Online Appendix - *Targeted Vouchers, Competition Among Schools, and the Academic Achievement of Poor Students*†

1 Details on Data Sources and Data Manipulation

1.1 Data Sources

The data used in this study comes from several administrative sources. The primary data used is matriculation data, standardized test score data, birth certificate data and Census block-level data. An important innovation that I have implemented in this paper is to start with the population of children born in Chile and use this as the base on which to merge other data. This generates a panel that allows for the careful verification of the quality of the data. This feature has the advantage of providing information on students' demographics at the time of their birth as well as linking them to their siblings through their mother. This arrangement allows for the construction of a database that can characterize the population of students and can do a better job of imputing socioeconomic status across populations that may be less likely to appear in some datasets. These data sets was possible through a collaboration between the Ministry of Health and the Ministry of Education during 2010-2012 and produced a series of research papers conducted to study the role of early health outcomes and socioeconomic status on educational outcomes (see Bharadwaj, Loken, and Neilson (2013) and Bharadwaj, Eberhard, and Neilson (2017) for other details).

Data on the Potential Student Population: The data on all registered births in Chile come from a dataset provided by the Ministry of Health. This dataset includes information on all children born between the years 1992 and 2010. It provides data on the individual identification number of the child born, as well as the sex, birth weight, length, weeks of gestation and several demographics of the parents such as age, education, and occupational status. In addition, the data set provides a variable identifying the mother and describing the type of birth, be it a single birth, double, triple, etc. More information is available from the department of statistics at the Ministry of Health. For more information see http://www.deis.cl/.

Data on Matriculation: The data on education outcomes and demographics come from two main sources. The first is the RECH/SIGE database that consists of administrative data on matriculation of every student in Chile between 2002 and 2011. The second source is the SIMCE database, which is a national test administered yearly to every 4th grader in Chile and on alternating years to 8th and 10th graders. Both of these databases were kindly provided by the Ministry of Education of Chile (MINEDUC). Today these data are downloadable in

† Last Updated on March 20th, 2020 (See most recent version here). This online appendix was made with the help from many collaborators. In particular, Claudia Allende, Alvaro Carril, Nicolas Muñoz, Maria Elena Guerrero, Franco Calle, Nicolas Rojas and especially Isabel Jacas helped a tremendous amount.

their most recent version, and IDs are provided for allowing linkages across data sets within the Ministry of Education. For more information see http://datosabiertos.mineduc.cl/
Data on Test Scores: The SIMCE test covers three main subjects: Mathematics, Science and Language Arts. Its objective is to be a census and be used to evaluate the progress of students regarding the national curriculum goals set out by MINEDUC. The test is constructed to be comparable across schools and time. This test is also accompanied by two surveys, one to parents and one to teachers. These surveys include questions about the income of the household as well as other demographics. For more information see http://www.simce.cl/. While coverage of students taking the test in 4th grade is over 93% throughout the period (this is the official statistic provided by MINEDUC) not all students' tests are associated with a valid ID. Given that the parent survey is a take-home survey, the rate of completion is much lower and, in addition, is not always linkable back to the relevant student.

Data on College Entrance Exams: The college entrance exam is a test that is taken nationally since the late 1960s. The data from this test was digitalized from written records as part of a data collection collaboration with DEMRE. This collaboration was implemented as part of the Proyecto 3E project described in Hastings, Neilson, and Zimmerman (2015, 2013). Test score records developed by this project are available from DEMRE for research purposes. For more information see http://www.demre.cl/.

1.2 Data manipulation

The manipulation of the microdata generates two distinct datasets. One is based on who takes the achievement tests in 4th grade and what their characteristics and school choices have been in the past (`TestScorePanel`). The second is the set of all 1st-grade entry-level students, their school choices, and demographics for all the markets of interest (`EntryStudentPanel`). To build both of these datasets, I will develop a panel of students from 1st to 4th grade for the years 2005 to 2016. Using information about the students and their achievement from multiple sources I determine stable observable types and can generate a database for estimating school quality (`TestScorePanel`) and for estimating demand off of school choice decisions documented in `EntryStudentPanel`.

Vital statistics are very useful because they come with information about the mother and father at the time of birth. This operates with a lag and is less precise but has the advantage of a much larger coverage and is a stable measurement over time as compared to the parent surveys conducted at the time of taking the standardized tests in 4th grade. These surveys attached to standardized testing are a final source of information about students and is very rich in some years and less so in others. While the vast majority of students take the exam at school, a smaller fraction (70%-80%) of parent surveys are completed and matched to the student level files.

Panel of Students from Birth to Fourth Grade: I build a panel based on the set of all children born in Chile between 1992 and 2010 and merge this with educational information regarding the progression of students over time. To avoid mistakes assigning student information to the wrong individuals I impose that the information link across MINEDUC ID, DOB, Sex and is consistent with normal progression in school (stay back or advance one level). In other words, we trace the trajectory of each student from birth to fourth grade by adding cross-section information on matriculation each year from 2005 to 2016. To this panel, achievement data is merged on at the appropriate years and grades.

Table 1: First Grade Students by Mothers Education (at birth)

Year	College	Tech	HS	Less HS	8th or less	Total
2005	7.1	12.6	34.3	29.7	16.3	100
2006	7.4	17.9	31.1	28.7	14.9	100
2007	7.7	17.7	31.7	28.3	14.6	100
2008	7.8	16.8	33.2	27.1	15.1	100
2009	8.5	11.9	35.4	24.4	19.7	100
2010	8.9	13.6	38.7	25.8	13.0	100
2011	9.4	14.0	38.9	24.7	12.9	100
2012	10.0	14.4	39.8	24.5	11.3	100
2013	10.4	14.6	40.1	24.0	10.8	100
2014	10.9	15.0	41.1	23.2	9.8	100
2015	12.1	15.9	40.8	21.9	9.1	100
2016	12.9	16.5	41.8	20.7	8.1	100

Note: This table presents the distribution of mothers education for different cohorts of first grade students across the country in Chile.

Determination of SES Types: For the analysis comparing the test scores across socioeconomic groups I use three measures. The first is actual program eligibility, which is available from 2008. I also use household income from the SIMCE parent surveys and categorized families into two groups, the 40% poorest and the rest. An alternative way to impute eligibility status is to impute program eligibility based on a regression using data from 2008 onward to then predict what students would be the poorest 40% in each year. This leverages the rich demographic data available for all students born in the country.

Geocoding Student Locations: Students in 2011 were associated with the nearest census block by geocoding their address provided by MINEDUC to a latitude and longitude. Census block locations were taken from the centroid of the polygon representing the census block shapefile data provided by the *Instituto Nacional de Estadisticas de Chile* (INE). For more information on shapefiles or census data see http://www.ine.cl/. Data from MINEDUC indicate the comuna (or neighborhood) the student lives in, and we keep location data only when the geocoded location lies within the polygon associated with the comuna. This way, we have different sources of information to check whether the data are consistent.

2 Market Construction and Description

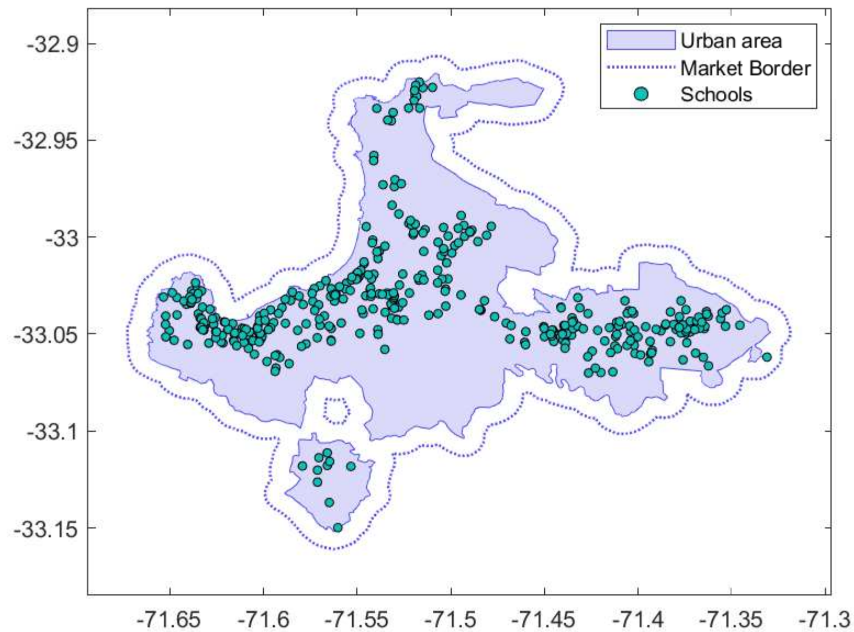
Market Boundaries: Defining the market is a difficult task in many settings when physical distance is a relevant characteristic. It is generally not easy to find a boundary where one market ends and one begins in broad urban areas. Papers that study retail markets typically have used political or administrative boundaries to define markets, such as cities or counties. An important example is Davis (2006). In some cases, such as small isolated communities, this works well but in large urban areas consumers close to the border of a political unit might also be close to firms in the next one. Therefore, it is possible for consumers to choose to cross market lines to buy from firms in neighboring "markets" in these cases. In this application, I take advantage of the relatively sparse distribution of the population in Chile, where communities tend to be far from each other. This creates a natural definition of a market based on the idea that consumers in one city will not travel very far across rural areas to go to school in another city but may well travel within the same urban area.

