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After-School Effects on Students' Academic Outcomes: Evidence from Chile

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Abstract

After-school care policies have been considered as a tool that can improve vulnerable students' outcomes. The evidence of after-school programs is incomplete and concentrated in developed countries. In this paper, we experimentally evaluate the impact of a publicly run after-school program in Chile. We found that the program had on average no effect upon academic outcomes (school attendance and grades). However, if the after-school programs are of good quality and replace other forms of non-paternal care, they positively affect grades, increasing the average GPA in 0.8-1 decimals and the probability of having a GPA above the median in around 10 pp. This evidence suggests that the program's impacts on children are determined both by the quality of institutionalized care and the nature of the alternative care available to them.

Keywords: Childcare; randomized control trial; after-school programs

JEL Codes: J13, I25

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1. Introduction

In an effort to increase the quality of education and/or to improve female access to the labor market, childcare policies have been implemented in several countries, raising global gross enrollment ratio (GER) for pre-primary education all over the world, from 33% in 1999 to 54% in 2012 (Shaeffer, 2015). However, ever since the seminal paper of Baker et al (2008) —which found that a universal subsidized childcare in Quebec for children younger than five years old had a negative impact on their socio-emotional and health outcomes— there has been a concern that childcare could have a positive impact on female labor force participation, but a negative effect on their children's development. This potential tradeoff has usually been studied separately, with a strand of the literature focused on the effects childcare programs have on children (Havnes and Mogstadd (2011, 2015), Cornelissen et al (2017) for example), and another one focused on their impact on the labor market (Gelbach, 2002; Lefebvre and Merrigan, 2008; Cascio 2009 for example).

The effect of childcare on children's outcomes has been intensively studied in infants and to a lesser extent in older children. The evidence regarding early childhood is not conclusive, but the quality of care and alternative care seems to be pivotal. For example, Bernal and Keane (2011) find a negative impact of informal childcare on children's cognitive outcomes, but not so of formal center-based care. Furthermore, Cascio and Schanzenbach (2013). Corneliseen et al (2017), and Havnes and Mogstad (2011, 2015) find that childcare access has greater impact on children of low-income families.

Increase in supervised time for school-age children has been studied typically in the form of more instructional time (more days of school per year or more school hours each day) and in after-school programs (ASP). In the first case, extra hours or days are devoted to academic activities. In the case of ASP, the extra hours are generally spent on more playful activities, such as arts, sports and games. This literature also overlaps with studies considering the effects of remedial academic programs (for disadvantaged kids) or programs whose only focus is to prevent risky behavior. The impact of having longer school days (more hours per day) has been studied in developing countries, finding a decrease in teen pregnancy (Berthelon and Kruger, 2011 for Chile), and improvements in both reading and math scores (Bellei, 2009; Berthelon et al, 2016, both for Chile; Hincapie, 2016 for Colombia; Cerdan, 2007 for Uruguay), especially among children from poorer backgrounds. In developed countries, longer school days also had a positive impact on college matriculation rates (Lavy and Scholoser, 2005) and performance in math, English and science (Lavy, 2012) in Israel and had large returns on math scores in Denmark (Jensen, 2013). In Italy, Battistin and Meroni (2015) also found that increasing instruction time has a positive impact on math scores, especially among poorer students.

ASPs are structured programs that are run under adult supervision in schools throughout the academic year. They usually include a variety of activities, such as homework, social interaction, snacks, sports, crafts, etc. Impact evaluations of ASP programs are scarce in developing countries. The evidence in developed countries is mixed (Goerlich et al., 2007, Kremer et al., 2015), but suggests that students at risk benefit from ASPs the most (Levine and Zimmerman, 2010). It also seems relevant to consider the alternative care children would have in the absence of an ASP program. The lower the quality of the alternative care, the greater the program's impact (Felfe and Zierow, 2012).

In this paper, we report the effects of an after-school program on students' academic outcomes in a developing country. The program was implemented in Chile, and consisted of three hours of care after school for children aged between 6 and 13. The intervention provided children recreational activities, time for homework and a snack. There was no direct support for academic activities. We randomly assigned applicants (mothers) to the program and reported the labor market effects in Martínez A. and Perticará (2017), finding that the program increased female employment and labor force participation. In this paper, we use the same variation to identify the program's impact on students' academic outcomes.

On average, ASPs had no impact on students' school attendance, and only a small positive effect on grades for physical education. As the literature reports that alternative care interacts with the effects of ASPs, we studied the effects in children who had been using childcare at baseline before the ASP program started. Consistent with previous the literature, we found that, for those children, the program increased grades (art, physical education and average GPA) and the probability of being above the median of grade distribution. Furthermore, we also studied the heterogeneity in the program's implementation and location (whether the program is given in the same school the child attends), and found positive impacts when the quality of the program was better and its location more convenient.

