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

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Abstract

This paper estimates the test-score effects of attending for-profit and nonprofit private-voucher secondary schools in Chile. Using administrative data and value-added, instrumental-variables, and structural models, I estimate both average and distributional treatment effects. I find that both school types raise achievement relative to public schools, with larger gains in nonprofit schools. Treatment effects are heterogeneous: nonprofit schools benefit low-ability students the most, whereas gains from for-profit schools are more compressed across the ability distribution. Even so, both for-profit and nonprofit schools generate positive gains relative to public schools throughout the distribution of unobserved ability.

Keywords: for-profit, nonprofit, private education, school vouchers.

JEL codes: I21, I28, L21, L33.

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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 et al., 2022; 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; Lavertu and Tran, 2025). 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.

Identifying the causal effects of attending for-profit and nonprofit schools is inherently difficult because school ownership is rarely assigned randomly and credible instruments are scarce. In the absence of lotteries or sharp policy discontinuities, many observable determinants of school choice—such as parental income, preferences, and geography—also affect 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. (2005a,b) show that conventional instrumental variables, including religious affiliation and proximity to Catholic schools, fail to satisfy validity conditions and often yield implausible estimates. This experience highlights the need for alternative strategies—such as value-added models or structural approaches—when studying sectors where credible instruments are lacking.

This paper asks whether the profit motive 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 empirical strategy combines three complementary identification approaches. First, I estimate value-added regressions of secondary-school test scores on school-type indicators, rich observed covariates, and prior test scores. Following the well-established value-added literature, conditioning on prior achievement and observables isolates subsequent test-score growth under standard assumptions. Second, I estimate instrumental-variables specifications that augment the value-added approach with school-type choice shifters based on local school availability, relative school effectiveness, and municipality characteristics. Because prior test scores already account for baseline achievement differences, these shifters provide additional variation in school-type attendance and identify the Local Average Treatment Effect (LATE) for compliers (Imbens and Angrist, 1994; Heckman et al., 2006). Third, I develop a structural model of school-type choice and academic performance in the spirit of Roy (1951), augmented with a measurement system that recovers latent ability from early test scores (Heckman et al., 2018). This framework jointly models choices and outcomes, identifies distributional treatment-effect parameters, and allows me to study heterogeneity along the ability distribution.

My results show that both types of private schools improve learning outcomes relative to public schools. The effects are robust across linear and nonlinear specifications. Average gains from for-profit attendance range from 0.029 to 0.070 standard deviations (σ) in verbal and from 0.098 to 0.121σ in mathematics, relative to public schools. Nonprofit attendance yields even larger gains, ranging from 0.144 to 0.238σ in verbal and from 0.225 to 0.341σ in mathematics.

Importantly, treatment effects are heterogeneous. In particular, the IV estimates show that the effects for compliers differ from the average effects in the population: compliers to for-profit attendance gain less than the average student, whereas compliers to nonprofit attendance gain more. The structural model also reveals that the gains associated with for-profit attendance are comparatively compressed, but not uniformly flat along the ability distribution: in verbal, students with the highest ability benefit more, whereas in mathematics the gains decrease with ability. By contrast, gains from nonprofit schools decline with unobserved ability, implying that nonprofit attendance is especially performance-improving for low-ability students. Notably, both for-profit and nonprofit gains are strictly positive throughout the ability distribution.

This paper contributes to the literature in two ways. First, it adds to the small but growing literature on the effectiveness of for-profit education institutions (Sahlgren, 2011; Cellini and Chaudhary, 2014; Elacqua, 2015; Elacqua et al., 2015; Cellini et al., 2020; Armona et al., 2022; Armona and Cao, 2024; Boggiano et al., 2026). A close predecessor is Singleton (2017), who studies for-profit management in Florida charter schools and finds that, for a given level of per-pupil spending, network for-profit charter schools raise test-score proficiency by 0.03σ relative to nonprofit charters. Lavertu and Tran (2025) provide related evidence from Ohio, showing that nonprofit charter schools that subcontract with for-profit education management organizations underperform comparable nonprofit charters by about 0.1σ in achievement. I extend this literature by using rich administrative data on prior test scores and choice shifters to identify causal gains from attending for-profit and nonprofit schools, and by estimating multiple moments of the treatment-effect distribution to characterize heterogeneity in those gains.