There are, however, many cases when urban areas are in close proximity and where one market ends and one begins becomes less obvious. I tackle this problem by defining ex ante a criteria and a procedure that will generate the markets. In practice, I use the Chilean census map data from 2012 of all urban areas to define a starting point. These consist of 499 polygons, which can vary in size from 0.12 km^2 to 121 km^2 (average: 7.7 km^2). I join all urban areas that are at most two kilometers apart at their closest distance. The union of all connected urban areas is defined as one market under the assumption that students could feasibly travel within this set of urban areas due to their proximity. I then add a buffer of one kilometer around the exterior of the joined polygons to include some semi urban areas that may be locations favored by schools given lower prices and that are still accessible by families near the edge of the urban boundary.

Assigning schools to markets: I use administrative data to collect the list of all schools that are categorized as urban and have matriculation in the first grade between the years 2005-2016. Specifically, I take all urban schools with an educational code *codigo ensenanza* of 110, which indicates regular primary education, that are classified as urban by The Ministry of Education, and have some students matriculated in the first grade. In 2011, for example, there were 7,854 schools that were providers of primary education services and 4,495 were urban and had at least one student in first grade.

Using the data on school addresses, virtually all urban schools identified were geocoded to a location (for example, out of the 4000+ schools in 2011, only four were not geocoded). I then assign schools to markets by their geographic location on the map, given the markets identified in the previous subsection. If the school lies within the boundaries of the market, it is assigned to that market. The total number of markets identified using the procedure described in the preceding subsection is 363.

Figure 1: Map of Market 52 (Viña del Mar and Valparaiso) with Schools



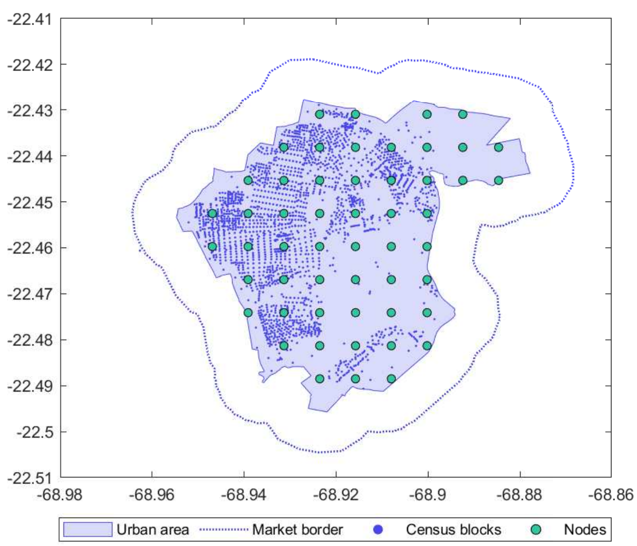
Note: This figure shows schools (green dots) located in the boundaries of the urban areas of the cities of Viña del Mar and Valparaiso. It can be seen that some schools are located just at the outskirts of the city and are captured by the market boundary given by the buffer zone.
Source: INE, Ministry of Education MINEDUC, own calculations.

Assigning students to markets: Students are assigned to markets through their school. In the previous subsection, I described how schools were assigned to markets through their location on the map. To get market shares, I use administrative aggregate data on all students at every school in every grade at a given point in time. Using this, I determine the total number of students in a market and thus the aggregate share of each firm in the market. If a school has been associated with a particular market, the students at that school are deemed to belong to that market. Since all students must attend some school and we observe the universe of schooling options, the total number of students in the market is then taken to be the sum of all students at all the schools in that market.

Having assigned schools to markets, and also students to markets (through their schools), I proceed to filter out some markets based on their size. Size is proxied in two ways: number of schools, and number of students in first grade. Specifically, I will focus on markets that 1) have at least 5 schools, in at least half of the years considered (2005-2016), and 2) have at least 100 students in the first grade of primary. These restrictions reduce our sample size to 74 markets. These markets are used for all estimations in the main paper and are the focus of the remainder of this section.

Location of students within markets: The Chilean census provides detailed block level data on every urban area and thus on every market I have identified in the previous step. Block level census data is used to describe the distribution of student characteristics in the market across a grid of L_m nodes. I group census blocks into squares approximately 0.8 km wide to define a node and aggregate the block level information to this level. Figure 2 shows one example of spreading nodes across the market. It shows the urban limits, the market boundaries, the centroids of census blocks (that fall within the urban limits), and the centroids of the nodes that were spread evenly on top. Figure 3 shows how this procedure helps diminish the dimensionality of the demand side problem while still keeping a flexible and detailed description of varying demand across space.

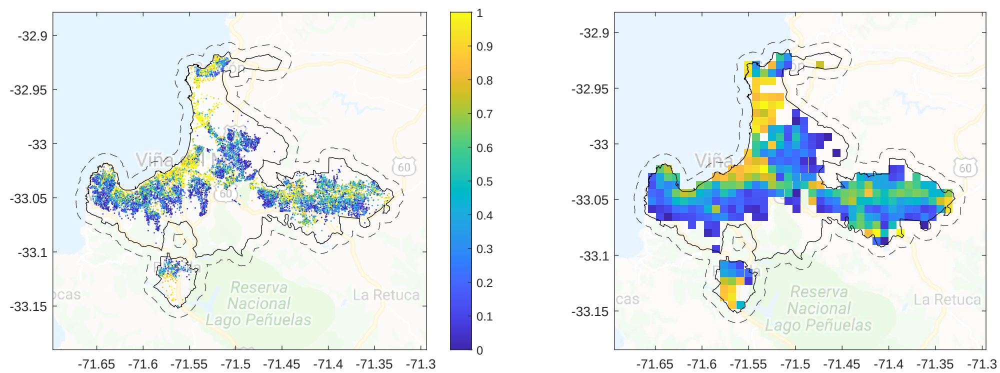
Figure 2: Map of Market 13 (Calama) with Census Blocks and Nodes



Note: This figure shows the centroids of nodes spread across the market. For each census block, I evaluate which node centroid is closest, and I aggregate demographic information at the node level. On average (considering all markets, not just the one in this figure), one node aggregates information from 26 blocks (standard deviation: 25).

Distribution of types within markets: The model uses as input the distribution of consumer types across nodes within each market. The type of the household is defined by their

Figure 3: Percentage of mothers with more than a high school education in the 2012 census



(a) At each block

(b) At each node

income (SEP=0,SEP=1) and the education of the mother (E=1,E=2,E=3)[1]. The empirical challenge is that the census does not report eligibility to the voucher program. Administrative data provides the total number of students of each type in the market but not where they live to the block level.

To estimate the joint distribution of household voucher program (SEP) eligibility and education of the mother across the geographic space within a market, I follow three steps. First, I characterize each node using the most recent available census data from 2012. Then, I use a sample of geocoded students (about half of the students in 2011) for whom I do know their eligibility status and their mothers' education. I relate the characteristics of the node such as the education of the adults, to the likelihood that a child of a mother of a given education level would be eligible for the voucher program (SEP=1). Finally, I project this across all nodes using the actual distribution of nodes' characteristics and population to estimate w_k^m which describes the distribution of a type k across nodes within a market.

Markets Descriptive Statistics: Table 2 shows the total number of elementary schools in the country (that teach first grade), along with their enrollment. It can be seen that urban schools represent 88% of total enrollment. Schools in the 74 selected markets represent roughly 90% of urban enrollment. Table 3 presents some descriptive statistics comparing both sets. Throughout the period considered they remain very similar in terms of first-grade class size, SEP adoption, private participation and average quality.

[1]For first grade students in 2011, the income groups definition, SEP = 0 and SEP = 1, represent 56% and 44% respectively. Regarding the level of education of the mother for first graders in 2011, 21% has less than high school, 58% has high school and 21% has more than high school.

