The Effects of For-profit and Nonprofit Subsidized Schools on Academic Performance

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Abstract

This paper studies the effects of attending for-profit and nonprofit private-voucher secondary schools on standardized test scores in Chile. I estimate linear models using rich information on prior tests scores and exclusion restrictions, and develop a structural model of school-type choice and academic performance to address selection concerns. Results show that both for-profit and nonprofit schools improve learning outcomes relative to public schools, with nonprofit schools yielding larger gains. Treatment effects are heterogeneous: for-profit gains are relatively flat along the ability distribution, while nonprofit gains are strongly decreasing, benefiting low-ability students the most. Both types of private schools add value relative to public provision for all students.

Keywords: for-profit schools, private education, Chile, vouchers

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1 Introduction

Debates over for-profit education hinge on a tension between market incentives and educational quality. Proponents argue that profit motives can expand capacity, respond quickly to demand, and innovate where public provision is constrained. Critics counter that when revenues depend more on enrollment than learning, providers may over-invest in marketing, under-invest in instruction, and target vulnerable students with optimistic claims that do not translate into completion or labor-market returns. In higher education, the U.S. experience documents rapid sector growth alongside aggressive recruitment, high tuition net of aid, low completion, and uneven outcomes, raising concerns about accountability and consumer protection (Cellini et al., 2020; Deming et al., 2012; Armona and Cao, 2024). In K–12, evidence from charter schools highlights cost efficiencies and network effects in some for-profit operators, but also persistent questions about selection, measurement, and alignment of incentives with student welfare (Singleton, 2017). Taken together, the literature frames a policy trade-off: for-profit institutions can increase access and choice, yet without robust oversight and transparent quality signals, the risks of misallocation and diminished student outcomes remain substantial.

Chile's voucher system offers a distinctive setting to study these issues. It combines universal parental choice with strong state oversight over curriculum, registration, and reporting, while sustaining a large private sector composed of both for-profit and nonprofit schools. This institutional design matters: robust supervision and transparent accountability reduce scope for low-quality provision, and the sizable presence of both ownership forms allows incentives and organizational missions to be compared within the same regulatory environment. Recent descriptive evidence suggests that for-profit voucher schools in Chile tend to enroll more disadvantaged students and rely on lower-cost inputs. Once observable characteristics are controlled for, differences in standardized test scores between for-profit and nonprofit schools largely disappear (Boggiano et al., 2025).

Identifying a causal effect of for-/nonprofit schools is inherently difficult because ownership status is rarely assigned randomly and credible instruments are scarce. In the absence of lotteries or sharp policy discontinuities, most observable determinants of school choice—such as parental income, preferences, and geography—also influence outcomes directly, making exclusion restrictions problematic. The U.S. literature on Catholic schools illustrates these challenges: despite large raw differences in graduation and college attendance, Altonji et al. (2005b) show that conventional instrumental variables, including religious affiliation and proximity to Catholic schools, fail to satisfy validity conditions and often yield implausible estimates. Their analysis underscores that selection on unobservables can be substantial even when rich controls are available, and that functional form assumptions in nonlinear models may drive identification more than true exogenous variation. Complementing this, Altonji et al. (2005a) demonstrate that even widely used instruments such as distance and religion interact poorly with outcome equations. This experience highlights the need for alternative strategies—such as structural approaches—when studying sectors where credible instruments are lacking.

This paper asks whether the profit motive (or the lack of it) in Chile's voucher system translates into measurable differences in student achievement, and how these effects vary across students. Specifically, I estimate the causal impact of attending a for-profit versus a nonprofit secondary school on standardized test scores, relative to public provision. I make use of both linear and nonlinear methods, building on the value-added literature (Rockoff, 2004; Rivkin et al., 2005; Kane and Staiger, 2008; Chetty et al., 2014a,b; Bau, 2022), as well as on the use of structural models to estimate treatment effects in education (Heckman et al., 2006, 2018).

My linear model approaches estimate test score gains from attending for-profit and nonprofit secondary schools relative to public schools, controlling for a rich set of observed covariates, including prior test scores. Potential endogeneity is addressed using instruments based on local school availability, aggregate measures of school effectivenes, and municipality characteristics.

While standard in the literature, the instruments just listed may be subject to violations of some of the identifying assumptions (Altonji et al., 2005a,b; Heckman et al., 2006). To address selection concerns, I develop a structural model of school-type choice and academic performance in the spirit of Roy (1951) and Willis and Rosen (1979), augmented with a measurement system that recovers latent ability from early test scores (Heckman et al., 2018). This framework allows me to jointly model counterfactual outcomes and choices, identify treatment parameters across various margins, and explore heterogeneity along the ability distribution.

My results show that private schools do a better job in increasing learning outcomes relative to public schools. The effects are robust across all linear and nonlinear specifications. Average gains of for-profit attendance range from 0.032 to 0.070 standard deviations (σ) for verbal, and from 0.099 to 0.121σ for mathematics, relative to public schools. Nonprofit attendance yields even larger gains, ranging from 0.144 to 242σ for verbal, and from 0.225 to 0.344σ for math. Formal statiscal tests confirm the larger effects from attending nonprofit schools than attending for-profit schools.

Importantly, treatment effects are heterogeneous, even after controlling for selection and prior test scores. The structural model reveals that the treatment gains associated with for-profit attendance are relatively flat along the ability distribution, while those of nonprofit schools are strongly decreasing—that is, nonprofit schools is a much more performance-improving choice for low-ability students than for higher-ability ones. Importantly, both for-profit and nonprofit gains are positive throughout the ability distribution, suggesting that both types of private schools add value relative to public provision for all students.

This paper contributes to the literature twofolds. First, it adds to the existing evidence on the effectiveness of private-voucher schools and, in particular, of for-profit institutions.[1] My closest predecessor is Singleton (2017), that studies for-profit management in charter schools in Florida. He finds that an equivalent level of per-pupil expenses purchases 0.03σ higher student proficiency in math and reading at network for-profit charter schools. However, such schools spend 11% less per pupil. Other papers include Sahlgren (2011), that finds no significant difference on academic performance between for-profit and nonprofit schools in Sweden, and Elacqua (2015), that documents a slightly poorer performance of profit-seeking schools in Chile. I extend and improve these papers' analyses by using rich administrative data on prior test scores and exclusion restrictions, and by estimating joint distributions of counterfactual gains from a model that accounts for school selection and individuals' unobserved heterogeneity.

I also contribute to the literature that analyzes for- and nonprofit operation in industries that, similar to education, feature mixed production (Malani et al., 2003; Steinberg and Weisbrod, 2005). The health sector is the focus of numerous comparisons (Keeler et al., 1999; Duggan, 2002; Sloan, 2000; Sloan et al., 2001; Deneffe and Masson, 2002; Ballou and Weisbrod, 2003; Silverman and Skinner, 2004; Lindrooth and Weisbrod, 2007). Overall, the evidence is mixed, and suggests that for- and nonprofit hospitals are more similar than different.

2 The Context

Schools in Chile can be grouped into three categories by administration and financing: public schools, private-voucher schools, and private fee-paying schools. Both public and private-voucher schools are financed by a per-student voucher subsidy paid by the government directly to schools. Private fee-paying schools are financed by fees charged to parents. They serve the country's richest families, and the high level of their fees makes them an unrealistic option for the vast majority of students in Chile (Sanchez, 2023). Private fee-paying schools enroll about 7% of all students, and transitions between these schools and public or private-voucher schools are very rare (around 3%).

Private-voucher schools can be either for-profit or nonprofit. Among for-profit schools, some belong to chains and others are independent. Chains are usually controlled by a group of owners and are characterized by networks of campuses. Independent schools are generally smaller and are often owned by former public school teachers. Nonprofit schools include religious and non-sectarian organizations. They receive donations and are often subsidized by the Church or local

[1] See Rouse (1998), Nechyba (2000), McEwan (2001), Angrist et al. (2002), Angrist et al. (2006), Rouse and Barrow (2009), Lara et al. (2011), Chung (2012), Cellini and Chaudhary (2014), Elacqua (2015), Singleton (2017), Abdulkadiroglu et al. (2018), Cellini et al. (2020), among others.

businesses. They are also characterized by networks of campuses (Elacqua et al., 2015).

