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

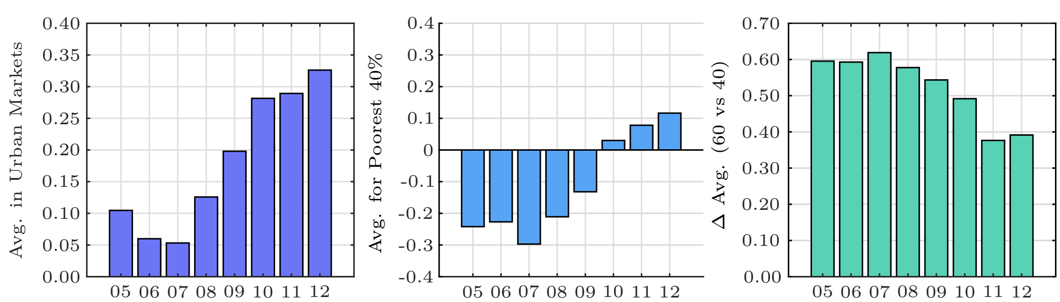
1 Additional Descriptive Statistics

In this section I document three facts that support the empirical evidence that academic achievement and equity improved in Chile during the period of interest.

1.1 Evolution in Academic Achievement by Measures of Socioeconomic Status

Prior to 2008, students from the poorest 40% of households scored between -0.2σ and -0.3σ below the baseline average depending on the year and exact definition of poor. The average student in the richest 60% of households had an average score between 0.3σ and 0.4σ above the baseline average over the same period. I present these empirical findings in Figure 1. The left panel shows the rise in average student achievement in urban areas, particularly for the poorest students (middle panel). The right panel shows that the achievement gap between the richest 60% and poorest 40% of students reduced significantly during this period.[1]

Figure 1: Evolution of Student Level Academic Achievement



Note: The left panel shows average Mathematics and Language test scores in fourth grade for students in urban schools. The middle panel shows the average for the poorest 40% of students. The right panel shows the difference between the average test scores of the richest 60% and the poorest 40% students. Different income definitions provide similar patterns in this Section.

The first fact that supports this finding is that by 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

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[1] Household survey data on income per capita, used for right panel of Figure 1, are only available until 2012, but in what follows, I show consistent evidence regarding achievement levels and gaps for the period between 2005 to 2016 using different measures of SES.

present evidence that the main driver of these patterns was not sorting of students into different schools.

The first column in Table 1 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 (**??** 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 2.

Table 1: Average Standarized Test Scores by Measures of Socioeconomic Status

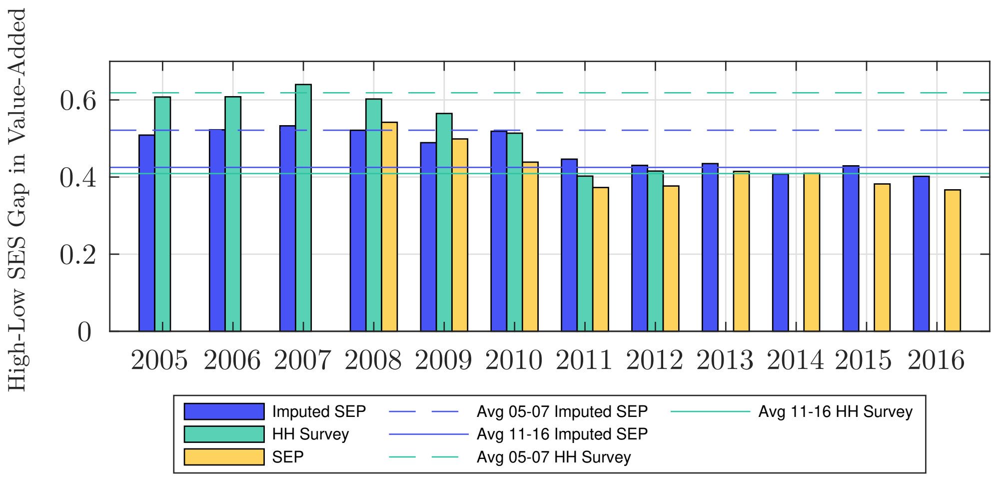
	Avg. Test	Imputed SES				SEP Eligibility		SES HH Survey		Value Added	
Year	Score	20% Low	40% Low	60% High	20% High	SEP	Non SEP	40% Low	60% High	40% Low	60% High
2005	0.13	-0.28	-0.19	0.53	0.75	.	.	-0.24	0.37	-0.22	0.13
2006	0.08	-0.34	-0.25	0.48	0.69	.	.	-0.23	0.38	-0.29	0.07
2007	0.08	-0.35	-0.26	0.48	0.71	.	.	-0.30	0.34	-0.30	0.07
2008	0.15	-0.27	-0.17	0.55	0.79	-0.22	0.32	-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

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 SES 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 SES level.