Table 2: Total schools, urban schools and schools in markets

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Total Elementary Schools	8,179	8,156	8,138	8,097	8,135	8,009	7,854	7,771	7,674	7,552	7,511	7,443
Total Enrollment on 1st grade	234,260	231,367	239,545	236,488	237,991	234,416	231,926	232,473	238,655	247,010	255,695	256,829
Urban Schools	4,258	4,308	4,342	4,388	4,458	4,517	4,495	4,518	4,530	4,567	4,582	4,558
% of Total Schools	52.1	52.8	53.3	54.2	54.8	56.4	57.2	58.1	59.0	60.5	61.0	61.2
Urban Enrollment	203,236	201,431	209,046	207,114	208,728	206,759	204,440	205,622	211,848	220,719	228,894	230,352
% of Total Enrollment	86.8	87.1	87.3	87.6	87.7	88.2	88.1	88.4	88.8	89.4	89.5	89.7
Schools in Markets	3,801	3,840	3,873	3,891	3,919	3,929	3,936	3,937	3,924	3,897	3,876	3,849
% of Urban Schools	89.3	89.1	89.2	88.7	87.9	87.0	87.6	87.1	86.6	85.3	84.6	84.4
Enrollment in 1st grade in Markets	186,107	180,798	186,909	184,075	183,577	181,182	179,910	181,102	185,268	192,033	198,616	199,599
% of Urban Enrollment	91.6	89.8	89.4	88.9	88.0	87.6	88.0	88.1	87.5	87.0	86.8	86.6

Note: This table shows the distribution of schools and enrollment on 1st grade considering all elementary schools, urban schools and schools in markets. Total Schools consider all elementary schools that have 1st grade. Markets contain 4,266 different schools throughout all the period.

Table 3: Urban schools and schools in markets

	Urban Schools				Schools in Markets			
Year	Avg 1st grade Enrollment	SEP Adoption	% Private Schools	Value Added	Avg 1st grade Enrollment	SEP Adoption	% Private Schools	Value Added
2005	47.7	0.0	55.0	-0.15	49.0	0.0	58.1	-0.14
2006	46.8	0.0	56.0	-0.21	47.1	0.0	59.0	-0.21
2007	48.1	0.0	56.6	-0.22	48.3	0.0	59.6	-0.22
2008	47.2	65.7	57.3	-0.15	47.3	63.0	60.1	-0.15
2009	46.8	70.3	58.0	-0.10	46.8	68.3	60.6	-0.10
2010	45.8	72.3	58.1	-0.03	46.1	70.2	61.2	-0.04
2011	45.5	76.6	58.9	-0.03	45.7	73.4	61.7	-0.03
2012	45.5	79.3	59.4	0.01	46.0	76.6	62.0	0.00
2013	46.8	81.4	59.9	-0.10	47.2	78.9	62.3	-0.10
2014	48.3	82.6	59.6	-0.09	49.3	80.3	62.4	-0.09
2015	50.0	83.6	59.3	-0.06	51.2	81.7	62.1	-0.06
2016	50.5	85.9	58.9	-0.02	51.9	84.3	61.7	-0.02

Note: This table compares all elementary urban schools and the schools in the 74 selected markets, across a set of relevant variables.

Entry and exit in urban markets: I describe entry and exit patterns by type of institution and by the school's exposure to the policy. Table 4 shows the entry and exit rate by type of school (public, private voucher, or private non-voucher). For public schools, entry and exit rates remained stable and low throughout the period of study. Entry and exit is higher among private voucher and private non-voucher schools. Table 4 shows a downward trend in the entry rate of private vouchers (from 3.17% in 2006 to 0.23% in 2016), while the exit rate presents a small decrease in 2007 and 2008 but stays rather stable in the subsequent years, consistently around 1%. I also document entry and exit patterns by exposure to the SEP policy. Table 5 shows that entry is higher in high exposure neighborhoods leading to an increase in the number of voucher schools from 349 to a peak of 401 in 2012. Exit rates also follow a similar trend during most of the period under study. There do not seem to be any significant changes around 2008, when the SEP policy was introduced.

Table 4: Entry rate, exit rate, and number of active schools, by type of school

	Public			Private voucher			Private non voucher		
Year	% Entry	% Exit	Active	% Entry	% Exit	Active	% Entry	% Exit	Active
2006	0.28%	0.79%	1397	3.17%	1.99%	2014	3.39%	1.46%	410
2007	0.29%	0.72%	1391	2.78%	1.66%	2053	2.93%	3.69%	406
2008	0.43%	0.86%	1389	2.48%	0.91%	2088	2.71%	1.24%	403
2009	0.36%	1.52%	1383	2.25%	1.08%	2129	3.23%	2.45%	408
2010	0.43%	1.54%	1367	2.21%	0.65%	2158	2.45%	2.23%	403
2011	0.44%	1.11%	1351	1.20%	1.38%	2172	2.23%	0.75%	402
2012	0.22%	1.34%	1341	1.57%	1.42%	2185	1.74%	2.47%	405
2013	0.37%	1.28%	1328	1.51%	1.18%	2197	1.48%	1.76%	397
2014	0.68%	0.38%	1317	0.36%	1.24%	2181	1.51%	1.52%	396
2015	0.61%	0.23%	1320	0.23%	1.39%	2162	1.01%	1.02%	394
2016	0.23%	0.30%	1324	0.23%	0.42%	2133	0.51%	0.51%	392

Note: This table shows, for all schools in urban markets, the entry rate, exit rate, and number of active schools, differentiating by type of school (public, private voucher, or private non-voucher). The entry rate in t is defined as the number of schools that appear in the registry of schools for the first time in t over the stock of active schools in $t-1$. The exit rate in t, is defined as the number of schools that appear for the last time in t, over the stock of active schools in t.

Table 5: Entry rate, exit rate, and active voucher schools, by exposure to SEP

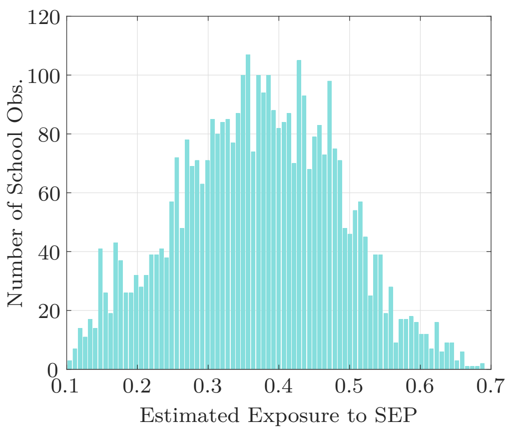
	High exposure			Low exposure		
Year	% Entry	% Exit	Active	% Entry	% Exit	Active
2006	2.04%	1.15%	349	2.15%	2.38%	336
2007	3.44%	1.37%	364	2.38%	2.61%	345
2008	3.02%	1.32%	378	3.19%	1.15%	348
2009	2.38%	1.56%	385	1.72%	1.99%	352
2010	3.38%	0.77%	391	1.70%	1.71%	351
2011	1.02%	0.51%	392	1.14%	0.86%	349
2012	2.30%	1.50%	401	2.01%	2.25%	356
2013	1.00%	1.25%	400	1.40%	1.13%	355
2014	0.50%	1.26%	398	0.00%	1.42%	351
2015	0.50%	1.51%	397	0.28%	2.02%	347
2016	0.00%	0.00%	389	0.86%	0.29%	343

Note: This table shows, for *voucher* schools in urban markets, the entry rate, exit rate, and number of active schools, differentiating by degree of exposure to the SEP policy. The measure of exposure to the policy is calculated as the share of SEP eligible students that live within a 1.5 km radius from the school. High exposure is defined as belonging to the top quintile of exposure to the policy and low exposure is defined as belonging to the bottom quintile (this means that around 40% of voucher schools are accounted for in this table). The entry rate in t is defined as the number of voucher schools that appear in the registry of schools for the first time in t over the stock of active voucher schools in $t-1$. The exit rate in t, is defined as the number of voucher schools that appear for the last time in t, over the stock of active voucher schools in t.