Our research offers two main contributions to the literature. On one hand, we are able to measure the causal effect of an ASP on academic outcomes using an RCT. As far as we know, this is the first evaluation of this kind of program with RCT methodology in a developing country. We found that the program's effects depend on the quality of the ASP and the alternative care available to students. On the other hand, we are able to shed light on the mechanism underlying this result. As was reported in Martínez and Perticará (2017), the program increases female employment, and therefore it is not clear what drives the students' outcomes Better grades can be related to better care or could also be indirectly linked to increasing family disposable income (Bernal (2008), Bernal and Keane (2010), Bernal and Keane (2011), Brilli (2014), Black et al (2014)). Our results suggest that the driving mechanism is the provision of formal care as opposed to informal care.

In the following sections, we will describe the interventions and the experimental design, data description, empirical strategy, results and conclusions.

2. The Intervention and Experimental Design

2.1 The Intervention

The "4-to-7" ASP program's objective was to increase the labor force participation of mothers or women responsible for taking care of children aged between 6 and 13, by providing playful activities in after-school hours during the academic year.

The ASP is run by the Ministry of Women and Gender Equity. The Ministry implemented the program in municipalities where a high demand was expected due to the number of children aged 6-13 and female labor force participation. Schools apply for hosting the program through their municipality, and are selected based on three criteria: whether they have an adequate infrastructure, whether they have other ASP programs, and, if possible, whether their SIMCE score had improved.

Mothers apply for the program through the schools. The eligibility requirements are all related to mother's characteristics: being economically active, older than 18 years old, working or living in the municipality where the participating school is located, and scoring low in the socioeconomic targeting scale. Funds are transferred to the municipalities, which then select the managing organizations (ONGs) through a bidding process. Most programs were open to children from schools other than the host.

The Ministry set up the terms of reference that established the minimum features of the ASP. The program was set up in each school with a maximum of 50 or 100 beneficiaries, where the number of slots was defined *ex ante* based on potential demand. Each program had a coordinator. Programs with 50 students must have two monitors, and programs with 100 students must have five. Coordinators were required to have formal training in the areas of education, psychology or business. It was recommended that monitors should be teachers of the implementing school. However, this was the case only in 85% of the monitors in our sample. Instructors were professionals or higher-education students in the areas of education, sports, arts, etc. 77.3% of the participating schools were assigned 50 slots, and the remaining 22.7% 100 slots.

The intervention consisted of three hours of after-school care during the school week. As the schools did not have the same daily schedule, the program's times varied across schools. However, most schools in the evaluation (18 out of 25) offered the program from 4 to 7 pm[2].

As specified in the terms of reference, the program should follow the following schedule: arrival (10 minutes), motivation (20 minutes), school-work support (30 minutes), a recess where a snack was provided (30 minutes), and a thematic workshop (90 minutes). School-work support was structured to help students with their homework, teach them study methods and reinforce lessons. Thematic workshops were related to art, sports or TICs. Each ASP program decided which thematic workshops were to be implemented, based on the students' interest and age. The most common were those related to arts (crafts, theater, dance, music, cinema, circus), followed by TICs and sports.

Concurrently with the impact evaluation, an independent process evaluation was performed in 22 out of the 25 schools participating in the study. Each ASP program was visited twice, with the purpose of documenting its implementation. The number of monitors required by

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[2] Only one school offered the program during the morning. In the rest of the schools, the program was run in the afternoon, the starting time varying from 2 pm to 5 pm.

protocols was met in 72.7% of the schools. The figure rose to 94% in schools which had been assigned 50 slots. Attendance was low, reaching an average of 17.5 students. Considering the low attendance rate, the ratio of monitors to students was higher than what was recommended in the program's terms of reference.

2.2 Experimental Design

The impact evaluation took place in 25 schools where the program was implemented for the first time in 2012. Mothers or legal guardians of 6-13 year-old children were invited to apply for the ASP. In order to do so, they were required to fill out an application form, specifying how many children were to attend and some demographic and schooling data. Women were also asked to answer a full questionnaire concerning their individual and family labor and socioeconomic characteristics.

As all schools were overenrolled, we randomized available spots. The unit of randomization was the mother, so that, if a woman was offered a spot in the program, all the children reported in her application form got an invitation to attend the ASP. This has to be done in order to abide by the main objective of the program, which as to help women find employment. For each available slot we had 1.7 applicants (mothers). Randomization was stratified considering the mothers' baseline work status and whether they had small children (younger than five). The offering process was done by the implementing agency.[3]

3. Data and Descriptive Statistics

3.1 Data

We used the administrative data provided by the Ministry of Education on attendance and grades in the implementing year. All outcome variables come from these data, and therefore are limited to the students' academic achievements. Monthly attendance is reported by the Ministry of Education as the fraction of the monthly school days each child attended. Grades are reported as end of the year average by subject and overall GPA.