1.2 Evolution in International Assessments

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 Mathematics and Science for fourth and eighth grade students. Chile participated in the TIMSS test for 8th grade in 1999, 2003, 2011, and 2015; and in the fourth 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. Figure 3 presents trends in equity and achievement. 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

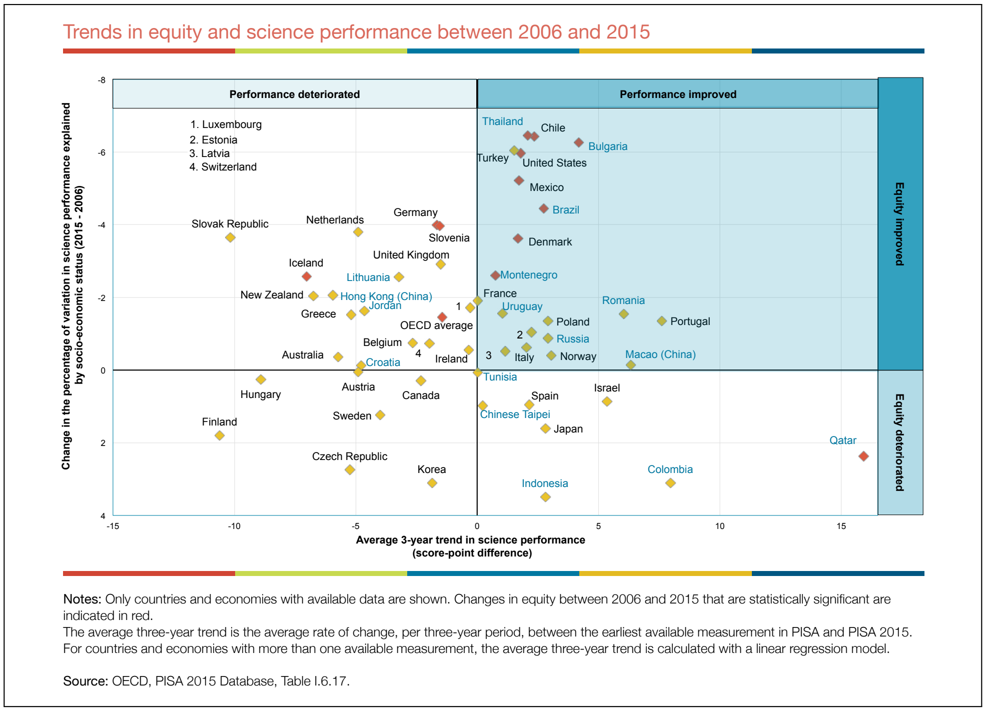
Figure 2: Evolution of the Gap in Academic Achievement High-Low SES



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 Mathematics 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) completed by 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).

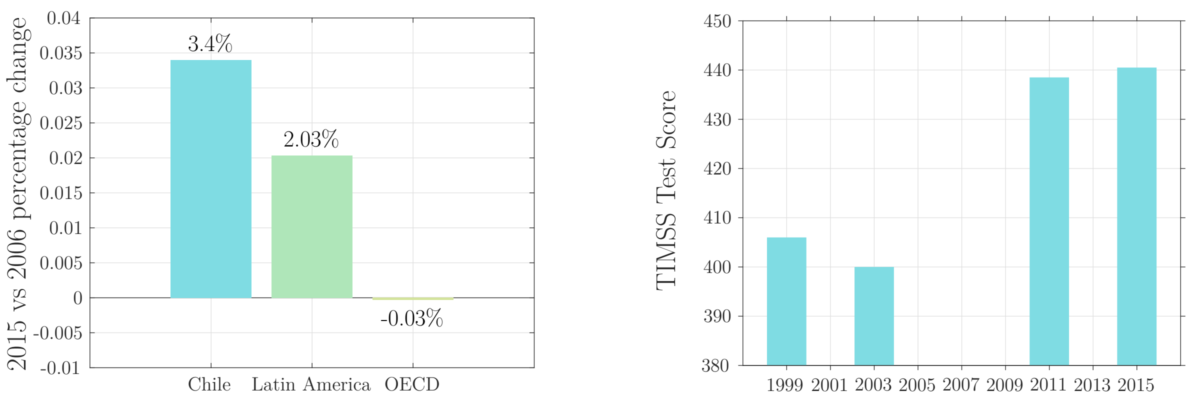
most. Additionally, Figure 4(a) shows that PISA international test scores from 2006 to 2015 also improved at a faster rate in Chile (3.4%) than in the rest of Latin America (2%) or the OECD (0%). Moreover, Figure 4(b) shows that TIMSS scores in Science and Mathematics averaged close to 405 in 1999 and 2003, but rose to 435 in 2011 and 2015, making Chile one of the countries with the fastest growth during that period.

Figure 3: Trends in Equity and Science Performance Between 2006 and 2015 (OECD, 2017)



Note: This figure has been retrieved from (OECD, 2017). The exact figure can be found in Table I.6.17.