In 2013, public schools represented the majority of institutions (55.7%) but enrolled only 39.7% of students (Table A.1 in Appendix A). Private-voucher schools accounted for 39.6% of schools and 52.5% of enrollment, split between for-profit (27.3% of schools; 32% of enrollment) and nonprofit (12.4%; 20.5%). Private fee-paying schools were marginal, with 4.7% of schools and 7.8% of enrollment. At the primary level, patterns were similar. In conventional secondary education, public schools fell to 25.2% of schools and 32.9% of enrollment, with for-profit voucher schools slightly surpassing public schools (33.1%). Nonprofit schools enrolled 21.7% of secondary students, and fee-paying schools became more prominent (12.3%).

In terms of regulation, teachers' contracts in public schools are governed by the Teacher Statute; wages are based on uniform pay scales, and schools face dismissal restrictions. In private schools, teachers' contracts are governed by the Labor Code, which allows schools to hire and dismiss teachers more freely. In addition, regulations for for-profit schools differ from those for nonprofits. The main difference is that nonprofit organizations in Chile are eligible for tax exemptions that for-profits are not, including exemptions on income, value-added, inheritance, and real estate taxes, as well as industrial and commercial patents, customs tariffs, and social security.[2] However, the process of creating a nonprofit organization is slower, more costly, and more bureaucratic than creating a for-profit organization.

Descriptive statistics reveal systematic differences across school types (Tables A.2–A.8 in Appendix A). Nonprofit schools are the largest, with average enrollment of 510 students and class sizes near 29, compared to 362 and 24.6 in for-profit schools and 220 and 17.8 in public schools. Tuition patterns show that most public schools charge no fees, while for-profit and nonprofit schools exhibit similar distributions, with roughly 45% charging no tuition and about 10% charging more than CLP 50,000. Teacher inputs differ modestly: public schools have lower pupil-teacher ratios (11 vs. 16–17) but fewer permanent contracts (47% vs. 57–61%). Nonprofit schools are more selective and predominantly Catholic (65%), while for-profit schools resemble public schools in religious orientation but apply stricter admission criteria than public schools. Location and demographics indicate that public schools serve poorer, more rural municipalities, whereas private schools cluster in urban areas with higher incomes. Finally, student outcomes and family background favor nonprofit schools: their students score highest on standardized tests (0.29σ in language, 0.37σ in math), followed by for-profit schools (0.04σ and 0.09σ), while public school students score below average. Parents of private school students are more educated and their households report higher income levels. How much of the test-score differences reflect school effectiveness versus selection remains an open question that this paper aims to address.

[2]For a description of the legal requirements of nonprofit organizations in Chile and the liability of their members, see Viveros (2007) and Chile-Transparente (2008).

3 Data

I use data from the SIMCE 2013 for 10th graders. SIMCE is a mandatory national standardized battery of tests aimed at measuring the degree of students' learning in a number of subjects at various educational levels. Specifically, SIMCE is taken by all students in 4th grade every year, and since 2005 it rotates between 8th and 10th grades in a yearly fashion. The subjects evaluated in 10th grade are verbal and mathematics. SIMCE data contain information on test scores, school characteristics, and student and family characteristics. I merge these data with tax records for school providers, so I can identify the for-/nonprofit status of the schools, and with CASEN 2011 and SIMCE 2012 for 10th graders data sets to construct exclusion restrictions variables that I use in the empirical implementation. CASEN is the national socioeconomic characterization household survey, and is representative at the national, regional, and municipal level. I use the year 2011 for CASEN as this is the year in which 10th graders in 2013 were in 8th grade, and were therefore deciding the school-type for their secondary education. Ideally, I would also use SIMCE data for 10th graders in 2011 to construct the instruments, but since SIMCE was not administered to 10th graders in 2011, I use the 2012 version instead.

As outcome variables I use test scores for the two subjects evaluated in the SIMCE 2013 exams. The exogenous variables that I use are: gender, mother's highest grade completed, father's highest grade completed, household composition, and region indicators.

In addition, I include the following exclusion restrictions as shifters for school-type choice: the difference between the average test scores of 10th grade students in for-profit schools in a municipality and the average test scores of 10th grade students in public schools in that municipality in 2012, the difference between the average test scores of 10th grade students in nonprofit schools in a municipality and the average test scores of 10th grade students in public schools in that municipality in 2012, the percentage of secondary schools that are for-profit in a municipality in 2012, the percentage of secondary schools that are nonprofit in a municipality in 2012, municipality's log population in 2011, and municipality's urbanization rate in 2011. For-/nonprofit test score advantage (relative to public schools) captures quality differences across school types that affect parental choices. A series of studies on school choice in Chile finds that parents value school effectiveness, and thus support the choice of these instruments (Allende, 2019; Sanchez, 2023; Gazmuri, 2024; Neilson, 2025). The percentage of for-/nonprofit schools captures the availability of each school type in a municipality, where a higher local presence of a type of school determines the choice of a school in that group—Heckman et al. (2018) use similar instruments in the context of higher education choice in the US. On the other hand, Hsieh and Urquiola (2006) document that when vouchers were initially introduced in Chile, the private sector grew more in larger, wealthier and more urban municipalities, which motivats the choice of municipality's population size and urbanization rate as exclusion restrictions.

I use 8th grade test scores from SIMCE 2011 as measures of scholastic ability. Students in this grade take exams in verbal, mathematics, social sciences, and natural sciences, and I use the scores from all four exams to either be included as covariates in linear regressions or as sources of identification for the distribution of unobserved ability in the nonlinear model.

The sample I use in the empirical analysis comprises the universe of students that were enrolled in 8th grade in a public school in 2011. Most of public primary schools offer only primary grades (88%), therefore the typical public primary school student is forced to choose a secondary school at the the end of 8th grade. In contrast, private-voucher primary schools are much more likely to offer secondary education (47%), making the secondary school choice less relevant for students enrolled in these schools at the end of 8th grade. Of all students in a public primary school in 2011, I keep only students that take all four standardized exams in 8th grade. I drop all individuals with a least one missing covariate, except for parents' education and the instruments of for-/nonprofit test score advantage, where I impute all missing observations with a value of zero, and include dummy indicator for non-missing in the original variable.[3] The estimates' interpretation for these transformed variables in a linear regressions is the usual derivative of the outcome with respect to the independent variable, for the subsample of observations with non-missing observations. I end up with a final data set consisting of 66,388 individuals, observed in 2011 when enrolled in 8th grade in a public primary school, and in 2013 when enrolled in secondary school (10th grade).

Table 1 shows summary statistics for the variables used in the empirical analysis. Panels A and B present the demographic variables measured in years 2011 and 2013, respectively. Almost half of the sample are male. Both parents have on average a little less than ten years of formal education, or an incomplete secondary education degree. The majority of the individuals in the sample live with both parents and with siblings, while 28% live with other relatives or non-relatives. Most of students (69%) reside in the central region, many of whom are located in the capital city, Santiago.

Panel C describes the exclusion restrictions that I use as shifters of the secondary school-type decision in the empirical analysis. These variables are constructed at the municipality level. The average percentage of for-profit schools in a municipality is 27%, while the average percentage of nonprofit schools is 26%. The differences in average standardized test scores between for-profit and public schools are positive both in verbal (0.32σ) and mathematics (0.43σ). The differences between nonprofit and public schools are even larger: 0.50σ in verbal and 0.63σ in mathematics.

[3]More specifically, a variable x that is imputed is transformed in the following way,

$$x' = x \times \mathbb{1}\left[x = \text{ non-missing}\right].$$

I include both x' and $\mathbb{1}\left[x = \text{ non-missing}\right]$ variables in the equations to be estimated.

The average log population in a municipality is 11.31, and the urbanization rate is 82%.