These administrative data are merged with the experimental data (treatment assignment, strata and baseline characteristics), and self-reported information on baseline childcare use provided by mothers in the ASP application form. It is also merged with a follow-up household survey with the sole purpose of use reported program take-up. Finally, we also merged in data from the process evaluation, to measure the program's quality.

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[3] It is important to mention that, as participating schools were not random, external validity could not be guaranteed. However, in our companion paper we report that there were no observable differences in school size, vulnerability, or in the mother's and children's characteristics in comparable schools.

Although the implementing agencies were required to collect attendance data for the ASP, this was not strictly enforced, and the collected data was unreliable. Therefore, we do not use this attendance rate in our impact analysis.

3.2 Baseline Characteristics and Balance

Table 1 presents the data on the outcome of the randomization process. The original sample of eligible children at baseline consisted of 1,358 children in the treatment group and 1,208 in the control group. Twenty-five percent of the children in the control group attended the program (as reported by their mothers); in the treatment group, this figure was 57% (column (4)). The low take-up decreased the power of the experiment, limiting therefore the probability of finding effects.

Descriptive statistics and balance are reported in Table 2. Panel A reports children's characteristics, panel B their mothers'. For each variable, we show the sample mean, standard deviation and number of observations at baseline (columns [1]-[3]), the treatment and control mean (columns [4] and [5]), and the p-value of the null that the treatment and control group means are equal (column [6]) [4].

Students were on average 9.7 years old and in 4th grade; 47% of them were female. Only 52% of the students were offered the ASP in their own school. Their average grade in the

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[4] Note that some of these variables are missing in some observations. For this reason, the sample size varies in each row of the table.

previous academic year was 5.6 (grades in Chile range between 1-7, with 4 being the minimum required for a pass), and their average attendance 89% (85% being required to pass, with some exceptions).

Mothers were on average 37 years old and had 2.2 children. 53% of them were household heads, and 61% were using some kind of childcare at baseline. Their average years of education were 9.4. The *per capita* household income was US$116. Their stress level was 7.1[5]. Finally, 63% of the children were in the stratum characterized by mothers working at baseline and not having children younger than five years old.

The p-values in column [6] show that the groups were balanced in all these variables. Therefore, the randomization could allow us to estimate the causal impact of the program, and it is not necessary to control any of these variables in our regressions.

3.3 Attrition

The two outcome variables (grades and attendance) are compiled in different data sets by the Ministry of Education, and therefore there are different attrition rates. Regarding attendance, we find approximately 93% of students at baseline. The level of attrition is

[5] The stress index is defined according to the Cohen-Kamarck-Mermelstein scale. This was adapted for Chile by Tapia et al. (2007).

higher (almost 11%) for grades in 2012. Hence, the final estimation sample comprised 2284 in the grade data and 2379 children in the attendance data.

We study whether attrition of attendance and grade is correlated with treatment assignment in Table 3. The dependent variable is the probability of being in the administrative data, and the parameters of interest are the coefficients of the treatment variable. Columns [1] and [4] report the correlation of treatment assignment with the probability of being in final regressions (for attendance and grades, respectively) without controls. Column [2] and Column [5] include control variables (child's age, gender and a dummy indicating if they used childcare at baseline, mother's age, education, household head, *per capita* household income and number of children). Finally, in column [3] and [6] we interact them with treatment assignment (not shown). In all cases, the coefficients of treatment assignment are not significant. Furthermore, the full set of interactions is jointly not different from zero. Therefore, there is no differential attrition by treatment arm.

However, we find that the older the children, the more likely they are to have follow-up data on their grades. Although the estimated coefficient is very small, we control age in all our regressions.

4. Results

4. 1 Estimated Equation and Interpretation

Our main equation is as follows:

$$Y_{ij} = \propto_j + \beta T_{ij} + \delta y_{ij,t-1} + \gamma age_{ik} + v_{ij} \ (1)$$

Where i refers to the individual, j to school strata (defined by the mother's working status and whether they have children younger than 5 at baseline). T_{ij} is and indicator of the treatment assignment, $y_{ij,t-1}$ is the lagged value of the dependent variable,age_{ij} is the student's age, and α_j are school-strata fixed effects. Whenever the baseline value of the dependent variable is missing, we impute a zero, and include a dummy indicating if the value was imputed. Standard errors are clustered at school level. β represents the Intent-to-Treat estimate. As there seems to be substantial imperfect compliance, these estimates might differ from the ATE.

To study heterogeneities for a given subgroup, we define a dummy variable $D_{ijk} = 1$ if individual i in school j and strata k belongs to this particular group, zero otherwise[6]. Then we estimate the following equation:

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[6] If the dummy is constant within school strata, the fixed effect captures the level effect of this dummy.

$$Y_{ijk} = \propto_{jk} + \beta T_{ijk} + \theta T_{ijk} * D_{ijk} + \pi D_{ijk} + \delta y_{ijk,t-1} + \gamma X_{ijk} + v_{ijk} \quad (2)$$

where θ represents the heterogeneous impact of the treatment on the sub-group D_i.

