“Long-run effects of lengthening the school day on students’ academic achievement: a longitudinal study of Full Day School Reform in Chile.

TESIS PARA OPTAR AL GRADO DE

MAGISTER EN ANÁLISIS ECONÓMICO

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Santiago, Mayo 2019

Long-run effects of lengthening the school day on students' academic achievement: a longitudinal study of Full Day School Reform in Chile.

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Abstract

This paper studies the effects of a large and gradual increase in the Chilean school day over students' academic achievement. I exploit a gradual and exogenous variation produced by the reform with an innovative measure of exposure to longer school day treatment. Using longitudinal data at individual level and a fixed-effect strategy, I find no relevant effect of the reform on the students' standardized test scores in the long-run. Also, this paper found heterogeneous response to additional instructional time by gender, type of school and geographic zone. Finally, these results are robust to the inclusion of several covariates and insensible to the cohort election.

Key Words: Instructional Time, Full School Day Reform, Student Achievement, Fixed Effects.

JEL Classification: I28; H43; H52

Draft: Updated to May 14, 2019.

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1 Introduction

Instructional time is considered as one of the most relevant educational resources (Brown and Saks, 1986; Carroll, 1963; Levin and Tsang, 1987). In first place, this input is a *scarce resource* in education production (Cattaneo, Oggenfuss, and Wolter, 2017). In the second place, change the level of this input (i.e., extending the school day and school year) have considerable logistic and monetary costs, with a limited education budget to implement it (Silva, 2007).

In the OECD economies, the annual instructional time is highly heterogeneous. On average, children from these countries have 7538 hours during the primary and lower secondary education, running from 5976 hours in Latvia to more than 10500 in Australia and Denmark (OECD, 2017). Nevertheless, international evidence from PISA results in this group of countries, show that students from economies with more instructional time do not necessarily have better academic achievement (Cattaneo, Oggenfuss, and Wolter, 2017).

This stylized fact leaves open a central question for schools' staff and policymakers of whether the additional instructional time is an *effective policy* to improve academic performance. In another perspective, establish the optimal amount of instructional time (i.e., length of school year and school day) arise as a relevant question of how to allocate public resources to effectively generate short and long-run human capital accumulation in a determinate country.

Most of the previous research related to this field have found a positive and small relationship between the amount of instructional time and students' academic performance. Beside this, there are also several studies that don't get this same result. Lavy (2015), using PISA 2006 dataset for more than 50 countries, find that instructional time has positive and significant effects on students' test scores. He also discovers that this effect is lower for developing countries. In opposition, Lee and Barro (2001) study the effect of the amount of annual instructional time on student results in the same international standardized test (PISA) in a cross-country sample, controlling for several covariates. They don't find effects of the duration of the academic year over this outcome.

Following this conceptual division of developed/developing countries, the work of Patall, Cooper, and Allen (2010), which consist in a meta-analysis of 15 different studies in the United States of the effects of extend the school day or year on various academic outcomes, suggest that the most robust research designs show a positive relationship between instructional time and students' academic achievement, *neutral at worst but no negative* (Yeşil Dağlı, 2018). For Germany, Pischke (2007) exploit an exogenous variation in the school year in 1966-67 and find that students that were exposed to shorter school year had more probabilities of repeated some grade in primary school and they reduced their chances of entering to high school.

For developing countries, different empirical researches have reached similar conclusions suggested by Lavy (2015). For Low-Income Countries, Ganimian and Murnane (2016) do a meta-analysis of multiple impact evaluation of various educational reforms between 2000 and 2015. They conclude that lengthening school day and year have brief improvements in student performance. For Latin America, Alfaro, Evans, and Holland (2015) analyze 19 papers that evaluated the impact of longer school schedules, founding generally positive effects, but with considerable heterogeneity among studies.

When we are studying the effects of extending instructional time on academic outcomes, it's important to divide between changing school day or school year. The reason for this is because there are several channels whereby changes in instructional time may affect students' academic achievement, and these may differ depending on the evaluated margin (i.e., school day or school year). For example, previous research has documented that increase the school day may produce changes in students' cycles of alertness (Klein, 2004) and sleeping patterns (Hansen, Janssen, Schiff, Zee, and Dubocovich, 2005). In the other hand, the effects of changes in the school year on students' performance operate in other channels, for example, the "summer learning gap" produced by students' socioeconomic background (Alexander, Entwisle, and Olson, 2007). The identification of which channel is operating in any of the margins is not an easy task.

Previous studies also suggest that extend instructional time have heterogeneous effects on academic performance across different groups of students. Literature has identify stronger effects of longer instructional time on two main groups: (i) *low-performing students* and (ii) those with *low socio-economic backgrounds*. For the first group, previous research identifies a positive effect of the amount of instructional time on the performance of slow-learners (Brown and Saks, 1986) and reduction on task-related anxiety (Guida, Ludlow, and Wilson, 1985). For the second group, literature show stronger effects of the amount of instructional time on socio-economic disadvantaged students associated with educational incentives (Lavy, 2015; Patall, Cooper, and Allen, 2010; Gromada and Shewbridge, 2016)

Another relevant issue that is highlighted about increasing instructional time is the critical amount of monetary resources for its implementation. In general, the literature shows that extend the school year and/or school day increase considerable the operational costs (e.g. teacher and school staff salaries) and infrastructural costs (e.g. facilities and equipment) (Gromada and Shewbridge, 2016). Although most of the research shows positive effects on the amount of instructional time on academic achievement, the cost-benefit analysis doesn't appear to support this kind of educational reform. Levin (1986) investigate the effects on students' academic attainment in math and reading test for four different educational interventions (i.e reduce the number of students in the classroom, extra-curricular classes, summer schools) in the United States, concluding that increasing instructional time turned out to be a comparatively ineffective intervention.

Following with an example of significant reform in school schedule of a country, Chilean authorities introduce the *"Full Day School Reform"* (*Jornada Escolar Completa* in Spanish, henceforth FDS) during 1997. The main objectives of this program were to improve the equity and quality of the learning process inside schools (Frei Ruiz-Tagle, 1996). They gradually increased the amount of time that students spent at school by approximately 30% without changing the school year of a significant part of school system (Valenzuela, 2005). More than 20 years later, the gradual nature of this reform (between and within[2] schools) implies that students were exposed to different levels of instructional time at different ages, opening an opportunity to evaluate the FDS in a long-run perspective.

Many academic researchers have taken advantage of the quasi-experimental variation that was produced by this intervention with the purpose of study causal effects of the program on students' educational achievement. The seminal paper in this literature is Bellei (2009). He compared two cohorts of high-school students (2001-2003) using a difference-in-difference identification strategy, concluding that the program had a small positive effect on math (0.00-0.12sd) and reading national standardized tests (0.05-0.07sd). Another investigation evaluating the reform is from García (2009). He studies the evolution of nationally standardized test scores at the individual level using 1999 and 2002 high-school repeated cross-section data. With simple differences a matching differences-in-differences estimator, he obtains increases in the range of 0-5 points ($\sim$0.00-0.10sd) for math and 3-8 points($\sim$0.06-0.16sd) for reading test.

Students' academic performance hasn't been the only studied outcome of the FDS reform. Berthelon and Kruger (2011) show that the program was effectively reducing the likelihood that adolescents engage in risky behaviors at the municipality level, measured as adolescent motherhood and juvenile crime. The authors argue that the incapacitation effect of a longer school day is the main channel that explains their results. Another relevant outcomes is studied by Contreras and Sepúlveda (2010). They find positive and significant effects of the reform on labor participation and female employment in all age groups and a negative effect on the number of hours worked.

However, the previous studies of the effects of FDS on students' test scores have several methodological limitations. First, as Bellei (2009) argued, few studies use longitudinal data to study the implications of the program, indicating the lack of causal evidence in this area. In other words, there can be other unobservable variables that are driving the effects instead of the longer school day. Second, there are practically no researches

[2] The same school could implement the program for some grades.

that investigate the impact of this reform with a long time period dataset. As it was presented above, most of the investigation done related to this program have compared the achievement of different cohorts of students of the same grade in a short period time (2 years).

This paper tries to deal with those limitations, studying the effects of the Full Day School reform over students' academic achievement in a long time period sample. Using longitudinal data from 1996-98 cohort, I observe students' performance in national standardized tests for math and reading in 4th, 8th and 10th grade for years 2007, 2011 and 2013 respectively. This investigation is in the frame of the literature that evaluates the effects of changes in the duration of the school day on students' academic outcomes.

The main innovation of my methodology is in the measure of exposure to a longer school day. To measure the number of years that a student was exposed to schools with longer schedules correctly, I use public administrative data to identify the whole school attendance record for each student. Doing this, I'm able to identify all the institutions where a determinate student attended and consequently the number of years that this student was enrolled in schools with longer school day from primary school to the year that he/she took the standardized test.

This identification strategy relies on the gradual nature of the implementation of this educational intervention, that allows me to exploit the within-variation in the years of exposure to the longer school day using a students' fixed-effects model.
This strategy has multiple methodological strengths. First, this study takes advantage of panel data to clean the effect of exposure to longer school day of confounding effects as the students' genetic, ability or parents preferences for determinate schools. Second, I count with a continuous measure of the longer school day (i.e., years of exposure to longer school day) that allow us to interpret the results intuitively and explore non-linearities in the returns of this kind of policies. Third, I count with a period of 10 years in my sample (1st grade-10th grade) that allow me to explore the effect of the reform in different periods of students' life.

Contrary to previous investigations of this reform, but in line with other researches in developing countries, I find no relevant effect of the policy on students' standardized test scores in the long-run. The impact is negative and not significant for Math score and negative and significant for reading. These results hold after the inclusion of covariates at several levels, but are no robust to changing the cohort of analysis (1998-2000). Anyway, all the estimates are not relevant from an economic point of view. Despite this, this paper does not support the hypothesis that the reform did not have any positive academic effects, but rather that those positive outcomes were produced through indirect channels as childcare, incapacitation effects or other misunderstood ones by this investigation.

This paper contributes to the understanding of how changes in the amount of instructional time affect human capital accumulation in a developing country. In specific, my investigation adds knowledge about the effects of changing the school day on students' academic achievement.

The rest of the paper is organized as follows. Section 2 describes some history and implementation of the Full Day School Reform. Section 3 explains the whole empirical framework, as the data, descriptive statistics, the construction of the explanatory variable and the identification strategy. Section 4 presents the results of the estimations and some robustness analysis. Section 5 contains a discussion about the results of the paper. Finally, Section 6 shows some conclusions.

2 Full Day School Reform: The Chilean experience

It's necessary to contextualize the Chilean educational system to understand this public policy correctly. During the 80's decade, military authorities introduce the "*voucher schools*", privately owned schools with a student voucher given by the central government, in addition to the existing *public* and *private* schools. The introduction of these type of institutions lead a critical growth in the supply of schools, and consequently an expansion in enrollment rates at the national level. This reform has been considered one of the more significant changes to the Chilean educational system (Cox, 2003; Valenzuela, 2005).

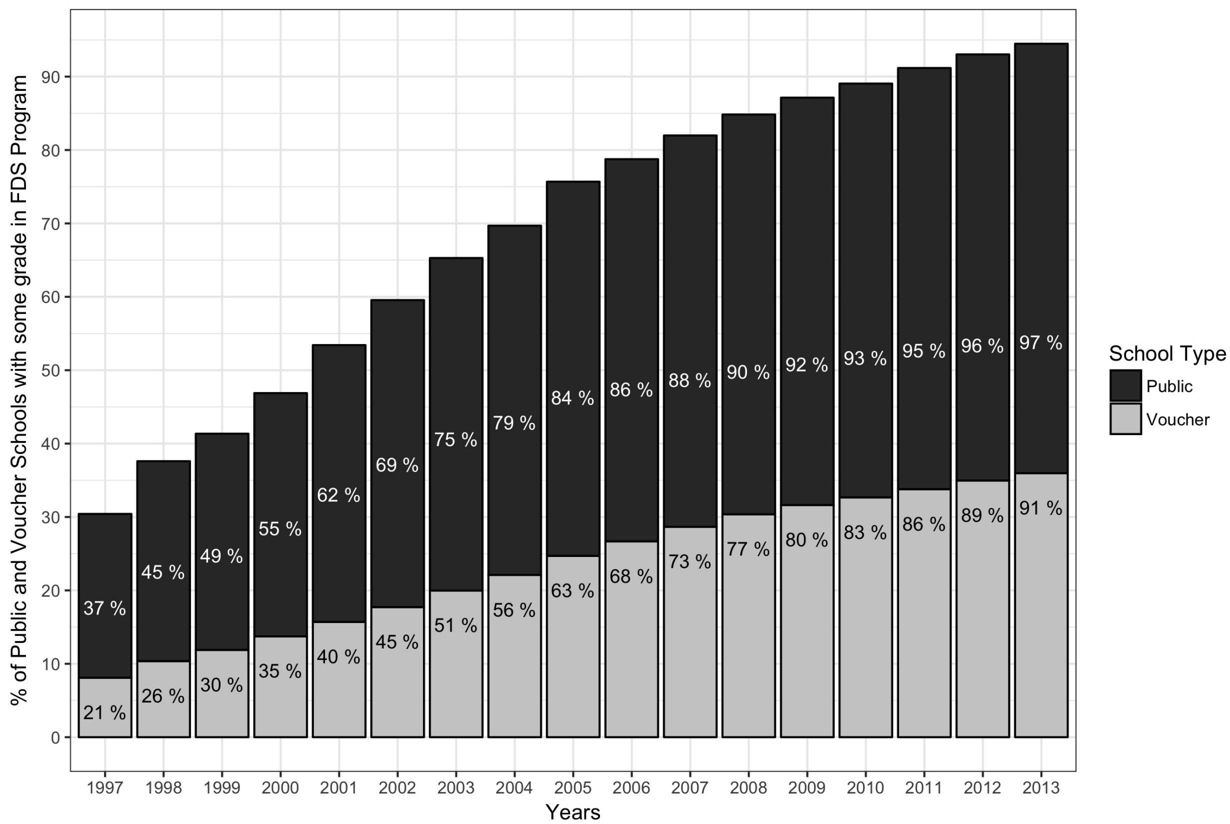
After the return of democracy in the 90's decade, the central government started a second reform process to the educational system: The Full Day School Reform. Since 1997, Chilean authorities gradually increased the amount of time that students spend in the school by approximately 30% without changing the school year in most of public and voucher schools (Bellei, 2009; Berthelon and Kruger, 2011; Valenzuela, 2005). The main objectives of the reform were to improve equity and quality of the learning process inside schools (Frei Ruiz-Tagle, 1996) and give better future opportunities for most students (Valenzuela, 2005).

This program was mandatory for all the schools that receive public funding (i.e., voucher and public schools) from 3rd grade to 12th grade[3]. The private schools and some voucher schools, mainly the ones with resources, didn't participate in the program because they establish their schedules autonomously. With the reform, schools transited from two half-day shifts (morning or/and afternoon) to one full-day schedule (morning and half afternoon). As a consequence, participant schools should modify their infrastructure to accommodate all their students in one full-day shift.

[3]For 1st and 2nd grade from primary the school that was in the program have the option to choose the schedule.

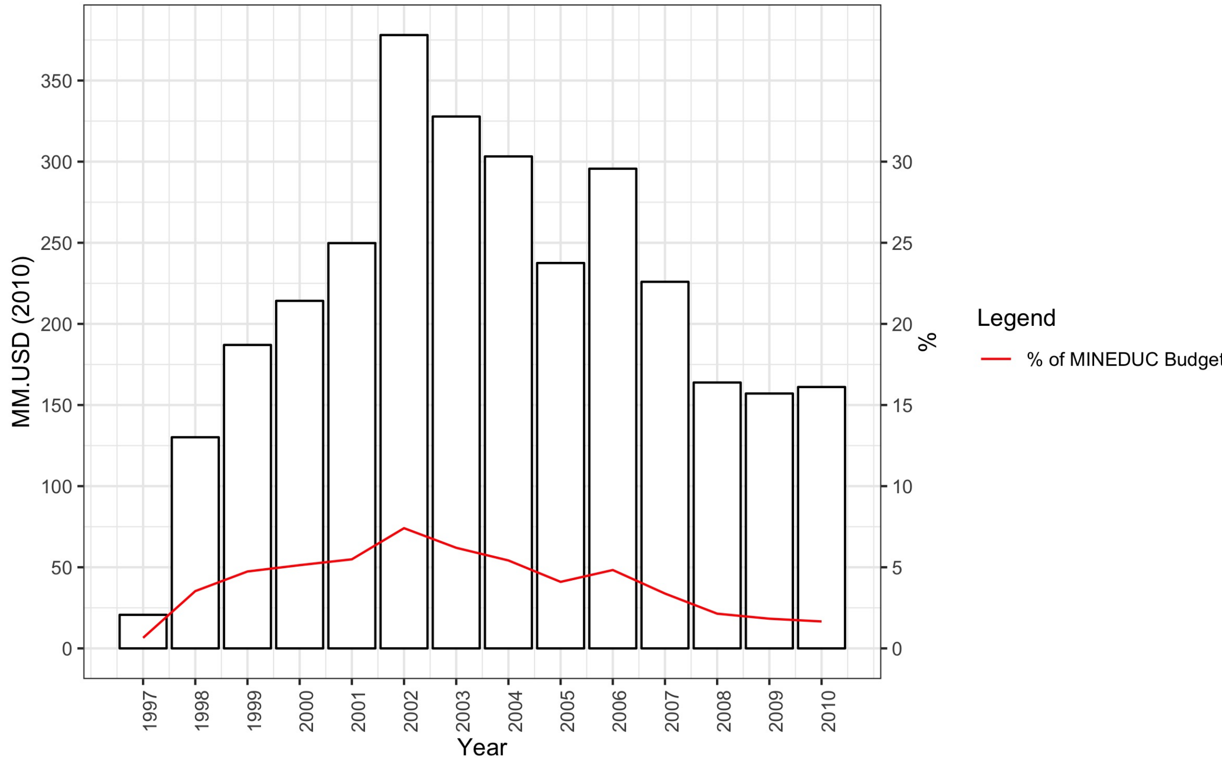
The execution of the reform was gradual due to the massive amounts of infrastructure investment. Figure 2.1 shows the progressive nature of this public policy. In 1997, only 30% of the participating schools had entered the program (37% of public and 21% of voucher schools respectively). By 2013, those numbers were over 90%. On the other hand, Figure 2.2 shows the annual cost of the program registered by the Chilean Budget and Treasury Department. The total monetary value of the Full Day School reform from 1997 to 2010, according to the budget office records, was over 3.000 million dollars, equivalent to 4% of the annual education budget of the Ministry of Education.

Figure 2.1: Implementation of FDS Program by type of School.



Notes: Own elaboration based on administrative data from the Ministry of Education. The Y-axis is the percentage of the participant schools that entered to the Full Day School reform with some grade. The number inside each bar represents the percentage of schools for each type of them that were in the program for the respective year.

Figure 2.2: Full Day School Reform Cost (2010 MM.USD)



Notes: Own elaboration based on DIPRES Annual Budget Law. Every amount is in 2010 USD. CPI series were extracted from Federal Reserve Bank of St.Louis (FRED). I used the average exchange rate of December 2010 (474,78 CLP/USD).

The first schools that entered the program were the ones with the capacity to easily reallocate their students from two half-day shifts to one full-day shift. Those schools were mainly from *rural zones*, because it was common to hold classes in just one shift due to the number of students, and *advantage socioeconomic institutions* that were able to accommodate their students without public funding.

To implement the Full Day School reform, most of the schools required public funding to finance the program. These costs came from two components: operative costs, financed with an increase of 40% of in the monthly voucher per student, and infrastructural costs, backed by a Capital Supply Fund (CSF). According to the information provided by the Budget and Treasury Department, the capital transfers constituted more than 70% of the annual cost of the reform.

The government called for applications two times per year to grant this CFS to voucher schools. All the owners of vouchers schools that were operating before 1998 could apply, with a technical project, to the CSF. The fund also considered applications to install new institutions in zones with school supply deficiencies. The central government rated these projects, assigning them a score, based on two criteria: academic and socioeconomic school vulnerability and required resources per student (Valenzuela, 2005). Public schools, in addition to the CFS, could obtain funding from the Regional Government and Municipality.

An example of the organization of the weekly hours and the main difference between FDS schools with the others is in Tables A.1, A.2, and A.3. These tables show that the FDS have free dispositions hours to organized their curriculum.