Figure 4: International Tests



(a) Growth in Mathematics-Reading Average PISA Scores Relative to Year 2006

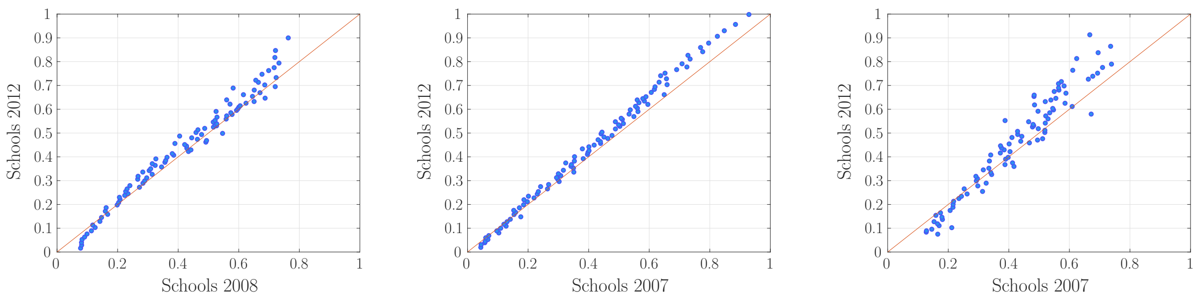
(b) TIMSS International Science and Mathematics Performance, 8th Grade

Note: The left panel shows how the average test score of Mathematics 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 from 2006 to 2009 was 2%, and from 2006 to 2012 it was 1.3%, showing a continuous growth on average PISA scores in Chile. Over all 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 Mathematics and Reading on TIMSS changed over time in Chile. Unfortunately, it is not available prior to 2011 for fourth grade students.

1.3 Limited Sorting

Figure 5 shows 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 5: 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 ?? of this Online Appendix.

2 Value-Added Estimation Results and Robustness

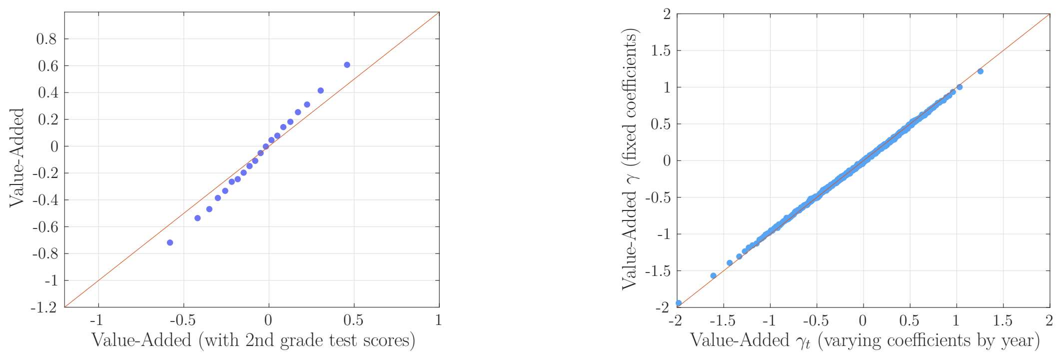
In this section I provide additional details on the procedure I followed to estimate schools' value-added. I also present four pieces of evidence to argue that these value-added estimates provide a reliable measure of school quality. Table 2 presents the coefficients for the value-added regression estimated 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 Mathematics scores.

2.1 Stability of Value-Added 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 6(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 6(b).

Figure 6: 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 second grade. This figure shows values for years 2014 to 2016, because the second grade test is only available since 2012, and I made the estimations for fourth 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 2: School Quality Estimation Regression

	Avg. Test Score in Fourth grade (Mathematics and Language)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pre SEP	All	Group	Pre SEP	All	Group	Group & Post
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 Mathematics D2				0.02 (0.01)	0.02 (0.00)	0.02 (0.00)	0.01 (0.01)
Mother PAA Mathematics D3				0.03 (0.01)	0.03 (0.00)	0.03 (0.00)	0.02 (0.01)
Mother PAA Mathematics D4				0.06 (0.01)	0.06 (0.00)	0.06 (0.00)	0.04 (0.01)
Mother PAA Mathematics D5				0.08 (0.01)	0.08 (0.00)	0.08 (0.01)	0.05 (0.01)
Mother PAA Mathematics D6				0.10 (0.01)	0.10 (0.00)	0.10 (0.01)	0.07 (0.01)
Mother PAA Mathematics D7				0.10 (0.01)	0.11 (0.00)	0.11 (0.01)	0.09 (0.01)
Mother PAA Mathematics D8				0.11 (0.01)	0.12 (0.01)	0.12 (0.01)	0.10 (0.01)
Mother PAA Mathematics D9				0.13 (0.01)	0.13 (0.01)	0.13 (0.01)	0.12 (0.01)
Mother PAA Mathematics D10				0.16 (0.01)	0.18 (0.01)	0.18 (0.01)	0.18 (0.01)
Mother PAA Language D2				0.08 (0.01)	0.08 (0.00)	0.08 (0.00)	0.03 (0.01)
Mother PAA Language D3				0.14 (0.01)	0.13 (0.00)	0.13 (0.01)	0.05 (0.01)
Mother PAA Language D4				0.18 (0.01)	0.17 (0.00)	0.17 (0.01)	0.06 (0.01)
Mother PAA Language D5				0.22 (0.01)	0.21 (0.00)	0.21 (0.01)	0.07 (0.01)
Mother PAA Language D6				0.26 (0.01)	0.24 (0.00)	0.23 (0.01)	0.08 (0.01)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mother PAA Language D7				0.31 (0.01)	0.27 (0.00)	0.27 (0.01)	0.10 (0.01)
Mother PAA Language D8				0.32 (0.01)	0.31 (0.01)	0.31 (0.01)	0.10 (0.01)
Mother PAA Language D9				0.38 (0.01)	0.35 (0.01)	0.35 (0.01)	0.10 (0.01)
Mother PAA Language 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)
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 at Hospital				-0.01 (0.02)	-0.02 (0.01)	-0.02 (0.01)	-0.01 (0.01)
Birth at House				-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 (x School)	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	566,857	2,166,840	1,808,350	561,039	2,048,593	1,693,042	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. PAA stands for college entry exam.