4.2 Average Effects

Average effects are presented in Table 4. Panel A shows the effects on attendance- and Panel B on grade-related outcomes, both in the implementing year (2012). Columns [1] and [2] report the program's impact on attendance rate for the period May-November (implementing months) and the probability of passing the 85% attendance rate, respectively. The latter is relevant because 85% is the minimum required for a pass in Chile. We observe that average attendance rates are high (90.7% in 2012,), and that the program had no impact upon any measurement of attendance. Point estimates are positive, but very small in magnitude and not significant.[7]

Regarding academic outcomes (Panel B), the point estimates of the program effects are all positive, but small in magnitude and only significant for grades on physical education. This result is consistent with the program's design, which assigned only 30 minutes for homework , and offered mostly workshops on arts and sports.

[7] We also do not find effects on attendance in 2013, the year after the implementation. Results can be made available upon request.

4.3 Heterogeneous Effects

The literature reports that the ASP program effects depend on the quality of the program, alternative childcare available, and the program activities. We study whether the program's effects depend on who take care of the children at baseline (Table 5) and on the program's quality (Table 6). Following the same structure of Table 4, we first report the impacts on attendance (Panel A), and on academic outcomes (Panel B).

Baseline Childcare

Regarding baseline childcare, mothers reported in the survey who takes care of the child after school. Almost 45% of the children stayed with one of their parents (4.5% with their father and 40% with their mother). Others forms of care included grandmothers (19%), and siblings, neighbors or other family (27%), while 11% were left at home alone. For the purposes of analysis, we defined a variable (non-parental care) that takes the value of 1 if the children used any kind of childcare after school or were left alone at baseline, and of 0 if they were taken care of by their parents.

Table 5, column [1] shows that there is no differential impact on attendance measures. However, the ASP had a positive impact on the grades of students that were not taken care of by their parents at baseline, increasing the overall GPA in almost a decimal (column [9]), the grade in art in 1.4 decimals (column [4]) and the grade in language and literature in 12.8 decimals. The program also increased the probability of being above the median in 7.1

percentage points (column [10]). The coefficients on other grade outcomes were also positive, but not significant. On the other hand, the coefficient of the program's assignment for the base category (parental care at baseline) is insignificant in all grades outcomes, but always negative, suggesting that substituting institutional care for parental care does not necessarily improve children's outcomes. But substituting it for informal care does have a positive impact on children's academic performance.

As all reported results correspond to ITT, it is relevant to look at the program's take-up in these two groups. Although take-up is slightly higher in children with non-parental care at baseline (what is consistent with families substituting the ASP for other forms of childcare), the difference is not statistically different from zero (Table 5, column [1]). Therefore, results are not mechanically driven by differences in use, but could be driven by differences in care quality.

We should also note that, as the program substitutes better childcare for a potentially low-quality one, different types of childcare at baseline (grandparents, other adults, siblings, etc.) could drive heterogeneous program effects. Table A-1 explores whether there are further heterogeneities associated with the quality of childcare at baseline, showing that positive effects in Table 5 are mostly observed in children that are either left alone at home or placed under the care of another adult (relatives and non-relatives). In fact, the greater effects are for children left alone, which could be related to the fact that the program provides them with a safe environment. For these children, there is also a strong impact (3.3 pp) on attendance rates, suggesting that the program might have had a deterring effect on absenteeism. This effect is relatively large, considering that attendance rates are high (around 91% for the control group). Again, although take-up is higher for some of these groups with different types of childcare at baseline, all these coefficients are not statistically different from zero.

Program Quality

The quality of the program also plays an important role when considering its potential impact, since what matters is how good the program is in relation to alternative care. In Table 6, we report the impact of high-quality programs, where quality was measured by an index that captures quality of infrastructure, teachers, materials and children's attitude. The program's quality was measured in the process evaluation. We found that quality does not affect school attendance (Panel A, Table 6). Consistently with the existent literature, when studying the impact on grades, all estimated effects of the interaction of treatment assignment and a high-quality dummy are positive, but are only significant for art (columns 4), for the overall GPA (column 9) and for the probability of being above the median in the grade distribution (column 10). Students in high-quality programs are 10 pp more likely to have a GPA above the median than students in low quality versions of the program. Students in low-quality versions of the program are less likely to have a GPA above the median (5 pp.)[8]. It is important to note that take-up does not differ by quality (around 30.0 pp higher than the control group), and that therefore the effects are again not mechanically driven by differences in use.

5. Discussion

On average, the after-school program had no impact on attendance and grades. However, the impacts are larger (and statistically significant) in better quality programs, and for children who were not taken care of by their parents during the program's hours at baseline.