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 fall into three categories defined by administration and financing: public schools, private-voucher schools, and private-non-voucher schools. Public and private-voucher schools are both financed through a per-student voucher scheme paid directly by the government to schools. Private-non-voucher schools rely on parent-paid tuition, which is often high. These schools enroll about 8% of all students, and transitions between them and either public or private-voucher schools are rare (about 3%).

Private-voucher schools can be either for-profit or nonprofit. For-profit schools may belong to chains or be independent. Chains are usually controlled by groups of owners and operate networks of campuses, whereas independent schools are smaller and often owned by former public school teachers. Nonprofit schools include religious and non-sectarian organizations. They receive donations, are often subsidized by the Church or local businesses, and also tend to operate networks of campuses (Elacqua et al., 2015).

In terms of regulation, teachers' contracts in public schools are governed by the Teacher Statute: wages follow uniform pay scales, and schools face dismissal restrictions. In private schools, teachers' contracts are governed by the Labor Code, which gives schools greater flexibility to hire and dismiss teachers. For-profit and nonprofit private schools also differ in their legal treatment. Nonprofit organizations in Chile are eligible for tax exemptions that do not apply to for-profits, including exemptions on income, value-added, inheritance, and real estate taxes, as well as industrial and commercial patents, customs tariffs, and social security (Viveros, 2007; Chile Transparente, 2008). In return, nonprofit entities must reinvest all surplus revenue in the organization rather than distribute it to owners or shareholders. Creating a nonprofit organization is also slower, more costly, and more bureaucratic than creating a for-profit organization.

In 2013, public schools represented the majority of institutions (56%) but enrolled only 40% of students (Table A.1 in Online Appendix A). Private-voucher schools accounted for 40% of schools and 53% of enrollment, split between for-profit (27% of schools; 32% of enrollment) and nonprofit (12%; 21%). Private-non-voucher schools were marginal, with 5% of schools and 8% of enrollment. At the primary level, patterns were similar. In conventional secondary education, public schools fell to 25% of schools and 33% of enrollment, with for-profit voucher schools roughly matching public schools at 33% of enrollment. Nonprofit schools enrolled 22% of secondary students, and private-non-voucher schools became more prominent (12%).

Descriptive statistics reveal systematic differences across school types (Tables A.2–A.8 in Online Appendix A). Nonprofit schools are the largest, with average enrollment of 510 students and class sizes near 29, compared with 362 and 25 in for-profit schools and 220 and 18 in public schools. Tuition patterns are similar across for-profit and nonprofit schools: roughly 45% charge no tuition and about 10% charge more than CLP 50,000. Teacher inputs differ only modestly, with public schools showing 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. Public schools serve poorer, more rural municipalities, whereas private schools cluster in urban areas with higher incomes. Student outcomes and family background also favor nonprofit schools: their students score highest on standardized tests (0.29σ in language and 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 report higher household incomes.