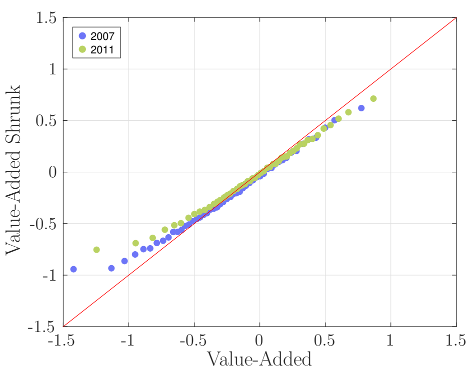
2.2 Shrinkage

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, as illustrated in Figure 7. 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.

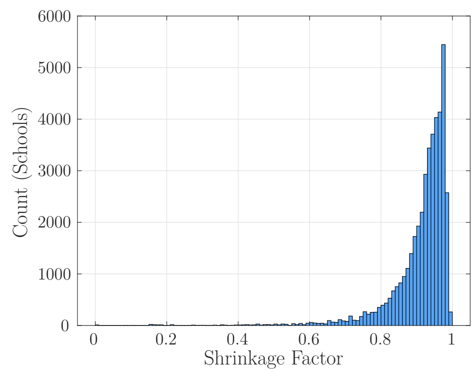
Even though most cases do not see substantial changes in value-added using shrinkage, I choose not to use shrinkage to estimate the model. First, while shrinking value-added estimates potentially reduces measurement error, it also eliminates potentially useful identifying information. In addition the procedure assumes a normal distribution but the model contradicts this assumption making the priors inconsistent with the equilibrium model of demand and supply. 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. In addition I have made attempts to mitigate any concerns about measurement error in the value-added estimates. This includes pooling additional years of data to estimate school-level value-added. Finally, as I explain in Section 7 of the paper, the instruments correct for any measurement error in the value-added estimates as long as they are orthogonal to the measurement error.

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.

Figure 7: Value-Added Shrinkage



(a) Value-Added vs. Value-Added Shrunk



(b) Shrinkage Factor Distribution

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

2.3 Correlation of Value-Added and School Inputs

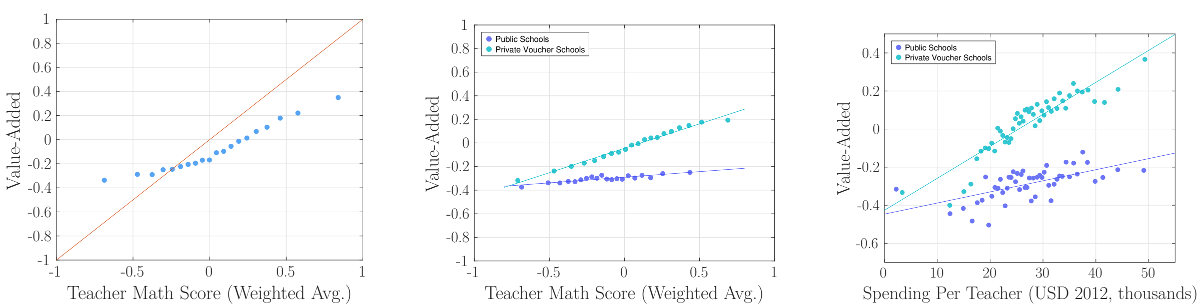
In the two first graphs shown in Figure 8 I present regressions of school inputs and measures of school academic quality. Measures of teacher quality and administrator human capital are positively correlated with higher value-added. Average wages per teacher at the school is also strongly correlated with higher measured school value-added. In the third graph of Figure 8 it can be seen that value-added is very correlated with teacher average per capita pay, especially among private voucher schools. Table 3 provides evidence that value-added likely reflects differences in measurable schooling inputs.

Table 3: School Characteristics, Inputs and the Estimated Value-Added

	Quality	Has Fine	Has SNED
AdminHC Mathematics	0.02 (0.01)	-0.00 (0.00)	0.02 (0.01)
AdminHC Language	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Teacher Mathematics	0.22 (0.03)	-0.03 (0.02)	0.12 (0.03)
Teacher Language	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: (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 Mathematics and Language average test scores of principals and teachers (AdminHC Mathematics, AdminHC Language, Teacher Mathematics and Teacher Language), marginal income per student (standardized, with an average of 1,266 USD dollars (std. dev. of 274), and if the school is traditional, for-profit, or religious. Results show that all inputs are positively related to value-added and to winning academic excellence prices (except for being a for-profit school). There are no effects statistically significant for "having fines".