[Insert Tables A.1, A.2 and A.3]

3 Empirical Framework

3.1 Data

To answer the research question, I use data from three different sources. The first dataset is an individual-level panel of SIMCE results for 4th, 8th and 10th grade taken on 2007, 2011 and 2013 respectively. SIMCE is the Chilean national testing system for primary and high school students for several subjects (math, language, natural science, social sciences). In particular, I am interested in math and reading due to the availability of comparable information about test scores for the three periods. The datasets also have background information of students provided by their parents and teachers.

The second dataset is school-based public information about the execution Full Day School Program, provided by the Chilean educational authorities. This record has information about the year of implementation of the program by school and grade, type of education[4] and different school characteristics.

The third dataset is an individual-level panel register of students' academic achievement at the school level and annual attendance rates from 1st to 12th grade. With this information, I'm able to identify students' school attendance record, and in consequence, the number of years that they were exposed to longer school days.

An important issue to mention about the data is attrition. For example, since there are students that have repeated grades in their school tracks, I'm not able to observe students in all the years of SIMCE test. Therefore, if a student doesn't follow the "normal" school track, he/she won't be observed. If I assume that the students that repeated are the ones with lower achievement, the attrition will produce a selection bias on the effect of longer school year over academic achievement. See Appendix A.3.1 for more information.

Finally, to recover information, I impute data for some covariates, mainly for students' socioeconomic characteristics (parents education, income, and the number of books). See Appendix A.4 for more information.

[4]Since Chile have various "realities" caused by its geography, there exist various kinds of education in high schools.

3.2 Explanatory Variable: Exposure to Full Day School Reform

As discussed above, the current impact evaluations of the FDS reform have usually compared different cohorts of students of the same grade to identify a causal effect of the program in a determinate student academic outcome (Bellei, 2009; García, 2009).

One of the key innovations of this paper is in the measure of the treatment variable (i.e., longer school day) of a particular student. I identify the students' school attendance record from 1st grade, and that allows me to isolate the number of years that they attended schools that implemented the program in the respective classes.
To explain in detail the construction of the measure, let's define an indicator variable $\mathcal{F}_{sgij}$:

$$\mathcal{F}_{sgij} = \begin{cases} 1, & \text{if school } s \text{ implemented FDS in grade } g \\ & \text{where the student } i \text{ assisted in year } j. \\ 0, & \text{otherwise} \end{cases}$$

Considering G_i as the year of entrance of student i to 1st grade and $t \in \{t_1, t_2, \ldots, t_N\}$, the exposure to FDS of student i up to the period t can be written as:

$$Exp_{it} = \sum_{j=0}^{t-(G_i-1)} \mathcal{F}_{sgij} \tag{3.1}$$

This approach has several advantages. In the first place, this methodology provides a continuous measure (i.e., years attended schools with longer school day) to identify the long-run effects of the reform. In the second place, since I observed a trajectory for each student, my measure takes over the fact that students move to different institutions for several reasons. Finally, the nature of the independent variable allows me to use fixed effects at the individual level to control for unobservable time-invariant variables as student's genetic, ability or parent's school preferences.

As the Full Day School Reform is almost complete, it's relevant to check if there is enough variation in the variable that I'm proposing. The reason for this is that it's crucial to have within-variation in the independent variable to identify the parameter of interest in the main specification. Figures A.5, A.6, A.7 and A.8 show the distribution of the Exposure variable for each of the years in the sample. Also, Figure A.9 show the distribution of the within-transformed variable.

3.3 Descriptive Statistics

Table 3.1 shows a summary of the sample. The first row show the variable *Exposure*, defined by Equation 3.1. Looking the Panel A, one might note that the data confirm the progressive nature of the reform, since the average years of exposure to the FDS is smaller than the maximum for each grade (four, eight and ten years respectively). Another interesting issue is that around the 46% of the sample are males, the school enrollment is concentrated mainly in the voucher schools, and an important number of students migrate from rural zones to urban high schools. Also, looking at the Panel B, one can see that parents education concentrated between 12 and 17 years.

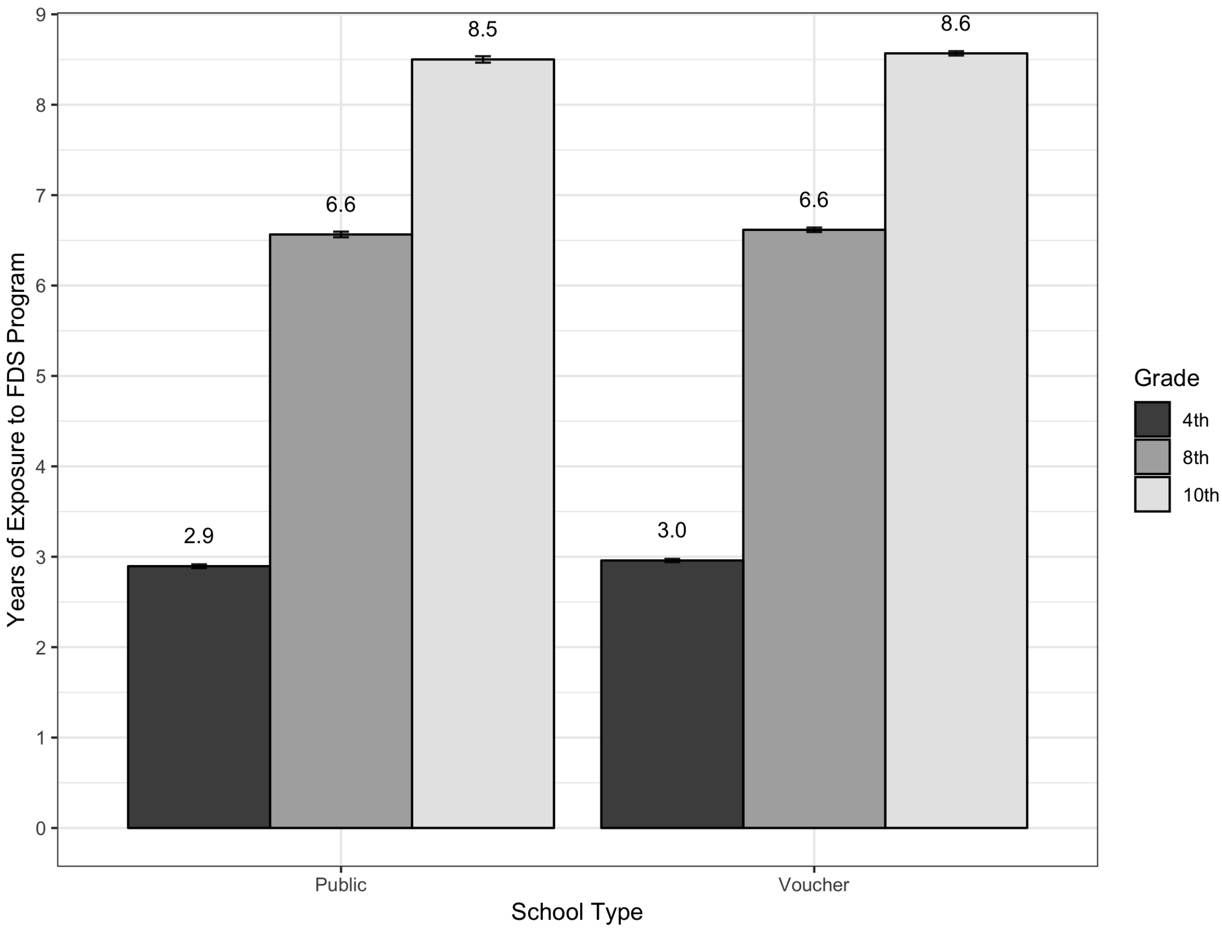
Table 3.1: Descriptive Statistics

	4*th* Grade 2007		8*th* Grade 2011		10*th* Grade 2013	
	$\overline{x}$	σ_x	$\overline{x}$	σ_x	$\overline{x}$	σ_x
Panel A						
Exposure to FDS	2.93	(1.27)	6.59	(1.86)	8.54	(1.90)
SIMCE Math	255.98	(50.92)	265.50	(45.96)	271.77	(61.72)
SIMCE Reading	263.76	(48.78)	262.33	(46.42)	258.97	(53.06)
Assistance(%)	95.10 %	(4.73)	94.36 %	(4.87)	92.83 %	(5.78)
School Grades	6.0	(0.49)	5.7	(0.51)	5.5	(0.53)
Male=1	0.464	(0.50)	0.464	(0.50)	0.464	(0.50)
Voucher=1	0.52	(0.50)	0.56	(0.50)	0.65	(0.48)
Income (M.CLP)	295.76 $	(236.14)	329.85 $	(258.72)	352.37 $	(226.06)
Rural=1	0.13	(0.34)	0.11	(0.31)	0.03	(0.18)
Panel B						
Father Education						
$[0,8)$ Years	13.73 %		12.37 %		12.31 %	
$[8,12)$ Years	28.34 %		28.44 %		28.60 %	
$[12,17)$ Years	41.77 %		42.56 %		42.43 %	
≥ 17 Years	16.17 %		16.63 %		16.65 %	
Mother Education						
$[0,8)$ Years	12.25 %		11.93 %		11.96 %	
$[8,12)$ Years	27.05 %		26.48 %		26.00 %	
$[12,17)$ Years	43.46 %		43.94 %		44.23 %	
≥ 17 Years	17.24 %		17.64 %		17.81 %	
N	35584		35584		35584	

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. Panel A shows the mean and standard deviation of several continuous and binary variables. Standard Deviations are in parentheses. Panel B shows the proportion of students in the sample by parents education.

Another important exercise is to explore heterogeneity in the implementation of the program. Since the government had a waiting list to provide resources, one may observe differences in the application depending on the school characteristics. Figure 3.1 shows the average years of exposure to the program by school type and grade. As can be seen, the implementation by school type is pretty similar since the average years of exposure is practically the same for public and voucher schools. This empirical issue suggests that the kind of school was not a relevant decision variable to allocate public resources in this program.

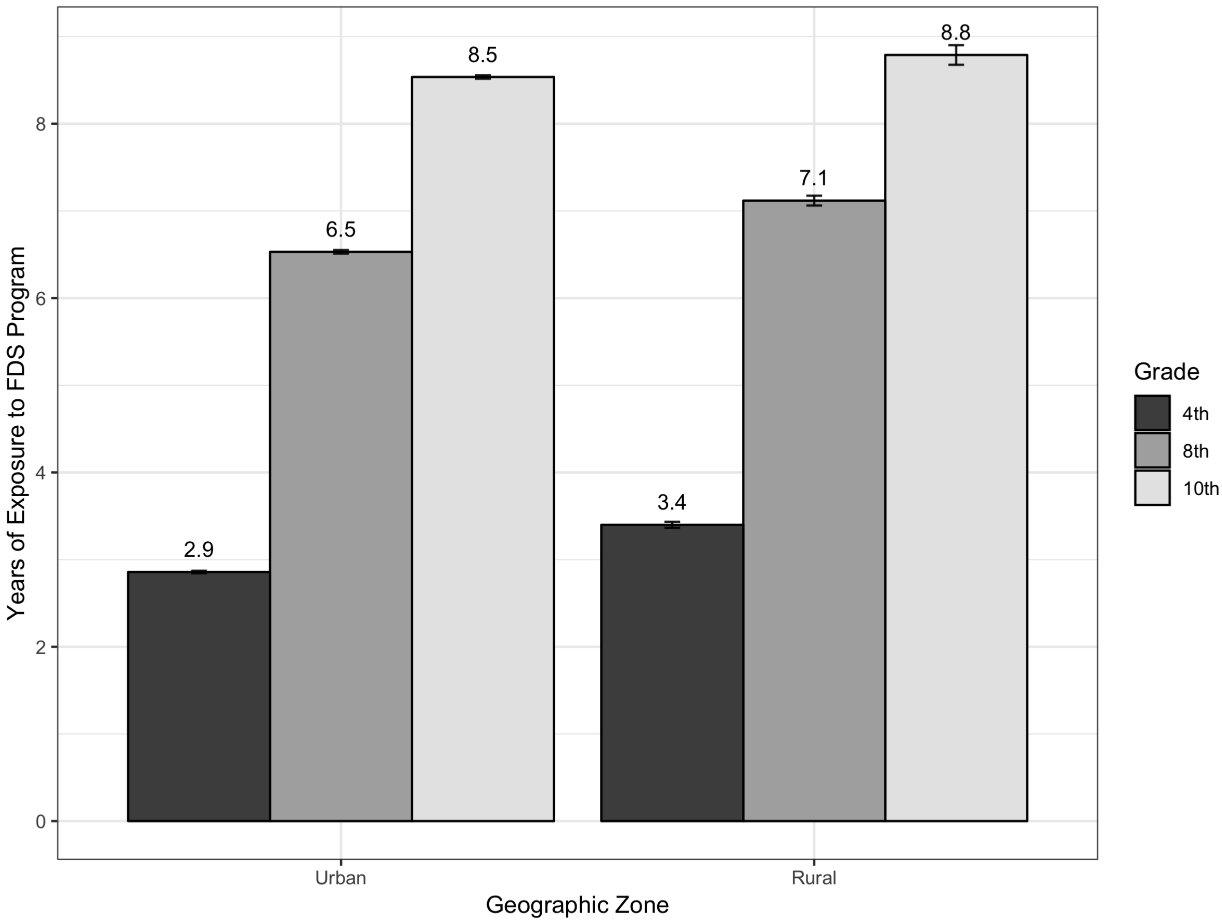
Figure 3.1: Years of Exposure to Full School Day by type of School.



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The Y-axis is the years of exposure to the longer school day defined by Equation 3.1. The column color represents the grade (4th, 8th or 10th grade). The line in the middle of each column is the 95% confidence interval.

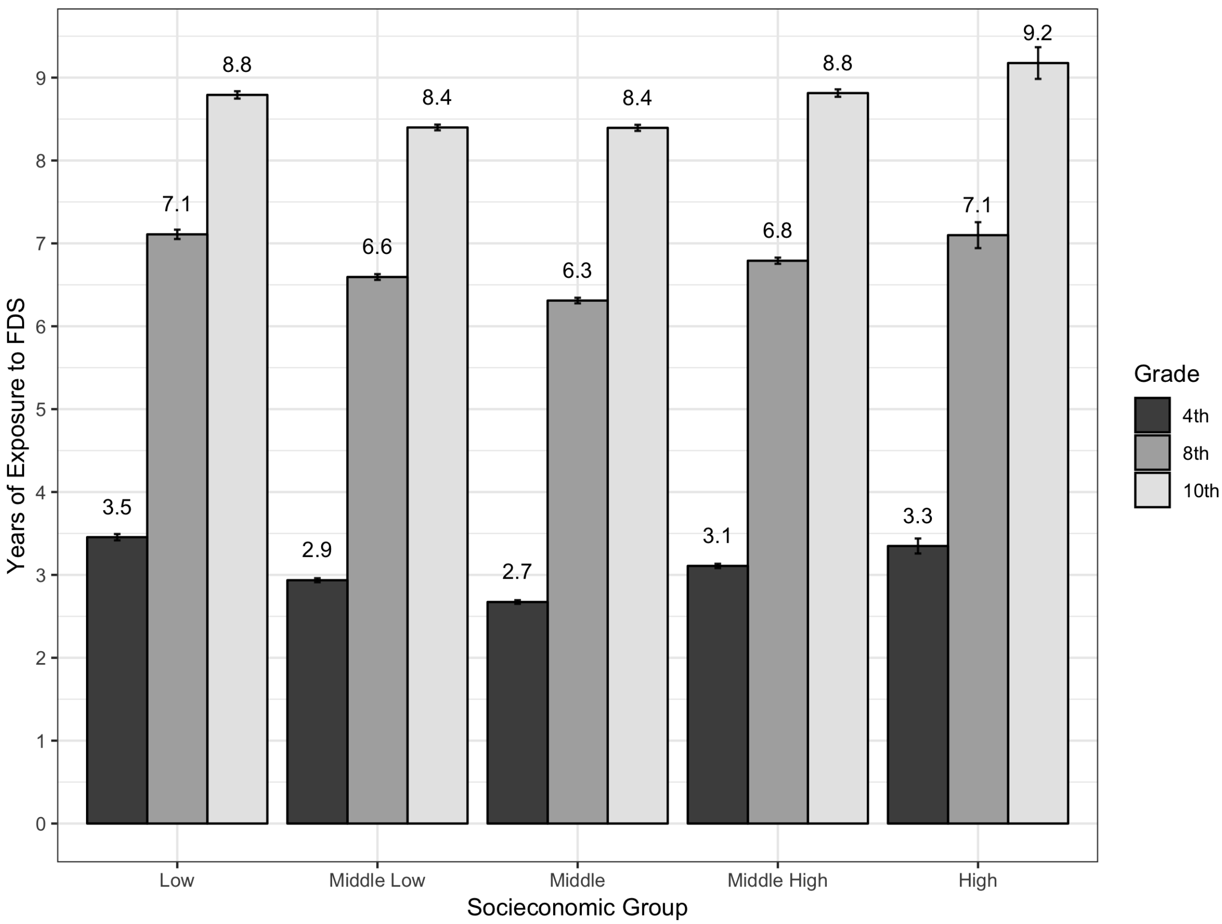
Visiting another school characteristics, Figures 3.2, and 3.3 show the average years of exposure to the program by school geographic zone and socioeconomic vulnerability respectively. The implementation of the extended school day was faster in rural zones, especially for primary education. Another interesting fact is that the government seems to have started the implementation of the FDS program in most vulnerable and less vulnerable schools (see Figure 3.3). As the mechanism of the assignation of public funds was not randomly assigned, a possible explanation for this stylized fact is that government concentrated their efforts firstly in vulnerable schools, leaving the ones with more resources later in the waiting list.

Figure 3.2: Years of Exposure to Full School Day by Geographic Zone.



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The Y-axis is the years of exposure to the longer school day defined by Equation 3.1. The column color represents the grade (4th, 8th or 10th grade). The line in the middle of each column is the 95% confidence interval.

Figure 3.3: Years of Exposure to JEC by Grade and School Socioeconomic Group



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The Y-axis is the years of exposure to the longer school day defined by Equation 3.1. The column color represents the grade (4th, 8th or 10th grade). The line in the middle of each column is the 95% confidence interval.

3.4 Identification Strategy

The main problem in the identification of the causal effect of increasing the instructional time on students' academic performance is the presence of confounding effects. In other words, since there exist unobservable variables that determine the exposure to longer school day (i.e., parents school preferences, students' ability) and the academic achievement, I won't be able to identify the causal effect with simple multivariate regression.

In this line, I propose two specifications to estimate the effect of lengthening the school day on students' academic achievement. In the first place, the first model analyzes if the years of exposure to longer school day have an impact on the standardized SIMCE score of student i in 10th grade. The specification is given by Equation 3.2:

$$Y_{is,t} = \beta_0 + \beta_1 Exp_{i,t} + \sum_{k=1}^{2} \beta_{k+1} Y_{is,t-k} + X_{is,t}\gamma + Z_{s,t}\psi + (\mu_{s,t} + \varepsilon_{is,t}) \tag{3.2}$$

Where $Y_{is,t}$ are standardized SIMCE scores of student i attending school s, $Y_{is,t-k}$ are the lags of the dependent variable, $Exposure_{i,t}$ is a variable of range $[0,10]$ defined by Equation 3.1, X_{is} is a vector of individual and socioeconomic covariates proposed by Bellei (2009)[5] and Z_s is a vector of school characteristics[6]. Finally, $\varepsilon_{is,t}$ is an individual error term and $\mu_{s,t}$ is a school-specific error term that justify grouping the error in clusters.

Since this OLS specification doesn't allow me to control for all relevant unobservable variables, the coefficient of interest (β_1) will be biased and inconsistent. To fix this, and to take advantage of the longitudinal nature of the dataset, I propose to estimate the effect with a Fixed Effect strategy (Equation 3.3):

$$Y_{is,t} = \alpha_i + \omega_t + \beta_1 Exp_{i,t} + X_{is,t}\gamma + Z_{s,t}\psi + \varepsilon_{is,t} \tag{3.3}$$

Where $Y_{is,t}$, $Exp_{i,t}$, $X_{is,t}$ and $Z_{s,t}$ are the same variables from OLS specification. α_i and ω_t are time-invariant individual dummys and temporal fixed effects respectively. The key assumption to validate this strategy and obtain a causal effect is that unobservable variables, like student's ability and parents preferences, are time-invariant from 1st to 10th grade.

Since SIMCE scores are standardized for time comparison purposes, all the coefficients are changes in standard deviations of the respective test scores. In both specifications, the parameter of interest is β_1. The interpretation of the coefficient is: *"An additional year assisting to a grade with longer school day increases in β_1 standard deviations the SIMCE score"*.