3 Data

I use data from SIMCE 2013 for 10th graders. SIMCE is a mandatory national standardized battery of tests aimed at measuring student learning in several subjects and grade levels. Specifically, SIMCE is administered to all students in 4th grade every year, and since 2005 it has rotated annually between 8th and 10th grades. 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 to identify the for-profit or nonprofit status of schools. I also merge them with CASEN 2011 and SIMCE 2012 datasets for 10th graders to construct the choice shifters used in the empirical analysis. CASEN is the national household survey, and is representative at the municipal level. I use CASEN 2011 because students who were in 10th grade in 2013 were finsishing primary (8th grade) in 2011 and were therefore deciding which type of secondary school to attend. Ideally, I would also use SIMCE data for 10th graders in 2011 to construct the instruments, but because 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 several school-type choice shifters: the differences between average 10th-grade test scores in for-profit and public schools within a municipality, the analogous differences between nonprofit and public schools, the percentages of for-profit and nonprofit secondary schools in each municipality, municipality log population, and municipality urbanization rate. The test-score advantage of for-profit and nonprofit schools relative to public schools captures quality differences across school types that may affect parental choices. A series of studies on school choice in Chile finds that parents value school effectiveness, which supports the use of these choice shifters (Allende, 2019; Gazmuri, 2024; Neilson, 2025; Sánchez, 2026). The shares of for-profit and nonprofit schools capture the local availability of each school type within a municipality: a greater local presence of a given type makes choosing that type more likely. Heckman et al. (2018) use similar choice shifters in the context of higher education choice in the U.S. In addition, 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 motivates using municipality population size and urbanization rate as choice shifters.

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 regression models 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 who were enrolled in 8th grade in a public school in 2011. Most public primary schools offer only primary grades (88%), so the typical public primary school student must choose a secondary school at the end of 8th grade. In contrast, private-voucher primary schools are much more likely to offer secondary education (47%), making the secondary school decision less salient for students already enrolled in those schools at the end of 8th grade. I begin with students in public primary schools in 2011 and keep those with non-missing scores on all four standardized 8th-grade exams. I then drop individuals with missing covariates, except for parents' education and the instruments based on the for-profit and nonprofit test-score advantage, for which I impute missing observations with zero and include a dummy indicator for whether the original variable is observed.[1] The linear-regression sample then differs by outcome availability. The full estimation sample contains 66,388 students with non-missing scores on the four 8th-grade exams, and I use that sample to identify the distribution of unobserved ability in the nonlinear model. Among those students, 56,383 have non-missing 10th-grade verbal scores and 56,356 have non-missing 10th-grade math scores. I therefore use 56,383 observations in the linear verbal regressions and 56,356 observations in the linear math regressions, while continuing to use the full sample of 66,388 students to estimate the structural model and recover treatment parameters.

Table 1 shows summary statistics for the variables used in the empirical analysis. Panels A and B present the demographic variables measured in 2011 and 2013, respectively. Almost half of the sample is male. On average, both parents have slightly less than ten years of formal schooling, roughly equivalent to incomplete secondary education. Most students live with both parents and with siblings, while 28% live with other relatives or non-relatives. Most students (69%) reside in the central region, many of them in Santiago.

Panel C describes the choice shifters used in secondary school-type choice. These variables are constructed at the municipality level. The average share of for-profit schools in a municipality is 27%, while the average share of nonprofit schools is 26%. The differences in average standardized test scores between for-profit and public schools are positive in both 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. The average municipality log population is 11.31, and the average urbanization rate is 82%.

[1] 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.

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. Choice shifters				
% 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 datasets. [a] Calculated at the municipality level.

4 Empirical Analysis

I employ three complementary empirical strategies to study the effects of attending a for-profit or nonprofit secondary school on academic performance, relative to attending a public secondary school. First, building on the value-added literature, I estimate linear regressions of secondary-school test scores on school-type indicators, 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). Under the standard value-added assumption that, conditional on observables and prior test scores, the remaining achievement innovation is unrelated to school-type choice, this strategy identifies average causal effects of school type on academic achievement. Second, I estimate an instrumental-variables (IV) specification using the local availability of for-profit and nonprofit schools, voucher schools' test-score advantage relative to public schools, and municipality size and urbanization, as described in the preceding section. Because prior test scores already absorb baseline achievement differences, these instruments act as additional choice shifters and identify the local average treatment effect (LATE) for compliers. Third, I estimate a structural model of school-type choice and academic performance that uses prior test scores to identify the distribution of unobserved scholastic ability and recovers a variety of treatment parameters such as the average treatment effect (ATE) and the average treatment effect on the treated (TT) (Heckman et al., 2018). Together, these three approaches provide a coherent set of treatment-effect estimates based on distinct but complementary sources of identifying variation.