Figure 8: Value-Added and Teachers Test Scores and Spending



(a) Teachers Test Scores

(b) Teachers Test Scores by Type of School

(c) Spending on Teachers

Note: The two first figures show the binscatter estimation of the regression between the estimated value-added and the score of the teachers' Mathematics college entrance exams, overall and by type of school. The last figure shows the relationship between estimated value-added and reported school spending on teachers divided by the number of teachers at the school (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)

2.4 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 4. 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 4. 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 4: Difference-in-Differences Estimates by Policy Exposure

	$\widehat{q}_{jt}$	$X_i\gamma$
Q5 % Poor within 0.5 km (T)	-0.418 (0.026)	-0.236 (0.009)
Q5 % Poor within 0.5 km (T) × 2006	-0.002 (0.017)	0.005 (0.003)
Q5 % Poor within 0.5 km (T) × 2007	-0.029 (0.020)	-0.002 (0.003)
Q5 % Poor within 0.5 km (T) × 2008	-0.002 (0.021)	0.000 (0.003)
Q5 % Poor within 0.5 km (T) × 2009	0.020 (0.022)	0.004 (0.004)
Q5 % Poor within 0.5 km (T) × 2010	0.063 (0.022)	-0.003 (0.004)
Q5 % Poor within 0.5 km (T) × 2011	0.138 (0.024)	-0.001 (0.004)
Q5 % Poor within 0.5 km (T) × 2012	0.163 (0.025)	-0.003 (0.005)
Q5 % Poor within 0.5 km (T) × 2013	0.131 (0.025)	0.000 (0.005)
Q5 % Poor within 0.5 km (T) × 2014	0.135 (0.024)	0.001 (0.005)
Q5 % Poor within 0.5 km (T) × 2015	0.126 (0.025)	0.005 (0.005)
Q5 % Poor within 0.5 km (T) × 2016	0.115 (0.025)	-0.011 (0.006)
Constant	0.204 (0.017)	0.342 (0.008)
R^2	0.197	0.441
N Obs	688,246	688,246

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.

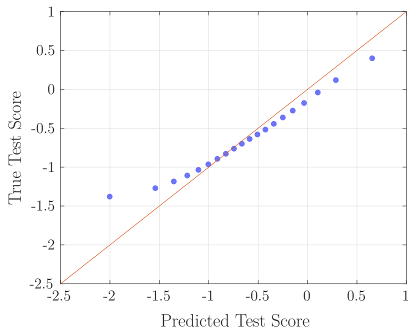
3 Additional Policy Evaluation Robustness Exercises

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.[2] 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.

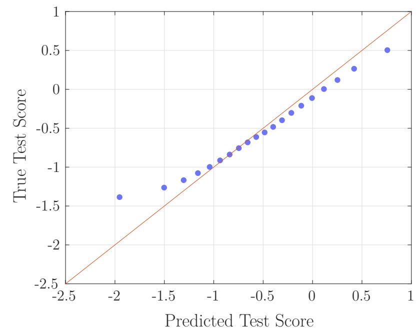
[2]For the same reason, Chile's Quality of Education Agency also refrains from publishing analyses or results for schools with fewer than 10 scores.

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 9 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.

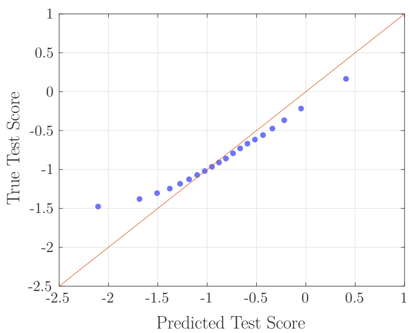
Figure 9: Imputation Model Check



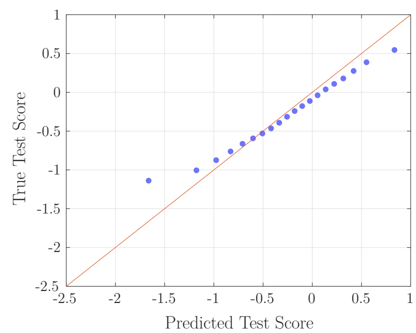
(a) All Students



(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 (13) from the main paper on having a missing data and repeat the main exercise after imputing the missing test scores as robustness checks. Table 5 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 5: Differences-in-Differences Estimation for Missings Non-Excused Test Scores