Table 1: Summary Statistics

	mean	std. dev.	min	max
A. Demographics in 2011				
male	0.49	0.50	0.00	1.00
father's years of education	9.80	3.18	0.00	22.00
mother's years of education	9.84	3.11	0.00	22.00
living with both parents	0.56	0.50	0.00	1.00
living with siblings	0.65	0.48	0.00	1.00
living with others	0.28	0.45	0.00	1.00
region: north	0.14	0.35	0.00	1.00
region: center	0.69	0.46	0.00	1.00
region: south	0.17	0.38	0.00	1.00
B. Demographics in 2013				
male	0.49	0.50	0.00	1.00
father's years of education	9.77	3.22	0.00	22.00
mother's years of education	9.88	3.12	0.00	22.00
region: north	0.14	0.35	0.00	1.00
region: center	0.69	0.46	0.00	1.00
region: south	0.17	0.38	0.00	1.00
C. Exlcusion Restrctions				
% for-profit schools[a]	0.27	0.20	0.00	0.94
% nonprofit schools[a]	0.26	0.17	0.00	1.00
avg. scores for-profit schools - avg. scores public schools: verbal[a]	0.32	0.52	-1.21	2.02
avg. scores nonprofit schools - avg. scores public schools: verbal[a]	0.50	0.45	-0.79	1.69
avg. scores for-profit schools - avg. scores public schools: math[a]	0.43	0.57	-1.36	1.84
avg. scores nonprofit schools - avg. scores public schools: math[a]	0.63	0.49	-0.83	2.05
log population[a]	11.31	1.15	6.83	13.67
urbanization rate[a]	0.82	0.19	0.00	1.00

Notes: Test scores are normalized to have an overall mean of zero and a standard deviation of one. The total number of observations is 66,388. All variables were constructed using SIMCE 2011, SIMCE 2012, SIMCE 2013, and CASEN 2011 data sets. [a] Calculated at the municipality level.

4 Empirical Analysis

I employ three different empirical strategies to study the effects of attending a for-profit/nonprofit secondary school on academic performance, compared to attending a public secondary school. First, building on the value-added literature, I run a linear regression of test scores in secondary on school-type indicators, a set of demographic covariates, and measures of prior academic performance (Rockoff, 2004; Rivkin et al., 2005; Kane and Staiger, 2008; Chetty et al., 2014a,b; Bau, 2022). Next, I recognize that, even conditioning on demographics and prior measured ability, school-type choice may be endogenous, and therefore implement an instrumental variables (IV) strategy to address this concern. I use as instruments the local availability of for-/noprofit schools, voucher schools' test score advantage relative to public school, and measures of municipality size and urbanization, as described in the preceding section. Given the potential limitations of the linear IV approach in this context (Altonji et al., 2005a,b; Heckman et al., 2006), I complement the analysis with a structural model of school-type choice and academic performance, that uses instruments as exclusion restrictions for the school-type choice, as well as prior test scores to identify unobserved scholastic ability (Heckman et al., 2018). I use the estimates from the model to define average treatment effect (ATE) and average treatment effect on the treated (TT) parameters of attending for-/noprofit secondary schools relative to public schools.

4.1 Linear Models

I begin the empirical analysis by estimating linear models of academic performance. The first model explains test scores in secondary school as a function of school-type indicators, a set of demographic covariates, and prior academic performance, as follows,

$$T_i = \omega_0 + \omega_1 D_i^{FP} + \omega_2 D_i^{NP} + X_i\beta + T_{i,-1}\delta + \varepsilon_i, \tag{1}$$

where T_i is the test score of student i in a particular subject (verbal or mathematics) in secondary school (10th grade), D_i^{FP} is a dummy variable that takes a value of one if student i attends a for-profit secondary school and zero otherwise, D_i^{NP} is a dummy variable that takes a value of one if student i attends a nonprofit secondary school and zero otherwise, X_i is a vector of demographic covariates, $T_{i,-1}$ is a vector of 8th grade test scores in verbal, mathematics, social sciences, and natural sciences for student i, and ε_i is an idiosyncratic error term. The parameters of interest are ω_1 and ω_2, which measure the effect of attending a for-profit and a nonprofit secondary school, respectively, relative to attending a public secondary school.

I estimate equation (1) using both ordinary least squares (OLS) and two-stage least squares (2SLS). I run separate regressions for each subject (verbal and mathematics). The 2SLS regressions use as instruments the local availability of for-/nonprofit schools, voucher schools' test score advantage relative to public school, and measures of municipality size and urbanization. Standard errors are clustered at the school level in all regressions.

Under the assumption that school-type choice is exogenous conditional on demographics and prior academic performance, OLS consistently estimates the Average Treatment Effect (ATE) parameter. However, if there are unobserved factors that simultaneously affect school-type choice and academic performance (e.g. ability, motivation), then school-type choice is endogenous, and OLS is inconsistent. The 2SLS approach addresses this potential endogeneity problem by isolating exogenous variation in school-type choice coming from the instruments. Under the assumption that the instruments are valid (i.e. correlated with school-type choice but uncorrelated with the error term in the test score equation), combined with some monotonicity assumptions (Heckman et al., 2006), 2SLS consistently estimates a weighted average of the mean gross gain to persons induced into a choice state by a change in the instruments compared to their next best alternative—i.e. the Local Average Treatment Effect, or LATE, (Heckman et al., 2006).

4.2 A Structural Model of School-Type Choice and Academic Performance

The Model. Following the literature on structural choice models with factor components, I approximate the school-type selection process of Chilean students with a discrete-continuous econometric model of school-type choice and test scores.[4] I assume that there are S types of secondary schools, and that parents choose the optimal type, s^*, according to a utility-maximizing argument:

$$s^* = \underset{s \in \{1,\ldots,S\}}{\operatorname{argmax}} \{I(s)\},$$

where I assume a linear-in-parameters form for $I(s)$:

$$I(s) = Z\gamma_s + \eta^D(s) \qquad \text{for each } s \in \{1,\ldots,S\}. \tag{2}$$

Z is a vector of observed variables relevant to the decision, and $\eta^D(s)$ is the error term that also contains unobserved (but relevant) characteristics. $I(s)$ should be interpreted as the value of the indirect utility function associated to the choice s. This indirect utility function is the result of a standard utility maximization problem, and consequently Z contains variables associated to the utility function and to the budget constraint. I allow $\eta^D(s)$ and $\eta^D(s')$ to be correlated for any $s \neq s'$. I impose a factor structure to the model. Specifically,

$$\eta^D(s) = \alpha_s^D f + \nu^D(s) \qquad \text{for each } s \in \{1,\ldots,S\}, \tag{3}$$

[4]See Aakvik et al. (1999), Cameron and Heckman (2001), Carneiro et al. (2003), Hansen et al. (2004), Aakvik et al. (2005), Urzua (2008), Heckman et al. (2018), and Sarzosa and Urzúa (2021) for applications of similar models in other contexts.

where f is one-dimensional and denotes the unobserved heterogeneity. $\nu^D(s)$ represents an idiosyncratic error term, and satisfies $\nu^D(s) \perp\!\!\!\perp \nu^D(s') \perp\!\!\!\perp f \perp\!\!\!\perp (Z, X)$ for any s and $s' \neq s$, where $\perp\!\!\!\perp$ denotes statistical independence.[5]

I also model academic performance for each school-type $s \in \{1, \ldots, S\}$ as test score equations. Let $T(s)$ denote a $J \times 1$ vector of test scores, given schooling choice s. I assume the following linear-in-parameters form for $T(s)$:

$$T(s) \quad = \quad X^T \beta_s^T + \alpha_s^T f + \nu^T(s) \qquad \text{for each } s \in \{1, \ldots, S\}, \tag{4}$$

where X^T contains observed variables determining test scores, and $\nu^T(s) \perp\!\!\!\perp \nu^T(s') \perp\!\!\!\perp f \perp\!\!\!\perp (Z, X)$ for any s and $s' \neq s$.

