	.238
Inc. high school	.014	.284	.014	.268	.014	.27	-.014	.254	-.013	.31	-.013	.306
High school	-.008	.655	-.007	.665	-.008	.62	.013	.426	.013	.42	.011	.486
Inc. college	.005	.39	.005	.415	.005	.387	.006	.304	.005	.416	.004	.442
College	.011	.12	.011	.132	.011	.116	.002	.819	.001	.875	.002	.843

Notes: The statistic (*Stat.*) reported in the balancing exercises is E(PAC=1) - E(PAC=0), that is, the difference in means between the treatment and the control groups. Baseline characteristics include student demographics and Mother's and father's education. Student demographics are *Female* (a dummy variable that takes value one if the student is a female and zero otherwise), *Low income* (a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country), *Nuclear, Extended,* and *Other* family (three dummies that indicate the family structure of the student), and *Nbr years failed* (a count variable that captures the number of primary school years the student had to retake previous to the forth grade). Mother's and father's education refer to the highest education level reached by the student's mother and father. These include *No education*, *Incomplete primary*, *Primary*, *Incomplete high school*, *High school*, *Incomplete college*, and *college.*

Table A7: Percent of schools by Socio Economic Status (SES)

	All Chilean schools		PAC eligible schools		PAC eligible schools excluding CLASS sample	
SES	2011	2012	Treatment	Control	Treatment	Control
Low	29	31	16.7	16.4	16.5	15.2
Medium-low	35	32	60.2	66.7	59.7	68
Medium	21	22	22.8	16.9	23.4	16.8
Medium-high	9	10	0.31	0	0.34	0
High	5	6	0	0	0	0
N	7740	7742	648	195	581	125

Notes: PAC stands for *Plan Apoyo Compartido.PAC eligible schools* refers to schools that were eligble to participate in the randomization. *Treatment* refers to schools randomly assigned to receive PAC and *Control* refers to schools randomly assigned not to receive PAC. *SES* variables refer to the school Socio Economic Status as described in this section 4.

Appendix C Compliance rates including all PAC schools

Table A8: Randomization and implementation, school level

		All schools		2011 sample		2012 sample	
		Implemented PAC					
		No	Yes	No	Yes	No	Yes
Randomized into PAC	No	176	19	194	0	176	19
	Yes	149	499	155	492	179	465

Notes: PAC stands for *Plan Apoyo Compartido*. *All schools* refers to the 843 schools that were considered eligible by the program and considered in the program evaluation at some point. The *2011 sample* consists of the 841 schools that were originally included in the program evaluation sample. The *2012 sample* consists of the 839 schools that remained in the program evaluation sample in the second year. *Implemented PAC* is a dummy variable that takes value one if the school participated in PAC and zero otherwise. *Randomized into PAC* is a dummy variable that takes value one if the school that randomly assigned to the treatment group and zero otherwise.

Table A9: First stage. Dependent variable: Implemented PAC.

	2011				
	All	**Girls**		**Boys**	
		Low Income	**High Income**	**Low Income**	**High Income**
	(1)	(2)	(3)	(4)	(5)
Randomized into PAC	0.761***	0.775***	0.721***	0.769***	0.745***
	[.734;.788]	[.746;.803]	[.68;.761]	[.707;.782]	[.74;.797]
Observations	31384	10938	2330	11492	2581
	2012				
	All	**Girls**		**Boys**	
		Low Income	**High Income**	**Low Income**	**High Income**
	(7)	(8)	(9)	(10)	(11)
Randomized into PAC	0.624***	0.634***	0.611***	0.636***	0.629***
	[.577;.668]	[.586;.679]	[.555;.663]	[.575;.681]	[.585;.687]
Observations	35835	10479	2587	10709	3043

Notes: PAC stands for *Plan Apoyo Compartido*. The dependent variable is *Implemented PAC*, a dummy variable that takes value one if the student attends a school that participated in PAC and zero otherwise. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *All* refers to all students pooled together. *Low Income* is a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country. *High Income* is a dummy that takes value one if *Low Income*= 0. 95% bootstrapped confidence intervals are shown in brackets. ***Variable significant at the 1% level. Clustering at the school level.