4 Results

4.1 *OLS*

Table 4.1 and Table 4.2 show the results of the Equation 3.2 for math and reading standardized tests respectively. In both cases, the estimates of this equation have different covariates sets to check the robustness of the parameter. Column (1) of Tables 4.1 and 4.2 show that, if I do not control for any observable characteristic, the years of exposure to

[5] This vector includes the following variables: gender, class size, assistance rate, number of books in the house, parents education and the logarithm of income.

[6] This vector includes the following variables: school type (public, voucher), socioeconomic group, geographic zone (urban, rural) and region.

the FDS program don't have any significant impact on the 10th-grade students' SIMCE scores. After controlling for various observable characteristics (at students', school and geographical level), the sign of the effect turns from positive to negative in Math and holds negative for Reading. In both tests, the effect of an additional year in the program is not statistically significant.

Table 4.1: OLS Model: Effect of Exposure to FDS in 10th grade SIMCE Score (Math)

y_{ist}=Math$_{2013}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	0.005	-0.001	0.001	-0.000	-0.001
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Male=1		0.078***	0.082***	0.112***	0.117***
		(0.01)	(0.01)	(0.01)	(0.01)
Math$_{2011}$		0.673***	0.634***	0.589***	0.581***
		(0.01)	(0.01)	(0.01)	(0.01)
Math$_{2007}$		0.260***	0.228***	0.200***	0.197***
		(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.388***	0.384***	0.416***	0.428***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			0.095***	0.008	0.020***
			(0.01)	(0.01)	(0.01)
Rural=1					0.011
					(0.06)
N	35,584	35,584	35,584	35,584	35,584
R^2	0.00	0.62	0.64	0.67	0.67
R^2_a	0.00	0.62	0.64	0.66	0.67
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table 4.2: OLS Model: Effect of Exposure to FDS in 10th grade SIMCE Score (Reading)

y_{ist}=Reading$_{2013}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.001	-0.002	-0.001	-0.002	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male=1		-0.067***	-0.073***	-0.068***	-0.068***
		(0.01)	(0.01)	(0.01)	(0.01)
Language$_{2011}$		0.464***	0.451***	0.435***	0.429***
		(0.01)	(0.01)	(0.01)	(0.01)
Language$_{2007}$		0.294***	0.276***	0.264***	0.262***
		(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.328***	0.318***	0.329***	0.339***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			0.044***	-0.001	0.007
			(0.01)	(0.01)	(0.01)
Rural=1					0.091**
					(0.04)
N	35,584	35,584	35,584	35,584	35,584
R^2	0.00	0.52	0.52	0.53	0.53
R^2_a	-0.00	0.52	0.52	0.53	0.53
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

It's necessary to be careful with the interpretation of these results since I am not able to control for non-observable characteristics, especially at individual and family level (i.e., students' ability, parents school preferences). Nevertheless, these parameters are an excellent *benchmark* for my preferred identification strategy.

4.2 *Fixed Effects*

Since there exists considerable unobserved heterogeneity in the estimation of Equation 3.2, interpret β as a causal effect seems implausible. As discussed above, the empirical strategy to avoid these estimation issues is the use of panel data and students' fixed effects. The primary assumption of this strategy is that the unobservables varies between individuals but are constant in time.

Table 4.3: FE Model: Effect of Exposure to FDS in SIMCE Score (Math)

y_{ist}=Math$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	0.001	-0.001	-0.001	-0.004	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
School Grades		0.247***	0.247***	0.274***	0.273***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.021***	-0.023***	-0.021***
			(0.01)	(0.01)	(0.01)
Voucher=1				0.014*	0.011
				(0.01)	(0.01)
Rural=1					0.116***
					(0.01)
N	106,752	106,752	106,752	106,752	106,752
$N_{students}$	35,584	35,584	35,584	35,584	35,584
R^2	0.06	0.10	0.10	0.12	0.12
R^2_a	0.06	0.10	0.10	0.12	0.12
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.4: FE Model: Effect of Exposure to FDS in SIMCE Score (Reading)

y_{ist}=Reading$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.012***	-0.014***	-0.014***	-0.016***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
School Grades		0.269***	0.268***	0.285***	0.284***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.004	-0.007	-0.004
			(0.01)	(0.01)	(0.01)
Voucher=1				0.044***	0.041***
				(0.01)	(0.01)
Rural=1					0.087***
					(0.01)
N	106,752	106,752	106,752	106,752	106,752
$N_{students}$	35,584	35,584	35,584	35,584	35,584
R^2	0.01	0.04	0.04	0.04	0.04
R^2_a	0.01	0.04	0.04	0.04	0.04
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table 4.3 report the results of Equation 3.3 for Standardized Math test. The coefficient of years of exposure is negative, on thre contrary to OLS specification, but it's not statistically significant at any level. This conclusion holds after controlling for several covariates. In Table 4.4, there is the same estimation but for reading test. Surprisingly, for this test, I find a negative and significant effect. As in math results, the size and direction of the effects are stable to the inclusion of covariates. The estimates using only the within-variation between 4th and 8th grade may be consulted in Appendix A.1.1

There are several comments about these results. In the first place, ignoring the statistical significance for one moment, the size of the return of one additional year of FDS program is virtually zero and is economically irrelevant in all the specifications for both tests (i.e., fraction of 1 SIMCE point). In the second place, it seems that the change of geographical zone status (rural to urban or/and vice versa) explain an essential part of the students' SIMCE score in both tests. To check that this variable is driving my results, I run the same model restricting the sample for students' that always lived in urban or rural places and the results remain unchanged.

An interesting issue about these results is that they are not in line with the previous findings of Bellei (2009) and García (2009). There are several reasons why my results may differ from those estimates. In the first place, the evidence that I present here evaluates the reform with a higher grade of completeness (i.e., 16 years after implementation) compared with the other authors (i.e., 2-6 years). Probably, the positive effects found by those investigators disappear with the cohorts that borned with the reform. In the second place, I use longitudinal information for one single cohort and the work of Bellei (2009) and García (2009) use repeated cross-section data to compare two groups of 10th-grade students. In this case, my estimates are not capturing the short term impact of a change of schedule in high school. However, the positive effects suggested by Bellei (2009) and García (2009) are not far away from my findings.

4.3 *Heterogeneous Effects*

In addition to the main results, two interesting empirical questions are (1) if this effect is linear in the independent variable (i.e., diminishing/increasing returns) and (2) if this effect varies depending on the group of students.

For answering the first question, I estimate Equation 3.3 adding square exposure:

$$Y_{is,t} = \alpha_i + \omega_t + \beta_1 Exp_{i,t} + \beta_2 Exp_{i,t}^2 + X_{is,t}\gamma + Z_{s,t}\psi + \varepsilon_{is,t} \tag{4.1}$$

From Equation 4.1, if the hypothesis $H_0 : \beta_2 = 0$ is rejected, the belief of non-linear returns of the program on students' standardized test scores can be hold.

For answering the second question, I estimate the following model:

$$Y_{is,t} = \alpha_i + \omega_t + \beta_1 Exp_{i,t} + \beta_2 D_{i,t} + \beta_3 Exp_{i,t} \times D_{i,t} + X_{is,t}\gamma + Z_{s,t}\psi + \varepsilon_{is,t} \tag{4.2}$$

Where $D_{i,j}$ is a dummy variable that takes the value one if student i belongs to a specific group a 0 otherwise. Estimating Equation 4.2, β_3 will specify the differences in the return of an additional year of the program between groups.

$$\beta_3 = \frac{\partial \mathbb{E}(Y_{is,t}|X,Z,D_{i,t}=1)}{\partial Exp_{i,t}} - \frac{\partial \mathbb{E}(Y_{is,t}|X,Z,D_{i,t}=0)}{\partial Exp_{i,t}}$$

The variables to explore heterogeneous effects are students' gender, school type and geographic zone.

Table 4.5 and 4.6 show the results for Equations 4.1 and 4.2 for math and reading respectively. The left panel of both tables show that the years of exposure to longer school day have *no quadratic effects* on academic achievement (i.e., diminishing or increasing returns) in any standardized test score. Since β_1 is near zero in all the estimates, it was predictable that I wouldn't find evidence about non-linearities.

Table 4.5: Heterogeneous Effects: Math

y_{ist}=Math$_{ist}$	Quadratic Effects	Heterogeneous Effects		
		$Male=1$	$Rural=1$	$Voucher=1$
Exposure	-0.006	-0.007*	-0.002	-0.066***
	(0.006)	(0.004)	(0.004)	(0.004)
Exposure^2	0.000			
	(0.000)			
Control		0.000	0.158***	-0.222***
		(.)	(0.019)	(0.012)
Exposure * Control		0.008***	-0.007***	0.038***
		(0.001)	(0.003)	(0.002)
N	106,752	106,752	106,752	106,752
N_{groups}	35,584	35,584	35,584	35,584
R^2	0.12	0.12	0.12	0.13
R^2_a	0.12	0.12	0.12	0.13
Student Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
School Controls	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. Each observation is a student-year unit. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Panel at left shows quadratic effects and panel at right shows interaction terms with several covariates. Robust standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.6: Heteregeneous Effects: Reading

y_{ist}=Reading$_{ist}$	Quadratic Effects	Heterogeneous Effects		
		$Male = 1$	$Rural = 1$	$Voucher = 1$
Exposure	-0.016***	-0.006	-0.015***	-0.030***
	(0.006)	(0.004)	(0.004)	(0.005)
Exposure^2	0.000			
	(0.000)			
Control		0.000	0.047**	-0.015
		(.)	(0.020)	(0.013)
Exposure * Control		-0.018***	0.007***	0.009***
		(0.002)	(0.003)	(0.002)
N	106,752	106,752	106,752	106,752
N_{groups}	35,584	35,584	35,584	35,584
R^2	0.04	0.05	0.04	0.05
R$_a^2$	0.04	0.05	0.04	0.04
Student Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
School Controls	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p <0.01, ** p <0.05, * p <0.1

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. Each observation is a student-year unit. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Panel at left shows quadratic effects and panel at right shows interaction terms with several covariates. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

The right panel of Tables 4.5 and 4.6 show the heterogeneous effects for males, rural and voucher schools respectively. In both standardized tests, I'm not able to identify the coefficient of sex control since this status doesn't change in time and the students' fixed effect capture this variable. However, I can identify the difference between groups with this specification. For Math test, and consistent with the literature, boys perform better than girls and show higher returns of an additional year with a longer school day. For the reading test, the opposite occurs. For rural and voucher schools, the results suggest higher returns in both standardized tests for this type of schools.

As in core results, the size of heterogeneous effects is not economically relevant. All of these effects are smaller than 0.04 *sd* ($\sim$ 2 - 2.5 SIMCE points). Another important issue is that, since the methodology is one of fixed effect strategy, the interaction term may not capture the real groups between-differences since some of the variables (i.e., school type and geographic zone) don't remain constant (students moves from schools to other ones). In other words, β_3 may reflect within and between differences, rather than pure between differences. More information about heterogeneous effects may be consulted in Appendix A.1.4.

4.4 *Robustness Check*

An essential exercise in any empirical investigation is to check the robustness of the main results. In this case, one possible factor that drives my findings is the cohort election. Since I'm using longitudinal data for ten years, the results can be affected if students' from a determinate cohort were exposed to specific shocks or educational reforms.

To provide robustness to my results, I estimate the Equation 3.3 using a sample of students born between 1998 and 2000. This cohort took the SIMCE test in 2009 (4th grade), 2013 (8th grade) and 2015 (10th grade). This cohort is, on average, two years younger than the one of the main results.

Tables 4.7 and 4.8 shows the results for the robustness check estimations for Math and Reading test. For Math, there is a significant and negative effect of years of exposure on academic achievement, and this conclusion holds for all the specifications of the table. For the reading test, the effect remains negative but is no longer statistically significant.

Table 4.7: Robustness Check: Effect of Exposure to FDS in SIMCE Score of Cohort 2009, 2013 and 2015 (Math)

y_{ist}=Math$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.011	-0.015**	-0.015**	-0.016**	-0.015**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.253***	0.255***	0.279***	0.277***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.009	-0.012**	-0.010*
			(0.01)	(0.01)	(0.01)
Voucher=1				0.064***	0.065***
				(0.01)	(0.01)
Rural=1					0.113***
					(0.01)
N	75,666	75,666	75,666	75,666	75,666
N_{groups}	25,222	25,222	25,222	25,222	25,222
R^2	0.00	0.03	0.03	0.04	0.04
R_a^2	0.00	0.03	0.03	0.04	0.04
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table 4.8: Robustness Check: Effect of Exposure to FDS in SIMCE Score of Cohort 2009, 2013 and 2015 (Reading)

y_{ist}=Reading$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.007	-0.011	-0.011	-0.012	-0.012
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.313***	0.313***	0.324***	0.322***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.005	-0.007	-0.006
			(0.01)	(0.01)	(0.01)
Voucher=1				0.056***	0.056***
				(0.01)	(0.01)
Rural=1					0.090***
					(0.01)
N	75,666	75,666	75,666	75,666	75,666
N_{groups}	25,222	25,222	25,222	25,222	25,222
R^2	0.00	0.03	0.03	0.03	0.03
R_a^2	0.00	0.03	0.03	0.03	0.03
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Since the negative and significant effect that I find above is virtually zero for math and reading tests, the robustness check confirms that my results are practically the same for the two cohorts.

5 Discussion

As every empirical research, this paper has several methodological limitations. For a correct understanding of these results is necessary to give a discussion about the possible problems that can be present in the identification of the effect.

In the first place, it's necessary to discuss the degree of exogeinity of the Full Day School reform. Since the government has priorities in the allocation of funds to implement the program, it's possible that some eligibles schools that needed the Capital Supply Fund to implement the program, strategically choose the timing to apply to it (Valenzuela, 2005). As long as the schools choose the timing of the implementation of the reform to maximize future students' academic achievement, the empirical strategy will be inadequate.

In the second place, my student fixed-effect strategy is unable to take care of school unobservables characteristics. Relevant variables as school climate, administrative quality, curriculum or students' selection process are not able in our data set and may determine the number of years that students have longer school days and their respective academic outcomes. The inclusion of school fixed effects may be consulted in Appendix A.1.2.

In third place, the measurement error in the explanatory variable is very implausible. Since I observe the school attendance of every student' for every grade with administrative data, I know exactly in which class and school he(she) assisted for every year of analysis. With this information, we can measure precisely the number of years that he(she) was exposed to the longer school year.

In fourth place, and as it was mentioned above, the attrition of our sample caused by grade repetition and missing information don't allow us to extrapolate the main conclusions of the empirical analysis to the whole population of school students. Nevertheless, since the estimates are robust to the sample election, it's reasonable to suppose that missing information will not change the main conclusions of this paper.

6 Conclusions

In this paper, I study the long-run effects of lengthening the school day on students' academic performance in a developing country as Chile. Taking advantage of the quasi-experimental nature of a significant and gradual reform that extended the school day by approximately 30%, I combine longitudinal data of standardized tests and administrative records of central government for more than ten years to estimate the effect of an additional year of exposure to longer school day on standardized test scores. This paper uses a methodology of individual fixed-effects to identify the causal effect, taking care of unobservable variables.

I find no relevant effect of an additional year of exposure to a longer school day on students' standardized test scores. This result is negative and not significant for the math test, and negative and significant, but near zero, for reading test. These findings are robust to the introduction of several covariates. Also, the estimates for Math are sensible to the cohort election, where I find a negative and significant effect of the exposure on academic achievement. On the other hand, reading results loss significance after changing it. Anyway, similar conclusions can be reached from both estimations.

These results have several public policy implications. In the first place, this paper is not able to support the hypothesis that the reform did not have any positive effects on students academic achievement. This public policy had many significant indirect effects that may contribute to the children human capital accumulation. In the other hand, it's reasonable to claim with my estimates that the positive academic effects of the reform may principally come from indirect channels (i.e., childcare, parents human capital accumulation) rather than direct ones (i.e., more time expended in the classroom, better use of the time in the classroom).

Since this and past research have found little impact of the *extensive* margin of instructional time on students' academic achievement, future investigations may focus on the *intensive* margin (e.g., curriculum, effective use of the time). There may be several channels in this margin that are explaining my results. Finally, since I only measure students' academic achievement with a single instrument (SIMCE test), extend this paper may include other relevant educational outcomes as the entrance to tertiary education and labor outcomes to understand more long-run effects of the instructional time on human capital accumulation.

Finally, another relevant limitation of this investigation is that I'm documenting only one of many possible dimensions of the Full Day School reform. With my results, I can't claim anything about students' well being, classroom environment, teachers' work conditions, and many other essential outcomes to elaborate public policy.

References

Alexander, K. L., D. R. Entwisle, and L. S. Olson (2007): "Lasting consequences of the summer learning gap," *American Sociological Review*, 72(2), 167–180.

Alfaro, P., D. Evans, and P. Holland (2015): "Extending the School Day in Latin America and the Caribbean," Policy Research Working Paper; no. WPS 7309, Impact Evaluation series. Washington, D.C. : World Bank Group.

Bellei, C. (2009): "Does Lengthening The School Day Increase Students' Academic achievement? Results from a Natural Experiment in Chile," *Economics of Education Review*, 28(5), 629 – 640.

Berthelon, M. E., and D. I. Kruger (2011): "Risky Behavior Among Youth: Incapacitation Effects of School on Adolescent Motherhood and Crime in Chile," *Journal of Public Economics*, 95(1-2), 41–53.

Brown, B. W., and D. H. Saks (1986): "Measuring the Effects of Instructional Time on Student Learning: Evidence from the Beginning Teacher Evaluation Study," *American Journal of Education*, 94(4), 480–500.

Carroll, J. B. (1963): "A Model of School Learning.," *Teachers College R ecord*, 64, 723–733.

Cattaneo, M. A., C. Oggenfuss, and S. C. Wolter (2017): "The More, the Better? The Impact of Instructional Time on Student Performance," *Education Economics*, 25(5), 433–445.

Contreras, D., and P. Sepúlveda (2010): "Effect of Lengthening the School Day on Mother's Labor Supply.," *World Bank Economic Review*, 31(3), 747–766.

Cox, C. (2003): "Las Políticas Educacionales de Chile en las Últimas dos Décadas del Siglo XX," *Políticas Educacionales en el Cambio de Siglo. La Reforma del Sistema Escolar en Chile*, pp. 19–113.

Frei Ruiz-Tagle, E. (1996): "Discurso de S.E el Presidente de la República Eduardo Frei Ruiz-Tagle en el Inicio de la Legislatura Ordinaria del Congreso Nacional," Accessed: 2018/08/08.

Ganimian, A. J., and R. J. Murnane (2016): "Improving Education in Developing Countries: Lessons from Rigorous Impact Evaluations," *Review of Educational Research*, 86(3), 719–755.

García, Á. (2009): "Evaluación del Impacto de la Jornada Escolar Completa," Master's thesis, Universidad de Chile.

Gromada, A., and C. Shewbridge (2016): "Student Learning Time: A Literature Review," Discussion paper, OECD Education Working Papers, No. 127, OECD Publishing, Paris.

Guida, F. V., L. H. Ludlow, and M. Wilson (1985): "The Mediating Effect of Time-on-Task on the Academic Anxiety/Achievement Interaction: A Structural Model.," *Journal of Research & Development in Education*.

Hansen, M., I. Janssen, A. Schiff, P. C. Zee, and M. L. Dubocovich (2005): "The impact of school daily schedule on adolescent sleep," *Pediatrics*, 115(6), 1555–1561.

Klein, J. (2004): "Planning middle school schedules for improved attention and achievement," *Scandinavian Journal of Educational Research*, 48(4), 441–450.

Lavy, V. (2015): "Do Differences in Schools' Instruction Time Explain International Achievement Gaps? Evidence from Developed and Developing Countries," *The Economic Journal*, 125(588), 397–424.

Lee, J., and R. J. Barro (2001): "Schooling Quality in a Cross–Section of Countries," *Economica*, 68(272), 465–488.

Levin, H. M. (1986): "Are Longer School Sessions a Good Investment?," *Contemporary Economic Policy*, 4(3), 63–75.

Levin, H. M., and M. C. Tsang (1987): "The Economics of Student Time," *Economics of education review*, 6(4), 357–364.

Ministerio de Educación (2002): "APRUEBA PLAN Y PROGRAMAS DE ESTUDIO PARA 8 AÑO (NB.6) DE ENSEÑANZA BASICA,"
https://www.leychile.cl/Navegar?idNorma=195384&idParte=&idVersion=.