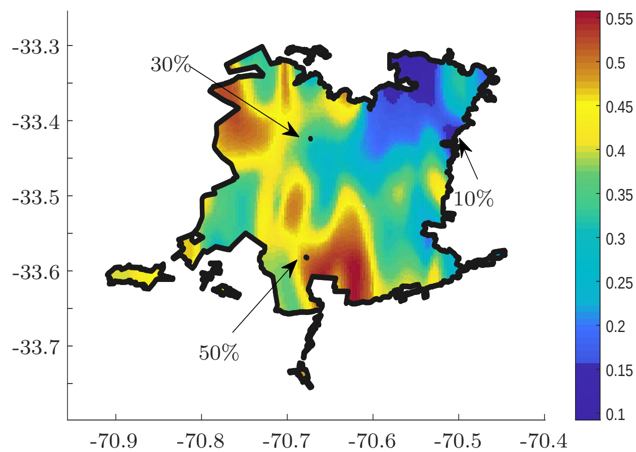
3 Additional Description of Policy Instrument

The SEP policy creates heterogeneous exposure within markets due to preexisting market structure and where eligible students lived. I use the percent of the students that live within 1km of the school as a measure of exposure of the neighborhood to the policy ands show this varies substantially across markets and within markets as seen in Figure 4. This measure interacted with time generates variation with a broad base that varies across and within markets and is possible because of the important policy change.

Figure 4: Exposure to Policy Across and Within Markets



(a) Histogram of Exposure



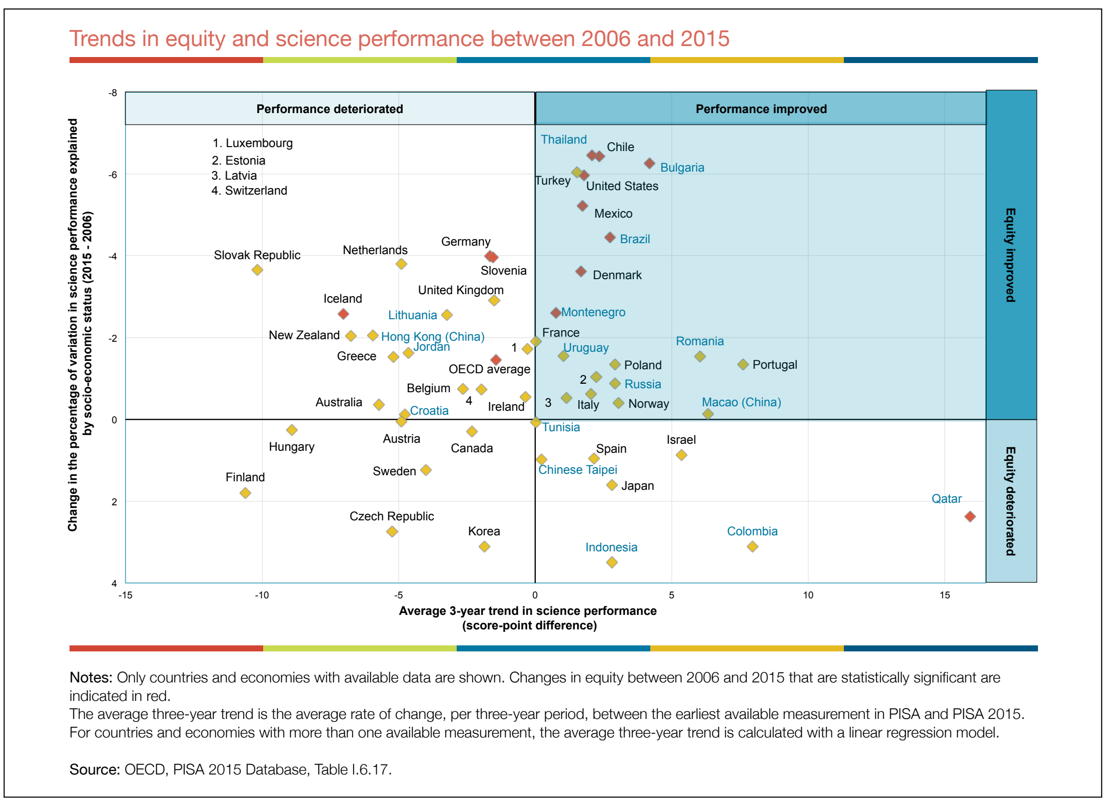
(b) Exposure in Santiago

Note: This figure shows the exposure to the policy across and within Markets. The left panel shows the distribution of the percent of students who would be eligible for the additional subsidy once the policy is in place that live approximately within 1km of each school. The histogram shows the distribution of exposure levels for schools in 2007. This is across and within market variation as it includes all schools. The right panel shows a map of one market (Santiago) to illustrate the heterogeneity within a market in the exposure to the policy.

4 Academic Achievement

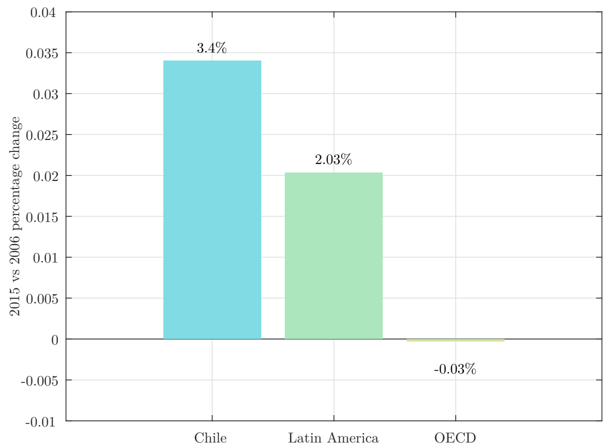
The Trends in International Mathematics and Science Study (TIMSS) is a series of international assessments of academic knowledge of students around the world, covering the subjects of Math and Science for 4th and 8th-grade students. Chile participated in the TIMSS test for 8th grade in 1999, 2003, 2011 and 2015; and in the 4th-grade tests in 2011 and 2015. The Program for International Student Assessment (PISA) test is a triennial international assessment to test the skills and knowledge of 15-year-old students. Trends in equity and achievement are presented by a publication provided by the OECD called *Where did equity in education improve over the past decade* - PISA In Focus 2017/68. Between 2006 and 2015, Chile is the country with the second highest growth in science performance and it is also among the countries that improved equity the most.

Figure 5: Trends in equity and science performance between 2006 and 2015, *Where did equity in education improve over the past decade* - PISA In Focus 2017/68



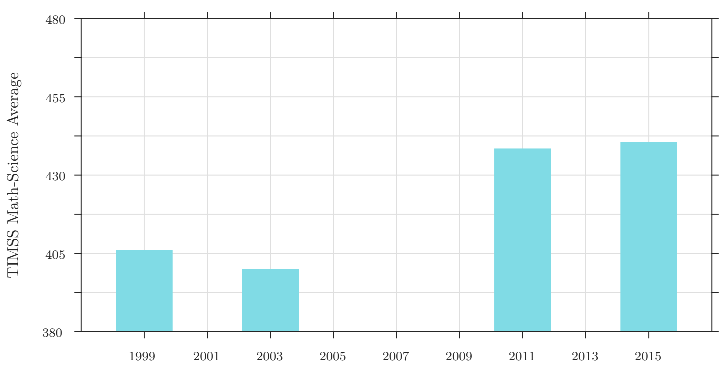
Data Source: Table I.6.17

Figure 6: Growth in math-reading average PISA scores relative to year 2006



Note: The figure shows how the average test score of Math and Reading changed over time in Chile in 2015 relative to 2006. The growth of Latin American countries and OECD countries is presented as comparison groups. The percentage change between 2009 and 2006 was 2% and between 2012 and 2006 was 1.3%, showing a continuous growth on average PISA scores in Chile. Over all of the 49 participating countries, Chile is 13th in the ranking of percentage change between 2015 and 2006 average PISA scores. Source: OECD.

Figure 7: TIMSS International Science and Math Performance, 8th Grade



Note: The figure shows how the average test score of Math and Reading on TIMSS changed over time in Chile. Unfortunately, it is not available prior to 2011 for 4th grade students.