Moreover, the stronger effects were found in children left alone at home at baseline and in children who were taken care of by non-relative adults. Informal care arrangements for young children are common in Chile, where massive public provision of childcare for small (and vulnerable) children is a relatively recent policy. A common practice is to leave older children with neighbors, extended family or alone at home. Our results show that providing them a safe and fun environment might increase attendance rates and their academic achievements.

Both Table 5 and Table 6 are consistent with the idea that the quality of both the program and the alternative care is what matters to predict the success (in terms of children's

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[8] We reject the view that the overall effect on students attending high-quality programs (of around 5.5 pp) is equal to zero.

outcomes) of an after-school program. In Table A-2, we present heterogeneous effects combining both the quality of the alternative care and the quality of the ASP program. The base category is for children exposed to low-quality programs, who were taken care of by their parents at baseline. From this table it can be seen that providing children with a low quality ASP program and replacing parental care always negatively affects their performance. All the coefficients are negative and statistically significant for Art, Math, Science, overall GPA and for the probability of being above the median of the grade distribution. For all the other three groups (children with parental care at baseline but in high quality programs, or children with non-parental care at both low-quality and high-quality programs) the impact of the program is positive and statistically different from zero for Art, overall GPA and the probability of being over the median. In fact, for kids with non-parental care at baseline placed in high-quality programs, the ASP program has a positive effect for all the outcomes considered.

The perception of the quality of the program might also matter. During the program's process evaluation, it was reported in several focus groups that mothers felt more comfortable sending their children to ASPs when the program was given in the same school attended by their children. Therefore, we could expect higher take-up and attendance rates in these cases[9]. In Table 7, we can see that take-up rates were much higher for kids that

[9] At the same time, the program did not provide transportation to the program's site, which could also have affected attendance and take-up rates.

attended ASPs and their regular classes at the same school. The program also has some effect on these kids' attendance outcomes. For example, offering the program in the same school where the kid attended increased the attendance rate in 2012 by 1.6 percentage points. The effects on grades were also positive, but only significant for physical education (column 5), overall GPA (column 9) and on the probability of being above the median (8.7 pp.).

As the program also increases female employment (Martínez A. and Perticará, 2017), one wonders what drives students' outcomes. The program can have a direct effect on their grades through the curriculum, providing better care than the alternative available to them. The effect could also be indirect by increasing the family disposable income through female employment and decreasing childcare cost.

Although the research design does not allow us to disentangle these mechanisms, we can shed light on them analyzing the program's impact in different groups. We do find that neither the type of childcare at baseline nor the quality of the program had any heterogeneous impact on the mothers' employment outcomes. Given that, it is precisely in these two groups where we find the stronger effects of the program, we interpret this as evidence that the driving mechanism is the provision of formal care as opposed to informal care.

4. Conclusions

We studied the impact of an after-school program on children's academic outcomes in Chile using an experimental strategy. We found that the program had no average impact on academic outcomes.

However, we do have compelling evidence that both the quality of the program and the quality of alternative care matters. The most robust results were found in art grades, overall GPA and the probability of being above the median of the grade distribution. The stronger effects for all outcomes were observed in children attending high-quality programs, who were placed at informal care arrangements at baseline. On the other hand, children with parental care at baseline, who were placed in low-quality programs, suffered adverse effects. For this group, the impact of the program was negative and statistically significant for all outcomes.

Overall, we do not find that take-up rates differ across these groups. Therefore, our results are not automatically driven by differences in use. But the program effects could be mitigated by the low take-up rates. Any attempt to escalate the program should change the program design to encourage its use and allow mothers more flexibility. At the same time, efforts should be made to increase and homogenize program's quality. Consistently with what has been found in developed countries, quality is the key ingredient for success in any childcare program.

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Table 1: Compliance Rates

	Base Line	In follow-up	Participating	Participation Rate
	[1]	[2]	[3]	[4]=[3]/[2]
Control	1.208	1.073	267	0,25
Treatment	1.358	1.184	668	0,56
Total	2.566	2.257	935	

Note: Columns [1] and [2] indicate the number of applicants who were surveyed at baseline and follow-up. Column [3] presents the number of applicants who reported having participated in the program (take-up).