——— (2003): "APRUEBA PROGRAMAS DE ESTUDIO PARA 1 Y 2 AÑO (NB.1) Y 3 Y 4 AÑO (NB.2) PARA LA ENSEÑANZA BASICA,"
https://www.leychile.cl/Navegar?idNorma=214200&idParte=&idVersion=2012-06-23.

——— (2011): "APRUEBA PLANES Y PROGRAMAS DE ESTUDIO PARA PRIMER Y SEGUNDO AÑO DE EDUCACIÓN MEDIA,"
https://www.leychile.cl/Navegar?idNorma=1028020&idParte=&idVersion=.

OECD (2017): *Education at a Glance 2017*.

Patall, E. A., H. Cooper, and A. B. Allen (2010): "Extending the School Day or School Year: A Systematic Review of Research (1985-2009)," *Review of Educational Research*, 80(3), 401–436.

Pischke, J.-S. (2007): "The Impact of Length of the School Year on Student Performance and Earnings: Evidence from the German Short School Years," *The Economic Journal*, 117(523), 1216–1242.

Silva, E. (2007): "On the Clock: Rethinking the Way Schools Use Time," Discussion paper, Retrieved from http://www.educationsector.org/usr_doc/OntheClock.pdf.

Valenzuela, J. P. (2005): "Partial Evaluation of a Big Reform in the Chilean Education System: From a Half Day to a Full Day Schooling," Ph.D. thesis, University of Michigan.

Yeşil Dağli, Ü. (2018): "Effect of Increased Instructional Time on Student Achievement," *Educational Review*, pp. 1–17.

A Appendix

A.1 Other Results

Table A.1: Curriculum: 4th grade 2007

Subject	Weekly Hours (FDS)	Weekly Hours (Not FDS)
Spanish and Reading	6	6
Math	6	6
Natural and Social Science	6	6
Technology	3	3
Art	4	4
Sports	3	3
Religion	2	2
Free Disposition Hours	8	0
Total	38	30

Notes: Own elaboration based on Ministry of Education. The exact law can be consulted in Ministerio de Educación (2003).

Table A.2: Curriculum: 8th grade 2011

Subject	Weekly Hours (FDS)	Weekly Hours (Not FDS)
Spanish and Reading	5	5
English	3	3
Math	5	5
Natural Science	4	4
Social Science	4	4
Technology	2	2
Art	4	4
Sports	2	2
Orientation	2	2
Religion	2	2
Free Disposition Hours	5	0
Total	38	33

Notes: Own elaboration based on Ministry of Education. The exact law can be consulted in Ministerio de Educación (2002).

Table A.3: Curriculum: 10th grade 2013

Subject	Weekly Hours (FDS)	Weekly Hours (Not FDS)
Spanish and Reading	6	6
English	3	3
Math	6	6
Natural Science	6	6
History and Social Science	4	4
Technology	1	1
Art	2	2
Sports	2	2
Orientation	1	1
Religion	2	2
Free Disposition Hours	6	0
Total	39	33

Notes: Own elaboration based on Ministry of Education. The exact law can be consulted in Ministerio de Educación (2011).

A.1.1 Estimates considering 1st to 8th grade.

Since there is an important amount of students that change their schools in 8th grade, I estimate the same model described by Equation 3.1 using the sample only for 4th and 8th grade. The results remain negative in both cases.

Table A.4: FE Model: Effect of Exposure to FDS in SIMCE Score (Math) to 8th grade.

y_{ist}=Math$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-8th grade)	-0.000	-0.003	-0.004	-0.005	-0.005
	(.)	(0.00)	(0.00)	(0.00)	(0.00)
School Grades		0.253***	0.251***	0.256***	0.256***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.000	-0.002	-0.002
			(0.01)	(0.01)	(0.01)
Voucher=1				0.022*	0.022*
				(0.01)	(0.01)
Rural=1					-0.015
					(0.02)
N	71,168	71,168	71,168	71,168	71,168
$N_{students}$	35,584	35,584	35,584	35,584	35,584
R^2	0.06	0.09	0.09	0.09	0.09
R^2_a	0.06	0.09	0.09	0.09	0.09
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table A.5: FE Model: Effect of Exposure to FDS in SIMCE Score (Reading) to 8th grade.

y_{ist}=Reading$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-8th grade)	-0.014	-0.017***	-0.018***	-0.018***	-0.018***
	(.)	(0.00)	(0.00)	(0.00)	(0.00)
School Grades		0.301***	0.299***	0.305***	0.305***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.006	-0.007	-0.006
			(0.01)	(0.01)	(0.01)
Voucher=1				0.040***	0.038***
				(0.01)	(0.01)
Rural=1					0.006
					(0.02)
N	71,168	71,168	71,168	71,168	71,168
$N_{students}$	35,584	35,584	35,584	35,584	35,584
R^2	0.00	0.04	0.04	0.04	0.04
R^2_a	0.00	0.04	0.04	0.04	0.04
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

A.1.2 Schools Fixed Effects

There exist many unobserved school characteristics that contribute simultaneously to the academic achievement and the effective use of time in classroom. I elaborate this Appendix to check if adding school fixed effects to my specification change the main results of my paper. I find that my estimates hold after including this variable and the main conclusions remain the same.

Table A.6: FE Model: Effect of Exposure to FDS in SIMCE Score (Math) including School FE.

y_{ist}=Math$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.000	-0.003	-0.004	-0.004	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.337***	0.336***	0.339***	0.339***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.015**	-0.012*	-0.011*
			(0.01)	(0.01)	(0.01)
Voucher=1				-0.232	-0.155
				(0.18)	(0.22)
Rural=1					0.200
					(0.29)
N	106,090	106,090	106,090	106,090	106,090
$N_{students}$					
R^2	0.83	0.84	0.84	0.84	0.84
R^2_a	0.72	0.74	0.74	0.74	0.74
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table A.7: FE Model: Effect of Exposure to FDS in SIMCE Score (Reading) including School FE.

y_{ist}=Reading$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.015**	-0.018***	-0.018***	-0.019***	-0.019***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.337***	0.335***	0.336***	0.336***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.003	-0.002	-0.002
			(0.01)	(0.01)	(0.01)
Voucher=1				-0.146	-0.290
				(0.22)	(0.28)
Rural=1					-0.287
					(0.28)
N	106,090	106,090	106,090	106,090	106,090
$N_{students}$					
R^2	0.79	0.80	0.80	0.80	0.80
R^2_a	0.66	0.68	0.68	0.68	0.68
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table A.8: FE Model: Effect of Exposure to FDS in SIMCE Score (Math) to 8th grade including School FE.

y_{ist}=Math$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-8th grade)	0.001	-0.002	-0.003	-0.004	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.285***	0.283***	0.282***	0.282***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.002	-0.002	-0.002
			(0.01)	(0.01)	(0.01)
Voucher=1				-0.119	-0.392
				(0.24)	(0.31)
Rural=1					-0.677**
					(0.33)
N	69,852	69,852	69,852	69,852	69,852
$N_{students}$					
R^2	0.87	0.87	0.88	0.88	0.88
R^2_a	0.70	0.71	0.71	0.71	0.71
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table A.9: FE Model: Effect of Exposure to FDS in SIMCE Score (Reading) to 8th grade including School FE.

y_{ist}=Reading$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-8th grade)	-0.014	-0.018*	-0.018*	-0.018**	-0.018**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.324***	0.321***	0.321***	0.321***
		(0.02)	(0.02)	(0.02)	(0.02)
ln(Income)			-0.002	-0.002	-0.002
			(0.01)	(0.01)	(0.01)
Voucher=1				-0.145	-0.367
				(0.25)	(0.36)
Rural=1					-0.503
					(0.36)
N	69,852	69,852	69,852	69,852	69,852
$N_{students}$					
R^2	0.85	0.86	0.86	0.86	0.86
R^2_a	0.66	0.67	0.67	0.67	0.67
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

A.1.3 Estimation using mixed cohorts.

Table A.10: FE Model: Effect of Exposure to FDS in SIMCE Score (Math). Mixed Cohorts.

y_{ist}=Math$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.002	-0.004	-0.004	-0.006*	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
School Grades		0.248***	0.249***	0.275***	0.274***
		(0.00)	(0.00)	(0.00)	(0.00)
ln(Income)			-0.016***	-0.019***	-0.017***
			(0.00)	(0.00)	(0.00)
Voucher=1				0.037***	0.036***
				(0.01)	(0.01)
Rural=1					0.115***
					(0.01)
N	182,418	182,418	182,418	182,418	182,418
$N_{students}$	60,806	60,806	60,806	60,806	60,806
R^2	0.04	0.07	0.07	0.08	0.09
R^2_a	0.04	0.07	0.07	0.08	0.09
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table A.11: FE Model: Effect of Exposure to FDS in SIMCE Score (Reading). Mixed Cohorts.

y_{ist}=Reading$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.011***	-0.013***	-0.013***	-0.015***	-0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
School Grades		0.286***	0.285***	0.300***	0.299***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.005	-0.007*	-0.005
			(0.00)	(0.00)	(0.00)
Voucher=1				0.052***	0.051***
				(0.01)	(0.01)
Rural=1					0.090***
					(0.01)
N	182,418	182,418	182,418	182,418	182,418
$N_{students}$	60,806	60,806	60,806	60,806	60,806
R^2	0.00	0.03	0.03	0.04	0.04
R_a^2	0.00	0.03	0.03	0.04	0.04
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

Table A.12: FE Model: Effect of Exposure to FDS in SIMCE Score (Math). Mixed Cohorts and School FE.

y_{ist}=Math$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.003	-0.006	-0.006	-0.006	-0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.338***	0.338***	0.340***	0.340***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.016***	-0.015***	-0.015***
			(0.00)	(0.00)	(0.00)
Voucher=1				-0.290*	-0.317**
				(0.16)	(0.16)
Rural=1					0.320
					(0.27)
N	181,772	181,772	181,772	181,772	181,772
$N_{students}$					
R^2	0.82	0.83	0.83	0.83	0.83
R^2_a	0.71	0.73	0.73	0.73	0.73
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

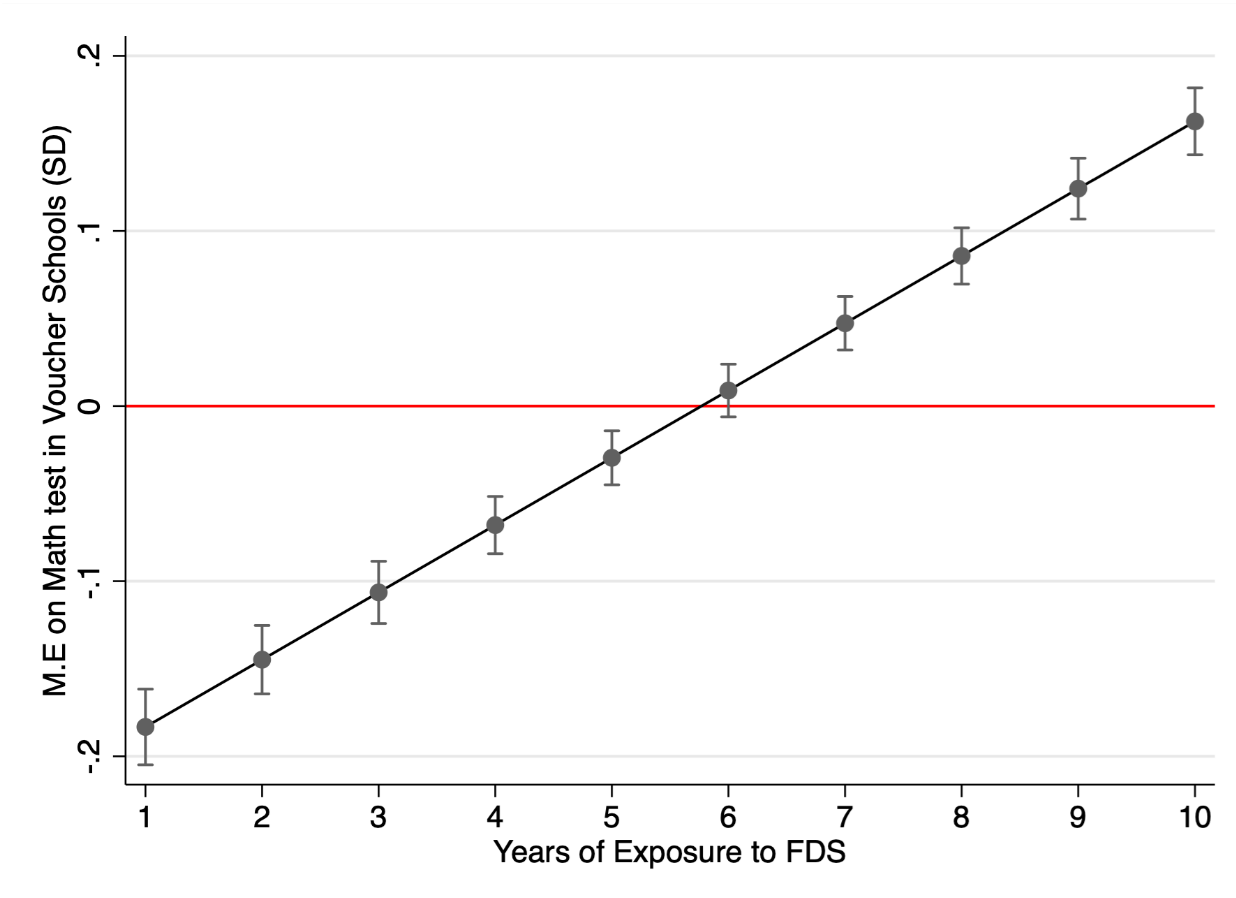
Table A.13: FE Model: Effect of Exposure to FDS in SIMCE Score (Reading). Mixed Cohorts and School FE.

y_{ist}=Reading$_{ist}$	(1)	(2)	(3)	(4)	(5)
Years of Exposure (1st-10th grade)	-0.012*	-0.015**	-0.015**	-0.015**	-0.015**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
School Grades		0.354***	0.353***	0.353***	0.352***
		(0.01)	(0.01)	(0.01)	(0.01)
ln(Income)			-0.006	-0.006	-0.006
			(0.01)	(0.01)	(0.01)
Voucher=1				-0.267	-0.375**
				(0.17)	(0.17)
Rural=1					-0.043
					(0.22)
N	181,772	181,772	181,772	181,772	181,772
$N_{students}$					
R^2	0.77	0.78	0.78	0.78	0.78
R^2_a	0.64	0.66	0.66	0.66	0.66
Student Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
School Controls	No	No	No	Yes	Yes
Geographic Controls	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The dependent variable is standardized by year for each test. *Years of Exposure* is the interest variable and is defined by Equation 3.1. Each observation is a student-year unit. Robust standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1

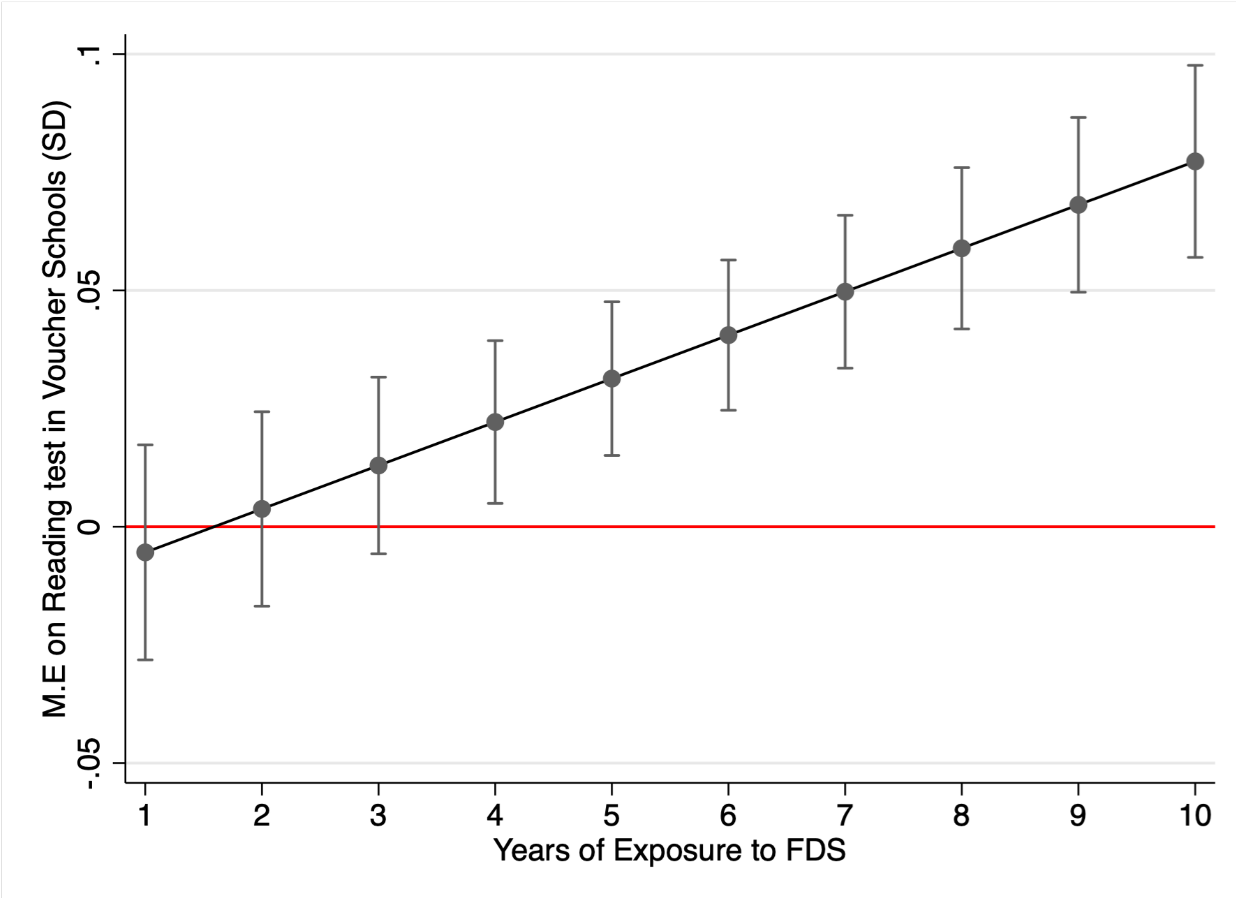
A.1.4 Heterogeneous Effects

Figure A.1: Marginal effects of the years of exposure on math test at Voucher schools



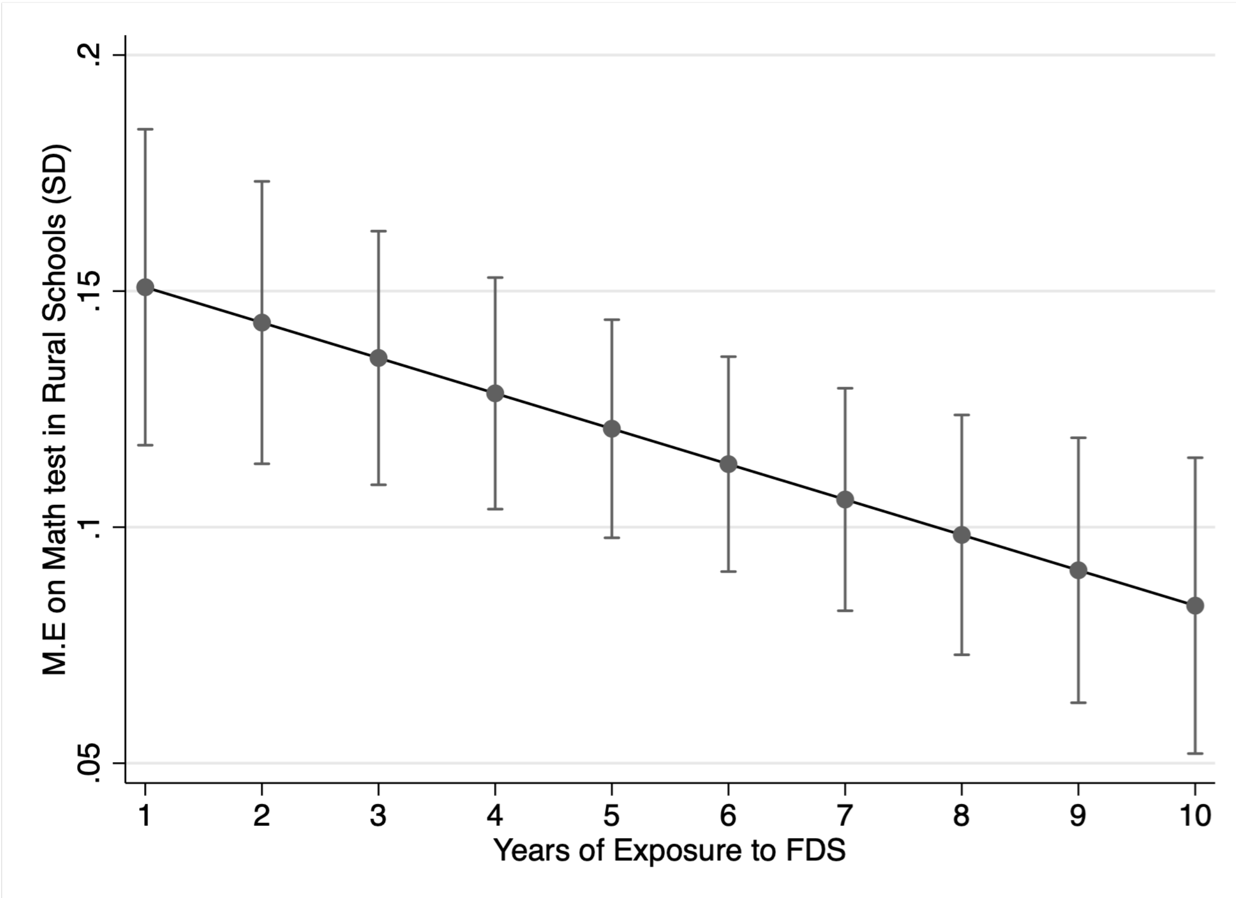
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education.