5 Robustness of Value-Added Estimates

Table 6: School Quality Estimation Regression

	Avg. Test Score (VA1) Coef.	StdErr	Avg. Test Score (VA2) Coef.	StdErr	Avg. Test Score (VA3) Coef.	StdErr
Constant	0.016***	(0.000)	-0.092***	(0.000)	-0.151***	(0.000)
Mother High School	0.226***	(0.000)	0.202***	(0.000)	0.208***	(0.000)
Mother More than High School	0.429***	(0.000)	0.276***	(0.000)	0.271***	(0.000)
Male	-0.051***	(0.000)	-0.064***	(0.000)	-0.052***	(0.000)
Parents Married	-	-	0.056***	(0.000)	0.072***	(0.000)
Single Birth	-	-	0.054***	(0.000)	0.058***	(0.000)
First Born	-	-	0.056***	(0.000)	0.074***	(0.000)
Mother Took PAA	-	-	-0.102***	(0.000)	-0.086***	(0.000)
Mother PAA Math D2	-	-	0.012***	(0.006)	0.016***	(0.009)
Mother PAA Math D3	-	-	0.029***	(0.000)	0.021***	(0.001)
Mother PAA Math D4	-	-	0.047***	(0.000)	0.042***	(0.000)
Mother PAA Math D5	-	-	0.068***	(0.000)	0.070***	(0.000)
Mother PAA Math D6	-	-	0.080***	(0.000)	0.082***	(0.000)
Mother PAA Math D7	-	-	0.094***	(0.000)	0.092***	(0.000)
Mother PAA Math D8	-	-	0.096***	(0.000)	0.102***	(0.000)
Mother PAA Math D9	-	-	0.109***	(0.000)	0.113***	(0.000)
Mother PAA Math D10	-	-	0.152***	(0.000)	0.154***	(0.000)
Mother PAA Lang D2	-	-	0.080***	(0.000)	0.081***	(0.000)
Mother PAA Lang D3	-	-	0.130***	(0.000)	0.136***	(0.000)
Mother PAA Lang D4	-	-	0.174***	(0.000)	0.179***	(0.000)
Mother PAA Lang D5	-	-	0.207***	(0.000)	0.223***	(0.000)
Mother PAA Lang D6	-	-	0.236***	(0.000)	0.247***	(0.000)
Mother PAA Lang D7	-	-	0.273***	(0.000)	0.286***	(0.000)
Mother PAA Lang D8	-	-	0.305***	(0.000)	0.318***	(0.000)
Mother PAA Lang D9	-	-	0.349***	(0.000)	0.359***	(0.000)
Mother PAA Lang D10	-	-	0.431***	(0.000)	0.436***	(0.000)
Birth Weigth D2	-	-	0.034***	(0.000)	0.039***	(0.000)
Birth Weigth D3	-	-	0.049***	(0.000)	0.054***	(0.000)
Birth Weigth D4	-	-	0.059***	(0.000)	0.064***	(0.000)
Birth Weigth D5	-	-	0.063***	(0.000)	0.068***	(0.000)
Birth Gestation D2	-	-	-0.008***	(0.000)	-0.007**	(0.035)
Birth Gestation D3	-	-	-0.026***	(0.000)	-0.023***	(0.000)
Birth Gestation D4	-	-	-0.044***	(0.000)	-0.040***	(0.000)
Birth Gestation D5	-	-	-0.057***	(0.000)	-0.054***	(0.000)
Birth Length D2	-	-	0.023***	(0.000)	0.023***	(0.000)
Birth Length D3	-	-	0.030***	(0.000)	0.033***	(0.000)
Birth Length D4	-	-	0.041***	(0.000)	0.046***	(0.000)
Birth Length D5	-	-	0.057***	(0.000)	0.061***	(0.000)
Birth Location D1	-	-	-0.032***	(0.000)	-0.040***	(0.000)
Birth Location D2	-	-	-0.099***	(0.000)	-0.112***	(0.000)
Region Birth FE			✓		✓	
School by Year FE	✓		✓			
School by Group Year FE					✓	
R^2	0.30		0.31		0.28	
N Obs	2,166,730		2,164,812		1,108,152	

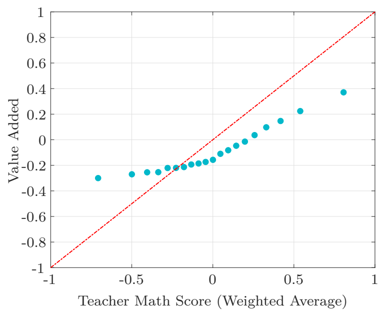
Note: This table presents regression results for estimates of test scores on a large vector of individual student-level characteristics. School quality is estimated as the school and year fixed effect for column (1) and (2), and as the school and year group fixed effect for column (3) (Groups are 2005-2007 and 2010-2012). Estimates of school quality have not been presented in this table.

Table 7: School Characteristics, Inputs and the Estimated Value Added

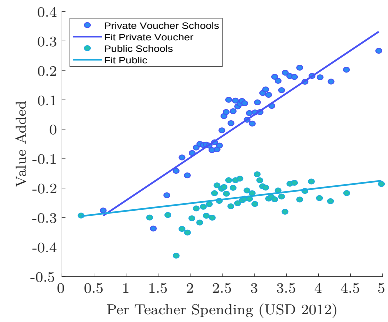
	(1)	(2)	(3)	(1)	(2)	(3)
	Quality	Has Fine	Has SNED	Quality	Has Fine	Has SNED
AdminHC Math	0.026***	0.001	0.018***	0.028***	0.002	0.017***
	(0.000)	(0.908)	(0.007)	(0.000)	(0.559)	(0.000)
AdminHC Lang	-0.007	0.006	-0.007	-0.005	0.002	0.003
	(0.311)	(0.367)	(0.359)	(0.251)	(0.520)	(0.518)
TeacherMath WeightedAve	0.282***	0.026	0.102***	0.299***	-0.014	0.154***
	(0.000)	(0.339)	(0.001)	(0.000)	(0.264)	(0.000)
TeacherLang WeightedAve	0.089***	-0.024	0.003	0.101***	-0.013	0.029
	(0.002)	(0.420)	(0.931)	(0.000)	(0.349)	(0.102)
SpendingPerTeacher	0.013***	-0.002***	0.019***			
	(0.000)	(0.001)	(0.000)			
Income per Student	0.041***	-0.001	-0.028**	0.164***	-0.006	0.032***
	(0.000)	(0.957)	(0.028)	(0.000)	(0.348)	(0.000)
Income per Student^2	-0.001***	-0.000	0.001*	-0.004***	-0.000	-0.001***
	(0.001)	(0.731)	(0.092)	(0.000)	(0.971)	(0.001)
Traditional	0.030***	0.011	0.012	0.056***	-0.003	0.089***
	(0.001)	(0.247)	(0.280)	(0.000)	(0.578)	(0.000)
For Profit	0.010	-0.001	0.016	-0.046***	0.022***	-0.096***
	(0.341)	(0.934)	(0.189)	(0.000)	(0.000)	(0.000)
Religious	-0.000	-0.007	0.026**	0.023***	-0.005	0.017***
	(0.970)	(0.465)	(0.023)	(0.000)	(0.358)	(0.009)
Constant	-0.497***	0.217***	-0.208***	-0.351***	0.160***	0.269***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Only 2014 - 2017	x	x	x			
Year FE	x	x	x	x	x	x
Market FE	x	x	x	x	x	x
R^2	0.243	0.039	0.156	0.204	0.133	0.081
N Obs	7,729	7,729	7,729	24,627	24,627	24,627

Note: This table shows the relationship between school characteristics, inputs and the estimated value added. The first three columns include data from 2014 to 2017 which is when school spending data is available. The dependent variables considered are: (i) estimated value added, (ii) if the school has been fined, and (iii) if the school has won a prize for academic excellence (SNED). The independent variables include the average college entrance exam scores for teachers and the school principal. Teacher score averages are weighted by hours employed at the school. Also included is the average spending per classroom teacher and the average school revenue per student. School characteristics include an indicator variable if the school has been open since 1995 and whether the school is for-profit and if it has a religious affiliation.

Figure 8: Inputs and Value Added Estimates



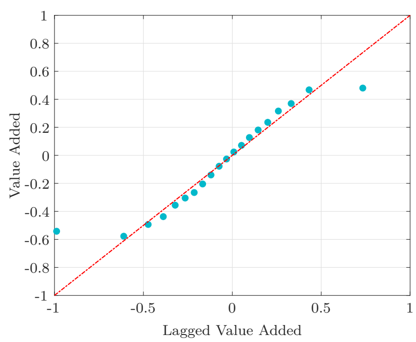
(a) $\widehat{q}_j$ and Teachers Test Scores



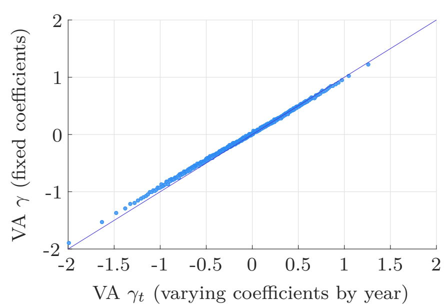
(b) $\widehat{q}_j$ and Spending on Teachers

Note: Panel (a) shows the binscatter estimated value added and the teacher quality as measured by the average teacher math score on their college entrance exams (see Calle, Gallegos, and Neilson (2019)). The second panel shows the relationship between estimated school quality and reported school spending on teachers divided by the number of teachers at the school.