Finally, I posit a linear measurement system to identify the distribution of the unobserved factor, f, that is independent of the observed optimal school-type s^*. I supplement the model described above with a vector of linear equations linking early taken test scores with observed characteristics and the unobserved heterogeneity. This allows me to interpret f as a combination of different latent abilities affecting measured ability.[6] I model each of the equations in the measurement system as:

$$M_l \quad = \quad X_l^M \beta_l^M + \alpha_l^M f + \nu_l^M \qquad \text{for each } l \in \{1, \ldots, L\}, \tag{5}$$

where L is the total number of linear equations in the system. The error term ν_l^M is statistically independent of the factor, the observable variables, and of $\nu^D(s)$ and $\nu^T(s')$ for any school-types s and s'.

This model of school-type choice and test scores shares the structure of the model in Hansen et al. (2004), and consequently I can directly apply their argument to prove its non-parametric identification. Specifically, I can apply Theorem 1 in Hansen et al. (2004) and Kotlarski Theorem (Kotlarski, 1967) to prove the identification of the distribution of the latent factor as well as the identification of the parameters in the latent utilities and test scores equations.

Estimation Strategy. I am able to observe the optimal school-type decisions (s^*), as well as the associated observable characteristics (Z, X). I also observe test scores as outcomes (T), which combine counterfactual scores and decisions in the following fashion:

$$T_i \quad = \quad \sum_{s=1}^{S} T_i(s) \times D_i(s),$$

[5] $X = (X^T, X^M)$ is a vector containing all the observable variables from the other parts of the model.

[6] In this setting, f includes unobserved factors that directly determine test scores such as cognitive and non-cognitive abilities.

where $D_i(s) \equiv \mathbb{1}[s = s^*]$, and $\mathbb{1}[\cdot]$ is an indicator function that takes a value of one if the argument is true, and zero otherwise. Also, $\sum_{s=1}^{S} D_i(s) = 1$. Finally, I observe early taken test scores (M).

The key insight of my approach is that, conditional on covariates (Z, X) and the unobserved heterogeneity (f), all error terms are mutually independent. Thus, the likelihood function can be written as:

$$\prod_{i=1}^{N} \int \left\{ \begin{array}{c} [g(\mathbf{T}_i(1)|X_i, f, D_i(1) = 1) Pr[D_i(1) = 1|Z_i, f]]^{D_i(1)} \\ \vdots \\ [g(\mathbf{T}_i(S)|X_i, f, D_i(S) = 1) Pr[D_i(S) = 1|Z_i, f]]^{D_i(S)} \end{array} \right\} \Pi_{j=1}^{J} h(M_{ij}|X_i, f) dG(f).$$

I also assume that f is distributed according to a three-component mixture of normals. Formally,

$$f \sim p_1 N(\mu_1, \sigma_1^2) + p_2 N(\mu_2, \sigma_2^2) + p_3 N(\mu_3, \sigma_3^2).$$

This assumption provides enough flexibility and does not impose normality a priori. I estimate the entire model using Markov Chain Monte Carlo methods, and I use the sampling proposed by Gibbs. My use of Bayesian methods is merely for computational reasons, and to avoid the computation of the integral in the likelihood function. I am interested primarily in the mean of the posterior distribution, and therefore my analysis follows the classical perspective and is interpreted as an estimator that has the same asymptotic sampling distribution as the maximum likelihood estimator. See Robert and Casella (1999) for more details. See also Appendix C in Hansen et al. (2004) for details on the estimation procedure.

As Hansen et al. (2004) note, the nonparametric identification of the distribution of the latent factor necessitates $S + K \geq 3$ for a one-dimensional factor, where S is the number of discrete choices and K is the number of equations in the measurement system. In my empirical application, I have three school-types $(S = 3)$, and I use four early taken test scores in the measurement system $(K = 4)$, thus, I secure the identification of the distribution of the factor. Furthermore, the model provides a sufficient number of equations to identify the distribution of two independent factors $(S + K \geq 6)$. However, I prefer to keep the model parsimonious and ease the interpretation of the unobserved heterogeneity by using only one factor.

Definition of Treatment Parameters of Interest. I am interested in estimating the effects of attending a school of type s, where s is either for-profit or nonprofit, relative to attending a public school.

I define two treatment effect parameters of interest: the Average Treatment Effect (ATE) and the Average Treatment Effect on the Treated (TT). The ATE of attending a school of type s

relative to attending a school of type k is defined as:

$$ATE(s,k) \quad = \quad E\left[Y_i(s) - Y_i(k)\right] \qquad \text{for } k \neq s,$$

where $Y_i(s)$ is the potential outcome (test score) of individual i when attending a school of type s. The ATE parameter compares the average outcome of attending a school of type s with the average outcome of attending a school of type k. I impose s to be either for-profit or nonprofit, and k to be the public school-type. The ATE parameter is of interest in any program where the treatment status is exogenously determined by the policymaker, as it informs about the effect of the program for the entire population.

The TT parameter of attending a school of type s^* relative to attending a school of type k compares the outcome of attending the school-type s^*, which is optimal in the choice set $\{1,\ldots,S\}$ relative to attending a school of type k. More formally,

$$TT(s^*,k) \quad = \quad E\left[Y_i(s^*) - Y_i(k) | D_i(s^*) = 1\right],$$

where $s^* = \text{argmax}_{s\in\{1,\ldots,S\}}\{I(s)\}$ is either for-profit or nonprofit, and k is the public school-type. That is, the TT parameter compares the for-profit/nonprofit school-type with the public school-type, for individuals whose optimal choice is s^*. The TT parameter is of interest in any program where the treatment status is endogenously determined by the agents, as it informs about the effect of the program for those who choose to be treated.

Discussion on Advantages and Assumptions of the Model. The main advantage of this structural approach is that it allows the estimation of the joint counterfactual distribution of outcomes for a policy intervention, and to move beyond estimating means of policy outcomes, which is the convention in the program evaluation literature. In other words, the model recovers $F\left(Y_1, Y_0 | X, Z\right)$, the joint distribution of counterfactuals, and therefore permits the identification of the mean, median, or any other quantile of the policy gains distribution. For instance, I can estimate the proportion of people benefitting from the program—$Pr\left(Y_1 > Y_0 | \, X, Z\right)$—or the distribution of gains at selected levels of the untreated population—$F\left(Y_1 - Y_0 | Y_0 = y_0, X, Z\right)$.

Moreover, I can answer any well-posed policy question, including standard treatment effects. The price one has to pay is the assumed independence between the factor f and the covariates (X, Z), and the independence of all uniquenesses with each other—the ν terms. This assumption rules out any random shock that may simultaneously affect both choices and outcomes, such as a job loss event within the household.

Another advantage of the structural approach is that it is natural to give an interpretation to the unobserved factor, which in this case is a combination of inherent abilities that directly determine academic performance. However, this also comes at a price, which is that I cannot argue that I am controlling for other sources of unobserved heterogeneity that affect school selection but not outcomes, such as preferences over peers and school amenities.

If one or more of the independence assumptions are not satisfied, then the full model turns to be misspecified, and the results are biased. Given the high nonlinearity of the model, it is not clear which sign the bias can take. Nevertheless, the ability of the model to mimic the actual data—described below—gives confidence on the plausibility of the assumptions.

5 Results

5.1 Structural Model Estimation

Estimates. The measurement system comprises four linear equations, one for each test taken in 8th grade (verbal, mathematics, social sciences, and natural sciences). Table A.9 in Appendix A presents the estimates for these equations. Female students outperform male students in verbal exams, and the opposite is true for all other tests. This pattern has already been documented for the case of Chile (Rodríguez et al., 2015). Both parents' education are significant determinants of test scores, with mother's education being somewhat more important. The indicators for household composition are not always statistically different from zero, and an interesting pattern is found for the dummy for living with siblings: it increases math scores, but decreases social sciences. Geographical variables are also important, and their effects vary across models. Residing in the South is associated with higher scores. The unobserved component of the model (ability) is a strong predictor of academic performance. It has a positive and significant effect in all equations. Note that to secure identification, I normalize the factor's loading to being equal to one in the math scores equation.