Table 2: Balance between treatment and control group at baseline

	Average	SD	Nº	Treatment	Control	P-value T=C
Variables	[1]	[2]	[3]	[4]	[5]	[6]
Age	9,72	2,26	2566	9,76	9,68	0.424
Female	0,47	0,50	2566	0,47	0,47	0.352
Grade	4,04	2,03	2557	4,06	4,03	0.775
=1 if s/he attends the school where the program takes place	0,52	0,50	2566	0,5	0,53	0.553
GPA (previous year)	5,59	0,65	2014	5,58	5,6	0.564
GPA (previous year) is missing	0,22	0,41	2566	0,22	0,21	0.671
Attendance rate (previous year)	0,89	0,13	2379	0,89	0,89	0.351
Attendance rate (previous year) is missing	0,07	0,26	2566	0,07	0,07	0.911
				Panel B: Mothers		
Age	36,89	8,55	2561	36,92	36,87	0.821
=1 if she is household head	0,53	0,50	2566	0,52	0,54	0.867
# of children	2,19	1,16	2566	2,19	2,18	0.950
=1 if she uses childcare at baseline	0,61	0,49	2105	0,60	0,63	0.732
Years of education	9,37	3,22	2482	9,35	9,39	0.822
Per capita income of household (US$)	116	86	2544	117	116	0.287
Stress Index	7,10	3,88	2382	7,24	6,96	0.702
Works and has children <5 years old	0,20	0,40	2566	0,20	0,20	0.246
Does not work and has children <5 years old	0,06	0,23	2566	0,06	0,06	0.679
Works and has children >5 years old	0,63	0,48	2566	0,63	0,62	0.343
Does not work and has children >5 years old	0,11	0,32	2566	0,11	0,12	0.680

Note: Baseline survey data collected from March to May 2012. The sample size varies according to the amount of data without observation for each variable. The income variable is measured in US dollars (march 2013). Columns [1], [2] and [3] show the variable mean for the total of the sample, the standard deviation and the number of observations, respectively. Column [4] and [5] show the variable mean for the treatment and control group, respectively. Column [6] the p-value of the null hypothesis that Treatment=Control.

Table 3: Attrition and Base Line Characteristics

	In final regressions (attendance)			In final regressions (grades)		
	[1]	[2]	[3]	[4]	[5]	[6]
Treatment	-0.001	-0.005	0.030	-0.008	-0.008	-0.086
	(0.012)	(0.011)	(0.053)	(0.012)	(0.011)	(0.072)
Child's gender		-0.008	-0.018		-0.010	-0.004
		(0.013)	(0.017)		(0.015)	(0.024)
Chid's age		0.004	0.005		0.017***	0.012***
		(0.003)	(0.003)		(0.003)	(0.004)
Mother's Age		-0.002*	-0.002		-0.002	-0.001
		(0.001)	(0.002)		(0.001)	(0.002)
Household Head		-0.002	0.009		-0.020	-0.017
		(0.016)	(0.019)		(0.015)	(0.023)
Number of children		-0.005	-0.010		-0.012	-0.017
		(0.008)	(0.010)		(0.010)	(0.021)
Used childcare at baseline		-0.008	0.002		0.000	-0.001
		(0.017)	(0.017)		(0.019)	(0.027)
Per capita household income		-0.000	-0.000		-0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Constant		1.005***	0.994***		0.855***	0.898***
		(0.073)	(0.084)		(0.075)	(0.106)
Observations		2,014	2,014		2,014	2,014
R-squared	0	0.135	0.136		0.125	0.126
F-test: all interactions with treatment are zero (p-value)			0.552			0.320
Specification	No controls	Controls	Controls and interactions of controls and treatment variable	No controls	Controls	Controls and interactions of controls and treatment variable

Note: The dependent variable takes a value of 1 if the individual was found on either attendance data (columns [1]-[3]) or grades data (columns [4]-[6]). The sample are all students participating in the study (with baseline). The sample size varies according to the missing covariate data. Standard error in brackets. *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 4: Intent-to-Treat Effects in Attendance and Grade (2012)

	Panel A: Attendance		Panel B: Grades						
	Attendance rate May-November	=1 if attendance rate is >0.85	Art	Physical Education	Language and Literature	Math	Science	GPA	=1 if above the median
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Treatment	0.006	0.024	0.043	0.055**	0.010	0.030	0.012	0.020	0.016
	(0.005)	(0.016)	(0.029)	(0.026)	(0.032)	(0.032)	(0.027)	(0.022)	(0.023)
Observations	2,379	2,379	2,280	2,277	2,280	2,280	2,280	2,284	2,284
R-squared	0.276	0.186	0.309	0.276	0.372	0.348	0.396	0.488	0.359
Control group mean	0.907	0.840	5.926	6.250	5.134	5.149	5.231	5.532	0.494

Note: Columns [1] - [9] report the intent-to-treat (ITT) estimates and standard errors (in parentheses) of program assignment. The sample size varies according to the number of observations with missing values in the respective outcome variable. All regressions include school-strata fixed effects and control for age. Cluster standard errors at school level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Heterogeneous Effects by Childcare Use at Baseline (2012)

