Online Appendix - *Targeted Vouchers, Competition Among Schools, and the Academic Achievement of Poor Students*† †Last Updated on May 31st, 2021 (See most recent version here). This online appendix was made with the help from many collaborators. In particular, Claudia Allende, Cecilia Moreira, Maria Elena Guerrero, Karl Schulze, Nicolas Rojas and especially Isabel Jacas helped a tremendous amount.

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 also has the advantage of providing information on students' demographics at the time of their birth, as well as allowing me to link them to their siblings through their mother. The resulting dataset provides a rich characterization of the population of students and allows me to do more accurate imputations of socioeconomic status for populations that may be less likely to appear in some datasets. This data build was possible through a collaboration between the Ministry of Health and the Ministry of Education during 2010-2012, and served a research agenda studying the effects of early health outcomes and socioeconomic status on educational outcomes (see Bharadwaj, Loken, and Neilson (2013) and Bharadwaj, Eberhard, and Neilson (2018) for other details).

Data on the Potential Student Population: The data on all registered births in Chile was 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 2nd, 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 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, it is not always possible to link it 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 and for estimating demand off of school choice decisions.

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, and Sex 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.

Determination of SES Types: For the analysis comparing the test scores across socioeconomic groups I use three measures of socioeconomic status. The first is actual program eligibility, which is available from 2008 onward and divides the student population into (roughly) the 40% eligible and the 60% non-eligible. I also use household income from the SIMCE parent surveys and categorize families into two groups: the poorest 40% and the rest. A third alternative measure is based on an imputed poverty score resulting from a logit estimation of the

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 in Chile.

probability of being a SEP-eligible student over a large vector of individual characteristics[1] and fixed effects by market. I run this 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. The 40% of students with the highest predicted probability of being SEP-eligible students are classified as low SES.

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 Additional Voucher Policy Information

2.1 Educational Vouchers

Public and private voucher schools receive public transfers made up of a base voucher, increases and discounts to that voucher, other minor subsidies, and assignations or bonuses for teachers. Over these transfers, private voucher schools can charge top-off fees to families. The **base voucher**[2] is the core of the public financing system for voucher schools. Created in 1980, it consists of a flat monthly payment to the establishment per student attended. This amount may differ depending on the level or grade of the student, the school day he attends (full or half day) and the educational modality that the school imparts. The base voucher in 2012 for elementary school with full school day is equal to 110 USD per student.

There are assignations or other vouchers that are added on top of the general voucher, like

[1] The vector of variables used in the imputation is the same used for school value added estimation, shown in Section 5 of this online appendix.

[2] Article 9 DFL No. 2/98 and its modifications.

the **geographic zone assignation**[3]. It consist of a percentage increase applied to the base voucher, depending on where the establishment is located, and it is intended to compensate teachers and other school workers. The percentage can go from 0% to 140%, being higher in areas where the cost of living could be higher because of transportation or connectivity issues. Table 2 shows the percentage of schools in each range of the zone assignation for 2012, disaggregated by region. The ranges represent the percentage of the base voucher that is added to its full value. We can see that in the most central regions, such as the Metropolitan Region (13th), where the capital Santiago is located, the area assignation is zero; while if we observe more remote regions, such as the southern part of the country (regions 11th and 12th) or the northern ones (15th and 1st), we can see much higher values for this assignation.

Table 2: Percentage of schools in each range of the Zone Assignation in 2012

Region	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0%	0	0	0	0	99	100	86	0	0	0	0	0	100	0	0
10-30%	0	52	80	100	1	0	13	99	95	57	0	0	0	100	0
35-70%	87	46	20	0	0	1	5	40	0	64	0	0	87		
80-105%	13	2	0	0	0	0	0	0	0	3	65	36	0	0	13
115-140%	0	0	0	0	0	0	0	0	0	0	35	1	0	0	0

Note: This table summarizes the percentage of schools in each range of the zone assignation, by region in 2012. 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.

As mentioned above, private voucher schools can charge top-off fees and enrollment charges to families for entering the school. There are certain conditions under which students do not pay charges, like being an eligible student for the SEP policy. Schools who charge top-off fees are called schools with *financiamiento compartido* or shared-funding[4]. These schools have a discount over the base voucher, based on the price that they charge (as shown in Table 3). The discount is known as **Shared-Funding Discount**.

Table 3: Groups of voucher discount for schools with shared-funding

Group	Average amount charged by shared-funding in 2012 USD	% of discount in general voucher
I	Less or equal to 19.6	0 %
II	Over 19.6 USD to 39.2	10 %
III	Over 39.2 USD to 78.5	20 %
IV	Over 78.5 USD to 157.0	35 %

Note: This table shows the groups for school voucher discount by shared funding amount charged established in Law No. 19,247 (1993). Values are in USD for 2012. With the Inclusion Law in 2015, the maximum amount charged for shared funding in that year was frozen in its nominal value, so that it decreases with the devaluation of the currency, while the decrease in resources is compensated with a nominal increase of the average school voucher and the application of new types of targeted vouchers for middle and low income families.

[3]Established in the 11th article of DFL No. 2.

[4]The shared-funding or co-payment was first announced in Law No. 18,768 (46th Article), in 1988, as a new regime only for school owners of private voucher schools. Later in 1993, Law No. 19,247 (9th Article) made more attractive this form of funding, increasing the co-payment limit and reducing the discount to the base voucher that was linked to the top-off fees charged.

In 2008, Law No. 20,248 established the **Preferential School Voucher** or ***Subvención Escolar Preferencial*** **(SEP)**. This voucher was the most important voucher that added resources on top of the base voucher because it raised the transfers per kid by 50% for low-income students, changing the voucher structure from a flat voucher to a targeted one. It is intended to increase funding to low-income families to improve their school choice and the students' performance. Eligible students are called *priority students*, and they are students that: (1) belong to the *Chile Solidario* program; (2) belong to the bottom 30% of the income distribution (measured by the score of the Social Protection Record[5]); (3) are affiliated to the lower-income segment in the public health insurance system; or (4) present vulnerable socioeconomic conditions (related to the education of the mother and the rurality and poverty of their *comuna* of residence).

There are two more vouchers related to the SEP policy. The first one is the **SEP Concentration Voucher**, which accounts for additional resources for schools with a higher concentration of priority students. The value of the voucher increases as the percentage of priority students in the school grows, starting from 15% upwards, defining four concentration segments: between 15 and 30%, between 30 and 45%, between 45 and 60%, and 60% and above. The second SEP-related voucher is the voucher for **Preferential Students**. It began in 2016 and it is an extension of the SEP voucher for students that are not priority students, but whose families are in the bottom 80% of the income distribution. This additional subsidy is half the value of the original SEP voucher.

Table 4 shows the annual values of the base voucher and SEP vouchers. Values are calculated using the official monthly value reported by the Ministry each year and multiplied for twelve months. These vouchers are paid based on the enrollment of the school according to the different types of students.

2.2 SEP Targeted Voucher Policy Adoption

The SEP policy was available to all voucher schools. Virtually all public schools joined the program because they already accomplished the requirements. Schools joined the program in large numbers, especially in poor neighborhoods. Figure 1 shows the proportion of private voucher schools enrolled in the SEP program in 2011 by percentage of exposure to the policy.

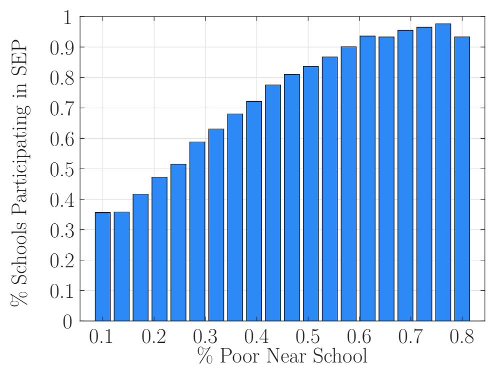
[5]The Social Protection Record is an instrument built by the Ministry of Social Development to identify vulnerable families, for them to apply to financial or social benefits given by the State. It was replaced in 2016 for a social support system called Social Household Registry (*Registro Social de Hogares*)

Table 4: Vouchers Value per Student

Year	Base Voucher	SEP	Preferential SEP	SEP Concentration
2005	974	-	-	-
2006	997	-	-	-
2007	973	-	-	-
2008	1,110	564	-	102
2009	1,238	629	-	113
2010	1,256	639	-	115
2011	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
2017	1,498	1,017	508	151

Note: This table shows the annual values in 2012 dollars of the base voucher and SEP-related vouchers. The values correspond to the subsidies that would receive a 1st-grade student that attends 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. For months that are not accounted in the scholar year, the voucher considers the three nearest "active" months before the month paid.

Figure 1: Share of private voucher schools in the SEP policy by Exposure to SEP



Note: This figure shows the percentage of private voucher schools in 2011 enrolled in the SEP program by exposure to SEP. The measure of exposure or % of poor students near the schools is calculated based on the percent of SEP-eligible students within a radius of 0.5km.

3 Market Construction and Description

Market Boundaries: Defining a 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. 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 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 because of lower prices, and that are still accessible by families near the edge of the urban boundary. The outermost border of this buffer delimits a market and is denoted by B^m in the paper.

Assigning schools to markets: Using administrative data, I identify all schools with an educational code (*codigo enseñanza*) of 110, which indicates regular primary education, that are classified as urban by the Ministry of Education, and that have some students matriculated in the first grade between the years 2005 and 2016. 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 on the map (for example, out of the 4000+ schools in 2011, only four were not geocoded). If the school lies within the boundaries of a market, it is assigned to that market (in terms of the model, it belongs to that market's F^m). Figure 2(a) shows, as an example, the location of the schools of interest that belong to the second largest educational market in Chile.