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,

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

where T_i is the test score of student i in a particular subject (verbal or mathematics), 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 prior 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 choice shifters the local availability of for-profit and nonprofit schools, voucher schools' test-score advantage relative to public schools, and measures of municipality size and urbanization. Standard errors are clustered at the primary-school level (the school attended in 8th grade) in all regressions.

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. 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. 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,

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

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.[2]

I also model academic performance for each school-type $s \in \{1, \dots, S\}$ 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 $T(s)$:

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

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 earlier test scores with observed characteristics and unobserved heterogeneity. This allows me to interpret f as a combination of latent abilities that affect measured performance.[3] I model each of the equations in the measurement system as:

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

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'.

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

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

This model of school-type choice and test scores shares the structure of the model in Hansen et al. (2004), so I can directly apply their argument to establish its nonparametric identification. Specifically, conditional on latent ability and observed covariates, identification relies on the mutual independence of the unobserved shocks in the choice, outcome, and measurement equations. Under that restriction, I can apply Theorem 1 in Hansen et al. (2004) and Kotlarski's theorem (Kotlarski, 1967) to identify the distribution of the latent factor as well as the parameters in the latent-utility and test-score equations. The exclusion restrictions included in Z still matter empirically because they shift school-type choices, but this identification argument does not require instruments; it follows from the factor structure and the measurement system, as in Hansen et al. (2004) and related applications such as Heckman et al. (2018).[4]

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:

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

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:

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

[4] This identification argument is common in the structural choice-model literature. See, e.g., Keane and Wolpin (1997), Todd and Wolpin (2006), Heckman et al. (2018), and Sarzosa and Urzúa (2021).

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, specifically Gibbs sampling. My use of Bayesian methods is purely computational and helps avoid direct evaluation of the integral in the likelihood function. I am primarily interested in the mean of the posterior distribution, so the analysis follows a classical perspective and is interpreted as an estimator with the same asymptotic sampling distribution as the maximum likelihood estimator. See Robert and Casella (1999) for more details, and Appendix C in Hansen et al. (2004) for details on the estimation procedure.

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 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.

A discussion of the advantages and assumptions of the structural model is provided in Online Appendix B.

5 Results

5.1 Estimates from Linear Models

Value-Added Estimates. Table A.9 in Online Appendix A reports estimates from the value-added specification. School-type coefficients are positive in both outcomes, with larger gains for nonprofit than for-profit schools. Prior test scores strongly predict later performance, especially within subject: 8th-grade verbal scores best predict 10th-grade verbal performance, and 8th-grade mathematics scores best predict 10th-grade mathematics performance. Male students score lower in verbal and higher in mathematics, parental education enters positively, and regional indicators have limited predictive power.

Value-Added with Choice Shifters Estimates. Table A.10 in Online Appendix A reports first-stage regressions for the value-added model augmented with choice shifters. Municipality shares of for-profit and nonprofit schools are the strongest predictors of school-type choice. A larger share of for-profit schools strongly raises for-profit attendance, while a larger share of nonprofit schools strongly raises nonprofit attendance. Municipality-level score differentials also help predict school choice, although their coefficients are smaller and less uniform across outcomes. The excluded-instrument F statistics range from 149.1 to 278.3, indicating that the choice shifters are highly relevant in both verbal and mathematics specifications.

Table A.11 in Online Appendix A reports the second-stage estimates. Control-variable coefficients are very similar to those in Table A.9, suggesting stable relationships between observed student characteristics and outcomes across specifications. The main differences lie in the treatment coefficients. The estimated effect of attending a for-profit school remains positive but falls in both subjects, while the estimated effect of attending a nonprofit school rises in both. Thus, relative to the value-added estimates, the IV specification implies smaller effects for for-profit schools and larger effects for nonprofit schools.