Table A.10 in Appendix A presents the estimates for the secondary school-type choice. The omitted choice is the public type. In general, being a male decreases the probability of choosing both a for-profit school and a nonprofit school. Parents' schooling increases such probabilities. Geographical variables are also important. Students from the South are more likely to choose schools of the public type. The availability of for-profit and nonprofit schools in the municipality is possibly the most important predictor of choice. Their associated coefficients are large and statistically significant. It is possible that this effect operates through distance to school; a higher share of for-profit schools in an individual's municipality might very well imply that there is a better chance that schools of such type are close to the individual's residence.[7] Average

[7] Hastings and Weinstein (2008), Walters (2018), Allende et al. (2019), Sanchez (2023), and Neilson (2025) document an important role of proximity to school when choosing schools.

differences in school test scores are also shown to be strong determinants of the choice. Large cities are associated to choosing a nonprofit school, and high urbanization rates increase the probability of choosing a for-profit school, but reduce the probability of choosing a nonprofit school. Finally, high-ability students choose nonprofit schools more frequently.

Table A.11 in Appendix A presents the estimates for the outcome equations—i.e. verbal and math scores in 10th grade. The results are in line with what I find for the measurement system. That is, females perform better than males in verbal exams but not in math, and parental and geographic variables are important determinants of academic performance. Once more, the factor determines strongly test scores, with its loadings being all positive and statistically different from zero.

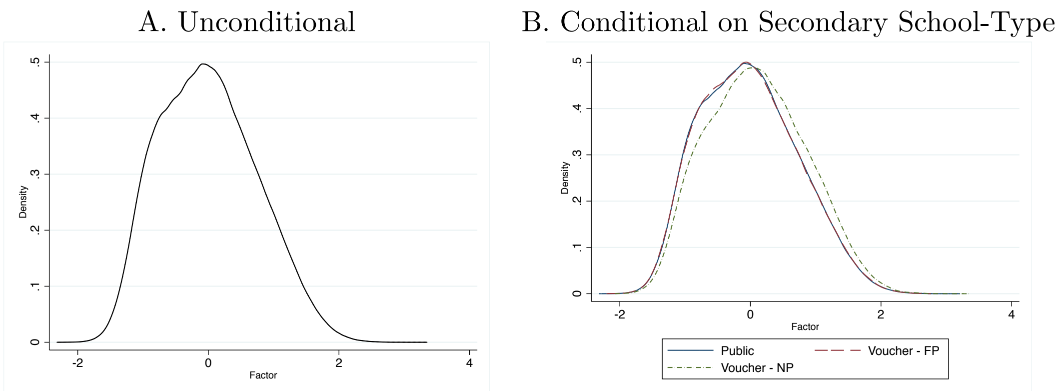
Goodness of Fit. To validate the model, I simulate 150,000 observations using the estimates for the covariates, the distributions of the factor and the error terms, as well as the sample data. The exercise is as follows. I randomly select an observation from the data, and draw a value for the factor and the error term from their estimated distribution functions. I then compute the predicted value of the indirect utility, $I(s)$, for each of the three school-type choices. Thus, I get $I(\text{public})$, $I(\text{for-profit})$, and $I(\text{nonprofit})$, and can compute the optimal choice, s^*, by selecting the school-type associated with the highest indirect utility level. I also predict counterfactual outcomes for each of the three school-type choices. I repeat this process 150,000 times.

Tables A.12-A.14 in Appendix A present the goodness of fit of the simulated model. Table A.12 compares the actual school type choices with the ones predicted by the models. The model does an excellent job in reproducing the actual choices. Similar is the conclusion for the measurement systems and the outcomes, as shown in Tables A.13 and A.14. The models predict well the first two moments of the actual distributions.

Distribution of the Unobserved Ability. Figure 1 presents the estimated distribution of the unobserved ability, unconditional (panel A) and conditional on the secondary school-type choice (panel B). The estimated parameters are presented at the bottom of the figure. The shape of the unconditional density confirms my approach of not assuming normality a priori. Moreover, the estimated probabilities show that all mixture components are needed to well approximate the distributions.

In panel B, we observe that nonprofit schools are able to attract more high-ability students than both public and for-profit schools. This result confirms the predictions of theoretical models of competition between public and private schools under voucher regimes, such as Epple and Romano (1998) and MacLeod and Urquiola (2015), that anticipate a concentration of high-ability students in private schools.

Figure 1: Distribution of Factor



$$f \sim p_1 N(\mu_1, \sigma_1^2) + p_2 N(\mu_2, \sigma_2^2) + p_3 N(\mu_3, \sigma_3^2)$$

where,

$$\mu = (-0.13, \quad -0.09, \quad 0.75)$$
$$\mathbf{1}/\sigma^{\mathbf{2}} = (4.86, \quad 11.25, \quad 3.53)$$
$$\mathbf{p} = (0.48, \quad 0.20, \quad 0.33)$$

Notes: The factor is simulated using the estimates of the model. The simulated data contain 150,000 observations.

5.2 Treatment Effects

Table 2 presents a summary of the estimated treatment effects using the linear and the structural models described above. The first two columns show the estimates obtained after estimating equation (1) by OLS and 2SLS, respectively, while the last two columns present the estimates for the ATE and TT parameters obtained using the structural model. The outcomes are scores (in standard deviations, σ) in verbal (panel A) and mathematics (panel B) exams. The OLS estimates show that attending a for-profit secondary school is associated with increases in test scores of 0.058σ in verbal and 0.106σ in math, relative to attending a public school. Attending a nonprofit secondary school is associated with even larger increases in test scores of 0.144σ in verbal and 0.226σ in math, relative to attending a public school. The 2SLS estimates indicate smaller effects for attending a for-profit secondary school than the OLS estimates (0.032σ in verbal and 0.099σ in math). In contrast, 2SLS estimates for attending a nonprofit secondary school are substantially larger than OLS–0.242σ in verbal and 0.344σ in math. Provided that the identification assumptions for OLS and 2SLS are valid—that is, OLS identifies the ATE parameter and 2SLS identifies LATE—these results suggest that subsample of compliers are individuals that benefit more from attending a nonprofit school than the average student, while the opposite is true for the treatment of attending a for-profit school.[8]

The structural model estimates indicate that attending a for-profit secondary school increases test scores of a randomly selected student by 0.070σ in verbal and 0.121σ in math, relative to attending a public school (ATE). Attending a nonprofit secondary school increases test scores of a randomly selected student by 0.153σ in verbal and 0.233σ in math, relative to attending a public school (ATE). The TT parameters are slightly smaller, but of similar magnitude.

In order to interpret the magnitude of the estimated effects, note that a standard deviation is the distance between the median student in the class and the 84th percentile. According to Allan and Fryer (2011), a student typically improves by about one standard deviation over the course of 1.4 academic school years, or 12.5 months. Therefore, an effect of 0.1σ translates into 1.25 months of schooling, and an effect of 0.2σ into 2.5 additional months.

I formally test whether the treatment effect of attending a for-profit school is equal to that of attending a nonprofit school, in each of the four estimation methods. The last row in each panel of Table 2 shows that this hypothesis is rejected in all models, confirming that attending a nonprofit secondary school is associated with larger increases in test scores than attending a for-profit secondary school.

The comparison of columns 1 and 3 of Table 2 is an informal test of the validity of the OLS identification assumption—i.e. whether there is no omitted variable bias after controlling for demographics and prior test scores. OLS estimates are not too far from the ATE parameters obtained from the structural model that controls for selection and unobserved ability, in addition to the OLS controls. This suggests that the bias in OLS due to selection on unobservables is not very large in this context.

The comparison of columns 2, 3 (or 1) and 4 of Table 2 provides evidence of treatment effect heterogeneity in the population. Were this not the case, 2SLS estimates would be similar to both ATE and TT parameters obtained from the structural model. Interestingly, however, the treated population's gains from attending a for-profit school are very similar to the average gains in the population, as the corresponding ATE and TT parameters are quite close to each other.

[8] 2SLS estimation has associated strong first stage results, with F statistics on exluded instruments ranging from 149 to 237.