Appendix D The impact of participating in CLASS on SIMCE

Table A10: Impact of participation in CLASS on SIMCE 2012

	PAC control group			**PAC treatment group**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
In CLASS sample	.229	.18	.206	-.043	-.014	-.024
	[.14;.33]	[.08;.3]	[.11;.32]	[-.14;.06]	[-.12;.1]	[-.12;.07]
Not in CLASS Mean	242.416	236.65	232.72	248.774	241.99	237.227
Not in CLASS SD	50.941	47.259	45.799	51.551	49.13	46.173
Number of Clusters	195	195	195	644	644	644
Observations	7141	7095	7105	23353	23273	23226

Notes: PAC stands for *Plan Apoyo Compartido*. *In CLASS sample* is a dummy variable that takes value one if the student attends a school that was randomized into the CLASS intervention and zero otherwise. The effects shown are in units of the *Not in CLASS sample* standard deviation. 95% bootstrapped confidence intervals are shown in brackets.

Appendix E Main results including all PAC schools

E.1 Overall effects

Table A11: Impact of PAC on SIMCE 2011 and 2012

	Intention to treat effect (ITT)					
	2011			2012-including contaminated schools		
	(1) Reading	(2) Math	(3) Science	(4) Reading	(5) Math	(6) Science
Randomized into PAC	.095	.068	.033	.04	.051	.012
	[.04;.15]	[.01;.13]	[-.03;.09]	[-.01;.09]	[-.01;.11]	[-.04;.07]
	(.01)	(.13)	(.34)	(.32)	(.27)	(.72)
Control Group Mean	244.787	235.756	236.836	245.937	239.432	235.461
Control Group SD	49.97	47.103	44.09	51.055	47.326	46.527
Number of Clusters	840	841	841	839	839	839
Observations	30736	30731	30765	30494	30368	30331
	Instrumental Variables					
	2011			**2012-including contaminated schools**		
	(7) Reading	(8) Math	(9) Science	(10) Reading	(11) Math	(12) Science
Implemented PAC	.125	.089	.044	.064	.081	.019
	[.05;.2]	[.01;.17]	[-.04;.12]	[-.02;.15]	[-.01;.18]	[-.06;.11]
	(.01)	(.13)	(.34)	(.32)	(.27)	(.72)
Control Group Mean	244.787	235.756	236.836	245.937	239.432	235.461
Control Group SD	49.97	47.103	44.09	51.055	47.326	46.527
Number of Clusters	840	841	841	839	839	839
Observations	30736	30731	30765	30494	30368	30331

Notes: PAC stands for *Plan Apoyo Compartido*. *Implemented PAC* is a dummy variable that takes value one if the student attends a school that participated in PAC and zero otherwise. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. The effects shown are in units of the control group standard deviation. 95% bootstrapped confidence intervals are shown in brackets. All 6 impacts in each panel are tested jointly to control for the Familywise Error Rate using the Romano-Wolf step down method. Romano-Wolf step down p-values from the two sided test are shown in parenthesis. Clustering at the school level. In the second panel the instrument is *Randomized into PAC*.

E.2 2012 results by school SES

Table A12: Impact of PAC on SIMCE 2012-including contaminated schools (ITT parameter), by school socio economic status

	Low SES			Medium SES		
	(7) Reading	(8) Math	(9) Science	(10) Reading	(11) Math	(12) Science
Randomized into PAC	.021	.022	-.013	.094	.158	.075
	[-.04;.08]	[-.04;.09]	[-.07;.05]	[-.02;.2]	[0;.31]	[-.05;.19]
	(.78)	(.78)	(.78)	(.5)	(.29)	(.64)
Control Group Mean	244.809	238.789	234.125	252.828	243.391	243.702
Control Group SD	51.155	47.545	46.651	49.913	45.774	44.906
Number of Clusters	681	681	681	158	158	158
Observations	24097	23976	23951	6397	6392	6380

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *SES* variables refer to the school Socio Economic Status as described in section 4. The effects shown are in units of the control group standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. All outcomes in this table are tested jointly to control for the Familywise Error Rate using the Romano-Wolf step down method. The resulting step down p-values from the two sided tests are shown in parenthesis. Clustering at the school level.

E.3 2012 results by gender and income

Table A13: Impact of PAC on SIMCE 2012-including contaminated schools (ITT parameter), by students' gender and income