Figure 9: Robustness on Value Added Estimates I



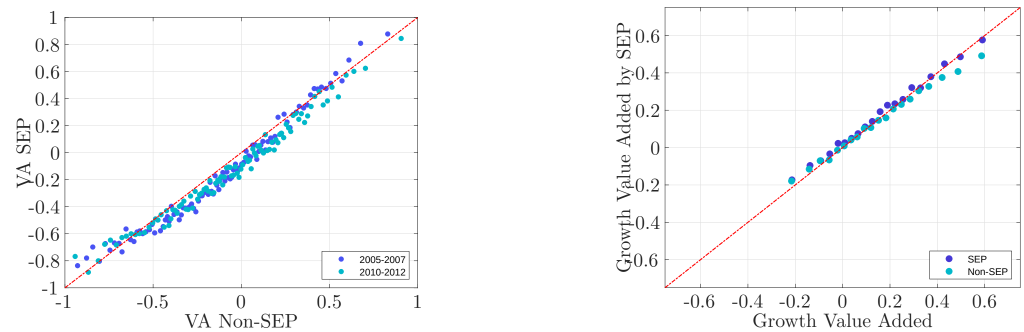
(a) Using Lagged Test Scores



(b) Varying Coef. γ_t vs γ

Note: The panel on the right shows the binscatter of estimated value added with and without considering lagged test scores of students when they were in 2nd grade. The panel on the right shows a binscatter plot where X-axis shows school-year value added estimated letting γ to vary each year. The Y-axis shows school-year value added fixing γ to not vary each year. Both cases produce estimates of value added that overall are quite similar.

Figure 10: Robustness on Value Added Estimates III



(a) Heterogeneous Value-Added

(b) Heterogeneous Growth

Note: The panel on the left shows a binscatter plot considering Value Added estimated only for SEP students is on the X-axis and value added considering only Non-SEP students is shown in the Y-axis. The panel on the right shows the growth in the same measurements of value added before and after the policy.

6 Additional Robustness Exercises

Missing data robustness exercise for differences in differences estimates: Missing test scores can lead to biased estimates if absences on the day of the test are not random. This issue is relevant for this setting because absenteeism during the test has risen over time, reaching almost 10% of the sample in 2016 and the impact of the policy could be confounded with sample selection. It could be less of a concern for the analysis in this paper because it is based on value-added estimates that already consider baseline characteristics of students and because the main results are based on differenes across neighborhoods. In the following analysis I starting from the raw data set and I drop 7.8% of the sample due to duplicated MINEDUC identifiers or because the student is not enrolled at the school by the end of the year. I drop 2% of observations that have schools with less than ten scores in any given year following the policy by the *Quality of Education Agency* in Chile which does not use results from schools with less than 10 scores for the same reason. In sum, 9.5% of the raw data set is dropped either because of double-counted students who transferred to other schools, students not enrolled at the end of the year, or students that were in small schools. This number decreases to nearly 8% after 2012 as SIMCE identifiers data quality increases. I label the rest of the observations are labeled as "usable observations". Nearly 4% of usable observations have missing values in only on the variables used to estimate value added, 7.8% only on test scores, and 1% on both. I re-estimates the differences-in-differences estimates from Equation (20) on having a missing data and repeat the main excersize after imputing the 7% of missing test scores as robustness checks. Table 8 shows the results of this estimation which is also presented in the Appendix of the paper in Figure 8. The estimated coefficient for the treatment is not statistically significant, nor are the estimates associated with the treatment at the years after the implementation of the policy. The significant coefficients correspond to annual trends that are not related to the policy.

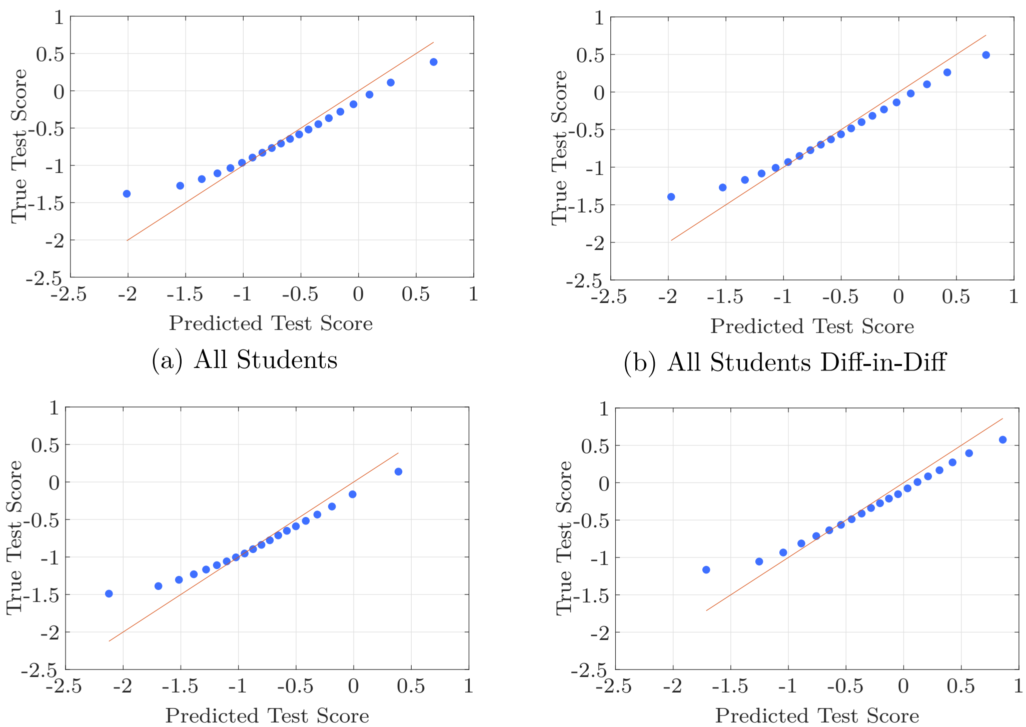
Table 8: Differences-in-differences estimation for Missings Non-Excused Test Scores

	Missing Test Score	
	Coef.	StdErr
Q5 % Poor within 1km (T)	-0.002	(0.785)
Q5 % Poor within 1km (T) ×2006	-0.003	(0.707)
Q5 % Poor within 1km (T) ×2007	-0.003	(0.752)
Q5 % Poor within 1km (T) ×2008	-0.005	(0.546)
Q5 % Poor within 1km (T) ×2009	0.004	(0.767)
Q5 % Poor within 1km (T) ×2010	0.005	(0.498)
Q5 % Poor within 1km (T) ×2011	0.006	(0.400)
Q5 % Poor within 1km (T) ×2012	0.005	(0.527)
Q5 % Poor within 1km (T) ×2013	-0.002	(0.814)
Q5 % Poor within 1km (T) ×2014	0.006	(0.400)
Q5 % Poor within 1km (T) ×2015	0.003	(0.708)
Q5 % Poor within 1km (T) ×2016	0.004	(0.594)
Constant	0.071***	(0.000)
Year FE	✓	
R^2	0.004	
N Obs	882,556	

Note: This table shows the estimation of a differences-in-differences methodology following Equation 20 of the paper. The dependent variable of the estimation is dichotomic and takes the value 1 if the test is missing on the data.

I implement a procedure to impute missing test scores following Cuesta, Gonzalez, and Larroulet (2017). It includes both excused and non-excused missing records. For each school I separately regress the test score equation for each school on a set of yearly dummies and GPA, GPA squared, an indicator of whether students were in fourth grade last year, and an indicator of whether students were in the same school last year. I use that regression to predict test scores for absent students and then estimate the value-added model using observed and imputed scores. To account for the uncertainty of the estimates, I draw 100 parameters from the asymptotic distribution from each school. This procedure allows for estimating 100 imputations for each missing score in each school. I pool these estimates into three different imputation measures. The first one averages all the imputations, the second one averages the lowest 25 imputations, and the last one averages the highest 25 imputations. To check the imputation model, I use the same cross-validation procedure from Cuesta, Gonzalez, and Larroulet (2017). First, I delete ten percent of the lowest GPA scores within each school year. Second, I run each school regression without those observations. Third, I draw 100 imputations for all missing data, including these new missing data. Last, I compare the imputed data against the real data. Figure 11 shows binscatter plots of true test scores against imputed scores. On average, we can see that the imputations match the true scores, which validates the use of the imputation model for this setting. I do observe some discrepancies for the lowest values. Imputations turn out to be smaller than the actual scores at the very bottom of the distribution. However, if anything, selective attendance would be more visible because a bad GPA is assigned a worse imputation than its real score. Also, there does not seem to be much difference between the Treatment and Control group.