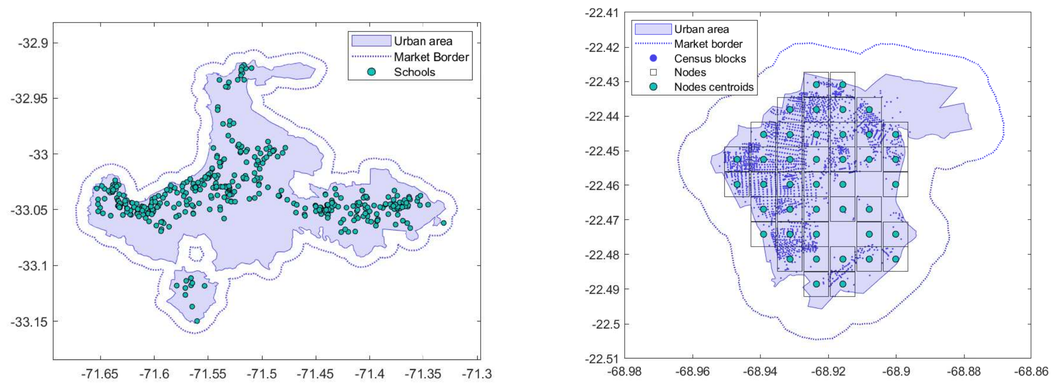
The total number of markets identified using the procedure described in the preceding subsection was 363. Out of these, 300 were assigned one or more of the schools considered. The remaining 63 markets were excluded from the analysis at this point.

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 (S^m in the model) 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 and availability of microdata. Specifically, I focus on markets that have 1) at least 5 elementary schools, in at least half of the years considered (2005-2016), 2) at least 500 students in the first grade of primary, 3) at least one private school, and 4) a geocoded sample of students available. As stated in the paper, this brings the final sample to 53 markets that contain over 3,600 schools and over 80% of all urban students in first grade on any given year between 2005 and 2016. 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. Because census blocks are very small and heterogeneous in shape and size, I divide the urban area of each market into a homogeneous grid of L^m square nodes (each 0.8 km wide), and aggregate block-level information to this new level. Figure 2(b) shows one example of spreading nodes across a 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: Examples of elements in markets



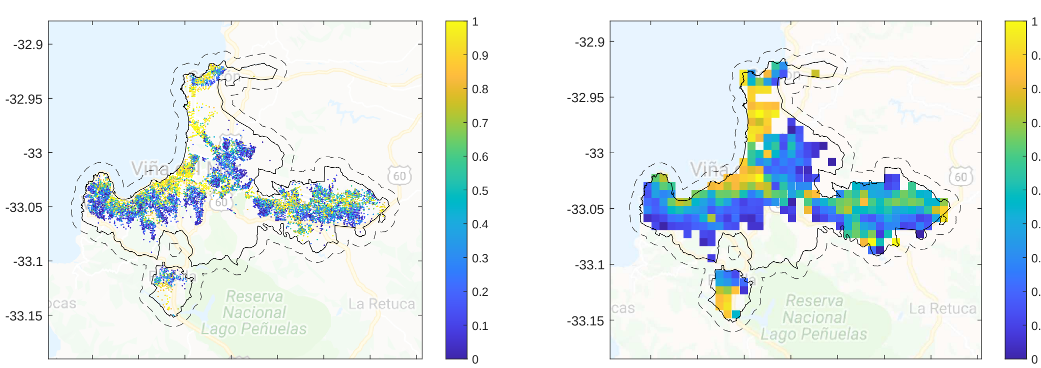
(a) Schools

(b) Census blocks and Nodes

Note: This figure shows schools (green dots) located within the boundaries of a market that includes the cities of Viña del Mar and Valparaiso. Some schools are located just at the outskirts of the urban area and are captured by the buffer zone. Source: INE, Ministry of Education MINEDUC, own calculations.

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 nodes in all markets), one node aggregates information from 26 blocks (standard deviation: 25).

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



(a) At each block

(b) At each node

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 income (SEP=0,SEP=1) and the education of the mother (E=1,E=2,E=3,E=4)[6]. 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 distribution (conditional on mother's education) of SEP-eligible students across markets, I use a subsample of geocoded students for whom I do have SEP eligibility. I assign these students to nodes, and attach node-level demographics by aggregating the most recently available census data. I then use these node-level covariates and the students' mothers' education to predict their SEP eligibility. I then extrapolate, conditional on a level of mother's education, the proportion of SEP-eligible students at each node in my broader sample. Combining this proportion with the population density at each node allows me to estimate w_k^m, or the proportion of all SEP-eligible students within a market that reside at a given node, given their mothers' education.

The estimation method underlying this process is a random forest. Athey and Imbens ("Machine learning methods that economists should know about," *Annual Review of Economics*, 2019) suggest using random forests as a flexible nonparametric estimation technique that is stable and requires little tuning. They suggest thinking of random forests as a nearest-neighbor estimation technique that creates kernel weights based on linear partitions of the covariates rather than on euclidean distance. In practice, I found that using a random forest did not dramatically improve in-sample error over a linear probability model.

Representativeness of selected markets: Even though not all schools in Chile are considered in the selected markets, it is important to emphasize that, since Chile is predominantly urban, this paper still deals with the vast majority of students in the country. Table 5 shows the total number of elementary schools in the country (that teach first grade), along with their enrollment. Schools classified as urban by MINEDUC represent 88% of total enrollment. Schools in the 53 selected markets represent 80% of urban enrollment. Table 6 compares urban schools to schools specifically in the markets of this paper. Throughout the period considered they remain very similar in terms of first-grade class size, SEP adoption, private participation and average quality.

[6] 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, 37% has less than high school, 39% has high school, 14% has a technical degree and 10% has a college degree.

Table 5: Total schools, urban schools and schools in markets

	2008	2009	2010	2011	2012
Total Elementary Schools	8,097	8,135	8,009	7,854	7,771
Total Enrollment in 1st grade	236,438	237,991	234,416	231,926	232,473
Urban Schools	4,388	4,458	4,517	4,495	4,518
% of Total Schools	54.2	54.8	56.4	57.2	58.1
Urban Enrollment	207,073	208,728	206,759	204,440	205,622
% of Total Enrollment	87.6	87.7	88.2	88.1	88.4
Schools in Markets	3,589	3,614	3,617	3,624	3,621
% of Urban Schools	81.8	81.1	80.1	80.6	80.1
Enrollment in 1st grade in Markets	168,376	167,673	165,465	163,934	164,804
% of Urban Enrollment	81.3	80.3	80.0	80.2	80.1

Note: This table shows the number 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 6: 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
2008	47.2	65.7	57.3	-0.13	46.9	62.0	60.9	-0.14
2009	46.8	70.3	58.0	-0.09	46.4	67.4	61.3	-0.09
2010	45.8	72.3	58.1	-0.03	45.7	69.2	61.9	-0.03
2011	45.5	76.6	58.9	-0.02	45.2	72.5	62.3	-0.03
2012	45.5	79.3	59.4	0.01	45.5	75.7	62.6	0.00

Note: This table compares all elementary urban schools and the schools in the 53 selected markets, across a set of relevant variables.

A note about entry and exit in selected markets: I describe entry and exit patterns by type of institution and by the school's exposure to the policy. Table 7 shows that, for public schools, entry and exit rates remained stable and low throughout the period of study. Entry and exit was higher among private voucher and private non-voucher schools. There was a downward trend in the entry rate of private vouchers (from 3.75% in 2006 to 0.2% in 2015), while the exit rate remained stable around 1%. I also document entry and exit patterns by exposure to the SEP policy. Table 8 shows that entry rates evolve very similarly for schools with high or low exposure to the policy. Exit rates also follow a similar trend during most of the period under study. Moreover, I do not find any remarkable change around 2008, when the SEP policy was introduced.

Table 7: 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	0.31%	0.87%	1266	3.75%	1.98%	1915	3.52%	1.61%	373
2007	0.32%	0.71%	1259	3.13%	1.60%	1937	3.75%	4.20%	381
2008	0.56%	0.95%	1257	2.68%	0.87%	1958	2.36%	1.34%	374
2009	0.40%	1.68%	1250	2.09%	1.06%	1982	3.48%	2.62%	382
2010	0.40%	1.46%	1234	2.12%	0.65%	2003	2.09%	2.37%	380
2011	0.57%	1.23%	1223	1.55%	1.43%	2021	2.37%	0.79%	380
2012	0.25%	1.40%	1211	1.68%	1.53%	2026	1.84%	2.60%	384
2013	0.41%	1.17%	1199	1.58%	1.23%	2027	1.30%	2.11%	379
2014	0.67%	0.34%	1193	0.35%	1.29%	2009	1.58%	1.86%	377
2015	0.59%	0.33%	1196	0.20%	1.51%	1987	1.33%	0.53%	375

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).

Table 8: Entry rate, exit rate, and active voucher schools, by exposure to SEP

	High exposure			Low exposure		
Year	% Entry	% Exit	Active	% Entry	% Exit	Active
2006	3.67%	1.19%	336	3.55%	2.63%	342
2007	3.57%	1.16%	344	4.09%	1.73%	347
2008	3.49%	1.42%	352	3.46%	1.13%	353
2009	1.42%	1.70%	352	1.70%	1.69%	355
2010	3.13%	0.28%	357	1.69%	0.85%	355
2011	2.24%	0.82%	364	2.25%	0.28%	360
2012	1.65%	1.36%	367	1.94%	2.19%	366
2013	2.18%	1.35%	370	1.37%	1.38%	363
2014	0.27%	1.91%	366	0.28%	2.51%	359
2015	0.27%	2.78%	360	0.28%	1.99%	351

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 0.5 km radius from the school. High (low) exposure is defined as having a level of exposure above (below) the 80^{th} (20^{th}) percentile of 2007's exposure distribution. This implies that close to 40% of voucher schools in urban markets are accounted for in this table).

4 Additional Descriptive Statistics

In this section I document three facts that support the claim that academic achievement and equity improved in Chile during the period of interest. The first fact is that employing multiple measures of socioeconomic status, I find a significant reduction of the gap in academic achievement (measured by national standardized tests) between poor and non-poor students. The second fact is that standardized international tests, administered independently, show the same pattern. Finally, I present evidence that the main driver of these patterns was not sorting of students into different schools.

The first column in Table 9 shows the evolution of average test scores from 2005 to 2016. The next four columns show the evolution of average test scores but focusing on specific socioeconomic groups. In 2005, the difference in average score between the bottom and top quintile of predicted poverty score was around 1 standard deviation (Section 1 contains more details about determination of SES types). From 2005 to 2016 the lowest and highest quintiles' average scores increased by 0.31 and 0.1 standard deviations, respectively. This means that by 2016 the gap in achievement had been reduced to 0.82 standard deviations. A very similar story is captured by Columns 8 and 9, which show the breakdown by SES status as measured from SIMCE's household survey. In Columns 6 and 7, SES breakdown is based on actual SEP eligibility, and therefore is only available from 2008 onwards, but also presents a similar pattern. The takeaway of this table is that different measures of socioeconomic status allow us to arrive at the same conclusion: the gap in achievement between high and low SES students closed during the time under study. A plot of the gap can be found in Figure 4.