	Girls					
	Low Income			**High Income**		
	(1) Reading	(2) Math	(3) Science	(4) Reading	(5) Math	(6) Science
Randomized into PAC	.039	.068	.025	.208	.117	.075
	[-.03;.11]	[0;.15]	[-.04;.1]	[.09;.32]	[0;.24]	[-.03;.18]
	(.80)	(.57)	(.87)	(.01)	(.45)	(.74)
Control Group Mean	251.989	236.495	232.941	256.406	244.927	242.931
Control Group SD	49.769	46.37	44.465	49.098	47.692	46.727
Number of Clusters	800	800	826	680	679	679
Observations	10030	10005	9973	2533	2522	2520
	Boys					
	Low Income			**High Income**		
	(7) Reading	(8) Math	(9) Science	(10) Reading	(11) Math	(12) Science
Randomized into PAC	.046	.072	.031	.026	.107	.013
	[-.02;.11]	[0;.15]	[-.03;.1]	[-.06;.12]	[.01;.2]	[-.08;.1]
	(.74)	(.47)	(.87)	(.87)	(.45)	(.87)
Control Group Mean	239.601	240.548	235.503	250.521	247.172	246.618
Control Group SD	51.678	47.936	48.001	51.718	47.433	46.927
Number of Clusters	803	803	803	693	696	693
Observations	10235	10191	10182	2950	2946	2930

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *Low Income* is a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country. *High Income* is a dummy that takes value one if *Low Income*= 0. The effects shown are in units of the control group standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. All outputs in this table are tested jointly to control for the Familywise Error Rate using the Romano-Wolf step down method. Romano-Wolf step down p-values from the two sided test are shown in parenthesis. Clustering at the school level.

Appendix F Main results with covariates

Table A14: Impact of PAC on SIMCE 2011 and 2012

	Intention to treat effect (ITT)					
	2011			2012		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.089	.059	.019	.112	.107	.076
	[.04;.14]	[0;.12]	[-.03;.08]	[.06;.17]	[.04;.18]	[.02;.14]
	(.02)	(.13)	(.57)	(.01)	(.04)	(.06)
Control Group Mean	244.787	235.756	236.836	242.416	236.65	232.72
Control Group SD	49.97	47.103	44.09	50.941	47.259	45.799
Number of Clusters	838	838	838	680	680	680
Observations	25894	25923	25949	20076	20168	20117
	Instrumental Variables					
	2011			2012		
	(7)	(8)	(9)	(10)	(11)	(12)
	Reading	Math	Science	Reading	Math	Science
Implemented PAC	.116	.077	.025	.172	.164	.117
	[.05;.18]	[0;.15]	[-.05;.1]	[.09;.26]	[.06;.28]	[.04;.21]
	(.03)	(.14)	(.57)	(.01)	(.05)	(.07)
Control Group Mean	244.787	235.756	236.836	242.416	236.65	232.72
Control Group SD	49.97	47.103	44.09	50.941	47.259	45.799
Number of Clusters	838	838	838	680	680	680
Observations	25894	25923	25949	20076	20168	20117

Notes: PAC stands for *Plan Apoyo Compartido*. *Implemented PAC* is a dummy variable that takes value one if the student attends a school that participated in PAC and zero otherwise. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. The effects shown are in units of the control group standard deviation. 95% bootstrapped confidence intervals are shown in brackets. In each panel, all 6 impacts are tested jointly to control for the Familywise Error Rate using the Romano-Wolf step down method. Romano-Wolf step down p-values from the two sided test are shown in parenthesis. All regressions include covariates: whether the students lives in a household with at least one parent and/or siblings; whether the student lives in a household with members of the extended family; the number of times the student failed a school year; mother's education: dummies for "no education", "inc primary", "primary", "inc high school", "high school", "some college", "college +"; father's education (same dummies as mother education). Clustering at the school level. In the second panel the instrument is *Randomized into PAC*. The 2012 sample excludes schools that implemented CLASS.

Table A15: Impact of PAC on SIMCE (ITT parameter), by school socio economic status, with cohort fixed effects

	Low SES			**Medium SES**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.073	.044	.005	.204	.238	.202
	[.03;.12]	[-.01;.1]	[-.05;.06]	[.1;.31]	[.12;.35]	[.11;.3]
	(.02)	(.31)	(.90)	(.01)	(.01)	(.01)
Control Group Mean	243.044	235.821	234.498	248.372	237.838	239.143
Control Group SD	50.123	47.287	44.845	51.608	46.427	44.543
Number of Clusters	706	706	706	194	194	194
Observations	35616	35701	35684	10293	10329	10321

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *SES* variables refer to the school Socio Economic Status as described in section 4. The effects shown are in units of the control group standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. All outcomes in this table are tested jointly to control for the Familywise Error Rate using the Romano-Wolf step down method. The resulting step down p-values from the two sided tests are shown in parenthesis. All regressions include cohort fixed effects. All regressions include covariates: whether the students lives in a household with at least one parent and/or siblings; whether the student lives in a household with members of the extended family; the number of times the student failed a school year; mother's education: dummies for "no education", "inc primary", "primary", "inc high school", "high school", "some college", "college +"; father's education (same dummies as mother education). Clustering at the school level. The 2012 sample excludes schools that implemented CLASS.