Figure A.2: Marginal effects of the years of exposure on reading test at Voucher schools



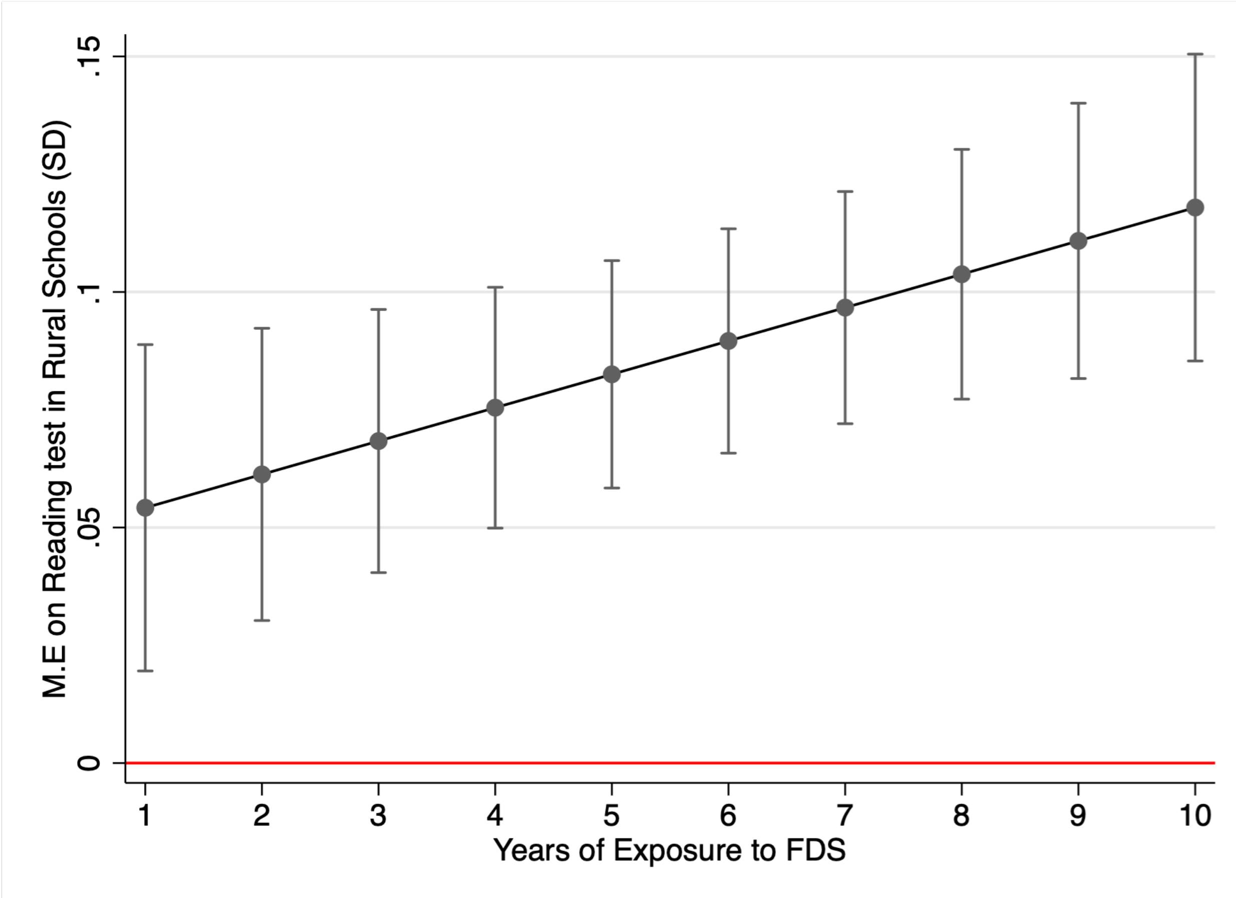
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education.

Figure A.3: Marginal effects of the years of exposure on math test at rural schools



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education.

Figure A.4: Marginal effects of the years of exposure on reading test at rural schools



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education.

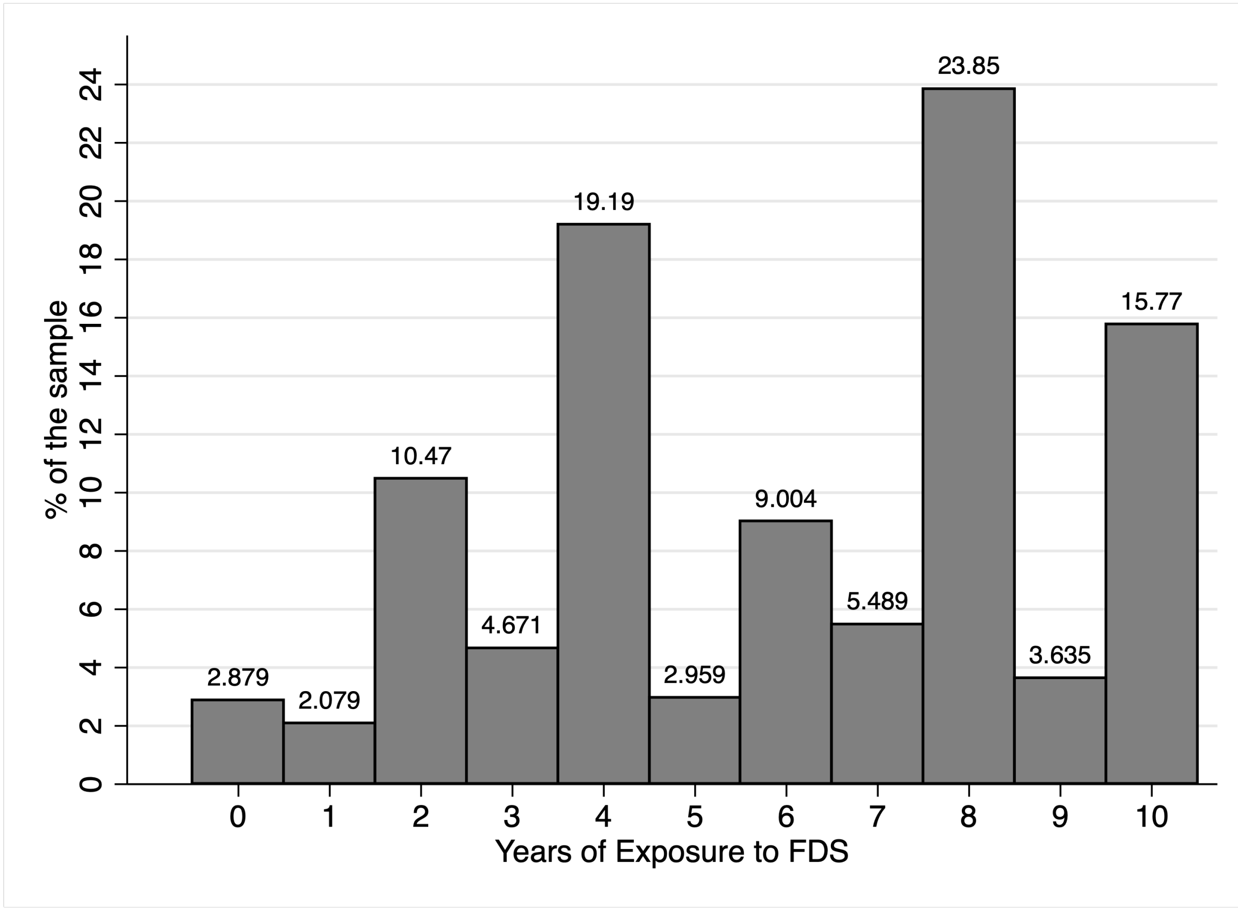
A.2 Figures and Tables

Table A.14: Full Day School Reform Cost (2010 MM.USD)

Year	FDS Cost	MINEDUC Budget	% of MINEDUC Budget
1997	20.68	3158.56	0.65 %
1998	130.13	3683.60	3.53 %
1999	187.03	3948.83	4.74 %
2000	214.21	4173.28	5.13 %
2001	249.79	4552.12	5.49 %
2002	378.04	5099.40	7.41 %
2003	327.82	5285.96	6.20 %
2004	303.22	5591.74	5.42 %
2005	237.53	5796.91	4.10 %
2006	295.66	6123.13	4.83 %
2007	225.94	6684.40	3.38 %
2008	163.87	7655.38	2.14 %
2009	157.09	8601.05	1.83 %
2010	161.10	9723.01	1.66 %
Total (Mean)	3052.12	80077.33	(4.04 %)

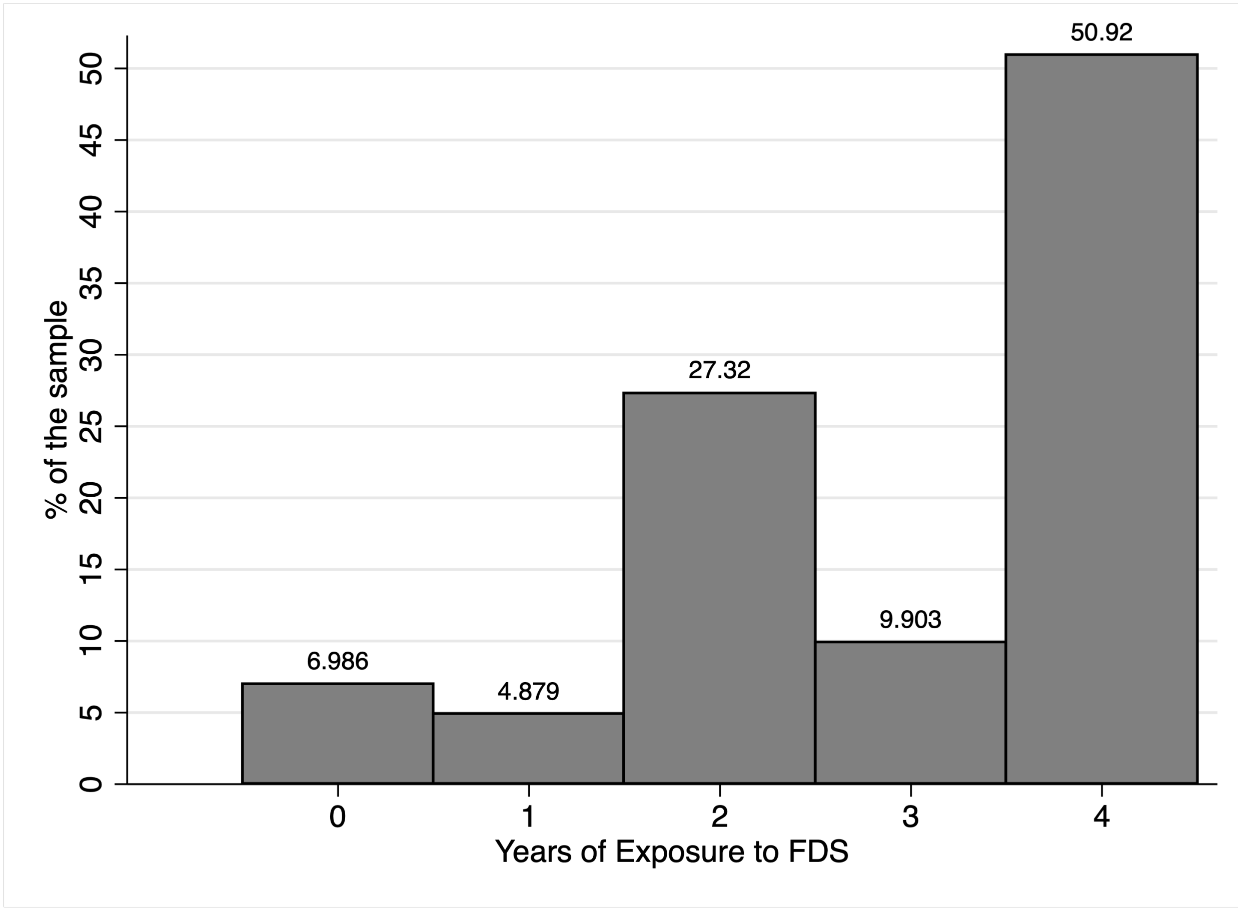
Notes: Own elaboration based on DIPRES Annual Budget Law. CPI series were extracted from Federal Reserve Bank of St.Louis (FRED). We used the average exchange rate of December 2010 (474,78 CLP/USD).

Figure A.5: Distribution of Explanatory Variable (Whole Sample).



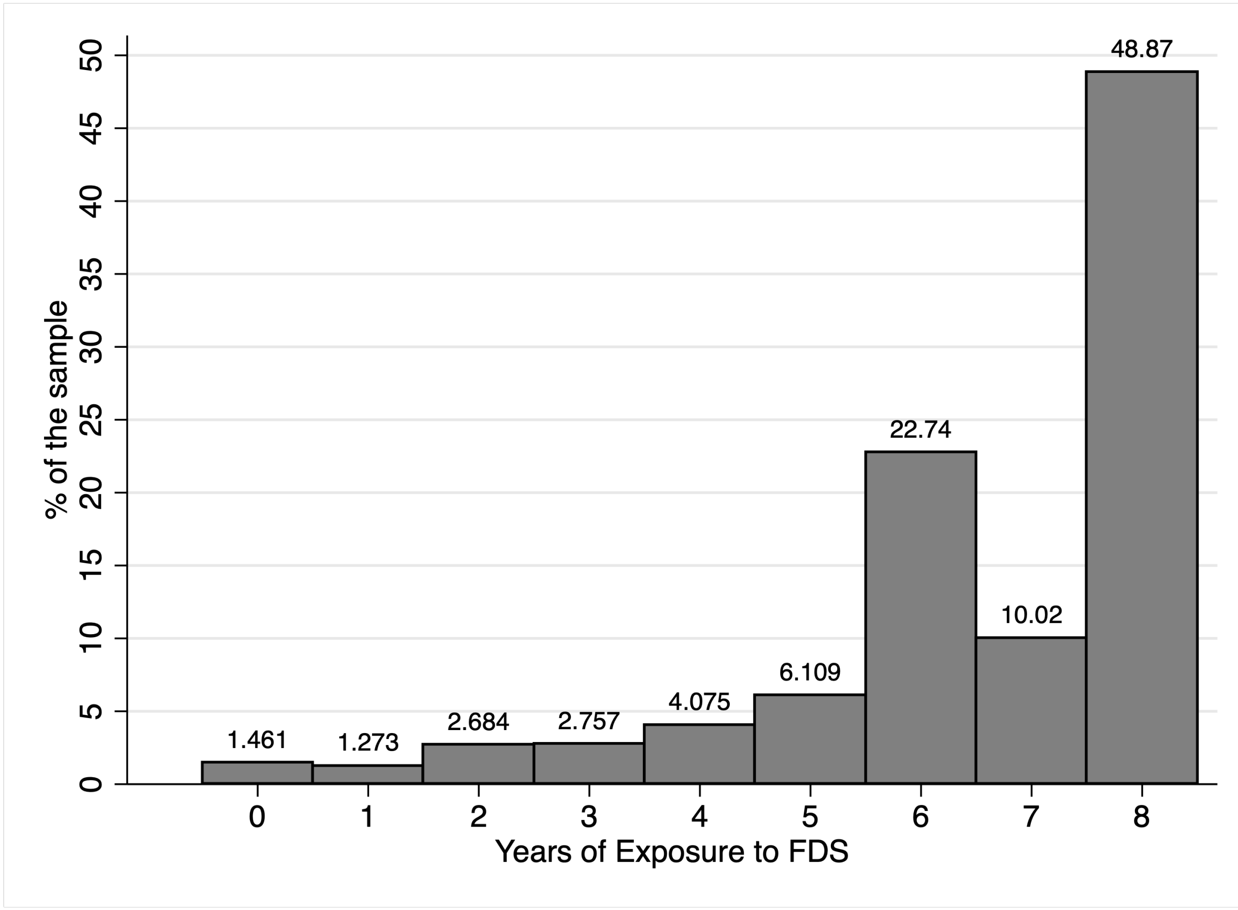
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis is the number of years of exposure to the longer school day defined by Equation 3.1. The Y-axis represents the percentage of the sample that has a determinate number of years of exposure to the program.

Figure A.6: Distribution of Explanatory Variable (2007, only 4th grade).



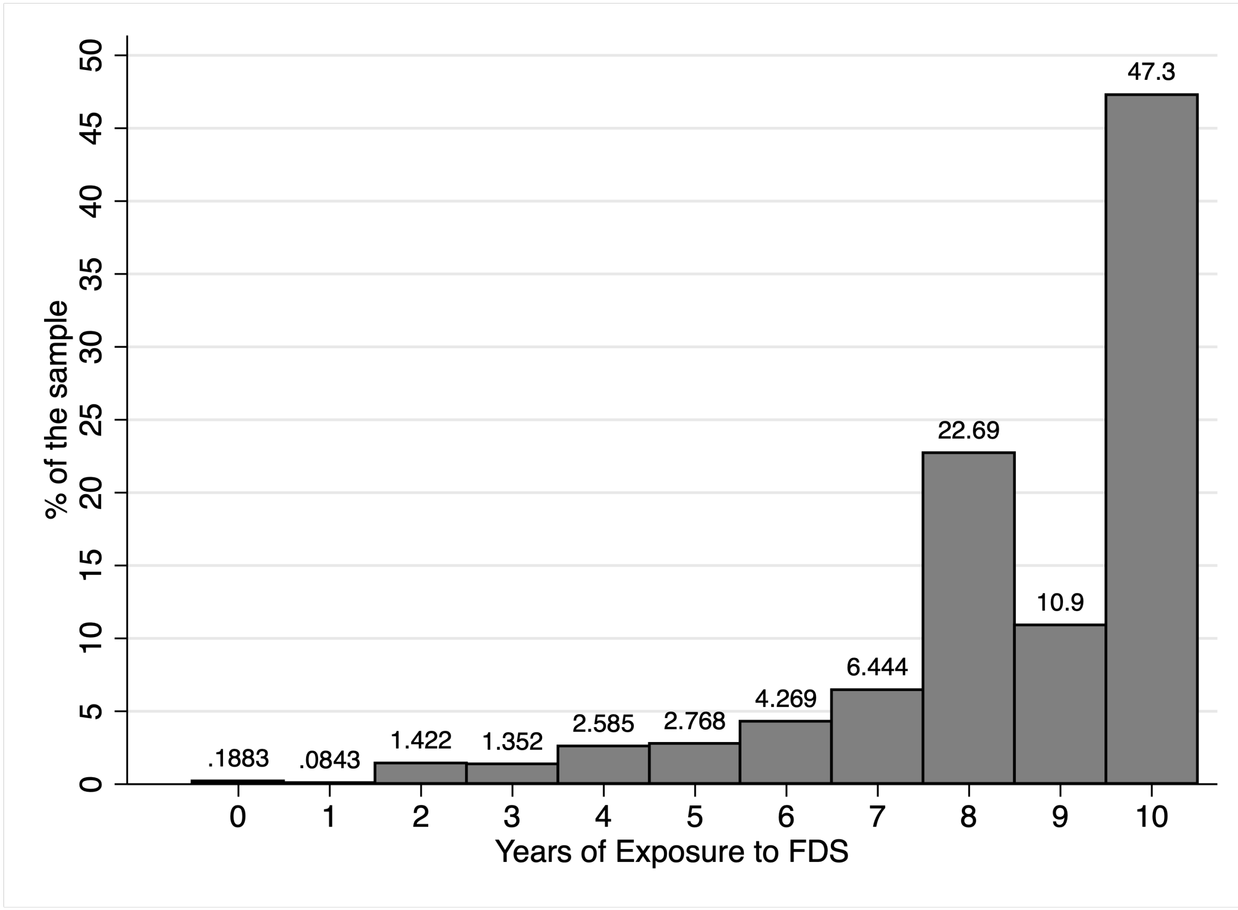
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis is the number of years of exposure to the longer school day defined by Equation 3.1. The Y-axis represents the percentage of the sample that has a determinate number of years of exposure to the program.