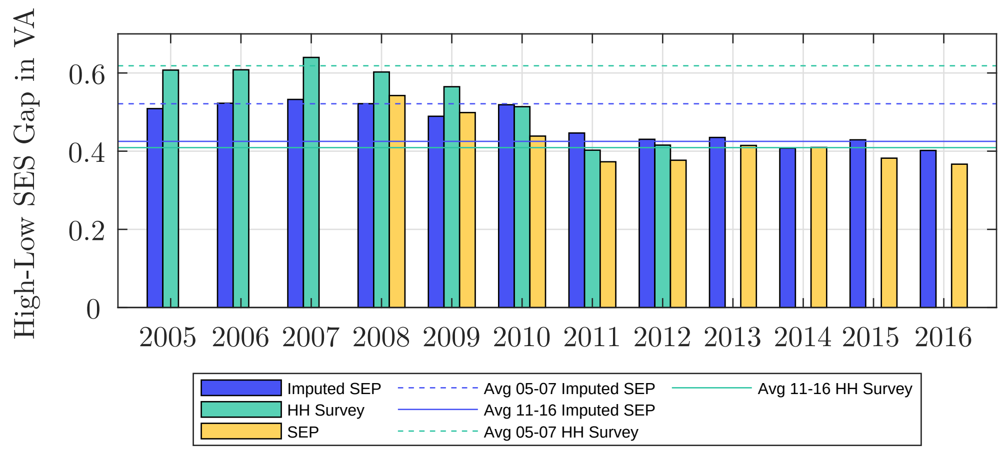
Table 9: Average Standarized Test Scores by Measures of Socioeconomic Status

	Avg. Test	Imputed SES				SEP Eligibility		SES HH Survey		Value Added	
Year	Score	20% Low	40% Low	60% High	20% High	SEP	Non SEP	40% Low	60% High	40% Low	60% High
2005	0.13	-0.28	-0.19	0.53	0.75	.	.	-0.24	0.37	-0.22	0.13
2006	0.08	-0.34	-0.25	0.48	0.69	.	.	-0.23	0.38	-0.29	0.07
2007	0.08	-0.35	-0.25	0.48	0.71	.	.	-0.30	0.34	-0.30	0.07
2008	0.15	-0.27	-0.17	0.55	0.79	-0.22	0.33	-0.22	0.38	-0.22	0.14
2009	0.22	-0.14	-0.08	0.56	0.78	-0.07	0.42	-0.14	0.43	-0.16	0.17
2010	0.30	-0.12	-0.02	0.65	0.85	0.02	0.46	0.02	0.54	-0.08	0.23
2011	0.30	-0.05	0.03	0.61	0.80	0.07	0.44	0.07	0.47	-0.06	0.20
2012	0.34	-0.01	0.07	0.65	0.83	0.11	0.48	0.10	0.52	-0.01	0.23
2013	0.25	-0.11	-0.02	0.56	0.75	0.02	0.44	.	.	-0.12	0.14
2014	0.25	-0.09	-0.01	0.54	0.74	0.02	0.43	.	.	-0.13	0.12
2015	0.30	-0.05	0.04	0.60	0.81	0.08	0.46	0.00	0.48	-0.06	0.19
2016	0.34	0.01	0.09	0.63	0.84	0.13	0.49	0.05	0.52	-0.01	0.23
2016	0.35	0.03	0.09	0.65	0.85	0.11	0.54	0.12	0.52	-0.04	0.23

Note: This table shows average test scores and value added over time and broken down by different definitions of socioeconomic status. The first column considers all students and schools in the study sample. The next four columns show averages by the imputed poverty index (Imputed SES). The following four show average scores by SEP eligibility and by the SE level from household income per capita measured in a household survey. The last two columns show the estimated value added using the imputed SES to divide the sample into the 40% lowest and 60% highest SE level.

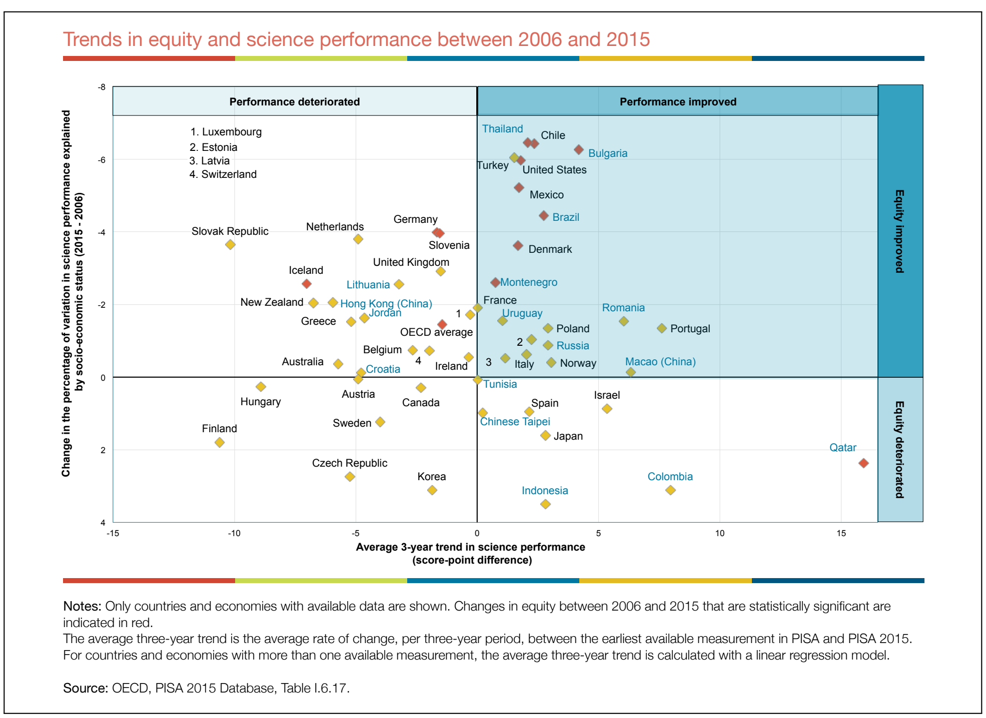
The Trends in International Mathematics and Science Study (TIMSS) is a series of international assessments of academic knowledge of students around the world, covering the subjects of Math and Science for 4th and 8th-grade students. Chile participated in the TIMSS test for 8th grade in 1999, 2003, 2011 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 4: Evolution of the Gap in Academic Achievement High-Low SES



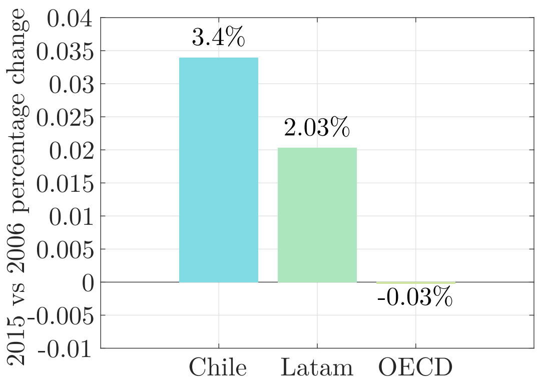
Note: This figure shows the difference in average standardized test scores between students in high SES and low SES categories. Test scores are comparable across years and are standardized relative to the benchmark set in 1999. The average test score indicates the average across math and reading test scores of all students in the 53 markets in the study. There are three groups considered in the comparison. The first comparison denominated (SEP) is the difference between the ineligible students and the eligible students for the SEP voucher. The eligible group roughly represents the 40% with the lowest SES, and this measure is available starting in 2008. A second comparison imputes eligibility for students based on their observable characteristics (Imputed SEP). Finally, I use income per capita reported in household surveys (HH Survey) taken by the parents of test taking students. This measure is only available until 2012 when the questions required to calculate household income per capita were discontinued. The average test score over the population 0.05σ in 2007, 0.29σ in 2011, and 0.33σ in 2016. The average gap across SES groups from 2005 to 2007 was 0.57σ (dotted line), while from 2011 to 2016 the average was 0.39σ (continuous line).

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

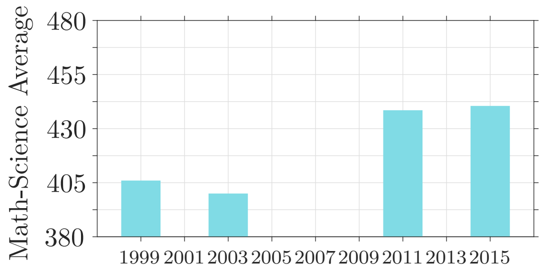


Data Source: Table I.6.17

Figure 6: International Tests



(a) Growth in math-reading average PISA scores relative to year 2006



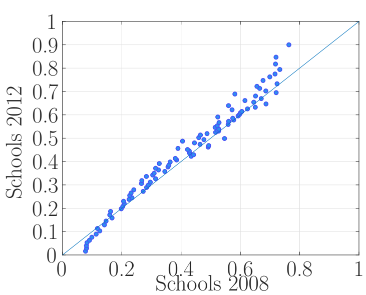
(b) TIMSS International Science and Math Performance, 8th Grade

Note: The left panel 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. The right panel 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.

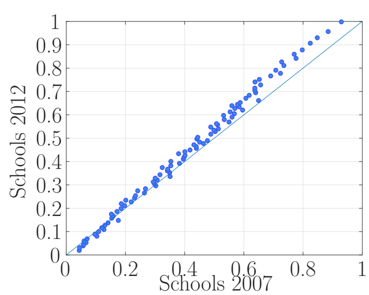
4.1 No sorting

The following figures show that the socioeconomic composition of schools remains very similar after the policy was implemented. This fact is robust to using different definitions of socioeconomic status. In particular, the correlation between the share of poor students at each school in 2007 and 2011 is 0.94. This absence of student reshuffling lends credibility to the idea that academic inequality decreased because of actual improvements in the quality provided by schools, especially those serving low income students.