	First Stage Program Participation	Panel A: Attendance		Panel B: Grades						
		Attendance rate May-November	=1 if attendance rate is >0.85	Art	Physical Education	Language and Literature	Math	Science	GPA 2012	=1 if above the median
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Treatment	0.259***	-0.001	0.010	-0.030	-0.014	-0.076	-0.029	-0.051	-0.050	-0.032
	(0.056)	(0.006)	(0.022)	(0.052)	(0.045)	(0.050)	(0.069)	(0.063)	(0.038)	(0.029)
Treatment * Non-parental care at baseline	0.051	0.012	0.030	0.147**	0.100	0.128*	0.073	0.106	0.123**	0.086**
	(0.058)	(0.009)	(0.043)	(0.054)	(0.069)	(0.071)	(0.082)	(0.080)	(0.053)	(0.037)
Observations	2,122	2,379	2,379	2,280	2,277	2,280	2,280	2,280	2,284	2,284
R-squared	0.233	0.277	0.186	0.313	0.280	0.373	0.349	0.398	0.489	0.362
Control group mean	0.253	0.907	0.840	5.926	6.250	5.134	5.149	5.231	5.532	0.494

Note: Columns [2] - [10] report the intent-to-treat (ITT) estimates and standard errors (in parentheses) of program assignment. Column [1] reports the first stage of program participation. The sample size varies according to the number of observations with missing values in the respective outcome variable. Non-parental care is a dummy variable that takes value of 1 for all the kids who were not taken care of by their parents at baseline, zero otherwise. All regressions include school-strata fixed effects and control for age. Cluster standard errors at school level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Heterogeneous Effects by Program Quality

	Panel A: Attendance			Panel B: Grades						
	First Stage Program Participation	Attendance rate May-November	=1 if attendance rate is >0.85	Art	Physical Education	Language and Literature	Math	Science	GPA	=1 if above the median
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Treatment	0.300***	0.004	0.010	-0.029	0.016	-0.025	-0.036	-0.042	-0.033	-0.054*
	(0.054)	(0.009)	(0.028)	(0.046)	(0.041)	(0.058)	(0.042)	(0.034)	(0.032)	(0.030)
Treatment * High Quality	-0.006	0.003	0.023	0.114**	0.061	0.057	0.104	0.086	0.084*	0.111***
	(0.078)	(0.011)	(0.034)	(0.052)	(0.051)	(0.069)	(0.061)	(0.051)	(0.041)	(0.039)
Observations	2,122	2,379	2,379	2,280	2,277	2,280	2,280	2,280	2,284	2,284
R-squared	0.230	0.276	0.186	0.310	0.277	0.372	0.349	0.397	0.489	0.361
Control group mean	0.253	0.907	0.840	5.926	6.250	5.134	5.149	5.231	5.532	0.494

Note: Columns [2] - [10] report the intent-to-treat (ITT) estimates and standard errors (in parentheses) of program assignment. Column [1] reports the first stage of program participation. The sample size varies according to the number of observations with missing values in the respective outcome variable. Non-parental care is a dummy variable that takes value of 1 for all the kids who were not taken care of by their parents at baseline, zero otherwise. All regressions include school-strata fixed effects and control for age. Cluster standard errors at school level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Program Is Given in the Same School

	Panel A: Attendance			Panel B: Grades						
	First Stage Program Participation	Attendance rate May-November	=1 if attendance rate is >0.85	Art	Physical Education	Language and Literature	Math	Science	GPA	=1 if above the median
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Treatment	0.217***	-0.003	0.009	0.002	-0.017	-0.027	0.005	-0.032	-0.028	-0.031
	(0.056)	(0.004)	(0.017)	(0.058)	(0.037)	(0.043)	(0.049)	(0.050)	(0.037)	(0.031)
Treatment * Same school	0.146*	0.016***	0.028	0.073	0.128***	0.068	0.044	0.081	0.088*	0.087*
	(0.073)	(0.006)	(0.022)	(0.074)	(0.043)	(0.067)	(0.061)	(0.064)	(0.045)	(0.042)
Observations	2,122	2,379	2,379	2,280	2,277	2,280	2,280	2,280	2,284	2,284
R-squared	0.267	0.278	0.187	0.309	0.279	0.372	0.348	0.397	0.489	0.361
Control group mean	0.253	0.907	0.840	5.926	6.250	5.134	5.149	5.231	5.532	0.494

Note: Columns [2] - [10] report the intent-to-treat (ITT) estimates and standard errors (in parentheses) of program assignment. Column [1] reports the first stage of program participation. The sample size varies according to the number of observations with missing values in the respective outcome variable. Same school is a dummy variable that takes value of 1 if the child attended a school were the program was given, zero otherwise. All regressions include school-strata fixed effects and control for age. Cluster standard errors at school level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A-1: Heterogeneous Effects by Childcare Use at Baseline (2012)