Figure 11: Imputation Model Check



(a) All Students

(b) All Students Diff-in-Diff

(c) Treatment Group

(d) Control Group

Note: These figures show binscatter plots of true test scores (y-axis) and predicted test scores (x-axis). Predicted test score are observations that were dropped randomly following the Cross-Validation procedure from Cuesta, Gonzalez, and Larroulet (2017). The red line is the Y = X line. Panels (b), (c) and (d) restrict the model to the universe of students considered in the Differences-in-Differences model from the main paper. Panels (c) and (d) consider only the treatment and control group, respectively. The treatment group is defined by belonging to the top quintile of the measure of school's exposure to the policy, while control group is defined by belonging to the bottom quintile. The measure of school's exposure to the policy is calculated as the share of SEP eligible students that live within a 1.5 km radius from the school.

7 Additional Voucher Policy Information

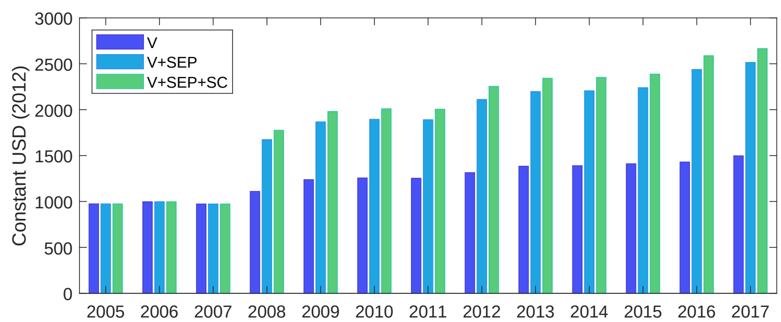
Evolution of Voucher Amounts: Table 9 shows the per capita yearly value of the Regular and SEP vouchers. There is a trend of increasing resources being transferred to schools, in particular schools with students from low-income socioeconomic groups. Figure 12 shows the evolution of Voucher per student, considering SEP and SEP Concentration voucher (in its highest level) each year for a 1st-grade student.

Table 9: Regular and SEP Vouchers transfers per Student

Year	Regular Voucher	SEP	Preferent SEP	SEP Concentration
2005	974	-	-	-
2006	997	-	-	-
2007	973	-	-	-
2008	1,110	564	-	102
2009	1,238	629	-	113
2010	1,256	639	-	115
2010	1,253	637	-	115
2012	1,314	798	-	142
2013	1,384	813	-	145
2014	1,390	816	-	146
2015	1,411	829	-	148
2016	1,430	1,008	504	150

Note: This table shows the annual values in 2012 dollars. The values correspond to the subsidies for a 1st-grade student at a school with a high concentration of priority students (more than 60%). Values are calculated using the official monthly value reported by the Ministry of Education each year, and it is multiplied for twelve months. These vouchers are paid based on the average enrollment of the school for the past three months.

Figure 12: Voucher Size Growth, Transfers in a Year



Note: This figure shows how the voucher evolved over time differentiating the baseline voucher (V), SEP eligible students (V+SEP), and SEP eligible students at schools with the highest concentration voucher (SC) at (*Jornada Completa (JEC)*).

One important adjustment to the base voucher is the **geographic zone adjustment**. It is a percentage increase applied to the general voucher, depending on where the establishment is located. The percentage can go from 0% to 140% and is higher in areas where the cost of living or opperating a school is higher. Table 10 shows the percentage of schools in each range of the zone assignation for 2012, disaggregated by region. In the central region where the capital is located, the adjustment is zero. In more remote regions, such as the southern part of the country (regions 11th and 12th) or the northern ones (15th and 1st), the adjustment is much higher.

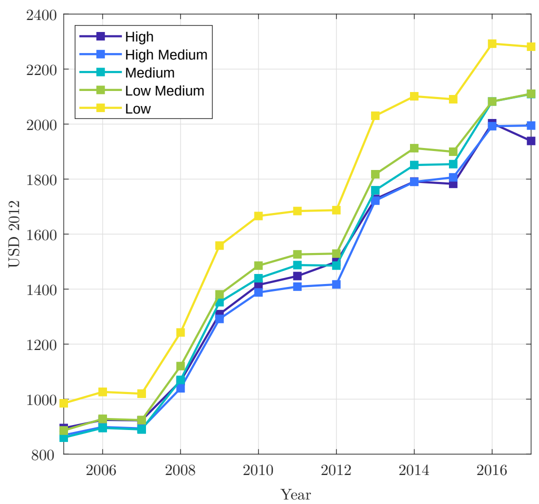
Table 10: Percentage Adjustment to Voucher in 2012

Region	0%	10-30%	35-70%	80-105%	115-140%
1	0	0	87	13	0
2	0	52	46	2	0
3	0	80	20	0	0
4	0	100	0	0	0
5	99	1	0	0	0
6	100	0	0	0	0
7	86	13	1	0	0
8	0	99	1	0	0
9	0	95	5	0	0
10	0	57	40	3	0
11	0	0	0	65	35
12	0	0	64	35	1
13	100	0	0	0	0
14	0	100	0	0	0
15	0	0	87	13	0

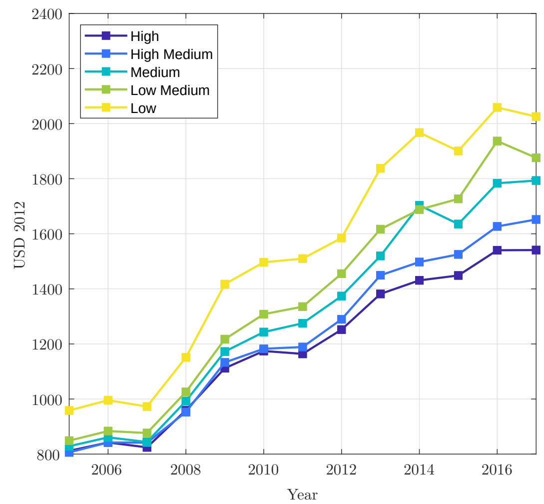
Note: This table summarizes the percentage of schools in each range of the zone assignation, by region in 2012. The percentage of increase can be: 0, 10, 15, 20, 25, 30, 35, 40, 50, 55, 60, 70, 80, 90, 95, 105. Remote regions have higher percentages for zone assignation because it compensates for the cost of living due to mobilization and connection issues. The 13th, 6th, and 5th regions are the ones with the lowest percentages because they are the central regions (the capital Santiago is located in the 13th region), while the southern (11th and 12th regions) and the northern regions(15th and 1st) are the ones with the highest percentages.

Evolution of Transfer Amounts to Schools: Figure 13 shows per-capita (per-student) revenues between 2005 and 2017, differentiating by socioeconomic context of the school. Panels (a) and (b) consider only public transfers for public and private voucher schools, respectively. The socioeconomic status of the school is defined by quintiles of exposure to the policy. We can see that per-capita revenue has been growing starting in 2008. It has grown significantly at Low SES schools relative to other schools. In the figures we can see three major jumps on schools revenue: the implementation of the SEP policy in 2008; then with the reforms implemented in 2012 that increased the value and the usage flexibility of the subsidy; and in 2015 with the Inclusion Law, which not only increased transfers to schools but also created a new category to receive resources from the SEP policy.

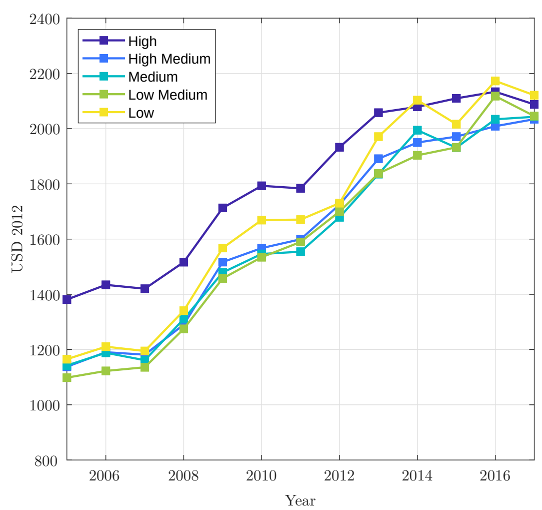
Figure 13: Per Capita Revenue by SES Group



(a) Public Schools



(b) Voucher Schools Transfers



(c) Voucher Schools Transfers + Co-Pay

Note: This figure shows the per capita annual revenue for public and private voucher schools differentiated by socioeconomic group. Revenues are composed of the general voucher, the SEP voucher, and the price charged for private voucher schools.