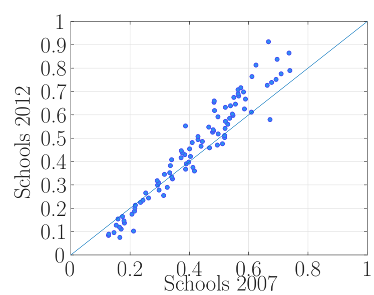
Figure 7: Share of poor students by school before and after the policy



(a) SEP Eligible



(b) Imputed Eligibility



(c) HH Survey

Note: These figures compare the shares of *poor* students at each school before and after the policy. Panel (a) shows the share of SEP students in 2008 and 2012 by school. Panel (b) shows the share of students with *imputed SEP* in 2007 and 2012. Panel (c) shows the share of poor students measured in the HH survey as the 40% lowest household income per capita, in 2007 and 2012. Details regarding the calculation of imputed priority are presented in Section 1 of this Online Appendix.

5 Additional Results and Robustness of Value-Added Estimates

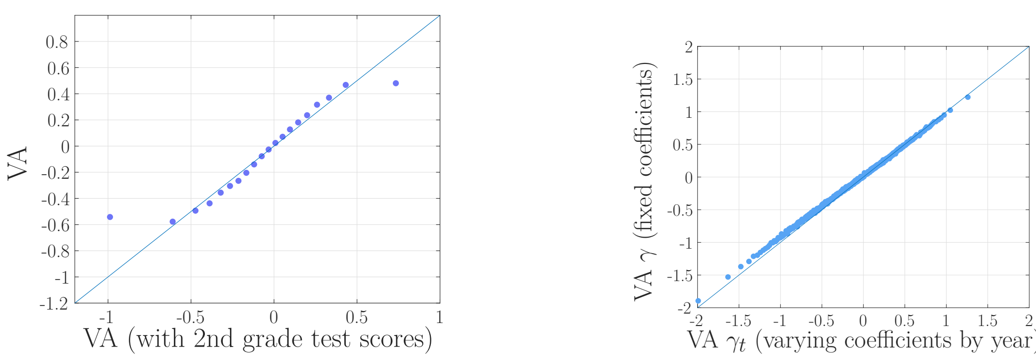
In this section I provide additional details on the procedure I followed to estimate schools' value added. I also present four pieces of evidence to argue that these value added estimates provide a reliable measure of school quality. Table 10 presents the coefficients for the value added regression estimated with different specifications and across different time periods. Mother's human capital and child health at birth are all important drivers of student outcomes. Taking into account mothers' college entrance exam scores by subject seems to be important as there is a steep gradient with mother math scores.

5.1 Stability of VA estimates

The resulting estimates of value added are stable to several robustness exercises. In one robustness exercise I add controls for **lagged student test scores** for the years these are available. I find very similar results for estimated value added as shown in a binscatter plot presented in Figure 8(a). These results suggest the observed characteristics in X_j are capturing much of the heterogeneity across students that lagged scores would capture.

While value added estimates control for the changing demographics of students taking the test over time, a remaining concern is that the observed increase in value added in poor areas could reflect a changing relationship between student characteristics and student test scores over time such that the larger estimated value added in poor neighborhoods is in fact the result of misspecification. Therefore, I present another robustness exercise where I allow **coefficients to vary over time**. The coefficients are reasonably stable and the resulting estimates of value added are similar as well, as shown in a binscatter plot presented in Figure 8(b).

Figure 8: Robustness of Value Added Estimates



(a) Using Lagged Test Scores

(b) Varying Coef. γ_t vs γ

Note: The panel on the left shows the binscatter of estimated value added with and without considering lagged test scores of students when they were in 2nd grade. This figure shows values for years 2014 to 2016, because the 2nd grade test is only available since 2012, and I made the estimations for 4th graders. The panel on the right shows a binscatter plot where X-axis shows school-year value added estimated letting γ 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.

Table 10: School Quality Estimation Regression

	Avg. Test Score in 4th grade (Math and Lang)													
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Pre SEP		All		Group		Pre SEP		All		Group		Group & Post	
Years	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Mother High School	0.29	(0.00)	0.24	(0.00)	0.24	(0.00)	0.24	(0.00)	0.21	(0.00)	0.21	(0.00)	0.09	(0.00)
Mother Technical	0.42	(0.01)	0.34	(0.00)	0.34	(0.00)	0.26	(0.01)	0.23	(0.00)	0.23	(0.00)	0.11	(0.00)
Mother College	0.55	(0.01)	0.47	(0.00)	0.47	(0.00)	0.27	(0.01)	0.23	(0.00)	0.23	(0.00)	0.11	(0.01)
Male	-0.02	(0.00)	-0.05	(0.00)	-0.05	(0.00)	-0.04	(0.00)	-0.06	(0.00)	-0.06	(0.00)	0.01	(0.00)
Mother Age D2 (20 to 24)							0.01	(0.00)	-0.00	(0.00)	-0.00	(0.00)	-0.01	(0.00)
Mother Age D3 (25 to 29)							0.06	(0.00)	0.05	(0.00)	0.05	(0.00)	0.01	(0.00)
Mother Age D4 (30 to 34)							0.10	(0.01)	0.09	(0.00)	0.08	(0.00)	0.03	(0.00)
Mother Age D5 (> 35)							0.14	(0.01)	0.12	(0.00)	0.11	(0.00)	0.04	(0.00)
Mother PAA Test							-0.13	(0.01)	-0.14	(0.00)	-0.14	(0.00)	-0.07	(0.01)
Mother PAA Math D2							0.02	(0.01)	0.02	(0.00)	0.02	(0.00)	0.01	(0.01)
Mother PAA Math D3							0.03	(0.01)	0.03	(0.00)	0.03	(0.00)	0.02	(0.01)
Mother PAA Math D4							0.06	(0.01)	0.06	(0.00)	0.06	(0.00)	0.04	(0.01)
Mother PAA Math D5							0.08	(0.01)	0.08	(0.00)	0.08	(0.01)	0.05	(0.01)
Mother PAA Math D6							0.10	(0.01)	0.10	(0.00)	0.10	(0.01)	0.07	(0.01)
Mother PAA Math D7							0.10	(0.01)	0.11	(0.00)	0.11	(0.01)	0.09	(0.01)
Mother PAA Math D8							0.12	(0.01)	0.12	(0.01)	0.12	(0.01)	0.10	(0.01)
Mother PAA Math D9							0.13	(0.01)	0.13	(0.01)	0.13	(0.01)	0.12	(0.01)
Mother PAA Math D10							0.16	(0.01)	0.18	(0.01)	0.18	(0.01)	0.18	(0.01)
Mother PAA Lang D2							0.08	(0.01)	0.08	(0.00)	0.08	(0.00)	0.03	(0.01)
Mother PAA Lang D3							0.14	(0.01)	0.13	(0.00)	0.13	(0.01)	0.05	(0.01)
Mother PAA Lang D4							0.18	(0.01)	0.17	(0.00)	0.17	(0.01)	0.06	(0.01)
Mother PAA Lang D5							0.22	(0.01)	0.21	(0.00)	0.21	(0.01)	0.07	(0.01)
Mother PAA Lang D6							0.26	(0.01)	0.24	(0.00)	0.23	(0.01)	0.08	(0.01)
Mother PAA Lang D7							0.31	(0.01)	0.27	(0.00)	0.27	(0.01)	0.10	(0.01)
Mother PAA Lang D8							0.32	(0.01)	0.31	(0.01)	0.31	(0.01)	0.10	(0.01)
Mother PAA Lang D9							0.38	(0.01)	0.35	(0.01)	0.35	(0.01)	0.10	(0.01)
Mother PAA Lang D10							0.46	(0.01)	0.44	(0.01)	0.43	(0.01)	0.14	(0.01)
Parents Married							0.05	(0.00)	0.04	(0.00)	0.05	(0.00)	0.02	(0.00)
Birth Weight D1 (< 3 kg)							-0.07	(0.01)	-0.06	(0.00)	-0.06	(0.00)	-0.04	(0.00)
Birth Weight D2 (3 to 3.25 kg)							-0.02	(0.00)	-0.02	(0.00)	-0.02	(0.00)	-0.02	(0.00)
Birth Weight D3 (3.25 to 3.49 kg)							-0.01	(0.00)	-0.01	(0.00)	-0.01	(0.00)	-0.00	(0.00)
Birth Weight D4 (3.49 to 3.75 kg)							0.00	(0.00)	-0.00	(0.00)	-0.00	(0.00)	-0.00	(0.00)
Birth Weeks Gest D1 (< 38 weeks)							0.04	(0.01)	0.05	(0.00)	0.05	(0.00)	0.02	(0.01)
Birth Weeks Gest D2 (38 weeks)							0.04	(0.00)	0.04	(0.00)	0.04	(0.00)	0.03	(0.00)
Birth Weeks Gest D3 (39 weeks)							0.03	(0.00)	0.03	(0.00)	0.03	(0.00)	0.01	(0.00)

Table 10 – *Continued from previous page*

	Avg. Test Score in 4th grade (Math and Lang)													
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Pre SEP		All		Group		Pre SEP		All		Group		Group & Post	
Years	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Birth Weeks Gest D4 (40 weeks)							0.02	(0.00)	0.01	(0.00)	0.01	(0.00)	0.01	(0.00)
Birth Length D2 (49 cm)							0.02	(0.00)	0.02	(0.00)	0.02	(0.00)	0.01	(0.00)
Birth Length D3 (50 cm)							0.03	(0.00)	0.03	(0.00)	0.03	(0.00)	0.01	(0.00)
Birth Length D4 (51 cm)							0.05	(0.00)	0.04	(0.00)	0.04	(0.00)	0.02	(0.00)
Birth Length D5 (> 51 cm)							0.06	(0.01)	0.06	(0.00)	0.06	(0.00)	0.02	(0.00)
Single Birth							0.06	(0.01)	0.06	(0.00)	0.05	(0.01)	-0.02	(0.01)
First Born							0.13	(0.00)	0.10	(0.00)	0.10	(0.00)	0.01	(0.00)
Birth Loc1							-0.01	(0.02)	-0.02	(0.01)	-0.02	(0.01)	-0.01	(0.01)
Birth Loc2							-0.08	(0.04)	-0.08	(0.02)	-0.09	(0.02)	-0.05	(0.04)
Father Employed							-0.05	(0.01)	-0.02	(0.00)	-0.03	(0.00)	-0.01	(0.00)
Mother Employed							0.03	(0.00)	0.03	(0.00)	0.03	(0.00)	0.02	(0.00)
Percentile Income Comuna							0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Avg. Test Score 2nd grade													0.01	(0.00)
Constant	-0.09	(0.00)	0.06	(0.00)	0.07	(0.00)	-0.31	(0.04)	-0.15	(0.01)	-0.13	(0.01)	-2.57	(0.02)
FE Type (xSchool)	Year		Year		Group		Year		Year		Group		Group	
R^2	0.30		0.31		0.27		0.31		0.32		0.28		0.55	
N Obs	566,912		2,166,941		1,808,410		561,096		2,048,694		1,693,104		385,846	

Note: This table shows the regression coefficients of the estimated production function with different subsamples of data. The first three columns show the estimation of value added using only the mother's education level, and the last three use a full set of covariates, considering socioeconomic, health and geographic characteristics. Columns (1) and (4) use only the subsample before the SEP policy, from 2005 to 2007. Columns (2) and (5) use all the available years, from 2005 to 2016. Finally, columns (3) and (6) use school by group of years fixed effects, which considers only years 2005-2007 and 2010-2012. Column (7) further controls for lagged (second grade) test scores. Because second grade SIMCE is only available starting in 2012, this estimation is restricted to years 2014, 2015, and 2016.