Figure A.7: Distribution of Explanatory Variable (2011, only 8th grade).



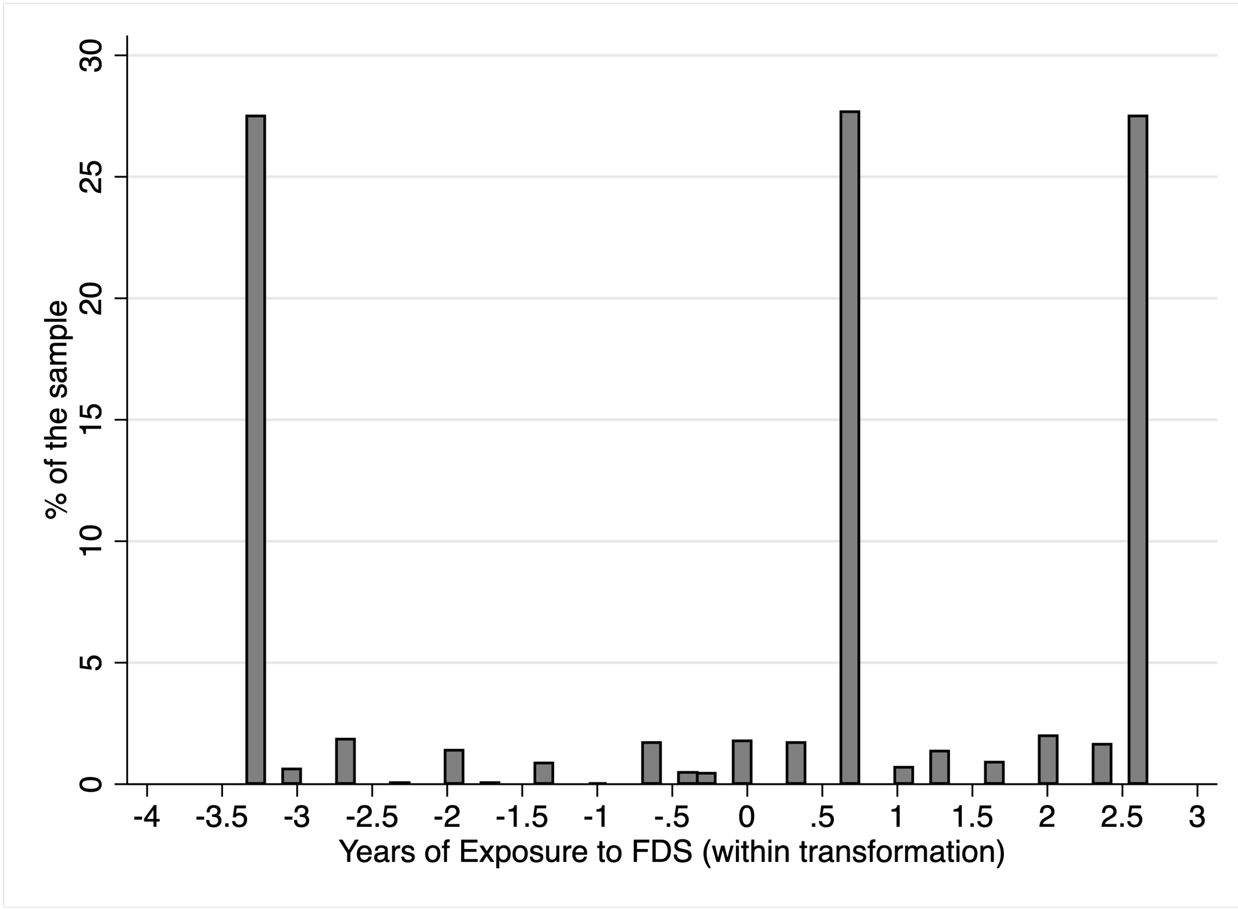
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis is the number of years of exposure to the longer school day defined by Equation 3.1. The Y-axis represents the percentage of the sample that has a determinate number of years of exposure to the program.

Figure A.8: Distribution of Explanatory Variable (2013, only 10th grade).



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis is the number of years of exposure to the longer school day defined by Equation 3.1. The Y-axis represents the percentage of the sample that has a determinate number of years of exposure to the program.

Figure A.9: Distribution of the Within Transformation of Explanatory Variable (Whole Sample).



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis show the within transformation of years of exposure to longer school day defined by Equation 3.1 (i.e. $Exp_{i,t} - \overline{Exp_i}$) . The Y-axis represents the percentage of the sample.

Table A.15: Characterization of the Sample.

	(1)	Only Students From 10th grade (2013)		
Variable	SIMCE 2013	SIMCE Panel	SIMCE Panel + Admin.Data	Sample
SIMCE Math (SD)	269.35	277.42	264.15	271.76
SIMCE Reading (SD)	256.57	262.66	252.82	258.97
Books	3.11	3.14	3.26	3.08
Mother's Education	1.73	1.75	1.68	1.68
Father's Education	1.71	1.72	1.65	1.63
Income (M.CLP)	358.96	361.02	354.13	352.37
N	144.763	75.958	45.402	35.584

Notes: Books it's a categorical variable that takes 9 different values. Father's and Mother's Education is also categorical variables for parents with incomplete primary education (0), incomplete secondary education (1), incomplete tertiary education (2) and complete tertiary education (3). Income is expressed in hundred thousands CLP.

A.3 Data Loss

A.3.1 Main Sample (2007-2013)

In this Appendix, I discuss the data set construction from raw data to the final sample. This exercise allows me to identify the sources of attrition in the sample. In summary, from a universe of 250.000 students that took the SIMCE test every year, I'm able to identify around 35.000 individuals to build longitudinal data. The steps taken to construct the data are explained in detail in Tables A.16, A.17, A.18 and A.19.

Table A.16: SIMCE Data Sets

Data Set	Whole Sample	Valid Observations
SIMCE 2007	244.724	181.994
SIMCE 2011	250.068	204.068
SIMCE 2013	254.580	157.929
Merge		81.985
Final Sample		245.955

Notes: Own elaboration based on SIMCE datasets. *Whole Sample* column represent the number of observations of the students' dataset for each year. *Valid Observations* represent the number of observations of the dataset after merging the students' information with the corresponding household survey and drop the duplicates of the ID variable. Final Sample corresponds to a reshape of the Merge row (Merge×3).

Table A.17: Assistance Administrative Records Data Sets 2004-2013

	Valid Observations	Merge
2004	354.747	.
2005	475.340	347.478
2006	594.308	343.203
2007	617.378	339.500
2008	617.110	336.155
2009	617.525	334.366
2010	617.215	332.670
2011	615.684	330.019
2012	611.725	324.997
2013	605.349	317.237
Final Sample		3.172.370

Notes: Own elaboration based on Assistance Administrative Records Data Sets of the Ministry of Education. *Valid Observations* represent the number of observations of the dataset after dropping the duplicates of the ID variable. Final Sample corresponds to a reshape of the last row (Merge×10).

Table A.18: FDS Administrative Record

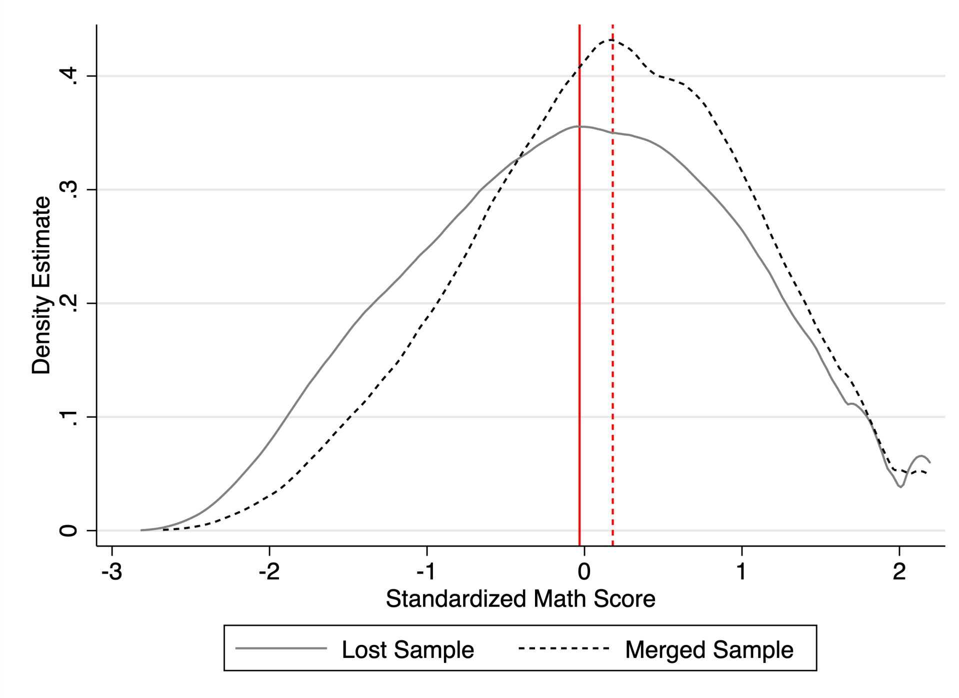
Schools	Merge with Assistance Record
7933	7345

Table A.19: Final Data Set

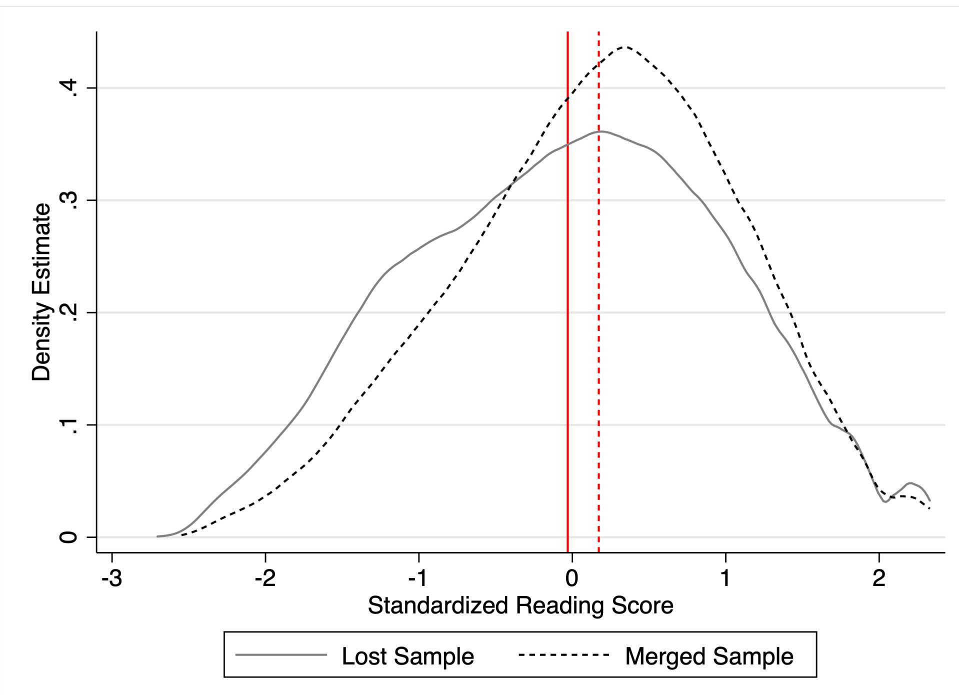
Step	Note	N	Δ^-
	Panel A: Final Merge		
1)	Assistance Record	3.172.370	0
2)	1) + FDS data	2.503.998	668.960
3)	2) + keeping 2007, 2011 and 2013	748.628	1.755.370
4)	3) + merge with SIMCE panel	206.391	542.237
	Panel B: Data Cleaning		
5)	4) + same gender in two datasets	205.479	912
6)	5) + excluding private schools	205.042	437
7)	6) + excluding students from other grades	198.916	6.126
8)	7) + excluding students that repeated some grade	189.986	8.930
9)	8) + students that don't take reading test in some period	175.436	14.550
10)	9) + students that don't take math test in some period	173.285	2.151
11)	10) + observations without books in any period	169.019	4.266
12)	11) + observations without father's education in any period	166.503	2516
13)	12) + observations without mother's education in any period	166.018	485
14)	13) + observations without income in any period	165.272	746
15)	14) + students' that don't appear in the three periods	106.752	58.520
	N Final Data Set	106.752	
	$N_{students}$ Final Data Set	35.584	

Since the sample is around the 14% (35.000/250.000) of the total of students that take the SIMCE test each year, it's necessary to check how representative is the data to identify possible sources of selection bias in the sample. The Figures A.10, A.11 and A.12 shows the distribution of the standardized math and reading test scores for each year of the sample. The results, in conjunction with the mean tests, suggest that the sample used in this paper have slightly better achievement than the lost sample.

Figure A.10: Distributions of Standardized Tests for Year 2007



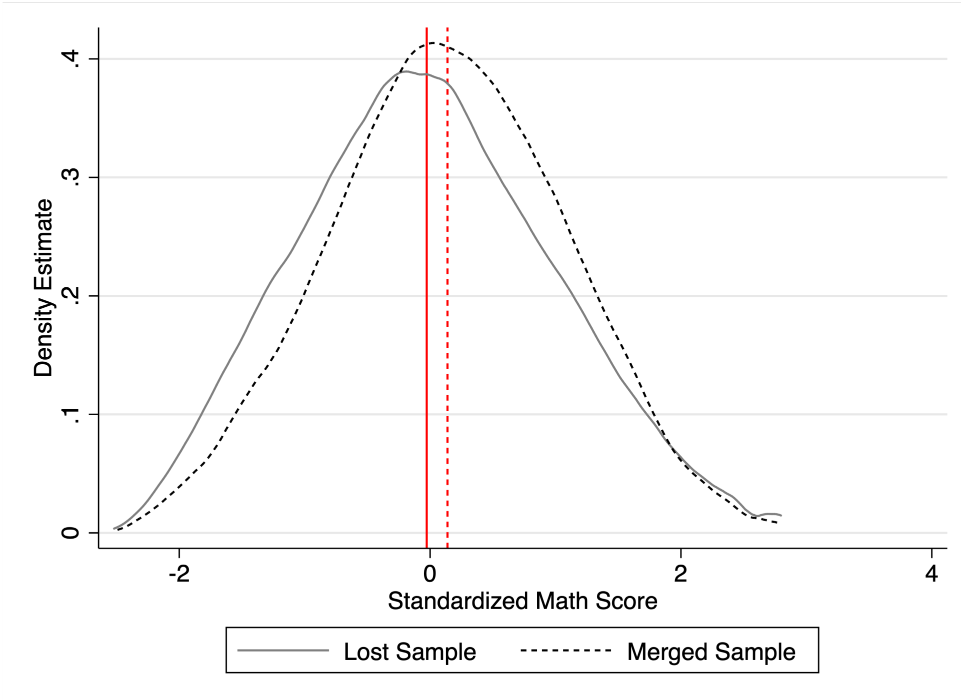
(a) Math



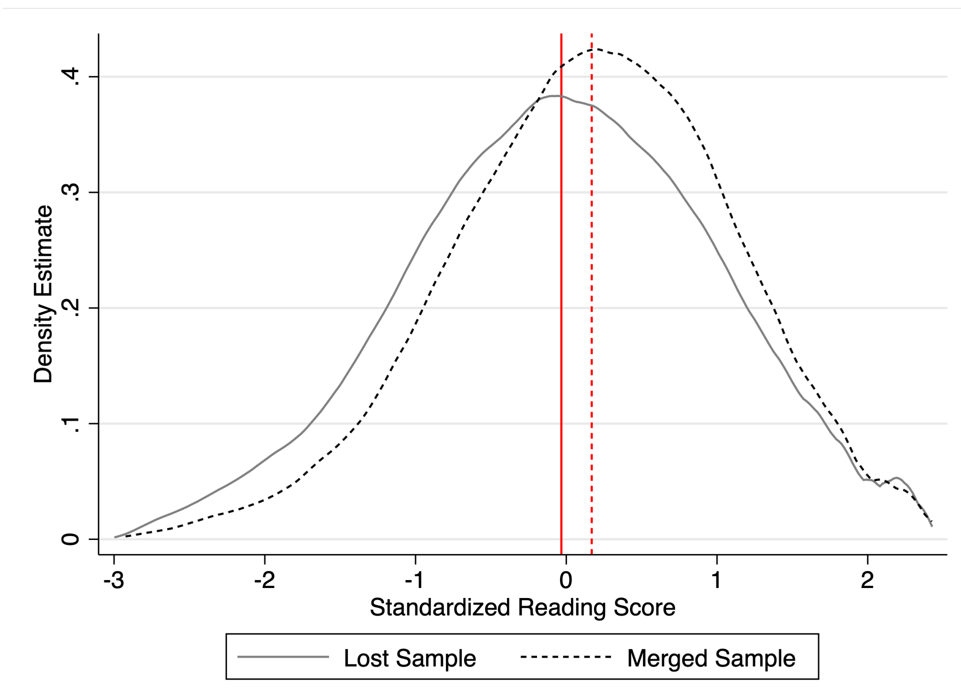
(b) Reading

Notes: Own elaboration based on SIMCE dataset. The vertical lines indicate the mean of each distribution. The pattern of the vertical line point of the distribution. I use the Epanechnikov Kernel function for all the density estimates.

Figure A.11: Distributions of Standardized Tests for Year 2011



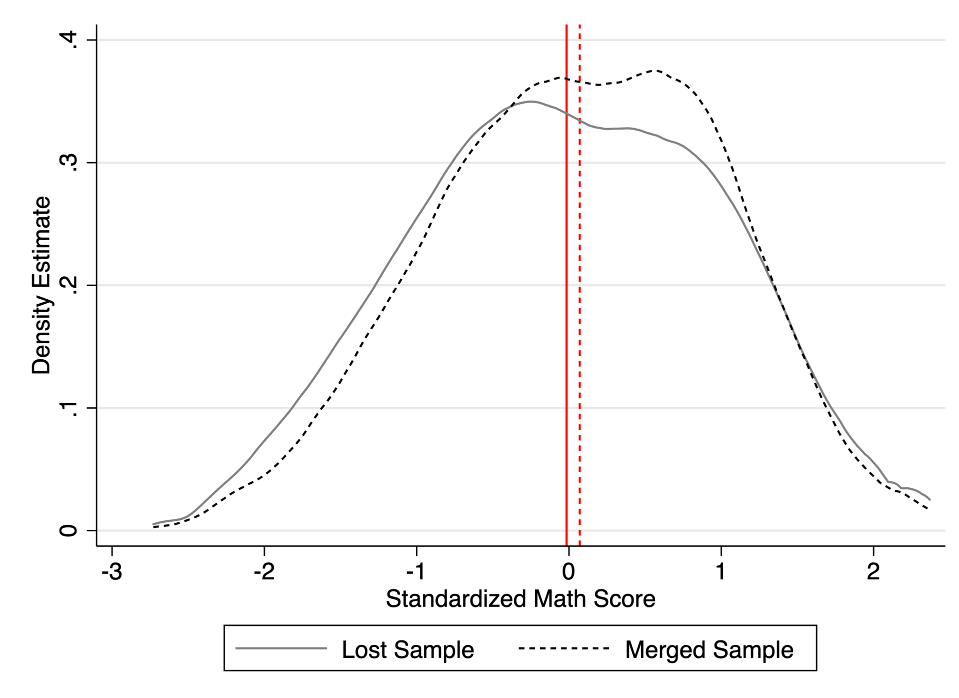
(a) Math



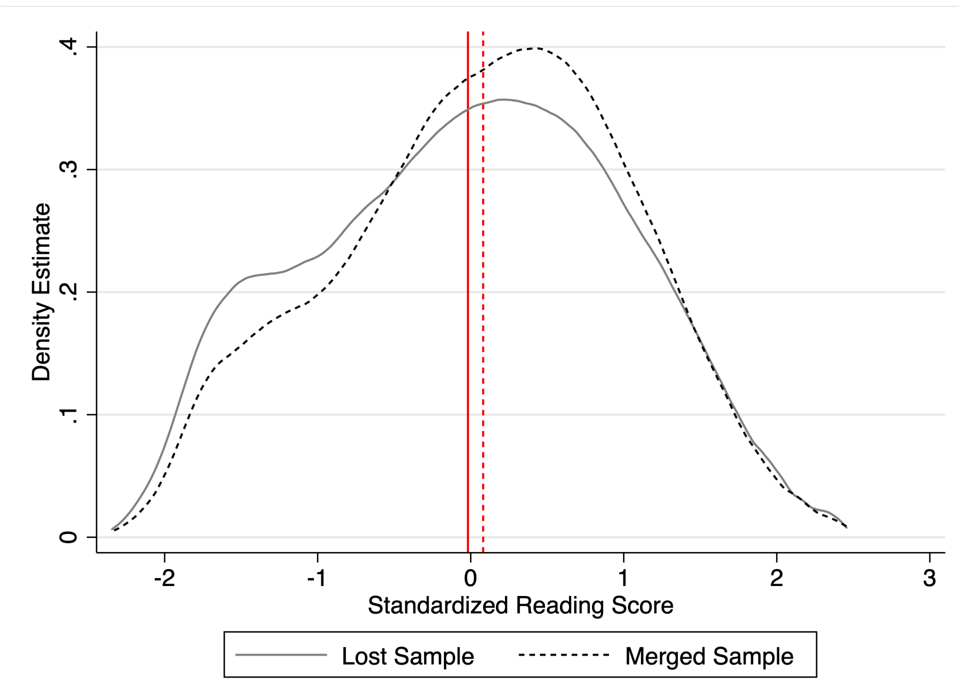
(b) Reading

Notes: Own elaboration based on SIMCE dataset. The vertical lines indicate the mean of each distribution. The pattern of the vertical line point of the distribution. I use the Epanechnikov Kernel function for all the density estimates.

