# The Schooling and Labor Market Effects of Vouchers* 

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#### Abstract

We investigate the effects of attending a private-voucher high school on short- and longer-term educational outcomes, namely test scores, college enrollment, and college degree attainment. We do so by estimating a sequential model of schooling decisions and outcomes using data from Chile, a middle-income country with more than thirty of years of experience with a nationwide voucher program. Our model allows for both observed and unobserved characteristics to influence decisions and outcomes, and for heterogeneity in the treatment effect, even after controlling for selection and observed characteristics. We find that attending a voucher high school has positive effects on test scores ( $0.07 \sigma$ and $0.01 \sigma$ in verbal and math, respectively), small effects on college enrollment ( 1.9 p.p.), and no effects on the likelihood of earning a college degree. We also find substantial heterogeneity in the treatment effects, where in general low-ability students benefit more from vouchers than high-ability students. At the moment, we are in the process of merging our current data with labor market records to uncover the effects of vouchers on employment and wages.


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## 1 Introduction

A fundamental question in the literature of educational vouchers relates to the effects that vouchers have on the students who use them (Epple et al., 2017). Consequently, a number of studies have emerged to answer this question, mostly focusing on the short-run test scores effects of attending a voucher school. ${ }^{1}$ The evidence is inconclusive, although the majority of the studies show that vouchers do little to students' performance (Epple et al., 2017). An arguably more important array in this question, but that has attracted much less attention from researchers, is whether vouchers affect longer-term outcomes, such as high-school graduation, college enrollment, college degree attainment, and even labor market outcomes. This paper directly addresses this question by investigating the effects that attending a voucher high school in Chile has on students' performance in college admission exams, college enrollment, and college degree attainment. ${ }^{2}$

Chile is an interesting scenario to study vouchers. With its more than thirty years of experience with a nationwide voucher program, it constitutes one of world's most important large-scale experiments of educational choice (Epple et al., 2017). ${ }^{3}$ Since its inception in 1981, the basic aspects of the system have remained fairly unchanged, with students exercising unrestricted choice among public and subsidized private schools. ${ }^{4}$ Each student is entitled to a voucher that is directly paid to the school of her choice, and that covers all or part of the school's tuition. ${ }^{5}$ Schools, on the other hand, use the vouchers they receive to fund their operations.

In this paper, we posit a sequential model of schooling decisions and outcomes, that incorpo-

[^1]rates all essential decision stages that students face as they go through the educational system, starting with the decision of attending a voucher school. Our model is a generalization of the well-studied Roy model (Roy, 1951; Heckman and Honoré, 1990), where individuals are assumed to make their decisions by comparing the net benefits associated to each of the alternatives at hand. ${ }^{6}$ Further, we allow for both observed and unobserved characteristics to influence decisions and outcomes, and our identification strategy facilitates the interpretation of students' unobserved heterogeneity as a combination of inherent scholastic abilities (Carneiro et al., 2003; Hansen et al., 2004; Heckman et al., 2006a). In addition, the model allows us to recover the distribution of the treatment effects associated to attending a voucher school. ${ }^{7}$

We fit our model to a panel of administrative data from Chile, that tracks individuals from middle school to the completion of their education. We use the model, its estimates, and simulations to compute a variety of treatment parameters for the effects of attending a voucher high school. We also compute the distribution of the corresponding treatment parameters. We find that attending a voucher high school has positive effects on college admission test scores, with average treatment effects of $0.07 \sigma$ and $0.01 \sigma$ for verbal and math, respectively. ${ }^{8}$ We also find positive effects of vouchers on the probability of enrolling in college, with an average treatment effect of 1.9 percentage points (p.p.), out of a base of $57 \%$. Finally, we find that attending a voucher high school increases the probability of graduating from college (conditional on having enrolled in college) for students actually attending voucher high schools in about 1.2 p.p., but decreases such probability for students actually attending public high schools in about $3.3 \mathrm{p} . \mathrm{p}$. We explain this last result by conjecturing that attending a voucher high school increases the chances not only of enrolling in college, but also of enrolling in higher-quality and more academically challenging colleges. In such institutions, graduation strongly depends on students' endowments and family background, which students in public high schools usually lack. We also find substantial

[^2]heterogeneity in the treatment effects, with low-ability students in general benefitting more of attending a voucher school than high-ability students.