Table 2: Estimated Treatment Effects

	OLS	2SLS	structural model ATE	structural model TT
A. Verbal				
for-profit vs. public	0.058	0.032	0.070	0.067
	(0.011)	(0.030)	(0.002)	(0.006)
nonprofit vs. public	0.144	0.242	0.153	0.144
	(0.012)	(0.045)	(0.002)	(0.006)
Prob(for-profit = nonprofit)	0.000	0.000	0.000	0.000
B. Mathematics				
for-profit vs. public	0.106	0.099	0.121	0.115
	(0.010)	(0.031)	(0.002)	(0.005)
nonprofit vs. public	0.226	0.344	0.233	0.225
	(0.012)	(0.045)	(0.002)	(0.006)
Prob(for-profit = nonprofit)	0.000	0.000	0.000	0.000
demographics	Y	Y	Y	Y
prior test scores	Y	Y	Y	Y
unobserved ability	N	N	Y	Y

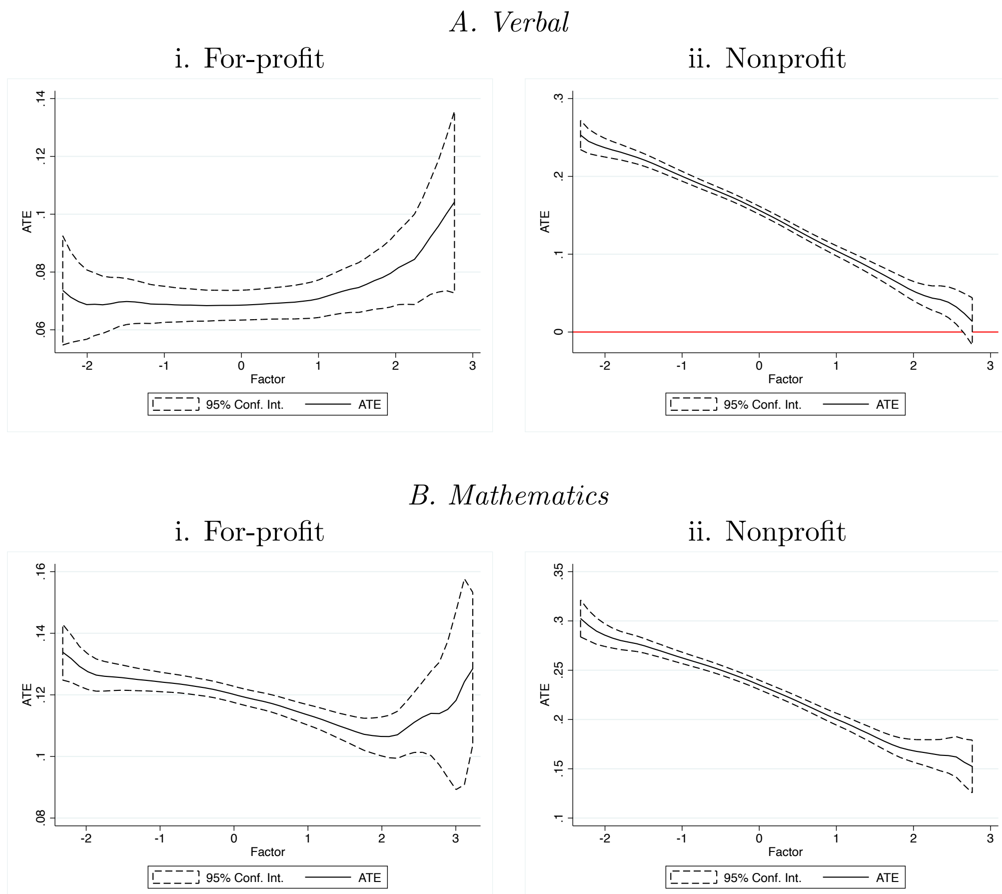
Notes: Column 1 presents OLS estimates of equation (1). Column 2 presents 2SLS estimates of equation (1), using as instruments the availability and average test scores of for-profit and nonprofit schools in the municipality, and population size and urbanitazion rate in the municipality. Columns 3 and 4 present the Average Treatment Effect (ATE) and Treatment Effect on the Treated (TT) parameters estimated using the structural model. The outcomes are test scores in standard deviations, σ. Standard errors (in parentheses) are clustered at the primary school level for the OLS and 2SLS estimates. Mean tests for the equality of the for-profit and nonprofit effects were computed as linear statistical tests for the OLS and 2SLS estimation methods. For the structural model, these tests were performed as mean tests on the simulated expressions for the ATE and TT parameters.

The structural model allows me to further study treatment effect heterogeneity. Figure 2 shows evidence of such heterogeneity along the distribution of unobserved ability. More specifically, it presents the distributional unconditional gains of attending a for-profit (panel A.i and B.i) or a nonprofit (panel A.ii and B.ii) secondary school, relative to attending a public school, for verbal and math exams, respectively—i.e. $(Y(s) - Y(k))$.

The first thing to note is that the unconditional gains of attending either a for-profit or a nonprofit secondary school are strictly positive at all levels of unobserved ability, for both verbal and math exams. This means that regardless of the level of ability, attending either a for-profit or a nonprofit secondary school is always a performance-improving choice when compared to attending a public school.

Next, the magnitude of the unconditional gains varies along the ability distribution. For both verbal and math exams, the unconditional gains of attending a for-profit secondary school are relatively flat across the ability distribution, suggesting that the benefits of attending nonprofit schools relative to public schools are more uniform across different levels of ability. In contrast, the unconditional gains of attending a nonprofit secondary school sharply decrease with ability, indicating that lower-ability students benefit more from attending nonprofit schools relative to public schools.

Figure 2: Unconditional Gains as a Function of Unobserved Ability



Notes: Panel A plots the distributional unconditional gains ($Y(s) - Y(k)$) of attending a for-profit (i.) or a nonprofit (ii.) secondary school (relative a public school) on verbal scores, as a function of the unobserved ability (factor). Panel B does similarly for mathematics. 95% confidence intervals in dashed lines.

In summary, my results show that private schools are more effective than public schools in increasing learning outcomes. I also show that the effect that private schools have on test scores varies according to the profit motive of the school, with nonprofit schools being more effective than for-profit schools in raising academic achievement. The evidence is robust across estimation methods, that include linear and nonlinear models. Moreover, treatment effects are found to be heterogenous, even after controlling for selection and prior test scores.

Heterogeneity of the estimated effects with respect to the unobserved ability is also documented. While the gains of attending a for-profit secondary school are relatively uniform across different levels of ability, the gains of attending a nonprofit secondary school are particularly large for low-ability students.

6 Conclusions

I have studied the relative effectiveness of voucher-subsidized for-profit and nonprofit secondary schools in Chile. I found that both types of private schools are more effective than public schools in increasing learning outcomes. Moreover, nonprofit schools are found to be more effective than for-profit schools in raising academic achievement. Treatment effects are found to be heterogenous, even after controlling for selection and prior test scores. Heterogeneity of the estimated effects with respect to students' inherent ability is also documented, with results indicating that while the gains of attending a for-profit secondary school are relatively uniform across different levels of ability, the gains of attending a nonprofit secondary school are larger for low-ability students than for higher-ability individuals.