5.2 Structural Model Estimates

Estimates. The measurement system comprises four equations, one for each 8th-grade test (verbal, mathematics, social sciences, and natural sciences). Table A.12 in Online Appendix A reports the estimates. As in the linear models, females outperform males in verbal, while the opposite holds in the other subjects. Both parents' education significantly affects test scores, with mother's education somewhat more important. Household-composition indicators are not always significant, and living with siblings raises math scores but lowers social-science scores. Geographic variables are also important: residing in the South is associated with higher scores. The unobserved component (ability) strongly predicts academic performance and has a positive, significant effect in all equations. To secure identification, I normalize the factor loading to one in the mathematics equation.

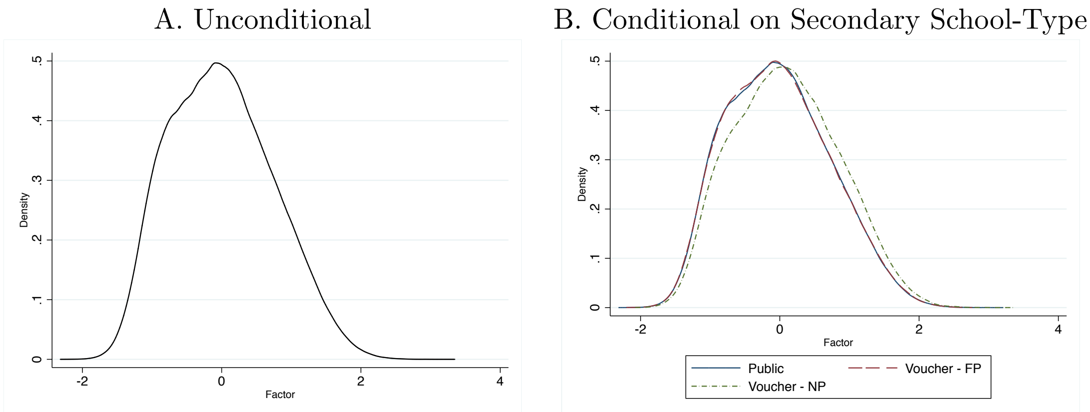
Table A.13 in Online Appendix A reports the estimates for secondary school-type choice. The omitted category is public school. In general, being male lowers the probability of choosing either a for-profit or a nonprofit school, while parents' schooling raises those probabilities. Geographic variables also matter: students from the South are more likely to choose public schools. Municipal availability of for-profit and nonprofit schools is the strongest predictor of choice, with large, statistically significant coefficients. Average differences in school test scores also strongly predict choice. Larger cities are associated with a higher probability of choosing a nonprofit school, while higher urbanization rates increase the probability of choosing a for-profit school and reduce the probability of choosing a nonprofit school. Finally, high-ability students choose nonprofit schools more frequently.

Table A.14 in Online Appendix A reports estimates for the outcome equations—i.e., verbal and math scores in 10th grade. The results are consistent with the measurement-system estimates: females perform better than males in verbal but not in math, and parental and geographic variables remain important determinants of academic performance. Again, the factor strongly predicts test scores, with all loadings positive and statistically different from zero.

Distribution of the Unobserved Ability. Figure 1 presents the estimated distribution of unobserved ability. Panel A shows the unconditional distribution, and panel B shows the distribution conditional on secondary school-type choice. The parameter estimates are reported at the bottom of the figure. The densities are based on simulations of 150,000 observations using the estimated covariate coefficients, the estimated distributions of the factor and the error terms, and the sample data. The shape of the unconditional density supports my decision not to impose normality a priori. The estimated mixture probabilities also indicate that all components are needed to approximate the distributions well.

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,

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

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

Goodness of Fit. Tables A.15-A.17 in Online Appendix A show how well the simulated model matches the data. Overall, the model matches actual school-type choices and the first two moments of the measurement system and outcome equation distributions well.