This paper contributes to the large literature of educational vouchers. ${ }^{9}$ More specifically, it adds to the small but growing set of papers that study the effects of vouchers on long-term outcomes. The evidence from the United States include Wolf et al. (2010a,b), Chingos and Peterson (2015), and Chingos (2018). Using data from the Washington DC Opportunity Scholarship Program, Wolf et al. (2010a,b) report that, while the program is shown to have no significant impact on short-run test scores, it substantially improved students' chances of graduating from high school, with an estimated effect of about 21 p.p. (from a base of $70 \%$ ). ${ }^{10}$ In contrast, subsequent evidence from the program shows no significant effects on college enrollment (Chingos, 2018). A similar result is found for the New York School Choice Scholarships Foundation (SCSF) Program. Chingos and Peterson (2015) show that the SCSF program had no significant impact on college enrollment or degree attainment for the population of students that received a voucher offer. However, when looking at heterogeneous effects, they find significant effects for some subgroups. In particular, they show that the program increased the likelihood that African Americans enroll in college ( 6 p.p., from a base of $42 \%$ ) and obtain a college degree ( 3 p.p., from a base of $6 \%$ ). The question of why the large effects on high school graduation do not translate into differences in college enrollment and degree attainment for the D.C. program remains a puzzle, and further research should be directed towards finding the mechanisms that help explain this result. Although, some may argue that the real puzzle is on the large high school graduation effects, given the nonexistent impact on short-run test scores. ${ }^{11}$ This paper's evidence from Chile, on the other hand, shows a consistent trend for the voucher effects, where positive effects on test scores

[^3]translate into positive effects on college enrollment and graduation (for treated individuals).
Angrist et al. (2006) look at the long-term effects of the PACES program in Colombia, a government initiative that offered students vouchers to attend private secondary schools in the nineties. This is perhaps the program with the most positive effects in the voucher literature. After a first study showing ninth-grade test score effects of $0.2 \sigma$ (Angrist et al., 2002), Angrist et al. (2006) find that test scores in high-stakes college entrance exams also increased by $0.2 \sigma$ due to the program, and that voucher recipients were 15-20 percent more likely to graduate from high school. Some of the requirements of the PACES program, however, make it difficult to attribute all of the effects of the program to the vouchers alone. In particular, the vouchers were renewable contingent on grade completion, and thus the program included a strong incentive component. The program also required that students had already been accepted in a private school before applying to the program. As a result, not only were the voucher recipients very likely to attend private schools (94\%), but so were the students in the control group (88\%). This is in contrast with our context, where the treatment and counterfactual are clearly defined as using vouchers to attend a private school, and attending a school in the public sector, respectively, as is the case in most of the studies in the literature.

In a study using the Chilean case, Bravo et al. (2010) investigate the long-term effects on schooling and work choices, and earnings, of the introduction of the universal voucher reform in 1981. They fit a structural dynamic model of education and labor market choices and outcomes on a sample of individuals that were differentially exposed to the voucher system while at school, i.e. some students attended school after the new regime was introduced, some experience their schooling both before and after the reform, and others attended school only before the voucher system was in place. Using their simulated model, they show that the reform increased high school graduation and the likelihood of completing at least two years of college. They also show that earnings inequality decreased and lifetime utility increased due to the reform. These results are encouraging, but as is the case with the PACES program, it is hard to disentangle the true
effect of the vouchers from the other components of the reform. ${ }^{12}$ For instance, the reform also included the decentralization of the public schools, and transferred their management from the central government to the municipalities (Gauri, 1998). Lastly, the education and labor sectors were impacted by many other shocks unrelated but contemporaneous to the voucher reform, putting additional noise to the interpretation of the results. ${ }^{13}$