Table A16: Impact of PAC on SIMCE (ITT parameter), by students' gender and income, with cohort fixed effects

	Girls					
	Low Income			**High Income**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.077	.065	.04	.158	.057	.022
	[.03;.13]	[0;.13]	[-.02;.09]	[.06;.25]	[-.04;.16]	[-.07;.11]
	(.08)	(.35)	(.62)	(.04)	(.62)	(.68)
Control Group Mean	250.338	233.869	232.225	253.927	242.733	242.244
Control Group SD	48.325	45.616	43.008	49.22	46.437	45.884
Number of Clusters	834	834	834	757	757	756
Observations	17603	17624	17589	4254	4243	4252
	Boys					
	Low Income			**High Income**		
	(7)	(8)	(9)	(10)	(11)	(12)
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.089	.068	.04	.116	.156	.058
	[.04;.14]	[0;.13]	[-.02;.1]	[.05;.19]	[.07;.24]	[-.02;.14]
	(.04)	(.35)	(.62)	(.05)	(.02)	(.62)
Control Group Mean	239.1	238.095	237.453	246.745	243.962	246.087
Control Group SD	51.182	48.044	45.424	52.926	48.676	46.585
Number of Clusters	836	836	836	773	774	774
Observations 18217	18204	18221	4825	4830	4810	

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *Low Income* is a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country. *High Income* is a dummy that takes value one if *Low Income*= 0. The effects shown are in units of the control group standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. All outcomes in this table are tested jointly to control for the Familywise Error Rate using the Romano-Wolf step down method. The resulting step down p-values from the two sided test are shown in parenthesis. All regressions include cohort fixed effects. All regressions include covariates: whether the students lives in a household with at least one parent and/or siblings; whether the student lives in a household with members of the extended family; the number of times the student failed a school year; mother's education: dummies for "no education", "inc primary", "primary", "inc high school", "high school", "some college", "college +"; father's education (same dummies as mother education). Clustering at the school level. The 2012 sample excludes schools that implemented CLASS.

Appendix G Results by gender and income (separately)

Table A17: Impact of PAC on SIMCE by gender, with cohort fixed effects

	Girls			Boys		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.109	.077	.058	.108	.097	.057
	[.06;.16]	[.02;.13]	[0;.11]	[.06;.16]	[.04;.16]	[0;.11]
	(.01)	(.08)	(.12)	(.01)	(.02)	(.12)
Control Group Mean	249.751	234.539	233.059	239.225	238.243	237.943
Control Group SD	48.659	45.635	43.42	51.38	48.142	45.678
Number of Clusters	835	836	836	837	838	838
Observations	26068	26045	26006	28101	27953	27954

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. The effects shown are in units of the control group standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. RW step down p-values allowing for all 6 hypotheses from the two sided tests are shown in parenthesis. All regressions include cohort fixed effects. Clustering at the school level. Schools that implemented CLASS are excluded from the 2012 sample.

Table A18: Impact of PAC on SIMCE by family income, with cohort fixed effects

	Low income			High income		
	(1)	(2)	(3)	(4)	(5)	(6)
	Reading	Math	Science	Reading	Math	Science
Randomized into PAC	.089	.074	.044	.167	.143	.071
	[.04;.14]	[.01;.13]	[-.01;.09]	[.11;.23]	[.07;.21]	[0;.14]
	(.01)	(.08)	(.18)	(.01)	(.01)	(.18)
Control Group Mean	244.302	235.801	234.677	249.877	243.23	244.358
Control Group SD	50.17	46.92	44.319	51.423	47.994	46.75
Number of Clusters	842	842	842	823	824	824
Observations	39879	39985	39961	9801	9819	9806

Notes: PAC stands for *Plan Apoyo Compartido*. *Randomized into PAC* is a dummy variable that takes value one if the student attends a school that was randomly assigned to the treatment group and zero otherwise. *Low Income* is a dummy variable that takes value one if the student's family monthly income is less than 300,000 Chilean pesos, the minimum wage in such country. *High Income* is a dummy that takes value one if *Low Income*= 0. The effects shown are in units of the control group standard deviation (SD). 95% bootstrapped confidence intervals are shown in brackets. RW step down p-values allowing for all 6 hypotheses from the two sided tests are shown in parenthesis. All regressions include cohort fixed effects. Clustering at the school level. Schools that implemented CLASS are excluded from the 2012 sample.