5.3 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) under the value-added (VA) and the value-added augmented with choice shifters (VA-CS) approaches, 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 VA 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 VA-CS estimates indicate smaller effects for attending a for-profit secondary school than the VA estimates (0.029σ in verbal and 0.098σ in math). In contrast, VA-CS estimates for attending a nonprofit secondary school are substantially larger than VA—0.238σ in verbal and 0.341σ in math. These results suggest that the subsample of compliers benefits more from attending a nonprofit school than does the average student, while the opposite is true for the treatment of attending a for-profit school.

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.

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 approaches, using versions of mean equality tests. 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 all four columns of Table 2 provides evidence of treatment effect heterogeneity in the population. Were this not the case, all four estimates would be very similar to each other. By contrast, column (2) shows that compliers' gains are smaller than the average gains in the population for attending a for-profit school, while the opposite is true for attending a nonprofit school. 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 VA, ATE and TT parameters are quite close to each other.

Table 2: Estimated Treatment Effects

			structural model	
	VA	VA-CS	ATE	TT
A. Verbal				
for-profit vs. public	0.058	0.029	0.070	0.067
	(0.011)	(0.030)	(0.002)	(0.006)
nonprofit vs. public	0.144	0.238	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	0.098	0.121	0.115
	(0.010)	(0.031)	(0.002)	(0.005)
nonprofit vs. public	0.226	0.341	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 reports estimates of equation (1) under the value-added approach (VA). Column 2 reports estimates of equation (1) under the value-added approach augmented with choice shifters (VA-CS), using as shifters the availability and average test scores of for-profit and nonprofit schools in the municipality, as well as municipality population size and urbanization rate. Columns 3 and 4 report the Average Treatment Effect (ATE) and Treatment Effect on the Treated (TT) parameters estimated using the structural model. The outcome variables are test scores, measured in standard deviations. Standard errors, reported in parentheses, are clustered at the primary-school level (the school attended in 8th grade) for the VA and VA-CS estimates. Equality of the for-profit and nonprofit effects was tested using linear mean tests in the VA and VA-CS models. For the structural model, these tests were performed as mean tests on the simulated expressions for the ATE and TT parameters.

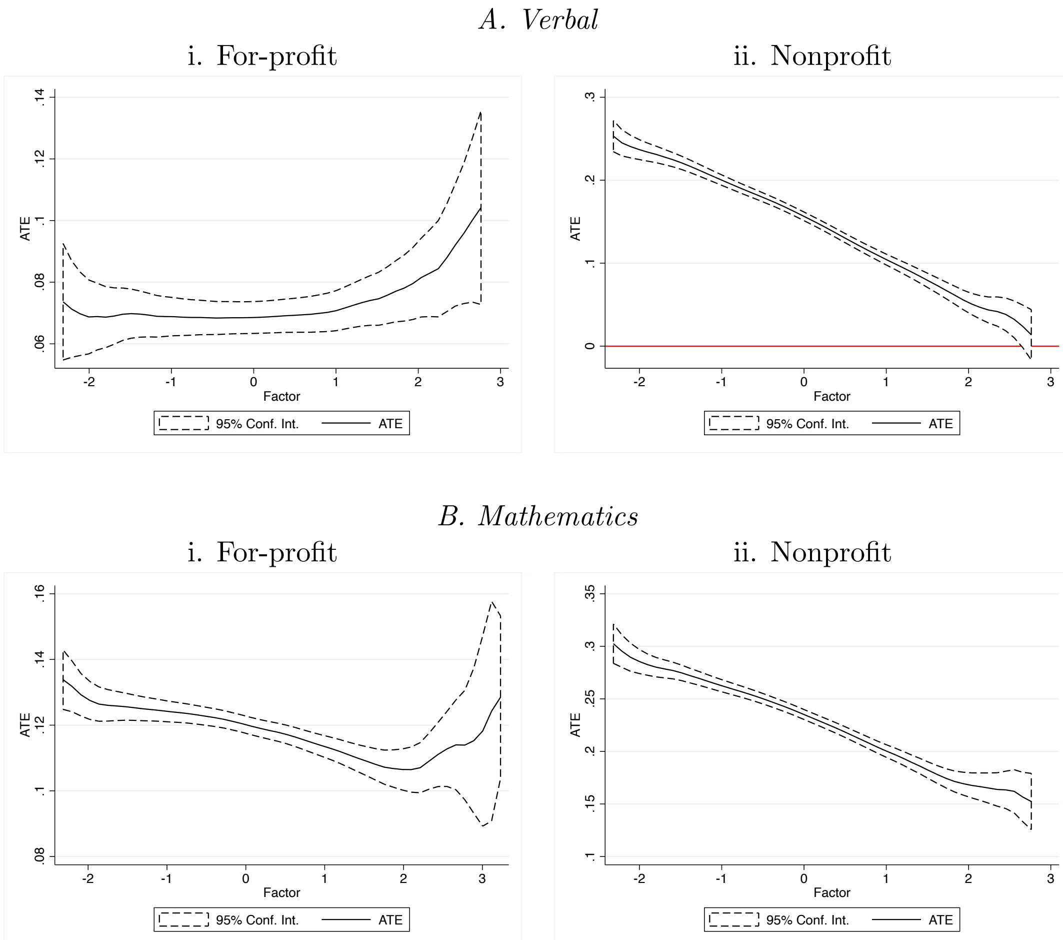
The structural model allows me to further study treatment effect heterogeneity. Figure 2 shows evidence of such heterogeneity along the distribution of unobserved ability. More specifically, it presents the distributional unconditional gains of attending a for-profit (panel A.i and B.i) or a nonprofit (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 for-profit schools, the gains are comparatively compressed, but they are not perfectly flat: while for verbal, they are larger for individuals with the highest ability; for math, they decrease with 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 to a public school, for verbal scores as a function of unobserved ability (factor). Panel B does the same for mathematics. Dashed lines indicate 95% confidence intervals.