Optimal prices under flat voucher : FOC for $p_{j,1}$ under flat voucher.

$$\frac{\partial \pi_j}{\partial p_{j,0}} : \sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \left[\frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial op_{j,k}} \frac{\partial op_{j,k}}{\partial p_{j,0}} \left[v_b^m + p_{j,0} - \text{MgC}\left(q_{j,0}\right) \right] + s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}}) \frac{\partial \text{MgR}(p_{j,0},k)}{\partial p_{j,0}} \right] = 0 \quad (1)$$

$$\sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial p_{j,0}} p_{j,0} = \sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \left[\frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial p_{j,0}} \left[v_b^m - \text{MgC}\left(q_{j,0}\right) \right] - s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}}) \right] \quad (2)$$

$$\sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial p_{j,0}} = \frac{\partial s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial p_{j,0}} \qquad \sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}}) = s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}}) \quad (3)$$

Using 3 in Equation 2:

$$p_{j,0}^* = \left[\text{MgC}\left(q_{j,0}\right) - v_b^m \right] - s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}}) \left[\frac{\partial s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial p_{j,0}} \right]^{-1} \quad (4)$$

Optimal prices under targeted voucher Since $\frac{\partial \text{op}(p_{j,2},k)}{p_{j,2}} = 0 \quad \frac{\partial \text{MgC}(q_{j,2})}{p_{j,2}} = 0 \quad \forall \quad k = \mathrm{E}$.

$$\frac{\partial \pi_j}{\partial p_{j,2}} : \sum_{k \in \not{\mathrm{E}}} \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \left[\frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}})}{\partial op_{j,k}} \frac{\partial op_{j,k}}{\partial p_{j,2}} \left[v_b^m + p_{j,2} - \text{MgC}\left(q_{j,2}\right) \right] + s_{j,k}^{\text{loc}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}}) \right] = 0 \quad (5)$$

$$\sum_{k \in \not{\mathrm{E}}} \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}})}{\partial p_{j,2}} = \frac{\partial s_{j,\not{\mathrm{E}}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}})}{\partial p_{j,2}} \qquad \sum_{k \in \not{\mathrm{E}}} \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k s_{j,k}^{\text{loc}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}}) = s_{j,\not{\mathrm{E}}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}}) \quad (6)$$

Using 6 in 5 and after calculations, the price under targeted voucher is:

$$p_{j,2}^* = \left[\text{MgC}\left(q_{j,2}\right) - v_b^m \right] - s_{j,\not{\mathrm{E}}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}}) \left[\frac{\partial s_{j,\not{\mathrm{E}}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}})}{\partial p_{j,2}} \right]^{-1} \quad (7)$$

Optimal quality under flat voucher : FOC for $q_{j,0}$ for profits with flat voucher policy.

$$\frac{\partial \pi_j(v^o)}{\partial q_{j,0}} : \sum_k^K \sum_{\text{loc}}^L w_k^{\text{loc}} \Pi_k \left[\frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial q_{j,k}} \left[p_{j,0} + v_b^m - c^m - \sum_l c_l w_j^l - c_q q_{j,0} \right] + s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}}) c_q \right] = 0 \quad (8)$$

Using 3 in 8:

$$c_q q_{j,0} \frac{\partial s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial q_{j,0}} = \frac{\partial s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial q_{j,0}} \left[v_b^m + p_{j,0} - c^m - \sum_l c_l w_j^l \right] + s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}}) c_q \quad (9)$$

$$q_{j,0}^* = \left[\frac{p_{j,0} + v_b^m - c^m - \sum_l c_l \omega_j^l}{c_q} \right] - s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}}) \left[\frac{\partial s_j(\mathbf{q}_0^{\text{e}}, \mathbf{op}_0^{\text{e}})}{\partial q_{j,0}} \right]^{-1} . \quad (10)$$

Optimal quality under targeted voucher : Assuming $\overline{c} = c^m + \sum_l c_l \omega_j^l$ and $\overline{p} = v_b^m + v_{sep}$ for $k = \mathrm{E}$

$$c_q q_{j,2} \sum_k \sum_{loc} w_k^{loc} \Pi_k \frac{\partial s_{j,k}^{loc}}{\partial q_{j,2}} = \sum_k \sum_{loc} w_k^{loc} \Pi_k \left[\frac{\partial s_{j,k}^{loc}}{\partial q_{j,2}} \left(\text{MgR}\left(p_{j,2}, k\right) - \overline{c} \right) + s_{j,k}^{\text{loc}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}}) c_q \right] \quad (11)$$

$$c_q q_{j,2} \frac{\partial s_j}{\partial q_{j,2}} = \left(\overline{p} - \overline{c} \right) \left[\sum_E \sum_{loc} w_k^{loc} \Pi_k \frac{\partial s_{jk}}{\partial q_{j,2}} + \sum_{\not{\mathrm{E}}} \sum_{loc} w_k^{loc} \Pi_k \frac{\partial s_{jk}}{\partial q_{j,2}} \right] + \left(v_b^m + p_{j,2} - \overline{p} \right) \frac{\partial s_{j,\not{\mathrm{E}}}}{\partial p_{j,2}} + s_j c_q \quad (12)$$

$$c_q q_{j,2} \frac{\partial s_j(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}})}{\partial q_{j,2}} = \left(\overline{p} - \overline{c} \right) \frac{\partial s_j(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}})}{\partial q_{j,2}} - \left(v_b^m + p_{j,2} - \overline{p} \right) \frac{\partial s_{j,\not{\mathrm{E}}}(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}})}{\partial q_{j,2}} + s_j(\mathbf{q}_2^{\text{e}}, \mathbf{op}_2^{\text{e}}) c_q \quad (13)$$

Replacing $\overline{c}$ and $\overline{p}$ in 13 and clearing $q_{j,2}$ in the left hand side.

$$q_{j,2}^* = \left[\frac{v_b^m + v_{\text{sep}} - c^m - \sum_l c_l \omega_j^l}{c_q} \right] - s_j \left[\frac{\partial s_j}{\partial q_{j,2}} \right]^{-1} - \left[\frac{v_{\text{sep}} - p_{j,2}}{c_q} \right] \left[\frac{\partial s_{j,\not{\mathrm{E}}}}{\partial q_{j,2}} \right] \left[\frac{\partial s_j}{\partial q_{j,2}} \right]^{-1} \quad (14)$$

Table 11: Policy Timeline

1981	**Education Reform[a]:** School administration was transferred to local governments, the school voucher was created and private agents were allowed to participate in the education sector.
1990	**900 Schools Program:** Program designed to improve the results of primary schools in poor areas (focused in the 10% of the schools with the lowest scores in SIMCE).
1992	**MECE Program:** Program focused in investments for primary education. Extended to secondary education in 1995.
1992	**ENLACES Program:** Program for incorporating the new technologies of information and communication to education.
1993	**Shared Funding** (*Financiamiento Compartido*[b]): Voucher schools and public secondary schools are allowed to charge a fee additional to the voucher.
1996	**Curriculum reform (Gradual)**
1997	**School day extension (Law N. 19,532)** (*Jornada Escolar Completa (JEC)):* Gradual extension of school day from partial to complete schedule. Involved important amounts of resources for infrastructure investments. In addition, creates a system of fees exemptions and scholarships for students of low-income families.
2003	**Pro-retention subsidy (Law N. 19,873) :** Payments to the holders of public and voucher schools that managed to retain students belonging to low income families.
2003	**Extension of Compulsory Education (Law N. 19,876) :** Up to completion of Secondary Education.
2008	**Targeted Vouchers (SEP) (Law N. 20,248)**
2008	**School Infrastructure Improvement Plan:** Involved resources for infrastructure for traditional public secondary schools.
2009	**General Law of Education (Law N. 20,370)** : New institutional and regulatory framework for the education system.
2011	**Quality and Equity in Education Law (Law N. 20,501) :** Amended various laws in order to introduce a new personnel management mechanism in public and voucher schools, with the aim of improving the quality of education.
2011	**National System of Quality Assurance (Law N. 20,529) :** Creation of two new institutions, one in charge of evaluating student learning and one that oversees educational law and regulations, as well as resources accountability.
2011	**Targeted Voucher increase (Law N. 20,550) :** 21% increase and flexibilization of the use of SEP resources.
2015	**Inclusion Law (Law N. 20,845) :** End to profit, selection and shared funding in schools that receive public funding[c]. It also increases SEP voucher by 20% and extends the benefit to those students who do not have the quality of a priority student, but whose families belong to the poorest 80%.
2016	**Teacher Professional Development System (Teacher Career) (Law N. 20,903) :** Set progress, evaluation and performance parameters for teachers.

[a] DL. 3,476 and DS 8,144: vouchers implementation. Decree 114 Exempt: summarizes all laws within the framework of educational reform.

[b] Indications in Law N. 18,768 (1988), and more deepening in Law N. 19,247 (1993)

[c] The end of shared funding is a progressive process where shared funded schools have to freeze their amounts of co-payment, decreasing in real terms until they reach the voucher value.

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