Chile's voucher system of education has a few unique features that are worth considering when extrapolating the results to other contexts. First, the per-student subsidy that private-voucher schools receive is the same as that of public schools. Second, both public and subsidized-private schools are subject to the same regulations regarding curriculum and students' learning assessments. Furthermore, learning assessments are very frequent and transparently reported to the community. Also, teachers' incentive programs are equally available to educators in both public and subsidized-private schools. Which of these factors is the determinant one in explaining Chile's success in aliging profit-seeking institutions with the government's educational agenda is still an open question for future research. Nevertheless, special attention must be given to regulation disciplining for-profit schools' behavior, such as learning requirements for schools that receive public funds. See, for instance, the stark contrast between Chile's targeted voucher experience (Sanchez, 2023; Gazmuri, 2024; Neilson, 2025), and that of the State of Lousiana (Abdulkadiroglu et al., 2018). Private schools-disciplining regulations are particularly lacking in the Louisiana experience.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process. During the preparation of this work the author used Github-Copilot in order to help coding and proofreading. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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A Additional Tables

Table A.1: Schools and Enrollment by Type of School

type of school		schools		enrollment	
		obs.	%	obs.	%
i. overall					
public		5,098	55.7	1,120,811	39.7
private-voucher					
	total	3,629	39.6	1,480,889	52.5
	for-profit	2,495	27.3	903,097	32.0
	nonprofit	1,134	12.4	577,792	20.5
private-fee-paying		428	4.7	219,487	7.8
ii. primary					
public		4,740	55.3	785,042	40.4
private-voucher					
	total	3,412	39.8	1,013,514	52.1
	for-profit	2,385	27.8	634,195	32.6
	nonprofit	1,027	12.0	379,319	19.5
private-fee-paying		419	4.9	145,805	7.5
iii. secondary - conventional					
public		624	25.2	196,532	32.9
private-voucher					
	total	1,476	59.6	327,820	54.8
	for-profit	926	37.4	198,078	33.1
	nonprofit	550	22.2	129,742	21.7
private-fee-paying		375	15.2	73,658	12.3
iv. secondary - vocational					
public		445	50.6	139,237	49.9
private-voucher					
	total	433	49.2	139,555	50.1
	for-profit	233	26.5	70,824	25.4
	nonprofit	200	22.7	68,731	24.7
private-fee-paying		2	0.2	24	0.0

Notes: Calculated using administrative data from the Ministry of Education. All figures are for the year 2013. Only schools offering primary and/or secondary education for children and adolescents are included. Schools that offer both primary and secondary levels are included in both the panel for primary education and in the respective panel for secondary level.

Table A.2: Enrollment and Classes by Type of School

	public	for-profit	nonprofit
i. overall			
enrollment	219.9	362.0	509.5
number of classes	8.9	12.1	15.2
class size	17.8	24.6	29.1
ii. primary			
enrollment	154.0	254.2	334.5
number of classes	6.8	8.8	10.1
class size	16.8	24.3	29.1
% of multigrade classes[a]	23.2	10.9	5.5
iii. secondary - conventional			
enrollment	38.6	79.4	114.4
number of classes	1.2	2.4	3.3
class size	30.2	31.1	32.9
iv. secondary - vocational			
enrollment	27.3	28.4	60.6
number of classes	0.9	0.9	1.8
class size	25.3	28.1	30.9

Notes: Calculated using administrative data from the Ministry of Education. All figures are for the year 2013. Only schools offering primary and/or secondary education for children and adolescents are included. [a] Multigrade classes are allowed only in preschool and primary levels. Schools can combine 1st to 6th grades and 7th and 8th grades for the case of primary education.

Table A.3: Monthly Tuition by Type of School - Schools Offering Primary and/or Secondary Education

	public	for-profit	nonprofit
no charge	96.1	45.6	42.2
1,000–10,000	2.3	8.4	7.9
10,001–25,000	0.2	19.8	19.5
25,001–50,000	0.0	16.5	17.5
50,001–100,000	0.0	9.0	9.6

Notes: Calculated using administrative data from the Ministry of Education. All figures are for the year 2013, and represent percentages of schools by each type of school. Only schools offering primary and/or secondary education for children and adolescents are included. Tuition values are in Chilean pesos. As of March 16th, 2015, one dollar exchanges for 640 Chilean pesos.

Table A.4: Monthly Tuition by Type of School - Schools Offering Secondary Education

	public	for-profit	nonprofit
no charge	84.6	16.1	24.2
1,000–10,000	13.4	8.1	9.9
10,001–25,000	1.3	26.1	22.5
25,001–50,000	0.0	30.7	25.3
50,001–100,000	0.0	18.7	15.5

Notes: Calculated using administrative data from the Ministry of Education. All figures are for the year 2013, and represent percentages of schools by each type of school. Only schools offering secondary education for children and adolescents are included. Tuition values are in Chilean pesos. As of March 16th, 2015, one dollar exchanges for 640 Chilean pesos.

Table A.5: Teacher Inputs by Type of School

	public	for-profit	nonprofit
i. overall			
pupil-teacher ratio	11.1	16.4	16.9
teachers' degree			
degree in education (%)[a]	96.1	95.2	94.3
institution attended: university (%)	90.0	89.4	91.0
institution attended: 2-y or 4-y technical (%)[b]	6.4	6.3	5.8
type of contract			
permanent (%)	46.8	57.2	60.6
contract (%)	43.8	37.9	35.3
ii. primary			
pupil-teacher ratio	10.7	15.8	16.4
teachers' degree			
degree in education (%)[a]	97.5	96.9	97.4
institution attended: university (%)	90.3	89.4	91.5
institution attended: 2-y or 4-y technical (%)[b]	6.2	6.5	5.8
type of contract			
permanent (%)	46.7	58.3	61.2
contract (%)	43.3	36.6	34.3
iii. secondary - conventional			
pupil-teacher ratio	12.5	13.0	12.7
teachers' degree			
degree in education (%)[a]	92.9	92.1	94.1
institution attended: university (%)	92.2	92.4	93.4
institution attended: 2-y or 4-y technical (%)[b]	4.1	2.7	3.4
type of contract			
permanent (%)	43.6	49.8	59.5
contract (%)	51.5	47.4	38.4
iv. secondary - vocational			
pupil-teacher ratio	16.7	19.2	16.6
teachers' degree			
degree in education (%)[a]	63.3	66.2	71.5
institution attended: university (%)	78.0	77.9	81.9
institution attended: 2-y or 4-y technical (%)[b]	15.9	15.9	12.5
type of contract			
permanent (%)	36.8	54.5	63.7
contract (%)	59.5	43.0	34.2

Notes: Calculated using administrative data from the Ministry of Education. All figures are for the year 2013. Only schools offering primary and/or secondary education for children and adolescents are included. [a] Only degrees in education obtained from higher education institutions are considered. [b] Only 2-years technical institutions (CFT) and 4-years professional institutes (IP) are considered.

Table A.6: Religious Orientation and Admission Criteria by Type of School

	public	for-profit	nonprofit
religious orientation (% of schools)[a]			
secular	52.0	54.0	17.9
catholic	40.9	30.5	65.0
other religion	7.1	15.4	13.7
admission requirements (% of schools)[a]			
preschool evaluation	18.1	24.0	29.4
civil marriage certificate	2.4	3.4	11.4
transcripts from former school	68.8	69.8	64.2
baptism and/or marriage through the Church certificates	0.9	2.1	28.5
income certificate	2.4	6.1	9.9
parents' interview	18.3	42.3	57.6
exam	20.6	41.7	55.5
psychological evaluation/report	19.6	26.3	25.3

Notes: Administrative data from the Ministry of Education for schools offering primary and/or secondary education for children and adolescents were used to construct the indicators on religious orientation. Responses to the SIMCE parents' questionnaire were used to construct the indicators on admission requirements. All figures are for the year 2013. [a] All numbers represent percentages of schools by each type of school.

Table A.7: Municipality Characteristics and Urban Status by Type of School

	public	for-profit	nonprofit
municipality's monthly income per capita (CLP)	305,158	325,939	328,806
municipality's poverty rate	17.6	14.4	15.3
municipality's population	121719	223629	168975
school urban status (%)	42.1	73.5	83.2

Notes: Municipality characteristics come from CASEN 2013 survey data. School's urban status comes from administrative data from the Ministry of Education for schools offering primary and/or secondary education for children and adolescents. All figures are for the year 2013. As of March 16th, 2015, one dollar exchanges for 640 Chilean pesos.

Table A.8: Average Tests Scores and Family Background Characteristics by Type of School

	public	for-profit	nonprofit
language score	-0.20	0.04	0.29
math score	-0.29	0.09	0.37
father's years of education	9.9	11.5	11.6
mother's years of education	10.0	11.5	11.7
household monthly income: less than 200,000 (%)^{b}	37.0	19.4	19.0
household monthly income: 200,001–300,000 (%)^{b}	26.3	21.5	21.5
household monthly income: 300,001–400,000 (%)^{b}	13.3	14.4	14.8
household monthly income: more than 400,000 (%)^{b}	20.1	41.7	41.9

Notes: Calculated using administrative data from SIMCE 2013 and SIMCE 2013 responses to parents' questionnaire, for 10th graders. I normalize test scores to have an overall mean of zero and standard deviation of one, by subject. ^{b} Monthly income values are in Chilean pesos. As of March 16th, 2015, one dollar exchanges for 640 Chilean pesos.