Figure A.12: Distributions of Standardized Tests for Year 2013



(a) Math



(b) Reading

Notes: Own elaboration based on SIMCE dataset. The vertical lines indicate the mean of each distribution. The pattern of the vertical line point of the distribution. I use the Epanechnikov Kernel function for all the density estimates.

A.3.2 Robustness Sample (2009-2015)

In this Appendix, I discuss the data set construction from raw data to the final sample. This exercise allows me to identify the sources of attrition in the sample. In summary, from a universe of 250.000 students that took the SIMCE test every year, I'm able to identify around 35.000 individuals to build longitudinal data. The steps taken to construct the data are explained in detail in Tables A.20, A.21, A.22 and A.23.

Table A.20: SIMCE Data Sets

Data Set	Whole Sample	Valid Observations
SIMCE 2009	254.823	201.744
SIMCE 2013	255.132	191.542
SIMCE 2015	245.160	164.253
Merge		97.971.985
Final Sample		293.913

Notes: Own elaboration based on SIMCE datasets. *Whole Sample* column represent the number of observations of the students' dataset for each year. *Valid Observations* represent the number of observations of the dataset after merging the students' information with the corresponding household survey and drop the duplicates of the ID variable. Final Sample corresponds to a reshape of the Merge row (Merge×3).

Table A.21: Assistance Administrative Records Data Sets 2004-2013

	Valid Observations	Merge
2006	594.664	.
2007	714.630	584.781
2008	737.114	577.872
2009	737.884	573.412
2010	737.643	570.883
2011	736.144	567.315
2012	732.183	561.306
2013	725.869	551.898
2014	657.671	482.247
2015	661.508	379.914
Final Sample		3.799.140

Notes: Own elaboration based on Assistance Administrative Records Data Sets of the Ministry of Education. *Valid Observations* represent the number of observations of the dataset after dropping the duplicates of the ID variable. Final Sample corresponds to a reshape of the last row (Merge×10).

Table A.22: FDS Administrative Record

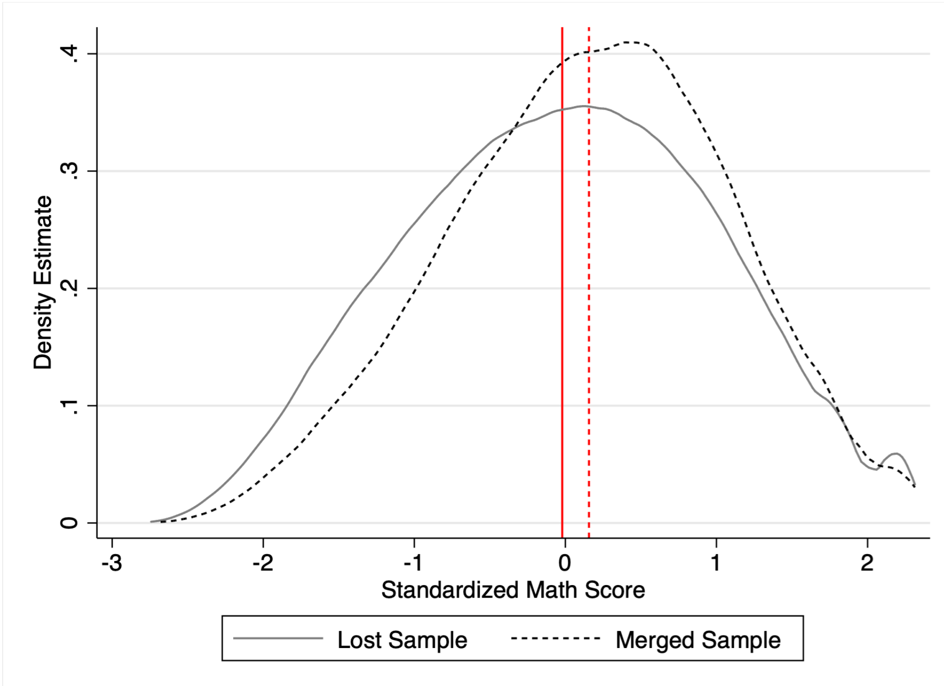
Schools	Merge with Assistance Record
7933	7457

Table A.23: Final Data Set

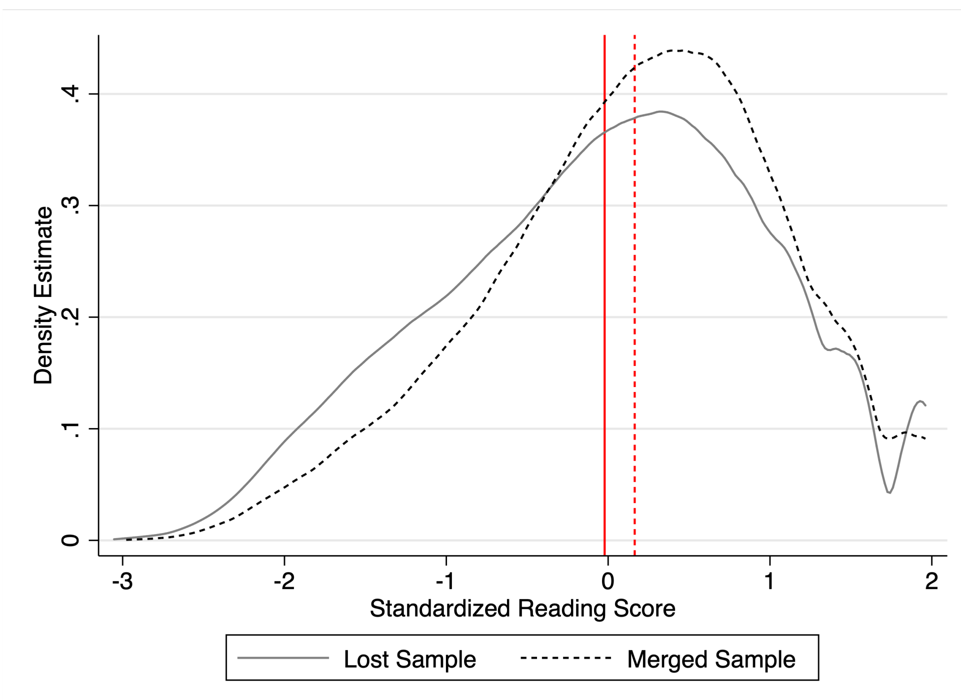
Step	Note	N	Δ^{-}
	Panel A: Final Merge		
1)	Assistance Record	3.799.140	0
2)	1) + FDS data	3.003.747	795.869
3)	2) + keeping 2007. 2011 and 2013	893.915	2.109.832
4)	3) + merge with SIMCE panel	111.944	963.940
	Panel B: Data Cleaning		
5)	4) + same gender in two datasets	111.867	77
6)	5) + excluding private schools	111.636	231
7)	6) + excluding students from other grades	111.625	11
8)	7) + excluding students that repeated some grade	108.979	2.646
9)	8) + students that don't take reading test in some period	106.174	2.805
10)	9) + students that don't take math test in some period	105.725	449
11)	10) + observations without books in any period	105.722	3
12)	11) + observations without father's education in any period	102.654	3.068
13)	12) + observations without mother's education in any period	102.163	491
14)	13) + observations without income in any period	101.807	356
15)	14) + students' that don't appear in the three periods	75.666	26.141
	N Final Data Set	75.666	
	$N_{students}$ Final Data Set	25.222	

Since the sample is around the 14% (35.000/250.000) of the total of students that take the SIMCE test each year, it's necessary to check how representative is the data to identify possible sources of selection bias in the sample. The Figures A.13, A.14 and A.15 shows the distribution of the standardized math and reading test scores for each year of the sample. The results, in conjunction with the mean tests, suggest that the sample used in this paper have slightly better achievement than the loss sample.

Figure A.13: Distributions of Standardized Tests for Year 2009 (4th grade)



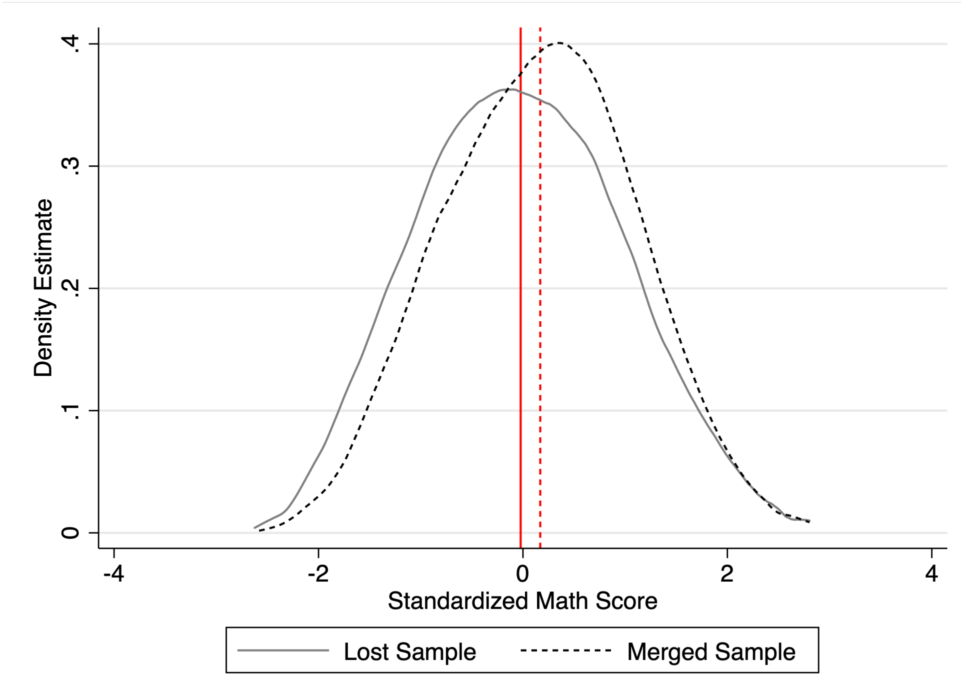
(a) Math



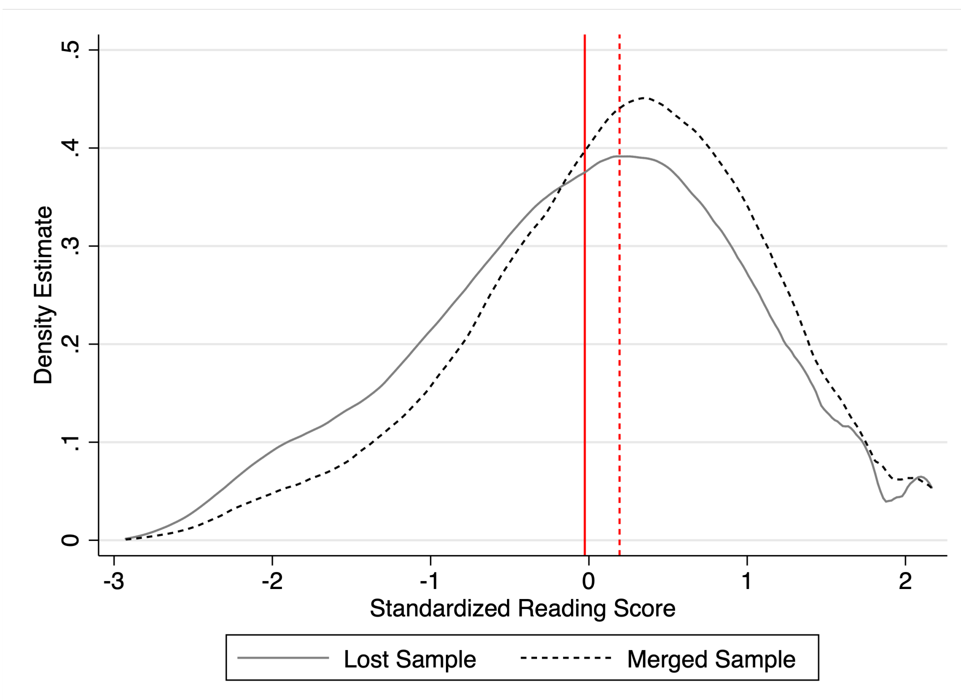
(b) Reading

Notes: Own elaboration based on SIMCE dataset. The vertical lines indicate the mean of each distribution. The pattern of the vertical line point of the distribution. I use the Epanechnikov Kernel function for all the density estimates.

Figure A.14: Distributions of Standardized Tests for Year 2013 (8th grade)



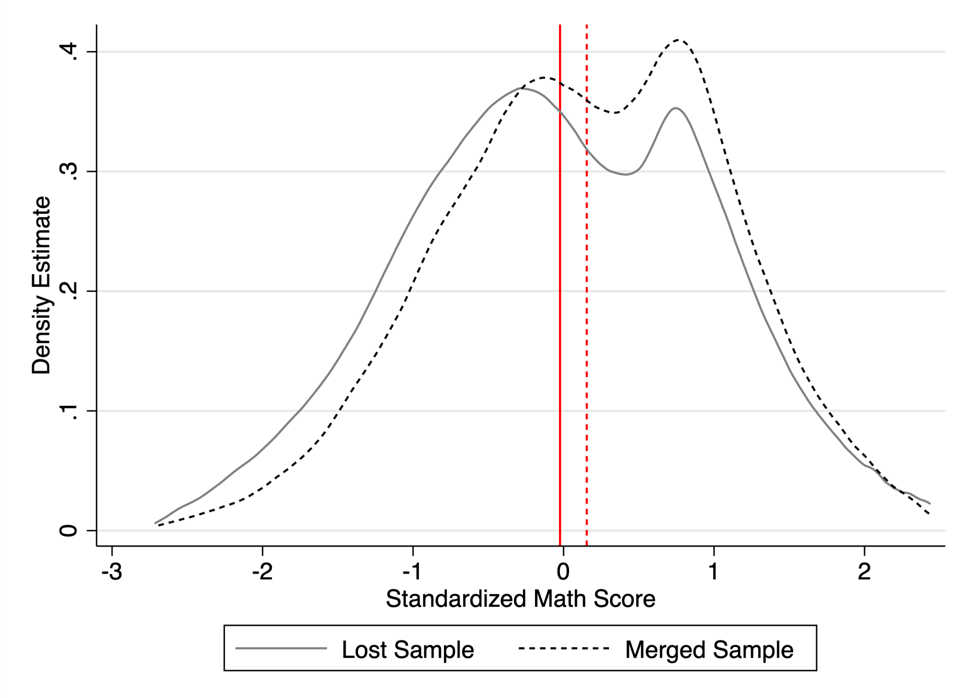
(a) Math



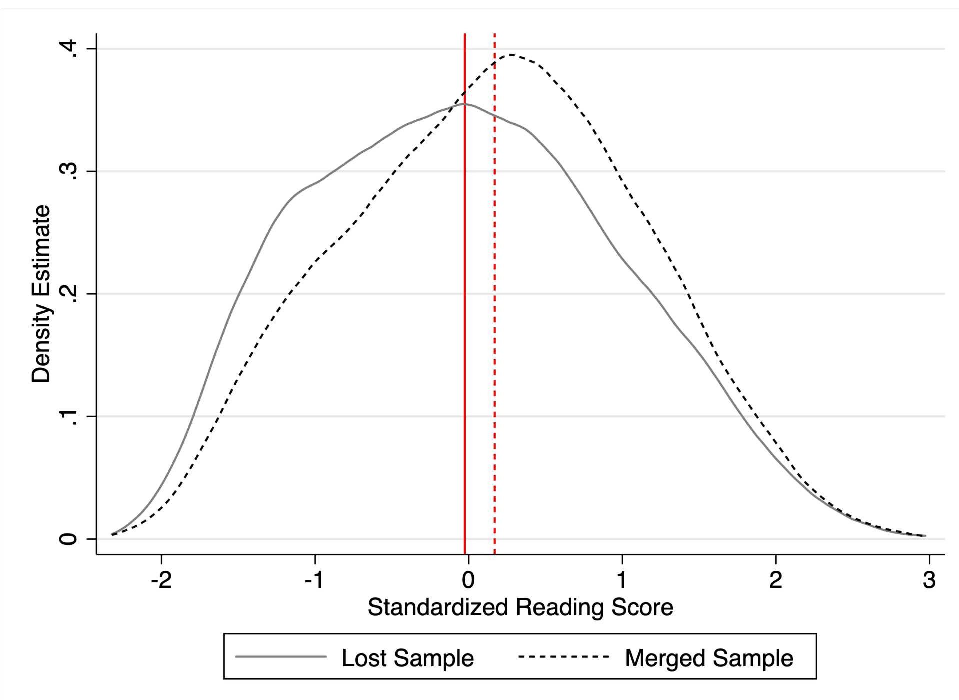
(b) Reading

Notes: Own elaboration based on SIMCE dataset. The vertical lines indicate the mean of each distribution. The pattern of the vertical line point of the distribution. I use the Epanechnikov Kernel function for all the density estimates.

Figure A.15: Distributions of Standardized Tests for Year 2015 (10th grade)



(a) Math



(b) Reading

Notes: Own elaboration based on SIMCE dataset. The vertical lines indicate the mean of each distribution. The pattern of the vertical line point of the distribution. I use the Epanechnikov Kernel function for all the density estimates.

A.4 Data Imputation

In this Appendix, I discuss the data imputation in the covariates of the main specification. Taking advantage of the longitudinal nature of the data, I recover information of a substantial number of students doing this. The criteria of the process for each of the variables that were imputed are the following:

1. **Books**: In the case of missing value, I impute the missing information with the observation available in the last period. For example, if I have data for books in the years 2007 and 2013, but no data for 2011, I impute that missing value with the one of 2013.

2. **Parent's Education**: In the case of missing value, I impute the missing information with the available observation in the nearest period to the missing one. For example, if the data do not have data about the mother's education in the year 2007, I impute that missing value with the mother's education reported in 2011. If this information it's also missing, I assign the value of 2013.

3. **Income**: In the case of missing value, the imputation criteria depend on the availability of information in the remain periods. For example, if one student has only one missing value in the three periods, I impute that missing value with the average of the other two periods. In the other hand, if a student only counts with income information for one period, I impute that missing value with the available data.

The Table A.24 show the number of impute observations by variable and year. These results show that around 64% of our sample had missing values in some of these variables before the imputation.