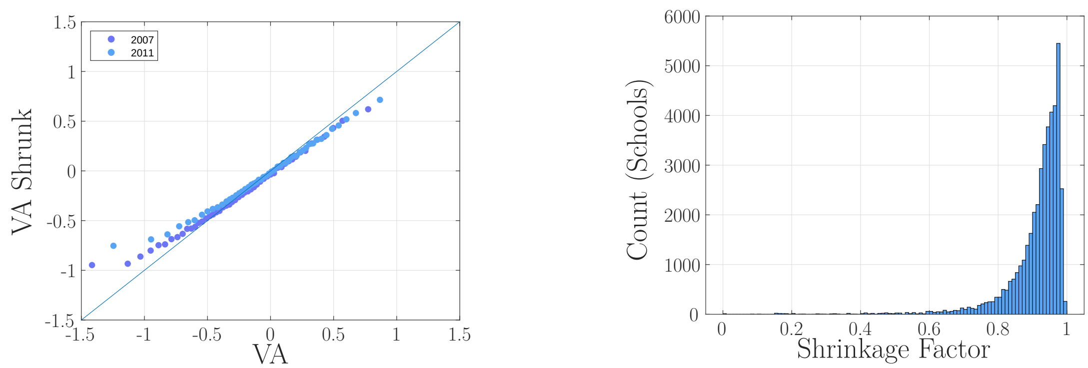
5.2 Shrinkage

I implement a shrinkage procedure to the value-added estimates following Kane and Staiger (2008) and present the results below. I find that in most cases, the estimates for value-added are very similar after the shrinkage procedure. This is because most schools typically have a reasonably large number of students taking the test, so the shrinkage does not have a remarkable effect. The only affected estimates are those of the smallest schools, which are shrunk more heavily towards the prior, which is the average for that type of school that year.

In what follows, I present the results using the assumption that the prior is given by the average of the school type (public, voucher private, non-voucher private) in the appropriate period, either before (2005-2007) or after (2010-2012) the policy. This defines three means before and three means after the policy change.

Even though most cases do not see substantial changes in VA using shrinkage, I choose not to use shrinkage to estimate the model for several reasons. First, while shrinking VA estimates potentially reduces measurement error, it also likely throws out useful identifying information because it makes schools appear more similar on this strategic characteristic. This is a particular concern in an equilibrium model such as is estimated in this paper. For example, shrinking the VA estimate of a small-N school towards its group mean will cause the model to rationalize that school's small market share by changing the mean utilities of all other schools in the market. Thus, adjusting for measurement error using shrinkage has unintended effects on other areas of estimation. Second, the objects of interest from the model are the structural parameter estimates and the resulting distribution of markups. This goal is very different from other settings that use shrinkage in a more linear context, e.g., to find the association between teacher VA and later-life outcomes. While there is perhaps an optimal level of shrinkage for this kind of model, it is a non-trivial question that the econometric literature should address and is out of the scope of this paper. Finally, and most importantly, I have made attempts to mitigate any concerns about measurement error in the VA estimates. This includes using the additional years of data to estimate school-level VA. Moreover, the instruments also correct for any measurement error in the VA estimates by having exogenous shifters of quality that are unrelated to this measurement error.

Figure 9: Value Added Shrinkage



(a) VA vs. VA Shrunk

(b) Shrinkage Factor Distribution

Note: The left panel shows a binscatter plot between the estimated VA and the VA Shrunk for schools in 2007 (dark blue) and 2011 (light blue).

5.3 Correlation of VAM and school inputs

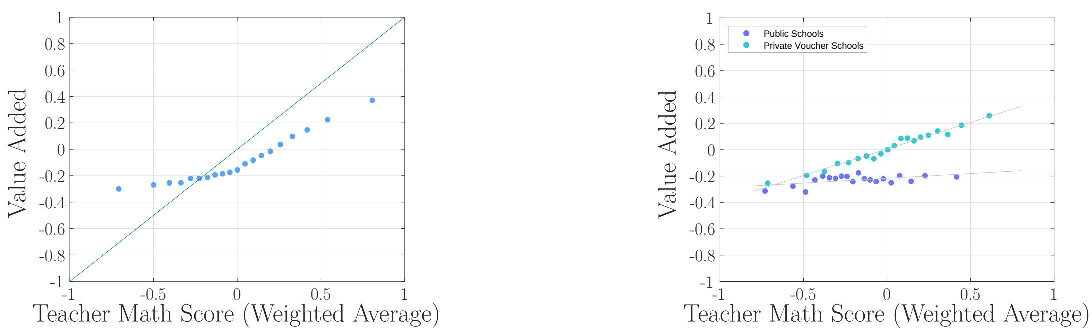
In Table 11 I present regressions of school inputs and measures of school academic quality. Measures of teacher quality and administrator human capital are positively correlated with higher value added. Average wages per teacher at the school is also strongly correlated with higher measured school value added. In Figure 11 it can be seen that value added is very correlated with teacher average per capita pay, especially among private voucher schools. These relationships provide evidence that value added is likely capturing differences in schooling inputs when we are able to measure them.

Table 11: School Characteristics, Inputs and the Estimated Value Added

	(1) Quality		(2) Has Fine		(3) Has SNED	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
AdminHC Math	0.02	(0.01)	-0.00	(0.00)	0.02	(0.01)
AdminHC Lang	0.00	(0.01)	0.01	(0.01)	0.01	(0.01)
Teacher Math	0.22	(0.03)	-0.03	(0.02)	0.12	(0.03)
Teacher Lang	0.04	(0.03)	0.01	(0.02)	0.02	(0.03)
Mg Value per Student (std)	0.20	(0.01)	-0.00	(0.00)	0.02	(0.01)
Traditional	0.09	(0.01)	-0.00	(0.01)	0.18	(0.01)
For Profit	-0.10	(0.01)	0.02	(0.01)	-0.16	(0.01)
Religious	0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Constant	-0.15	(0.02)	0.07	(0.01)	0.25	(0.02)
Year and Markets FE	✓		✓		✓	
R^2	0.282		0.034		0.136	
N Obs	4,746		4,899		4,899	

Note: This table shows the relationship between relevant schools' input related to quality with estimated value added and other outputs in the same line. The dependent variables considered are: (i) estimated value added, (ii) if the school has fines, and (iii) if the school has won a prize for academic excellence (SNED). The independent variables are school inputs like math and language average test scores of principals and teachers (AdminHC Math, AdminHC Lang, Teacher Math and Teacher Lang), marginal income per student (standardized, with an average value of 1,266 USD dollars and a standard deviation of 274), and if the school is traditional, for-profit or religious. The estimations show that all inputs are positively related to value added and to winning academic excellence prices (except for being a for-profit school). In general, the coefficients are not statistically different from zero in regressions that have "having fines" as the outcome variable.

Figure 10: Value Added and Teachers Test Scores

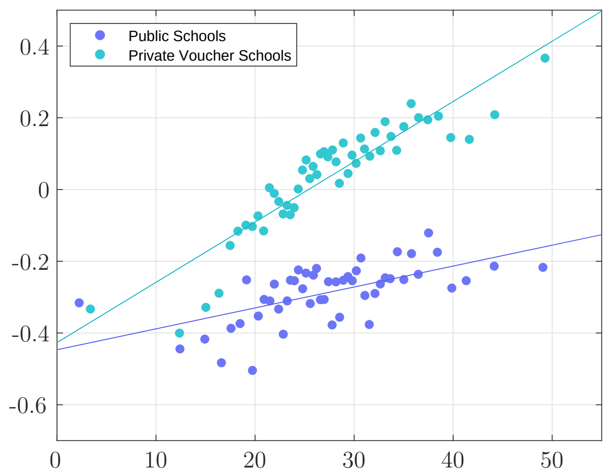


(a) Overall

(b) By Type of School

Note: This figure shows the binscatter estimation of the regression between the estimated value added and the score of the teachers' math college entrance exams

Figure 11: $\widehat{q}_j$ and Spending on Teachers



Note: The figure shows the relationship between estimated school quality (Y axis) and reported school spending on teachers divided by the number of teachers at the school (X axis, in thousands). Detailed data on spending is available only after 2013 so is not used directly in the model but provides support for the estimated value added capturing real differences in the quality of the learning experience at the school. Further results relating teacher quality and school academic quality is presented in Calle, Gallegos, and Neilson (2019).

5.4 Value Added and Exposure to SEP: Difference-in-Differences

One of the results shown in the paper is that exposure to the policy implies significant positive effects on schools' quality, measured as the estimated value added. Here we show these results in detail.

Schools are categorized in a measure of exposure to the policy based on the concentration of eligible students in the neighborhood. Precisely, it is calculated as the share of SEP eligible students that live within a 0.5 km radius from the school. According to this, I run a difference-in-differences regression, exploiting time and cross-sectional variation, considering schools in the highest and the lowest quintiles of the measure of exposure.