	(1) Missing	(2) No Imputations	(3) Lowest 25	(4) Imputations All	(5) Highest 25
Q5 % Poor within 0.5km (T)	-0.002 (0.006)	-0.418 (0.026)	-0.496 (0.027)	-0.494 (0.027)	-0.493 (0.027)
Q5 % Poor within 0.5km (T) × 2006	-0.005 (0.006)	-0.002 (0.017)	-0.001 (0.017)	-0.001 (0.017)	0.000 (0.017)
Q5 % Poor within 0.5km (T) × 2007	0.005 (0.006)	-0.029 (0.020)	-0.027 (0.020)	-0.025 (0.020)	-0.024 (0.020)
Q5 % Poor within 0.5km (T) × 2008	-0.002 (0.006)	-0.002 (0.021)	0.003 (0.021)	0.004 (0.021)	0.005 (0.021)
Q5 % Poor within 0.5km (T) × 2009	0.003 (0.011)	0.020 (0.022)	0.017 (0.022)	0.021 (0.022)	0.026 (0.022)
Q5 % Poor within 0.5km (T) × 2010	0.007 (0.007)	0.063 (0.022)	0.061 (0.022)	0.063 (0.022)	0.066 (0.022)
Q5 % Poor within 0.5km (T) × 2011	0.009 (0.008)	0.138 (0.024)	0.133 (0.024)	0.137 (0.024)	0.141 (0.024)
Q5 % Poor within 0.5km (T) × 2012	0.008 (0.007)	0.163 (0.025)	0.156 (0.025)	0.160 (0.025)	0.163 (0.025)
Q5 % Poor within 0.5km (T) × 2013	-0.001 (0.008)	0.131 (0.025)	0.129 (0.025)	0.131 (0.025)	0.133 (0.025)
Q5 % Poor within 0.5km (T) × 2014	0.002 (0.008)	0.135 (0.024)	0.127 (0.024)	0.129 (0.024)	0.131 (0.024)
Q5 % Poor within 0.5km (T) × 2015	-0.001 (0.007)	0.126 (0.025)	0.112 (0.025)	0.114 (0.025)	0.115 (0.0245)
Q5 % Poor within 0.5km (T) × 2016	-0.002 (0.009)	0.115 (0.025)	0.099 (0.025)	0.101 (0.025)	0.104 (0.025)
Constant	0.071 (0.005)	0.204 (0.017)	0.241 (0.018)	0.233 (0.018)	0.224 (0.018)
Year FE	✓	✓	✓	✓	✓
R^2	0.003	0.197	0.226	0.229	0.232
N Obs	814,724	688,246	797,865	797,865	797,865

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.

4 Additional Information Regarding the Model Derivations

4.1 Model Derivations

Optimal Prices Under Flat Voucher: FOC for $p_{j,1}$ under flat voucher.

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

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

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

Using Equation (4) in Equation (3)

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

Optimal Prices Under Targeted Voucher: Since $\frac{\partial \text{op}(p_{j,1},k)}{p_{j,1}} = 0 \quad \frac{\partial \text{MgC}(q_{j,1})}{p_{j,1}} = 0 \quad \forall \quad k = \mathtt{E}$
.

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

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

Using Equation (7) in Equation (6) and after calculations, the price under targeted voucher is

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

Optimal Quality Under Flat Voucher: FOC for $q_{j,0}$ for profits with flat voucher policy.

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

Using Equation (4) in Equation (9)

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

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

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 $k = \mathtt{E}$

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

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

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

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

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

4.2 Difference in Equilibrium Prices

The change in policy leads to a change in prices driven partly by the increase in costs due to changes in quality and the changes in market power

$$p^{e}_{j,1} - p^{e}_{j,0} = s_j(\mathbf{q}^{e}_0, \mathbf{op}^{e}_0) \left[\frac{s_j(\mathbf{q}^{e}_0, \mathbf{op}^{e}_0)}{\partial p_{j,0}} \right]^{-1} - s_{j,\not{E}}(\mathbf{q}^{e}_1, \mathbf{op}^{e}_1) \left[\frac{\partial s_{j,\not{E}}(\mathbf{q}^{e}_1, \mathbf{op}^{e}_1)}{\partial p_{j,1}} \right]^{-1} + v^{m}_{b,0} - v^{m}_{b,1} + c_q \left(q^{e}_{j,1} - q^{e}_{j,0} \right). \quad (16)$$

The policy leads participating schools to choose sticker prices considering only the ineligible students. If these families are less price elastic, the new policy will push prices higher. Higher quality levels will increase marginal costs, which will push towards higher prices as well. At the same time, a more competitive environment, with smaller markups and markdowns, can lead schools to price more aggressively, leading them to eventually have lower prices.

5 Information on the Estimation of the Demand Model

5.1 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

$$\begin{aligned} r^h &= f(\delta^h) - \delta^h \\ v^h &= f(f(\delta^h)) - 2f(\delta^h) + \delta^h \\ \alpha^h &= \frac{(v^h)' r^h}{(v^h)' r^h} \\ \delta^{h+1} &= \delta^h - 2\alpha^h r^h + (\alpha^h)^2 v^h \end{aligned} \quad (17)$$

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.

$$\sqrt{N}(\hat{\theta} - \theta_0) \to^d N(0, V) \tag{18}$$

where N is the number of schools and

$$\hat{V}(\theta) = (\hat{J}(\theta)' \hat{S}(\theta)^{-1} \hat{J}(\theta))^{-1} \tag{19}$$

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

$$dev_i(\theta) = \begin{bmatrix} d_{\text{loc(i)},j} - \sum_n^{N_m} \sum_j^{N^f_{m,t}} s^{nk}_{jt}(\theta) \cdot w^m_{\text{loc},k} \cdot d_{\text{loc},j} \\ q_{i,k} - \sum_n^{N_m} \sum_j^{N^f_{m,t}} s^{nk}_{jt}(\theta) \cdot w^m_{nk} \cdot q_{jt} \\ \text{op}_{j,k(i)} - \sum_n^{N_m} \sum_j^{N^f_{m,t}} s^{nk}_{jt}(\theta) \cdot w^m_{nk} \cdot \text{op}_{j,k} \end{bmatrix} \tag{20}$$