Finally, this paper fits into a literature that uses structural and semi-structural models to estimate economically interpretable and policy-relevant treatment effects. This literature uses a variety of sources of identification, including exclusion restrictions, conditional independence assumptions about unobservables, and functional form assumptions. It also identifies causal effects at well-defined margins of choice, and can evaluate the impacts of policies that have not yet been implemented (Heckman, 2010; Heckman and Urzua, 2010; Heckman et al., 2016b). This paper's methodology is closest to Aakvik et al. (2005), Sarzosa and Urzúa (2015), Heckman et al. (2016b), Rodríguez et al. (2016), and Prada and Urzúa (2017) in that literature.

## 2 Chile's Universal Voucher System: A Brief Overview

Since 1981, Chile's educational system operates under a nationwide voucher agenda. It combines families' preferences with (public and private) schools competition for attracting students. Funding comes from the government, that pays voucher subsidies directly to the schools. Residential restrictions are nonexistent, and therefore students can attend any school that they are willing to travel to (and pay for).

For the period that our data spans, the educational system operated under a universal voucher design. That is, all public and almost all private schools participate in the program, which implies that they fund their operations through a per-student voucher subsidy that they receive directly from the government. Participating private schools are also allowed to charge a complementary

[^4]fee to parents, although only about half of them opt to do so (Gazmuri, 2015). Every student, poor and rich, is entitled to a voucher that can be used to pay part or all of the tuition charged by voucher schools.

A third group of schools exists, and includes private schools that do not participate in the voucher program, and therefore do not receive subsidies from the government. Students cannot use their vouchers to offset tuition at these schools, and as a result the fees charged by the nonvoucher schools are about ten times higher than the fees charged by the private-voucher schools (Sánchez, 2018b). The share of students attending the non-voucher schools is only about $8 \%$ (Bravo et al., 2010; Sánchez, 2018a). For our empirical analysis, we follow the standard practice in the related literature, and disregard this group of schools (Contreras et al., 2010; Lara et al., 2011; Correa et al., 2014). We therefore focus our analysis only on the public and private-voucher schools, that include all of the schools that are part of the voucher system, and that enroll more than $90 \%$ of the student population. ${ }^{14}$

## 3 Data

Our sample consists in the universe of 8th grade students enrolled in public primary schools that do not offer secondary grades, in the year 2000. The majority of these students are 14 years old by then. We follow these students through high school. Once graduated from high school, we observe whether they take the national college admission exams, and if so their performance on the exams. Then, regardless of whether they take the admission exams, we observe whether they enroll in college. Lastly, for students enrolled in college, we observe whether they complete their degree on or before their 30th birthday (year 2016).

To understand our selection criteria, it is worth noting some institutional aspects of Chile's education system. Primary education consists in grades 1st-8th, and secondary education consists in grades 9 th-12th. Schools, public and private, offer either only primary education grades, only

[^5]secondary education grades, or both primary and secondary education grades. As a consequence, students enrolled in schools offering only primary grades are forced to choose a new school to pursue their secondary education. The new school may be one that offers only secondary education grades or both primary and secondary education grades. For these students (and their families), the period right after completing 8th grade is of intensive school shopping. This is in contrast with students enrolled in schools offering both primary and secondary grades, where the end of 8th grade is not too different than the end of 7 th or 9 th grades, and consequently the majority of these students continue their secondary education in the same school they attend in 8th grade. For this reason, and since we are interested in students' high school decisions, we restrict our analysis to students enrolled in schools offering only primary education grades. Furthermore, we follow Lara et al. (2011), and drop students enrolled in private primary schools. Thus we focus our analysis on arguably the most vulnerable students, for whom the public policy lessons we draw from this paper are most relevant. Additionally, and as discussed in section 2, we follow the related literature and disregard students enrolling in private-non-voucher high schools (Contreras et al., 2010; Lara et al., 2011; Correa et al., 2014). These schools do not take up vouchers and have strict admission requirements, and therefore are not part of the school choice framework of public and private-voucher schools. Only about $2 \%$ of students in primary public schools that do not offer secondary grades pursue their secondary education in a private-non-voucher high school. Next, and because we do not have information on the high school attended for students that do not earn a high school diploma, we decide to disregard these students. They represent about $13 \%$ of students. In a final step, we only keep observations with no missing covariates. This last step brings our final sample size from 95,802 to 66,009 .