The difference-in-differences model was the following:

$$\hat{q}_{j,t} = \psi_0 + \psi_1 \cdot \text{High Exposure}_j + \sum_{y=2006}^{2016} \text{D}_y(t) \cdot \text{High Exposure}_j \cdot \psi_{2,y} + \sum_{y=2006}^{2016} \text{D}_y(t) \cdot \psi_{3,y} + \varepsilon_{j,t}, \quad (1)$$

where the dummy variable High Exposure$_j$ takes the value 1 if school j is in the top quintile and 0 if school j is in the bottom quintile. $\text{D}_y(t)$ is a dummy variable that takes the value of 1 if $y = t$ and 0 otherwise. $\psi_{2,t}$ is the difference between high and low exposure to the policy in each year relative to 2005 which I fix as the baseline year. The coefficients $\psi_{3,t}$ denote year fixed effects for 2006 to 2016.

This model is also used to analyze students sorting because of the policy. I perform the same model using fitted test-scores based on students' observables estimated on the pre-policy period $(X_i\gamma)$.

Results of the difference-in-differences model for value added are shown in Figure 7 of the main paper and in the first column of Table 12. I find that there are no observable pre-trends before SEP is in place, and there are significant effects on school quality in the poorest neighborhoods relative to the richest ones.

Results for fitted test-scores are shown in the second column of Table 12. While school value added estimates are large and significant after the policy, estimates for predicted test score index are minimal. This leads us to the conclusion that student characteristics are not changing across schools in different neighborhoods.

Table 12: Difference-in-Differences Estimates by Policy Exposure

	$\widehat{q}_{jt}$		$X_i\gamma$	
	Coef.	Std.Err	Coef.	Std.Err
Q5 % Poor within 0.5km (T)	-0.426***	(0.025)	-0.237***	(0.009)
Q5 % Poor within 0.5km (T) ×2006	-0.002	(0.017)	0.005*	(0.003)
Q5 % Poor within 0.5km (T) ×2007	-0.028	(0.020)	-0.001	(0.003)
Q5 % Poor within 0.5km (T) ×2008	-0.001	(0.021)	0.000	(0.003)
Q5 % Poor within 0.5km (T) ×2009	0.022	(0.022)	0.005	(0.004)
Q5 % Poor within 0.5km (T) ×2010	0.064***	(0.022)	-0.002	(0.004)
Q5 % Poor within 0.5km (T) ×2011	0.135***	(0.024)	-0.000	(0.004)
Q5 % Poor within 0.5km (T) ×2012	0.163***	(0.025)	-0.002	(0.005)
Q5 % Poor within 0.5km (T) ×2013	0.135***	(0.025)	0.000	(0.005)
Q5 % Poor within 0.5km (T) ×2014	0.136***	(0.024)	0.002	(0.005)
Q5 % Poor within 0.5km (T) ×2015	0.124***	(0.025)	0.006	(0.005)
Q5 % Poor within 0.5km (T) ×2016	0.113***	(0.025)	-0.010*	(0.006)
2006	-0.059***	(0.011)	-0.001	(0.002)
2007	-0.042***	(0.013)	0.006**	(0.003)
2008	0.019	(0.014)	0.003	(0.003)
2009	0.073***	(0.014)	0.003	(0.004)
2010	0.097***	(0.014)	0.021***	(0.004)
2011	0.060***	(0.015)	0.025***	(0.004)
2012	0.080***	(0.016)	0.030***	(0.004)
2013	-0.011	(0.016)	0.032***	(0.004)
2014	-0.016	(0.016)	0.033***	(0.004)
2015	0.059***	(0.016)	0.037***	(0.004)
2016	0.121***	(0.016)	0.054***	(0.005)
Constant	0.203***	(0.017)	0.342***	(0.008)
R^2	0.208		0.440	
N Obs	687,076		687,076	

Note: This table shows the estimated coefficients from a difference-in-differences estimation on school quality $\widehat{q}_{jt}$ (Value Added) and the predicted test scores $X_i\gamma$ as an index of student characteristics. The treatment group correspond to the highest quintile of school level exposure to eligible students, and the control group corresponds to the lowest quintile. The measure of exposure to the policy is calculated as the share of SEP eligible students that live within a 0.5 km radius from the school.

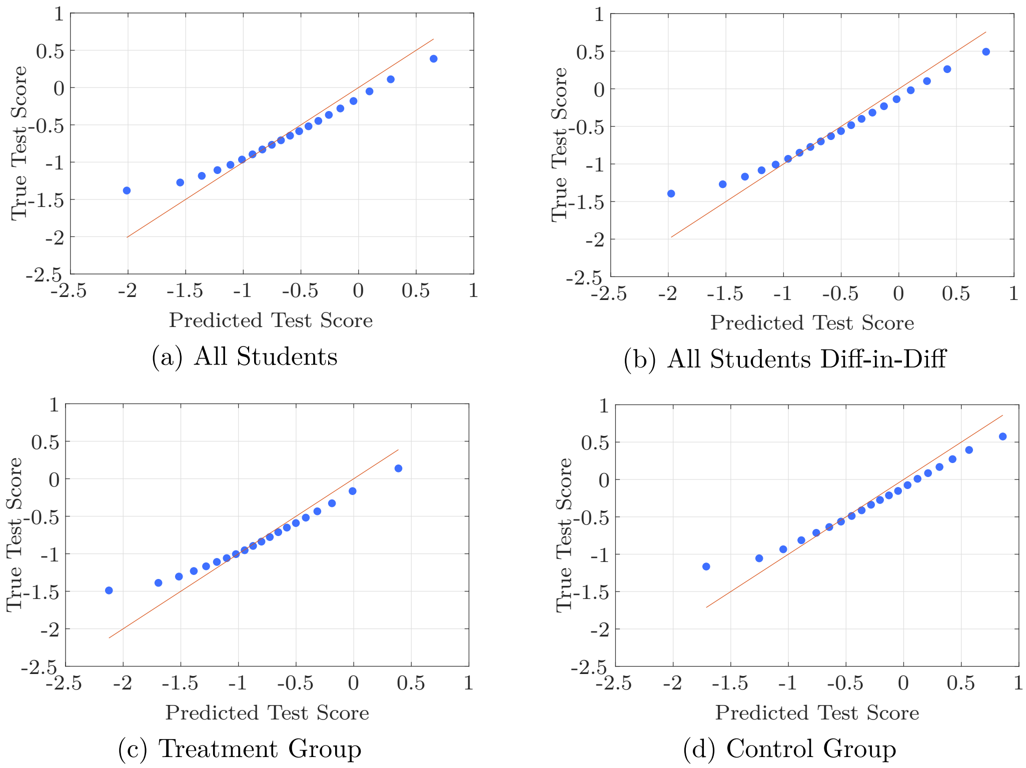
6 Additional Policy Evaluation Robustness Exercises

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. In the following analysis I start from the raw data set and 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, which may lead to scores that are too unreliable[7]. 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 as "usable observations". Within usable observations, 3.9% have missing values on the variables used to estimate value added, 7.8% have missing values on test scores, and 0.9% on both.

I implement a procedure to impute missing test scores following Cuesta, González, and Larroulet (2020). 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, González, and Larroulet (2020). 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 12 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.

[7] The *Quality of Education Agency* in Chile also avoids making public analysis and results with schools with less than 10 scores for the same reason.

Figure 12: 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, González, and Larroulet (2020). 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 0.5 km radius from the school.

I re-estimate the differences-in-differences estimates from Equation (14) on having a missing data and repeat the main exercise after imputing the missing test scores as robustness checks. Table 13 shows the results of this estimation. As shown in the first column, the estimated coefficient for the treatment on missing data is not statistically significant, nor are the estimates associated with the treatment at the years after the implementation of the policy.

Table 13: Differences-in-differences estimation for Missings Non-Excused Test Scores

	(1)	(2)	(3)	(4)	(5)
	Missing	No Imputations		Imputations	
			Lowest 25	All	Highest 25
Q5 % Poor within 0.5km (T)	-0.002	-0.426***	-0.443***	-0.442***	-0.441***
	(0.006)	(0.025)	(0.026)	(0.026)	(0.026)
Q5 % Poor within 0.5km (T) ×2006	-0.005	-0.002	0.009	0.009	0.009
	(0.009)	(0.017)	(0.017)	(0.017)	(0.017)
Q5 % Poor within 0.5km (T) ×2007	0.005	-0.028	0.020	0.021	0.021
	(0.009)	(0.020)	(0.019)	(0.019)	(0.019)
Q5 % Poor within 0.5km (T) ×2008	-0.002	-0.001	0.003	0.003	0.004
	(0.009)	(0.021)	(0.020)	(0.020)	(0.020)
Q5 % Poor within 0.5km (T) ×2009	0.003	0.022	0.033	0.038*	0.042**
	(0.013)	(0.022)	(0.022)	(0.021)	(0.021)
Q5 % Poor within 0.5km (T) ×2010	0.007	0.064***	0.091***	0.094***	0.097***
	(0.007)	(0.022)	(0.022)	(0.022)	(0.022)
Q5 % Poor within 0.5km (T) ×2011	0.009	0.135***	0.145***	0.149***	0.154***
	(0.008)	(0.024)	(0.023)	(0.023)	(0.023)
Q5 % Poor within 0.5km (T) ×2012	0.008	0.163***	0.169***	0.173***	0.177***
	(0.008)	(0.025)	(0.025)	(0.025)	(0.025)
Q5 % Poor within 0.5km (T) ×2013	-0.002	0.135***	0.143***	0.145***	0.147***
	(0.008)	(0.025)	(0.024)	(0.024)	(0.024)
Q5 % Poor within 0.5km (T) ×2014	0.002	0.136***	0.146***	0.149***	0.153***
	(0.008)	(0.024)	(0.024)	(0.024)	(0.024)
Q5 % Poor within 0.5km (T) ×2015	-0.001	0.124***	0.136***	0.137***	0.137***
	(0.007)	(0.025)	(0.024)	(0.024)	(0.024)
Q5 % Poor within 0.5km (T) ×2016	-0.002	0.113***	0.132***	0.135***	0.137***
	(0.009)	(0.025)	(0.025)	(0.025)	(0.025)
Constant	0.071***	0.213***	0.205***	0.342***	0.197***
	(0.005)	(0.019)	(0.019)	(0.008)	(0.019)
Year FE	✓	✓	✓	✓	✓
R^2	0.003	0.208	0.400	0.177	0.183
N Obs	816,452	687,076	856,486	856,486	856,486

Note: This table shows the estimation of a differences-in-differences methodology following Equation 14 of the paper. In column (1), the dependent variable of the estimation is dichotomic and takes the value 1 if the test is missing on the data. Column (2) shows the original estimation, and columns (3) to (5) repeat this estimation using the imputation procedure for missing data.