In summary, private schools are more effective than public schools at raising learning outcomes. Their effects also vary by profit status, with nonprofit schools generating larger achievement gains than for-profit schools. These findings are robust across both linear and nonlinear models. Moreover, the effects of attending either a for-profit or a nonprofit secondary school are heterogeneous across the population. In particular, compliers to for-profit attendance gain less than the average student, while compliers to nonprofit attendance gain more than the average student.

Heterogeneity with respect to unobserved ability is also clear. Gains from for-profit attendance are comparatively compressed, increasing with ability in verbal and decreasing with ability in mathematics. By contrast, gains from nonprofit attendance are larger for lower-ability students in both subjects.

6 Conclusions

I have studied the relative effectiveness of voucher-subsidized for-profit and nonprofit secondary schools in Chile. I find that both types of private schools are more effective than public schools at improving learning outcomes. Moreover, nonprofit schools are more effective than for-profit schools at raising academic achievement. Treatment effects are robustly heterogeneous. In particular, the average effects for compliers differ from the effects in the general population: compliers to for-profit attendance gain less than the average student, whereas compliers to nonprofit attendance gain more. Heterogeneity with respect to students' inherent ability is also evident: the gains from attending a for-profit secondary school are comparatively compressed, increasing with ability in verbal and decreasing with ability in mathematics, while the gains from attending a nonprofit secondary school are larger for low-ability students than for higher-ability students. Notably, the gains from attending either a for-profit or a nonprofit secondary school are positive at all levels of unobserved ability.

Chile's voucher system has several distinctive features that are worth considering when extrapolating these results to other contexts. First, private-voucher schools receive the same per-student subsidy as public schools. Second, public and subsidized-private schools are subject to the same regulations regarding curriculum and student assessments. Learning assessments are frequent and their results are publicly reported. In addition, teacher incentive programs are equally available to educators in both public and subsidized-private schools. Which of these features matters most in explaining Chile's success in aligning profit-seeking institutions with the government's educational agenda remains an open question for future research. Nevertheless, special attention should be paid to regulations that discipline the behavior of for-profit schools, such as performance requirements for schools that receive public funds.

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