	First Stage Program Participation	Panel A: Attendance		Panel B: Grades						
		Attendance rate May-November	=1 if attendance rate is >0.85	Art	Physical Education	Language and Literature	Math	Science	GPA 2012	=1 if above the median
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Treatment	0.243***	-0.003	0.007	-0.040	-0.003	-0.062	-0.038	-0.053	-0.047	-0.039
	(0.062)	(0.007)	(0.025)	(0.053)	(0.041)	(0.055)	(0.071)	(0.068)	(0.041)	(0.031)
Treatment * Father	0.137	0.013	0.021	0.092	-0.100	-0.128	0.064	0.002	-0.036	0.071
	(0.177)	(0.020)	(0.091)	(0.157)	(0.189)	(0.127)	(0.135)	(0.123)	(0.099)	(0.093)
Treatment * Grandmother	-0.015	0.009	0.019	0.171*	0.093	0.059	0.082	0.091	0.093	0.084
	(0.077)	(0.013)	(0.050)	(0.093)	(0.077)	(0.095)	(0.102)	(0.102)	(0.078)	(0.055)
Treatment * Other adult	0.095	0.008	0.029	0.142	0.137*	0.183*	0.151	0.226*	0.186***	0.110***
	(0.099)	(0.010)	(0.050)	(0.094)	(0.069)	(0.095)	(0.105)	(0.125)	(0.064)	(0.037)
Treatment * Siblings	0.093	0.011	0.027	0.049	-0.028	-0.033	-0.119	-0.109	-0.048	0.012
	(0.105)	(0.017)	(0.073)	(0.095)	(0.099)	(0.152)	(0.170)	(0.137)	(0.105)	(0.076)
Treatment * Alone	0.131	0.033**	0.071	0.234***	0.098	0.203*	0.127	0.104	0.183***	0.141*
	(0.097)	(0.012)	(0.067)	(0.069)	(0.088)	(0.116)	(0.100)	(0.100)	(0.061)	(0.080)
Observations	2,122	2,379	2,379	2,280	2,277	2,280	2,280	2,280	2,284	2,284
R-squared	0.236	0.280	0.190	0.314	0.282	0.375	0.351	0.401	0.491	0.363
Control group mean	0.253	0.907	0.840	5.926	6.250	5.134	5.149	5.231	5.532	0.494

Note: Columns [2] - [10] report the intent-to-treat (ITT) estimates and standard errors (in parentheses) of program assignment. Column [1] reports the first stage of program participation. The sample size varies according to the number of observations with missing values in the respective outcome variable. Childcare at baseline could be provided by the father, grandmother, other adults, siblings or the child could have been left alone. Dummy variables for all these categories are defined and this table presents the heterogeneous effects of the program for all these groups. All regressions include school-strata fixed effects and control for age. Cluster standard errors at school level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A-2: Heterogeneous Effects by Type of Childcare Use at Baseline and Quality of the Program (2012)

	First Stage Program Participation	Panel A: Attendance		Panel B: Grades						
		Attendance rate May-November	=1 if attendance rate is >0.85	Art	Physical Education	Language and Literature	Math	Science	GPA 2012	=1 if above the median
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Treatment	0.270***	0.002	0.016	-0.123**	-0.027	-0.098	-0.107*	-0.109*	-0.106**	-0.112***
	(0.065)	(0.011)	(0.038)	(0.056)	(0.061)	(0.068)	(0.062)	(0.059)	(0.043)	(0.031)
Treatment * Parental-childcare and high quality	-0.020	-0.006	-0.012	0.159**	0.019	0.036	0.131*	0.096	0.094*	0.135***
	(0.093)	(0.011)	(0.037)	(0.063)	(0.066)	(0.077)	(0.068)	(0.076)	(0.046)	(0.034)
Treatment * Non-parental-childcare and low quality	0.036	-0.000	-0.015	0.210***	0.042	0.109	0.106	0.121	0.140**	0.117**
	(0.082)	(0.011)	(0.048)	(0.071)	(0.084)	(0.079)	(0.078)	(0.087)	(0.065)	(0.044)
Treatment * Non-parental-childcare and high quality	0.043	0.015	0.048	0.251***	0.154*	0.173*	0.171*	0.184**	0.196***	0.188***
	(0.088)	(0.014)	(0.058)	(0.061)	(0.086)	(0.094)	(0.091)	(0.079)	(0.061)	(0.050)
Observations	2,122	2,379	2,379	2,280	2,277	2,280	2,280	2,280	2,284	2,284
R-squared	0.233	0.279	0.188	0.314	0.281	0.374	0.350	0.398	0.490	0.364
Control group mean	0.253	0.907	0.840	5.926	6.250	5.134	5.149	5.231	5.532	0.494

Note: Columns [2] - [10] report the intent-to-treat (ITT) estimates and standard errors (in parentheses) of program assignment. Column [1] reports the first stage of program participation. The sample size varies according to the number of observations with missing values in the respective outcome variable. Childcare at baseline could be provided by the father, grandmother, other adults, siblings or the child could have been left alone. Dummy variables for all these categories are defined and this table presents the heterogeneous effects of the program for all these groups. All regressions include school-strata fixed effects and control for age. Cluster standard errors at school level are given in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.