7 Additional Information Regarding the Model Derivations

7.1 Model Derivations

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

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

$$\sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial p_{j,0}} p_{j,0} = \sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \left[\frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial p_{j,0}} \left[\text{MgC}\left(q_{j,0}\right) - v_b^m\right] - s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}}) \right] \tag{3}$$

$$\sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial p_{j,0}} = \frac{\partial s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial p_{j,0}} \qquad \sum_k^K \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}}) = s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}}) \tag{4}$$

Using 4 in Equation 3:

$$p_{j,0}^* = \left[\text{MgC}\left(q_{j,0}\right) - v_b^m\right] - s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}}) \left[\frac{\partial s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial p_{j,0}} \right]^{-1} \tag{5}$$

Optimal prices under targeted voucher Since $\frac{\partial \text{op}(p_{j,1},k)}{p_{j,1}} = 0 \quad \frac{\partial \text{MgC}(q_{j,1})}{p_{j,1}} = 0 \quad \forall \quad k = \mathtt{E}$.

$$\frac{\partial \pi_j}{\partial p_{j,1}} : \sum_{k \in \not{\mathtt{E}}} \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \left[\frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}})}{\partial op_{j,k}} \frac{\partial op_{j,k}}{\partial p_{j,1}} \left[v_b^m + p_{j,1} - \text{MgC}\left(q_{j,1}\right)\right] + s_{j,k}^{\text{loc}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}}) \right] = 0 \tag{6}$$

$$\sum_{k \in \not{\mathtt{E}}} \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k \frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}})}{\partial p_{j,1}} = \frac{\partial s_{j,\not{\mathtt{E}}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}})}{\partial p_{j,1}} \qquad \sum_{k \in \not{\mathtt{E}}} \sum_{\text{loc}} w_k^{\text{loc}} \Pi_k s_{j,k}^{\text{loc}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}}) = s_{j,\not{\mathtt{E}}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}}) \tag{7}$$

Using 7 in 6 and after calculations, the price under targeted voucher is:

$$p_{j,1}^* = \left[\text{MgC}\left(q_{j,1}\right) - v_b^m\right] - s_{j,\not{\mathtt{E}}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}}) \left[\frac{\partial s_{j,\not{\mathtt{E}}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}})}{\partial p_{j,1}} \right]^{-1} \tag{8}$$

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

$$\frac{\partial \pi_j(v^o)}{\partial q_{j,0}} : \sum_k^K \sum_{\text{loc}}^L w_k^{\text{loc}} \Pi_k \left[\frac{\partial s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial q_{j,k}} \left[p_{j,0} + v_b^m - c^m - \sum_l c_l w_j^l - c_q q_{j,0} \right] + s_{j,k}^{\text{loc}}(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}}) c_q \right] = 0 \tag{9}$$

Using 4 in 9:

$$c_q q_{j,0} \frac{\partial s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial q_{j,0}} = \frac{\partial s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial q_{j,0}} \left[v_b^m + p_{j,0} - c^m - \sum_l c_l w_j^l \right] + s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}}) c_q \tag{10}$$

$$q_{j,0}^* = \left[\frac{p_{j,0} + v_b^m - c^m - \sum\limits_l c_l \omega_j^l}{c_q} \right] - s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}}) \left[\frac{\partial s_j(\mathbf{q}_0^{\mathtt{e}}, \mathbf{op}_0^{\mathtt{e}})}{\partial q_{j,0}} \right]^{-1} . \tag{11}$$

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 $k = \mathtt{E}$

$$c_q q_{j,1} \sum_k \sum_{loc} w_k^{loc} \Pi_k \frac{\partial s_{j,k}^{loc}}{\partial q_{j,1}} = \sum_k \sum_{loc} w_k^{loc} \Pi_k \left[\frac{\partial s_{j,k}^{loc}}{\partial q_{j,1}} \left(\text{MgR}\left(p_{j,1}, k\right) - \overline{c}\right) + s_{j,k}^{\text{loc}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}}) c_q \right] \tag{12}$$

$$c_q q_{j,1} \frac{\partial s_j}{\partial q_{j,1}} = (\overline{p} - \overline{c}) \left[\sum_E \sum_{loc} w_k^{loc} \Pi_k \frac{\partial s_{jk}}{\partial q_{j,1}} + \sum_{\not{\mathtt{E}}} \sum_{loc} w_k^{loc} \Pi_k \frac{\partial s_{jk}}{\partial q_{j,1}} \right] + (v_b^m + p_{j,1} - \overline{p}) \frac{\partial s_{j,\not{\mathtt{E}}}}{\partial p_{j,1}} + s_j c_q \tag{13}$$

$$c_q q_{j,1} \frac{\partial s_j(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}})}{\partial q_{j,1}} = (\overline{p} - \overline{c}) \frac{\partial s_j(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}})}{\partial q_{j,1}} - (v_b^m + p_{j,1} - \overline{p}) \frac{\partial s_{j,\not{\mathtt{E}}}(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}})}{\partial q_{j,1}} + s_j(\mathbf{q}_1^{\mathtt{e}}, \mathbf{op}_1^{\mathtt{e}}) c_q \tag{14}$$

Replacing $\overline{c}$ and $\overline{p}$ in 14 and clearing $q_{j,1}$ in the left hand side.

$$q_{j,1}^* = \left[\frac{v_b^m + v_{\text{sep}} - c^m - \sum_l c_l \omega_j^l}{c_q} \right] - s_j \left[\frac{\partial s_j}{\partial q_{j,1}} \right]^{-1} - \left[\frac{v_{\text{sep}} - p_{j,1}}{c_q} \right] \left[\frac{\partial s_{j,\not{\mathtt{E}}}}{\partial q_{j,1}} \right] \left[\frac{\partial s_j}{\partial q_{j,1}} \right]^{-1} \tag{15}$$

8 Information on the Estimation of the Demand Model

8.1 Additional Estimation Details

This section discusses details regarding the estimation procedure and construction of the standard errors. See (Berry, Levinsohn, and Pakes, 1995) and (Conlon and Gortmaker, 2020) for further clarification.

Implementation of the nested fixed-point algorithm: Denote θ_2 to be the non-linear parameters affecting demand. This includes the coefficients that vary by family type as well as σ. Denote θ_1 to be the linear parameters affecting demand. Since distance and price vary at the individual-level in this model, θ_1 includes the coefficients on x_j and the mean preference for quality. Let $\delta(\theta_2)$ to be the implied vector of mean utilities given θ_2 so market shares in the data and model match exactly: $\bar{s}_{j,t} = s_{j,t}(\theta_2, \delta(\theta_2))$. As shown in (Berry, Levinsohn, and Pakes, 1995), this leads to a fixed point relationship which is a contraction mapping:

$$\delta_{j,t} = f(\bar{s}_{j,t}, \delta_{j,t}) = \delta_{j,t} + log\ \bar{s}_{j,t} - log\ s_{j,t}(\delta, \theta_2)$$

I use the SQUAREM accelerated fixed point algorithm of (Varadhan and Roland, 2008) to invert this equality and recover $\delta(\theta_2)$. This algorithm works by using multiple evaluations to approximate the Jacobian of the fixed point. On each iteration h, I update the current guess of δ^h according to:

$$\begin{aligned}
r^h &= f(\delta^h) - \delta^h \\
v^h &= f(f(\delta^h)) - 2f(\delta^h) + \delta^h \\
\alpha^h &= \frac{(v^h)' r^h}{(v^h)' r^h} \\
\delta^{h+1} &= \delta^h - 2\alpha^h r^h + (\alpha^h)^2 v^h \qquad (16)
\end{aligned}$$

Since there is no outside option, I also implement the normalization for δ^h on each iteration to preserve uniqueness of the fixed point.

Once $\delta(\theta_2)$ has been recovered given a guess of θ_2, ξ and the components of θ_1 are recovered through two-stage least squares using q_j and x_j as second-stage covariates and instrumenting for q_j using IV_j in the first-stage. $\xi_{j,t}$ is then the residual from the second-stage regression for each school.

Construction of the weight matrix and standard errors: Standard errors are constructed using the standard GMM formula.

$$\sqrt{N}(\hat{\theta} - \theta_0) \to^d N(0, V) \qquad (17)$$

where N is the number of schools and:

$$\hat{V}(\theta) = (\hat{J}(\theta)' \hat{S}(\theta)^{-1} \hat{J}(\theta))^{-1} \qquad (18)$$

is a consistent estimate of V. $\hat{S}(\theta)$ is the estimated variance-covariance of the moments and $\hat{J}(\theta)$ is the estimated Jacobian of the moments with respect to θ.

$\hat{S}(\theta)$ is a consistent estimate of the variance-covariance of the moments computed over the observations used to construct them. The covariance across micro-moments and orthogonality conditions is assumed to be zero. Thus, $\hat{S}(\theta)$ is block diagonal: $\hat{S}(\theta) = \begin{bmatrix} \hat{S}^M(\theta) & 0 \\ 0 & \hat{S}^{IV}(\theta) \end{bmatrix}$. Further, the covariance across markets and types for the micro-moments is zero by construction so that $\hat{S}^M(\theta)$ is block-diagonal with blocks $\hat{S}^M(\theta)_{k,m,y}$ specific to market, type, and period.