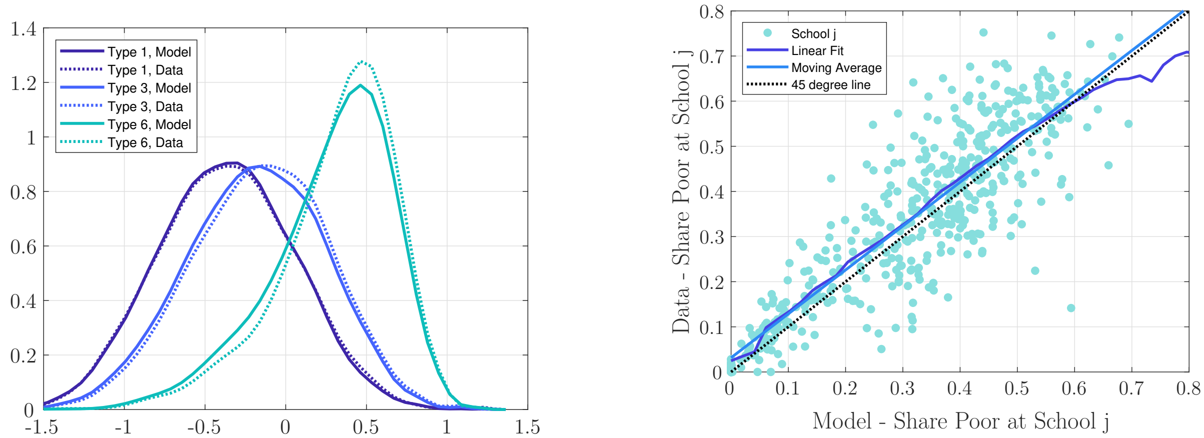
Following Conlon and Gortmaker (2020), these deviations are scaled by $\frac{\sqrt{N}}{\sqrt{N^m_{k,t}}}$, where N is the total number of schools and $N^m_{k,t}$ is the number of observations used to compute the moment. This accounts for the fact that asymptotics are taken at the level of the number 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.

5.2 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 10 shows the distribution of quality from the observed micro-data 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 10.

Figure 10: Model Fit



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

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

5.3 Demand Model Estimates Robustness Exercises

Table 6 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 6: Demand Model Estimates - Robustness

	Baseline	Drop Santiago	Comuna FE By School Type	Only Policy IVs	Average Test Score	Shrinkage
Parameters:						
Quality	1.40 (0.00)	1.58 (0.00)	2.07 (0.01)	3.19 (0.01)	1.48 (0.01)	1.46 (0.01)
Voucher School	-0.87 (0.04)	-0.39 (0.04)		-1.62 (0.06)	-1.29 (0.07)	-1.08 (0.07)
For-Profit × Voucher	-0.54 (0.02)	-0.56 (0.03)	-0.07 (0.04)	-0.41 (0.04)	-0.35 (0.05)	-0.37 (0.05)
Religious - Catholic × Voucher	0.08 (0.04)	0.14 (0.05)	-0.13 (0.06)	-0.37 (0.06)	-0.05 (0.07)	0.04 (0.07)
Religious - Non-Catholic × Voucher	0.12 (0.04)	-0.07 (0.04)	0.07 (0.06)	0.35 (0.06)	0.17 (0.07)	0.18 (0.07)
Has High School × Voucher	0.07 (0.02)	-0.05 (0.03)	-0.05 (0.04)	-0.54 (0.03)	-0.12 (0.04)	-0.01 (0.04)
Old × Voucher	0.84 (0.02)	0.39 (0.03)	0.37 (0.04)	0.91 (0.04)	0.93 (0.04)	0.79 (0.04)
Brand New × Voucher	0.64 (0.06)	0.87 (0.07)	0.53 (0.09)	1.16 (0.09)	0.75 (0.10)	0.74 (0.10)
Private Non-Voucher School	2.41 (0.17)	2.30 (0.26)		2.26 (0.30)	0.09 (0.27)	1.49 (0.27)
Religious × Private	0.50 (0.08)	0.20 (0.08)	0.65 (0.29)	1.40 (0.12)	1.46 (0.14)	0.87 (0.13)
Religious - Catholic × Private	-0.03 (0.08)	-0.65 (0.09)	-0.39 (0.30)	-0.86 (0.12)	-0.92 (0.15)	-0.37 (0.14)
Has High School × Private	-0.94 (0.18)	-2.61 (0.26)	-1.21 (0.18)	-2.76 (0.30)	-1.05 (0.28)	-0.78 (0.27)
Old × Private	0.70 (0.06)	0.65 (0.06)	-0.11 (0.11)	0.33 (0.09)	0.81 (0.10)	0.55 (0.10)
Brand New × Private	0.41 (0.15)	0.53 (0.15)	0.51 (0.24)	-0.37 (0.24)	0.30 (0.28)	0.60 (0.25)
Price × Non-High School Mother	-2.70 (0.06)	-2.86 (0.07)	-2.79 (0.10)	-2.81 (0.10)	-2.53 (0.12)	-2.60 (0.11)
Price × High School Mother	-0.56 (0.05)	-0.55 (0.05)	-0.57 (0.08)	-0.57 (0.09)	-0.65 (0.10)	-0.57 (0.10)
Price × 2y Technical Degree Mother	-0.25 (0.05)	-0.26 (0.05)	-0.25 (0.08)	-0.25 (0.09)	-0.35 (0.10)	-0.25 (0.10)
Price × 4y College Degree Mother	0.00 (0.05)	0.00 (0.05)	0.00 (0.08)	0.00 (0.09)	-0.11 (0.10)	0.00 (0.10)
Price × Poor	-1.47 (0.03)	-1.74 (0.04)	-1.70 (0.05)	-1.71 (0.05)	-1.63 (0.06)	-1.67 (0.06)
Quality × High School Mother	0.56 (0.02)	0.60 (0.02)	0.59 (0.03)	0.62 (0.03)	1.43 (0.07)	1.38 (0.06)
Quality × 2y Technical Degree Mother	0.86 (0.03)	0.92 (0.04)	0.88 (0.05)	0.93 (0.05)	2.32 (0.12)	2.10 (0.10)
Quality × 4y College Degree Mother	1.13 (0.04)	1.30 (0.05)	1.20 (0.06)	1.27 (0.07)	3.31 (0.17)	2.86 (0.14)
Quality × Poor	-0.33 (0.01)	-0.36 (0.01)	-0.29 (0.02)	-0.31 (0.02)	-0.75 (0.04)	-0.70 (0.03)
Distance × Non-High School Mother	-1.29 (0.01)	-1.26 (0.02)	-1.31 (0.02)	-1.34 (0.02)	-1.36 (0.02)	-1.27 (0.02)