Table A.9: Estimates: Measurement System

	verbal	mathematics	social sciences	natural sciences
male	-0.218	0.173	0.172	0.098
	(0.007)	(0.007)	(0.007)	(0.007)
father's years of education[a]	0.011	0.011	0.013	0.012
	(0.001)	(0.001)	(0.001)	(0.001)
mother's years of education[a]	0.017	0.020	0.024	0.019
	(0.001)	(0.001)	(0.001)	(0.001)
living with both parents	0.006	0.003	0.022	0.019
	(0.007)	(0.007)	(0.007)	(0.006)
living with siblings	0.009	0.040	-0.024	0.011
	(0.007)	(0.006)	(0.006)	(0.006)
living with others	0.011	-0.004	0.000	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)
region: north	-0.190	-0.151	-0.205	-0.176
	(0.013)	(0.012)	(0.012)	(0.013)
region: center	-0.150	-0.038	-0.094	-0.099
	(0.010)	(0.009)	(0.009)	(0.010)
non-missing: father's years of education[b]	-0.110	-0.118	-0.149	-0.117
	(0.016)	(0.016)	(0.017)	(0.015)
non-missing: mother's years of education[b]	-0.108	-0.137	-0.204	-0.149
	(0.020)	(0.020)	(0.021)	(0.020)
intercept	-0.027	-0.368	-0.261	-0.277
	(0.020)	(0.019)	(0.020)	(0.019)
factor	1.063	1.000	0.943	1.053
	(0.005)		(0.005)	(0.004)

Notes: Estimates from the measurement system part of the model, where coefficients for a linear-in-parameters equation are estimated. All explanatory variables come from SIMCE 2011 for 8th graders database. Standard errors in parentheses. The total number of observations is 66,388. [a] Missing values replaced with a zero. [b] Dummy variable being equal to one if the corresponding variable is non-missing, and zero otherwise.

Table A.10: Estimates: Secondary School-Type Choice

	choice:	
	voucher for-profit	voucher nonprofit
male	-0.145	-0.016
	(0.018)	(0.018)
father's years of education[a]	0.015	0.010
	(0.004)	(0.004)
mother's years of education[a]	0.025	0.029
	(0.004)	(0.004)
region: north	-0.475	-0.237
	(0.036)	(0.036)
region: center	-0.143	-0.288
	(0.026)	(0.025)
% for-profit schools[b]	3.772	
	(0.050)	
% nonprofit schools[b]		2.953
		(0.060)
avg. scores for-profit schools - avg. scores public schools: verbal[a,b]	-0.125	
	(0.056)	
avg. scores nonprofit schools - avg. scores public schools: verbal[a,b]		0.719
		(0.054)
avg. scores for-profit schools - avg. scores public schools: math[a,b]	-0.072	
	(0.051)	
avg. scores nonprofit schools - avg. scores public schools: math[a,b]		-0.805
		(0.050)
log population[b]	-0.105	0.133
	(0.013)	(0.014)
urbanization rate[b]	0.928	-0.327
	(0.083)	(0.079)
non-missing: father's years of education[c]	-0.151	0.052
	(0.055)	(0.059)
non-missing: mother's years of education[c]	-0.028	-0.115
	(0.057)	(0.059)
non-missing: avg. score difference for-profit vs. public (verbal and math)[c]	1.825	
	(0.101)	
non-missing: avg. score difference for-profit vs. public (verbal)[c]		1.203
		(0.340)
non-missing: avg. score difference for-profit vs. public (math)[c]		0.090
		(0.342)
intercept	-3.481	-4.501
	(0.136)	(0.127)
factor	-0.004	0.168
	(0.013)	(0.013)

Notes: Estimates from the multinomial choice part of the model, where the base school type choice is "public"—that is, all estimated coefficients are relative to the choice of choosing a public school in 10th grade. All variables were constructed using CASEN 2011, SIMCE 2012, and SIMCE 2013 data sets. Standard errors in parentheses. The total number of observations is 66,388. [a] Missing values replaced with a zero. [b] Calculated at the municipality level. [c] Dummy variable being equal to one if the corresponding variable is non-missing, and zero otherwise.

Table A.11: Estimates: Test Scores in 10th Grade

	verbal			mathematics		
school type in 10th grade:	public	for-profit	nonprofit	public	for-profit	nonprofit
male	-0.214	-0.211	-0.229	0.166	0.123	0.182
	(0.009)	(0.014)	(0.016)	(0.008)	(0.014)	(0.014)
father's years of education[a]	0.014	0.010	0.012	0.016	0.015	0.019
	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
mother's years of education[a]	0.019	0.012	0.020	0.027	0.023	0.023
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
region: north	-0.118	-0.225	-0.146	-0.105	-0.108	-0.030
	(0.015)	(0.030)	(0.028)	(0.014)	(0.029)	(0.028)
region: center	-0.143	-0.204	-0.179	-0.014	-0.114	-0.077
	(0.012)	(0.022)	(0.020)	(0.011)	(0.022)	(0.018)
non-missing: father's years of education[b]	-0.109	-0.066	-0.171	-0.120	-0.131	-0.159
	(0.022)	(0.041)	(0.047)	(0.020)	(0.038)	(0.045)
non-missing: mother's years of education[b]	-0.096	-0.048	-0.118	-0.186	-0.148	-0.153
	(0.022)	(0.042)	(0.05)	(0.021)	(0.041)	(0.046)
intercept	-0.152	-0.010	0.097	-0.542	-0.317	-0.282
	(0.013)	(0.024)	(0.022)	(0.012)	(0.025)	(0.021)
factor	0.919	0.927	0.842	0.927	0.919	0.876
	(0.006)	(0.011)	(0.012)	(0.005)	(0.010)	(0.011)

Notes: Estimates from the outcomes part of the model, where coefficients for a linear-in-parameters equation are estimated. All variables were constructed using CASEN 2011, SIMCE 2012, and SIMCE 2013 data sets. Standard errors in parentheses. The total number of observations is 66,388. [a] Missing values replaced with a zero. [b]Dummy variable being equal to one if the corresponding variable is non-missing, and zero otherwise.

Table A.12: Goodness of Fit - School-Type Decisions

	school type 10th grade:					
	public		for-profit		nonprofit	
	actual	model	actual	model	actual	model
percentage	67.60	67.55	18.26	18.23	14.14	14.22

Notes: The simulated data (model) contain 150,000 observations generated using the model's estimates. The actual data (actual) contain 66,388 observations from SIMCE 2011 and SIMCE 2013 data sets. Each cell displays the percentage of individuals choosing a corresponding school type.

Table A.13: Goodness of Fit - Measurement System

	mean		std. dev.	
	actual	model	actual	model
verbal	-0.198	-0.199	0.984	0.976
mathematics	-0.252	-0.253	0.948	0.936
social sc.	-0.258	-0.258	0.945	0.934
natural sc.	-0.263	-0.264	0.957	0.946

Notes: The simulated data (model) contain 150,000 observations generated using the model's estimates. The actual data (actual) contain 66,388 observations from SIMCE 2011 and SIMCE 2013 data sets.

Table A.14: Goodness of Fit - Test Scores in 10th grade

		mean		std. dev.	
school-type in 10th grade	test	actual	model	actual	model
public					
	verbal	-0.267	-0.314	0.977	0.964
	mathematics	-0.384	-0.433	0.948	0.928
for-profit					
	verbal	-0.232	-0.234	0.959	0.966
	mathematics	-0.304	-0.305	0.929	0.932
nonprofit					
	verbal	0.006	-0.045	0.934	0.933
	mathematics	-0.017	-0.073	0.918	0.913

Notes: The simulated data (model) contain 150,000 observations generated using the model's estimates. The actual data (actual) contain 66,388 observations from SIMCE 2011 and SIMCE 2013 data sets.