Our data come from the national standardized exams for primary and secondary education levels (SIMCE), the censuses of students and schools, the national standardized college admission exams (PSU), the census of students attending higher education institutions, and the census of students earning a higher education degree. We use several years for each of these data sets, spanning the period 1998-2016. In addition, we use data from the 2003, 2006, and 2009
versions of the national household survey (CASEN) to construct the instruments we use as part of our identification strategy. These variables relate to the local availability of private-voucher schools, local labor market tightness and opportunities, and local availability of higher education institutions. See appendix A for a more detailed description of each of the data sets we use.

## 4 A Sequential Model of Schooling Decisions and Out-

## comes

We postulate a model of sequential schooling decisions, that starts with the choice of whether to enroll in a private-voucher or public high school, and is followed by all major schooling decisions the student makes thereon, including taking the college admission exams, enrolling in college, and obtaining a college degree. Figure 1 displays the complete diagram of the decisions incorporated in our model. We adjoin students' performance in the college admission exams to our sequential schooling decisions model.

Figure 1: Diagram of Sequential Schooling Decisions


Notes: This figure displays the multistage decision process we incorporate in our model. Node $D_{1}$ relates to the decision of attending a private-voucher or a public high school. Nodes $D_{2}$ and $D_{3}$ relate to the decision of whether to take the college admission exams. Nodes $D_{4}-D_{7}$ relate to the decision of whether to enroll in college. Nodes $D_{8}-D_{11}$ relate to the decision of whether to graduate from college. A terminal node is denoted by a dot at the end of a branch.

Our model is a generalization of the Roy framework (Roy, 1951; Heckman and Honoré, 1990).
We characterize each schooling decision using a flexible discrete choice model, and recognize that
individuals make decisions by taking into account the consequences of their choices. In that sense, our model approximates a dynamic discrete choice model without being explicit about the precise rules used by individuals or about their information sets. ${ }^{15}$ On the other hand, and similar to reduced-form strategies, we use exclusion restrictions as a source of identification. However, unlike that literature, we are able to define a variety of treatment effects at well-defined margins of choice. We also allow for unobserved heterogeneity to play a key role in determining choices and outcomes. Moreover, we are able to interpret the unobserved heterogeneity as a combination of students' inherent scholastic abilities, following the identification argument in Carneiro et al. (2003), and Hansen et al. (2004). ${ }^{16}$

### 4.1 Schooling Decisions and Counterfactual Outcomes

Let $D_{j^{\prime} \mid j}$ denote the decision of attaining schooling level $j^{\prime}$ given that the student attained schooling level $j$. For instance, $D_{j^{\prime} \mid j}$ may denote the decision of graduating from college given that the student enrolled in college (nodes $D_{8}-D_{11}$ in Figure 1). The optimal decision process is assumed to be characterized by an index threshold-crossing model,

$$
D_{j^{\prime} \mid j}= \begin{cases}1 & \text { if } I_{j^{\prime} \mid j} \geq 0 \\ 0 & \text { otherwise }\end{cases}
$$

where $I_{j^{\prime} \mid j}$ is the perceived value of attaining schooling level $j^{\prime}$ for a student with schooling level $j$.

In addition, we model performance in college admission exams for individuals deciding to take the exams. In the context of our application and diagram of decisions (Figure 1), let $Y_{j^{\prime}}^{k}$ be the score in exam of subject $k$ for a student attaining schooling level $j^{\prime} \in\{4,6\}$ (i.e. deciding to take

[^6]the exams). Then,
$$
Y^{k}=D_{j^{\prime} \mid j} Y_{j^{\prime}}^{k}, \quad \text { for } j^{\prime}=4,6 \text { and } j^{\prime} \mid j \in\{4 \mid 2\} \cup\{6 \mid 3\}
$$
is the observed exam $k$ score. In other words, the scores are observed only if the student reaches node $j^{\prime} \in\{4,6\}$.