Table 6 – *Continued from previous page*

	Baseline	Drop Santiago	Comuna FE By School Type	Only Policy IVs	Average Test Score	Shrinkage
Distance × High School Mother	-1.09 (0.01)	-1.02 (0.01)	-1.18 (0.01)	-1.21 (0.01)	-1.24 (0.02)	-1.16 (0.01)
Distance × 2y Technical Degree Mother	-1.04 (0.01)	-0.96 (0.02)	-1.12 (0.01)	-1.15 (0.02)	-1.17 (0.02)	-1.10 (0.02)
Distance × 4y College Degree Mother	-0.96 (0.01)	-0.88 (0.02)	-1.05 (0.02)	-1.08 (0.02)	-1.08 (0.02)	-1.02 (0.02)
Distance × Poor	-0.06 (0.01)	-0.07 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.04 (0.01)	0.00 (0.01)
Sigma Preference - Quality	0.85 (0.05)	0.97 (0.06)	0.85 (0.07)	0.93 (0.08)	2.20 (0.12)	2.04 (0.11)
Quality Markdowns:						
10th Percentile, 2007	0.215	0.199	0.177	0.128	0.122	0.134
50th Percentile, 2007	0.319	0.313	0.242	0.164	0.275	0.282
90th Percentile, 2007	0.559	0.622	0.368	0.228	1.421	0.99
Corr(Markdown, SEP), 2007	0.282	0.129	0.431	0.432	0.048	0.032
10th Percentile, 2010	0.225	0.209	0.185	0.132	0.131	0.144
50th Percentile, 2010	0.319	0.312	0.243	0.164	0.284	0.294
90th Percentile, 2010	0.541	0.587	0.358	0.224	1.524	1.052
Corr(Markdown, SEP), 2010	0.141	0.002	0.278	0.266	-0.032	0.002

5.4 Modeling Limitations

I have made several assumptions in order to derive my empirical model of school choice and competition. Some of these simplifying assumptions fail to capture important components of real education markets. However, I argue that in this particular application these limitations are less problematic and allow for a parsimonious model that provides useful insights.

One important assumption is that unobservable preferences for quality are not correlated with residential location. I estimate the model using data both before and after the policy change, and I require that families chose their location before knowing about the policy and do not change location in the next five years as a result of the policy change. Second, I assume that families are fully aware of all the schools in the market and their characteristics. A lack of awareness is likely to induce downward bias in the estimated preferences for school quality, but my approach will accurately capture the trade-offs schools face when they decide price and quality. I further assume that students can attend any school in their market, ruling out selection, and capacity constraints. While some schools may have excess demand and reject students, I argue this is not common in the Chilean education market and rather it is prices, distance, and residential segregation that drive inequality in school choice. First, regulation during this period makes it illegal for voucher schools to select students at the primary level. I see limited evidence in the data for capacity constraints or selection.[3] Finally, for-profit schools can eliminate excess demand by raising prices or lowering their quality, and over time can expand capacity or open new locations. Therefore, it is unlikely that a significant number of schools will have excess demand in equilibrium. This assumption is more restrictive following a large policy change, so I avoid using data from years immediately after the policy change when I estimate my model.

[3]While the legal class size limit is 45 students (established in *Decreto 8144, 1980*), this cap binds in only 2% of urban primary schools. In 2009, parents of fourth grade students were asked the main reasons why they chose their current school and only 2% indicated they prefered another school but had been turned away.

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