Table A.24: Data Imputation Record

Year	2007	2011	2013	All periods
	N	*N*	*N*	*N*
Books	7069	1943	6580	15592
Father's Education	7367	3472	8423	17733
Mother's Education	7191	2711	7219	17121
Income	7311	2904	7536	17751
Total	28938	11030	29758	68197

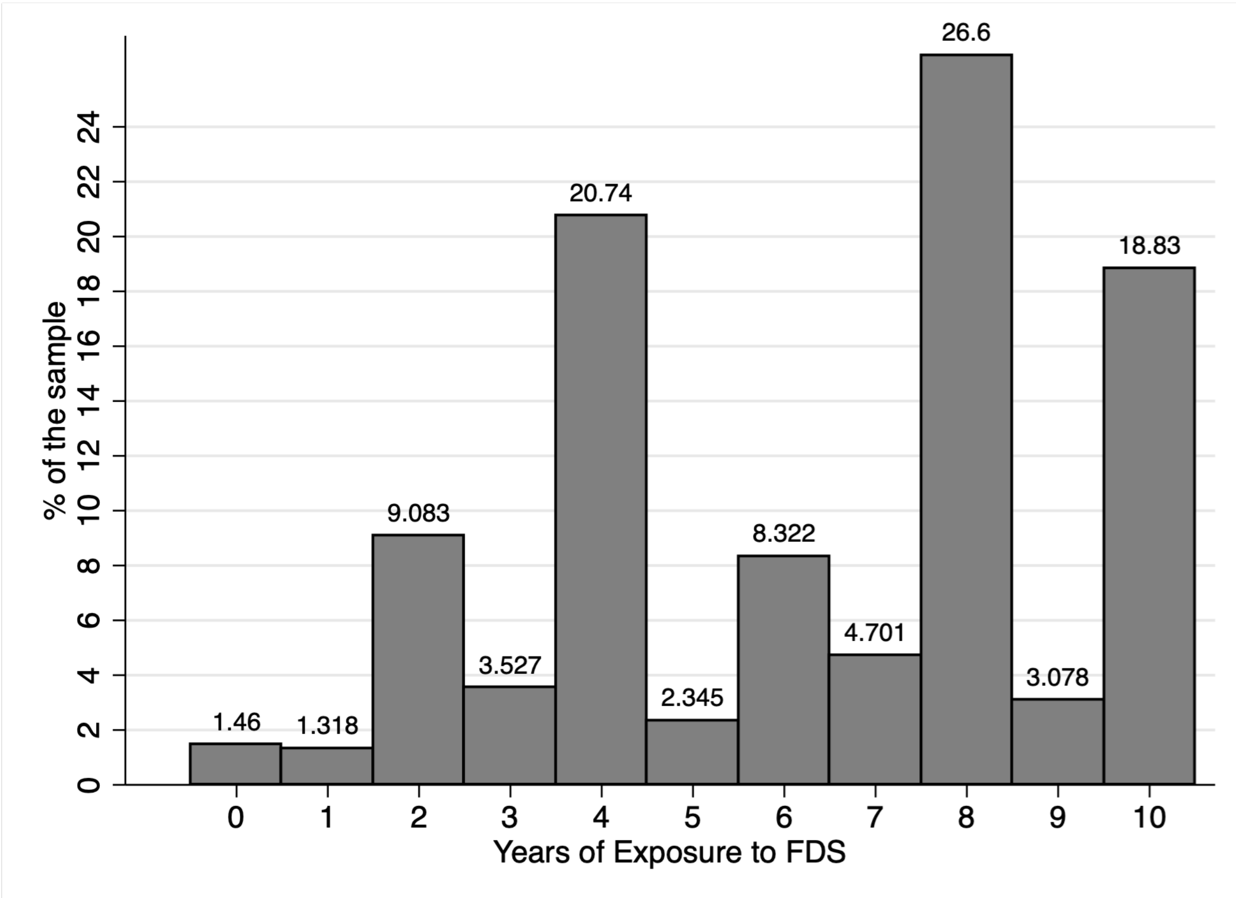
A.4.1 Miscellaneous

Table A.25: Descriptive Statistics

	4th Grade 2009		8th Grade 2013		10th Grade 2015	
	$\overline{x}$	σ_x	$\overline{x}$	σ_x	$\overline{x}$	σ_x
Panel A						
Exposure to FDS	3.15	(1.15)	6.98	(1.48)	8.96	(1.49)
SIMCE Math	261.58	(50.83)	269.92	(45.57)	272.56	(61.32)
SIMCE Reading	270.79	(48.89)	264.79	(46.39)	256.15	(50.51)
Assistance(%)	94.43 %	(4.74)	94.32 %	(4.79)	93.48 %	(5.51)
School Grades	6.0	(0.48)	5.7	(0.51)	5.6	(0.53)
Male=1	0.450	(0.50)	0.450	(0.50)	0.450	(0.50)
Voucher=1	0.57	(0.49)	0.59	(0.49)	0.66	(0.47)
Income (M.CLP)	312.06 $	(248.58)	391.14 $	(283.00)	429.01 $	(292.54)
Rural=1	0.13	(0.34)	0.11	(0.31)	0.03	(0.18)
Panel B						
Father Education						
$[0,8)$ Years	21.46 %		9.09 %		9.62 %	
$[8,12)$ Years	14.71 %		24.84 %		24.36 %	
$[12,17)$ Years	45.89 %		48.57 %		47.45 %	
$\geq$ 17 Years	17.94 %		17.50 %		18.58 %	
Mother Education						
$[0,8)$ Years	21.18 %		8.14 %		8.23 %	
$[8,12)$ Years	16.62 %		23.61 %		22.70 %	
$[12,17)$ Years	44.95 %		49.39 %		48.88 %	
$\geq$ 17 Years	17.25 %		18.85 %		20.20 %	
N	25222		25222		25222	

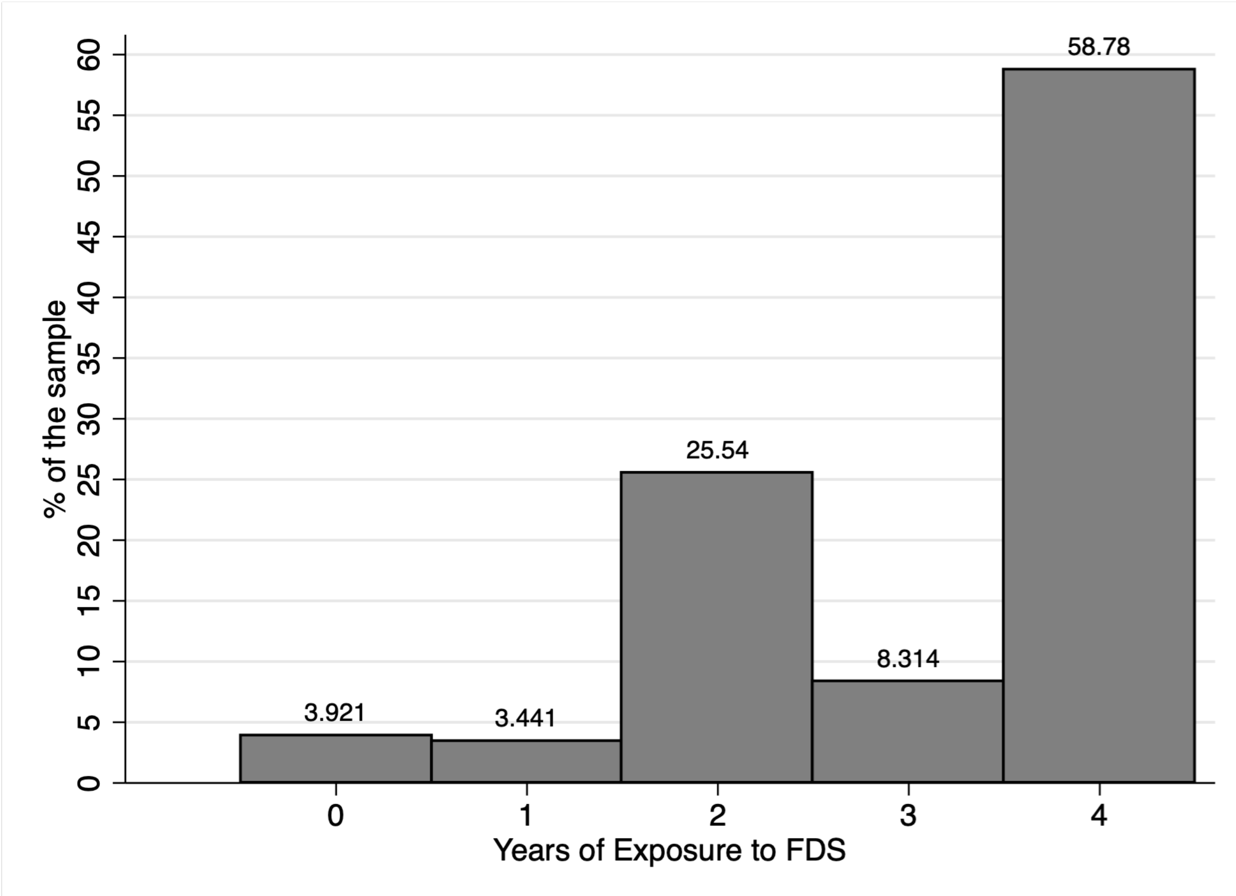
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. Panel A shows the mean and standard deviation of several continuous and binary variables. Standard Deviations are in parentheses. Panel B shows the proportion of students in the sample by parents education.

Figure A.16: Distribution of Explanatory Variable (2009-2015, whole sample).



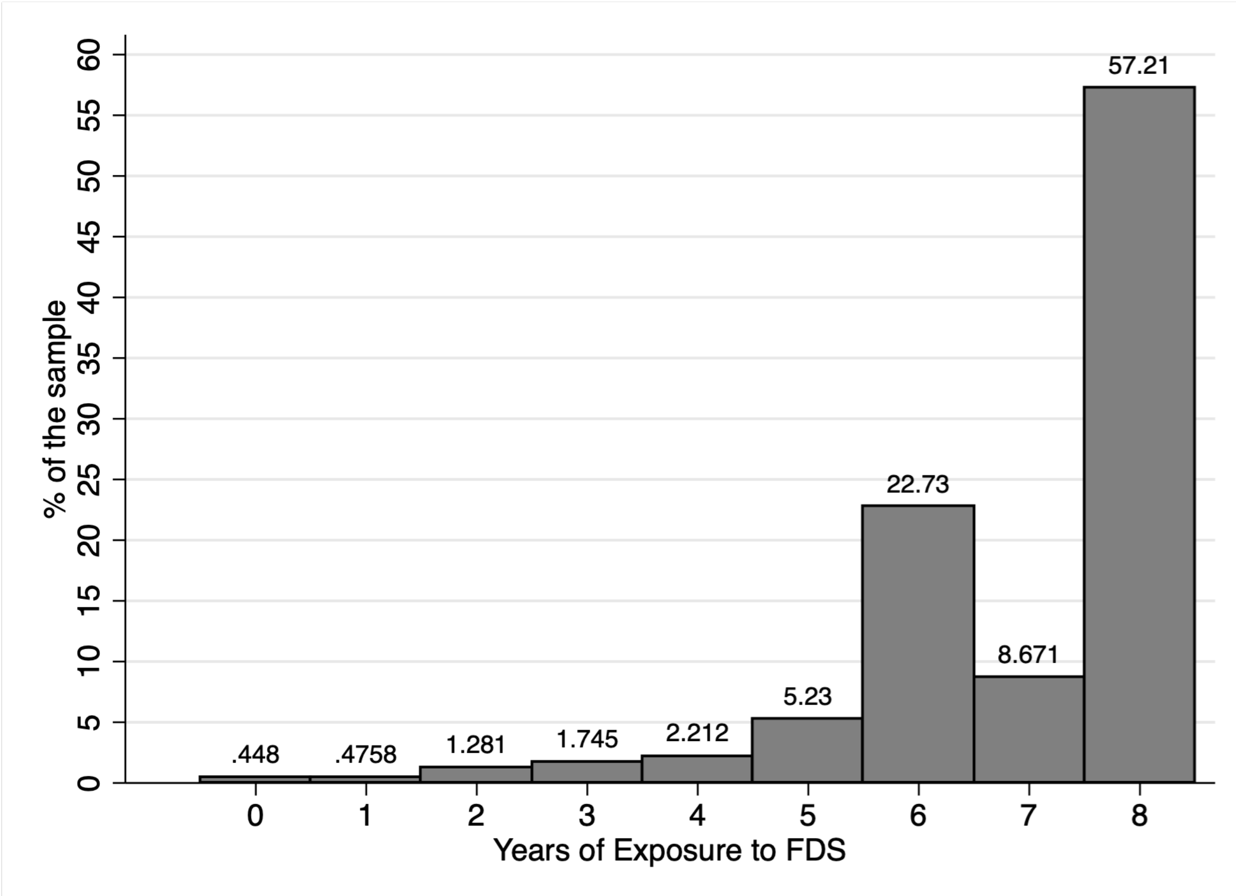
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis is the number of years of exposure to the longer school day defined by Equation 3.1. The Y-axis represents the percentage of the sample that has a determinate number of years of exposure to the program.

Figure A.17: Distribution of Explanatory Variable (2009, only 4th grade).



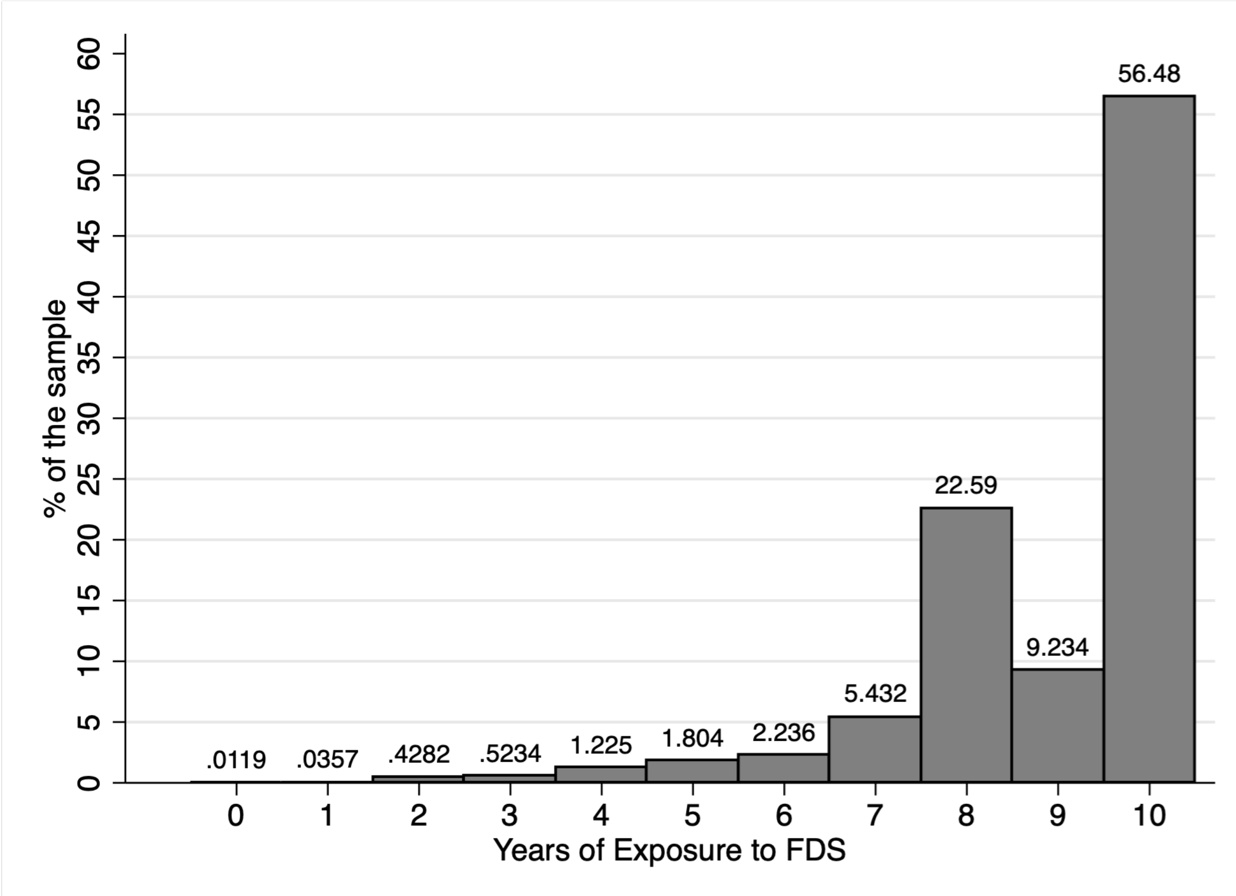
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis is the number of years of exposure to the longer school day defined by Equation 3.1. The Y-axis represents the percentage of the sample that has a determinate number of years of exposure to the program.

Figure A.18: Distribution of Explanatory Variable (2013, only 8th grade).



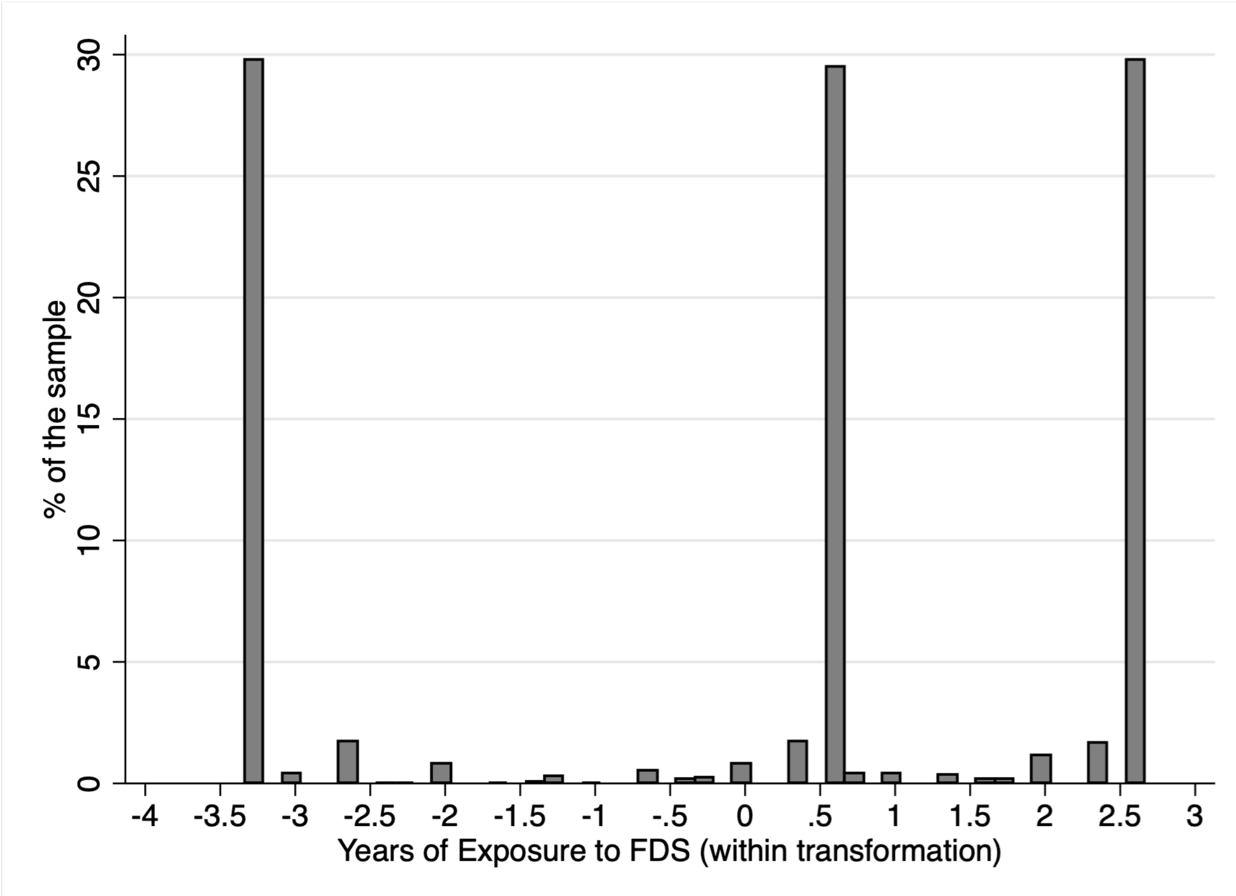
Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis is the number of years of exposure to the longer school day defined by Equation 3.1. The Y-axis represents the percentage of the sample that has a determinate number of years of exposure to the program.

Figure A.19: Distribution of Explanatory Variable (2015, only 10th grade).



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis is the number of years of exposure to the longer school day defined by Equation 3.1. The Y-axis represents the percentage of the sample that has a determinate number of years of exposure to the program.

Figure A.20: Distribution of the Within Transformation of Explanatory Variable (2009-2015, whole sample).



Notes: Own elaboration based on SIMCE datasets and public administrative data of the Ministry of Education. The X-axis show the within transformation of years of exposure to longer school day defined by Equation 3.1 (i.e. $Exp_{i,t} - \overline{Exp_i}$) . The Y-axis represents the percentage of the sample.