To construct $\hat{S}^M(\theta)_{k,m,t}$, I compute individual-level deviations between the chosen characteristic for individual i and the model-based moment:

$$dev_i(\theta) = \begin{bmatrix} d_{\text{loc(i)},j} - \sum_n^{N_m} \sum_j^{N^f_{m,t}} s^{nk}_{jt}(\theta) \cdot w^m_{\text{loc},k} \cdot d_{\text{loc},j} \\ q_{i,k} - \sum_n^{N_m} \sum_j^{N^f_{m,t}} s^{nk}_{jt}(\theta) \cdot w^m_{nk} \cdot q_{jt} \\ \text{op}_{j,k(i)} - \sum_n^{N_m} \sum_j^{N^f_{m,t}} s^{nk}_{jt}(\theta) \cdot w^m_{nk} \cdot \text{op}_{j,k} \end{bmatrix} \tag{19}$$

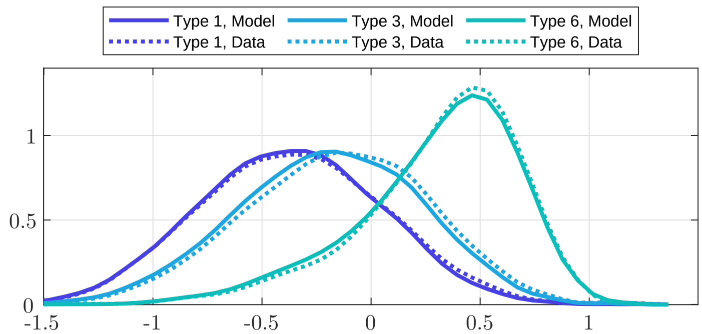
Following Conlon and Gortmaker (2020), these deviations are scaled by $\frac{\sqrt{N}}{\sqrt{N^m_{k,t}}}$, where N is the total number of schools and $N^m_{k,t}$ is the number of observations used to compute the moment. This accounts for the fact that asymptotics are taken at the level of the number of schools and not all observations are used to compute each micro-moment. Then, I take the variance-covariance of these deviations: $\hat{S}^M(\theta)_{k,m,t} = VCOV(dev_i(\theta))$. To construct $\hat{S}^{IV}(\theta)$, I compute $g^{IV}_j(\theta) = \xi_j Z_j$ for each firm and then take the variance-covariance of these moments across all firms: $\hat{S}^{IV}(\theta) = VCOV(g^{IV}_j(\theta))$.

I use an analytic derivation of $\hat{J}(\theta))$ in my solution, which I checked was consistent with numerical results. Details of the construction of $\hat{J}(\theta))$ are available upon request.

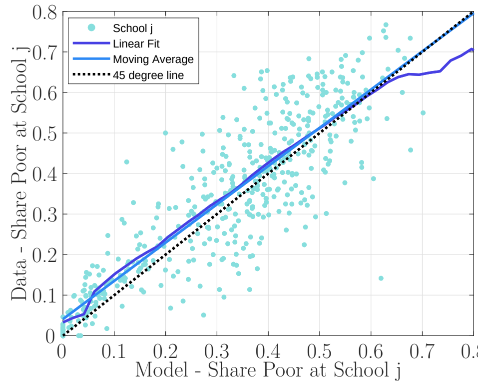
8.2 Some Description of Model Fit

I present here two figures that summarize how well the model fits the data under the main specification. The left panel of Figure 13 shows the distribution of quality from the observed microdata vs. the estimated model for family types 1 (less than high school, low income), 3 (high school, low income), and 6 (college, not low income). In all three cases the model does a good job at replicating the actual distribution of quality. It is also noteworthy that the model closely predicts the share of low income students at each school, although it was not trained to do so. This result is shown in the right panel of Figure 13.

Figure 13: Model Fit



(a) Distribution of Academic Quality by Type: Model and Data (2007)



(b) Share of Poor Students: Model and Data (2007)

8.3 Demand Model Estimates Robustness Exercises

Table 14 shows the demand estimates from the baseline specification in the first column, along with other versions with different sets of instruments, markets and sets of fixed effects.

Table 14: Demand Model Estimates - Robustness

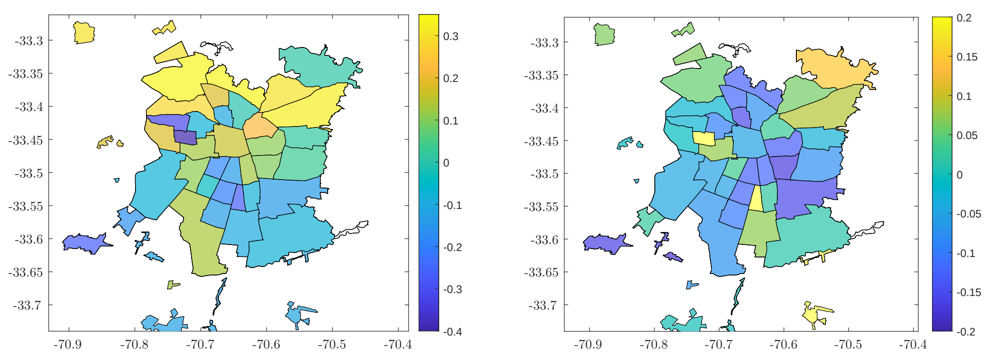
	Baseline	Drop Santiago	Comuna FE For Public Only	Comuna FE By School Type	Only Policy IVs
Parameters:					
Quality	1.512 (0.005)	1.572 (0.007)	1.270 (0.005)	2.072 (0.005)	3.192 (0.005)
Voucher School	-0.903 (0.057)	-0.282 (0.061)	-1.102 (0.066)		-1.616 (0.059)
For Profit X Voucher	-0.586 (0.037)	-0.642 (0.04)	-0.628 (0.038)	-0.068 (0.039)	-0.411 (0.038)
Religious - Catholic X Voucher	0.091 (0.059)	0.205 (0.063)	0.162 (0.058)	-0.133 (0.058)	-0.371 (0.063)
Religious - Non Catholic X Voucher	0.053 (0.057)	-0.202 (0.061)	0.033 (0.058)	0.068 (0.06)	0.353 (0.06)
Has High School X Voucher	0.100 (0.033)	0.033 (0.035)	0.215 (0.034)	-0.052 (0.035)	-0.535 (0.034)
Old X Voucher	0.866 (0.034)	0.339 (0.037)	0.880 (0.036)	0.372 (0.035)	0.907 (0.036)
Brand New X Voucher	0.751 (0.086)	0.891 (0.089)	0.678 (0.086)	0.531 (0.087)	1.157 (0.089)
Private Non Voucher School	2.225 (0.251)	1.986 (0.378)	1.958 (0.235)		2.258 (0.296)
Religious X Private	0.925 (0.119)	0.684 (0.120)	0.985 (0.134)	0.654 (0.294)	1.398 (0.121)
Religious - Catholic X Private	-0.293 (0.122)	-0.899 (0.124)	-0.330 (0.136)	-0.386 (0.295)	-0.864 (0.124)
Has High School X Private	-0.949 (0.255)	-2.470 (0.372)	-0.706 (0.236)	-1.207 (0.183)	-2.761 (0.302)
Old X Private	0.797 (0.088)	0.575 (0.095)	0.900 (0.089)	-0.108 (0.113)	0.329 (0.091)
Brand New X Private	-0.017 (0.235)	-0.241 (0.236)	0.029 (0.234)	0.513 (0.235)	-0.370 (0.243)
Price x Non High School Mother	-2.782 (0.096)	-2.924 (0.106)	-2.778 (0.095)	-2.789 (0.097)	-2.808 (0.100)
Price x High School Mother	-0.565 (0.080)	-0.556 (0.086)	-0.564 (0.079)	-0.568 (0.082)	-0.573 (0.085)
Price x 2 year Technical Degree Mother	-0.248 (0.081)	-0.263 (0.087)	-0.248 (0.08)	-0.250 (0.082)	-0.252 (0.086)
Price x 4 year College Degree Mother	0.000 (0.081)	0.000 (0.087)	0.000 (0.080)	0.000 (0.082)	0.000 (0.086)
Price x Poor	-1.694 (0.052)	-1.918 (0.066)	-1.691 (0.048)	-1.697 (0.048)	-1.708 (0.053)
Quality x High School Mother	0.591 (0.029)	0.656 (0.035)	0.582 (0.028)	0.587 (0.028)	0.619 (0.030)
Quality x 2 year Technical Degree Mother	0.890 (0.046)	1.000 (0.056)	0.875 (0.044)	0.883 (0.045)	0.933 (0.048)
Quality x 4 year College Degree Mother	1.211 (0.063)	1.458 (0.079)	1.191 (0.061)	1.203 (0.062)	1.273 (0.067)
Quality x Poor	-0.292 (0.016)	-0.321 (0.021)	-0.287 (0.016)	-0.290 (0.016)	-0.306 (0.017)
Distance x Non High School Mother	-1.288 (0.016)	-1.240 (0.018)	-1.285 (0.015)	-1.305 (0.016)	-1.335 (0.017)
Distance x High School Mother	-1.159 (0.013)	-1.075 (0.016)	-1.157 (0.013)	-1.178 (0.014)	-1.205 (0.014)
Distance x 2 year Technical Degree Mother	-1.100 (0.014)	-0.996 (0.017)	-1.099 (0.014)	-1.120 (0.014)	-1.146 (0.015)
Distance x 4 year College Degree Mother	-1.025 (0.014)	-0.928 (0.018)	-1.025 (0.014)	-1.051 (0.015)	-1.077 (0.016)
Distance x Poor	-0.011 (0.009)	-0.030 (0.010)	-0.011 (0.009)	-0.011 (0.009)	-0.012 (0.010)
Sigma Preference - Quality	0.859 (0.073)	1.021 (0.082)	0.834 (0.072)	0.848 (0.072)	0.931 (0.076)

Table 14 – *Continued from previous page*

	Baseline	Drop Santiago	Comuna FE For Public Only	Comuna FE By School Type	Only Policy IVs
Quality Markdowns:					
10th Percentile, 2007	0.215	0.199	0.241	0.177	0.128
50th Percentile, 2007	0.319	0.313	0.368	0.242	0.164
90th Percentile, 2007	0.559	0.622	0.679	0.368	0.228
Corr(Markdown,SEP), 2007	0.282	0.129	0.231	0.431	0.432
10th Percentile, 2010	0.225	0.209	0.252	0.185	0.132
50th Percentile, 2010	0.319	0.312	0.368	0.243	0.164
90th Percentile, 2010	0.541	0.587	0.656	0.358	0.224
Corr(Markdown,SEP), 2010	0.141	0.002	0.088	0.278	0.266

8.4 Additional Description of Instruments

Figure 14: Labor Costs by Comuna (Santiago)



(a) Other Industries Workers (b) Educational Workers

Note: These maps shows the variation in $\omega_{\ell,t}$ for each comuna in Santiago in 2012. The left panel shows the variation for education workers and the right one for workers in other industries, that have above average test score.

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