### 4.2 Parameterization and Assumptions About Unobservables

We use a linear-in-the-parameters model to approximate student's perceived value of transitioning from schooling level $j$ to schooling level $j^{\prime}$,

$$
I_{j^{\prime} \mid j}=Z_{j^{\prime} \mid j} \gamma_{j^{\prime} \mid j}+\theta \lambda_{j^{\prime} \mid j}+\nu_{j^{\prime} \mid j},
$$

where $Z_{j^{\prime} \mid j}$ is a vector of contemporaneous observed variables that affect the schooling decision, $\theta$ is student's unobserved (to the econometrician) heterogeneity, and $\nu_{j^{\prime} \mid j}$ is an idiosyncratic error term. Notice that we do not impose forward-looking behavior or any type of rationality, which adds flexibility to our model, at the cost of not being able to identify fully structural preference parameters.

We also use a linear-in-the-parameters formulation to model the performance in college admission exams,

$$
Y_{j^{\prime}}^{k}=X^{Y} \beta_{k}+\theta \alpha_{k}+\eta_{j^{\prime}}^{k},
$$

where $X^{Y}$ is a vector of observed variables determining test scores, and $\eta_{j^{\prime}}^{k}$ is an idiosyncratic error term.

The individual's unobserved heterogeneity plays an important role in our methodology. ${ }^{17}$ In particular, we assume that, after controlling for observables, the unobserved heterogeneity drives all statistical dependence between the equations in our model. That is, if the researcher were

[^7]able to observe $\theta$, she could use matching on $(Z, X, \theta)$ to fully identify the model (Carneiro et al., 2003). ${ }^{18}$

Let $\Perp$ denote statistical independence. We assume that, conditional on $(Z, X)$,

$$
\begin{aligned}
\nu_{j^{\prime} \mid j} \Perp \nu_{j^{\prime \prime \prime} \mid j^{\prime \prime}}, & \text { for any } j^{\prime}\left|j \neq j^{\prime \prime \prime}\right| j^{\prime \prime} \\
\eta_{j^{\prime}}^{k} \Perp \eta_{j^{\prime}}^{k^{\prime}} \Perp \eta_{j^{\prime \prime}}^{k^{\prime}}, & \text { for any } j^{\prime} \neq j^{\prime \prime}, k \neq k^{\prime} \\
\nu \Perp \eta, & \\
(\nu, \eta) \Perp \theta, &
\end{aligned}
$$

where $\nu$ is the stacked vector of all $\nu_{j^{\prime} \mid j}$ terms, and $\eta$ is the stacked vector of all $\eta_{j^{\prime}}^{k}$ terms. In addition, we assume that all unobservables are statistically independent from the observable variables, i.e $(\nu, \eta, \theta) \Perp(Z, X)$.

### 4.3 Measurement System for the Unobserved Heterogeneity

We adjoin to our model a measurement system of equations to help identify the distribution of the unobserved heterogeneity, $\theta$, as well as to facilitate its interpretation. Notice that the use of a measurement system is not strictly necessary for the model of schooling decisions and outcomes to be identified, and we could instead treat the unobserved heterogeneity as a nuisance or random effect, as is usual in the structural literature (see, e.g., Keane and Wolpin, 1997, and Aguirregabiria and Mira, 2010). However, the use of a measurement system allows us to give a clear interpretation to the unobserved factor as a proxy of the measurements (Carneiro et al., 2003; Hansen et al., 2004).

The measurement system is given by,

$$
M_{l}=X^{M} \delta_{l}+\theta \psi_{l}+\epsilon_{l},
$$

[^8]where $M_{l}$ is the $l$-th measurement, $X^{M}$ is a vector of observed variables determining the measurement, and $\epsilon_{l}$ is an idiosyncratic error term. Notice that the measurements do not depend on the schooling levels, and therefore are observed for all students independent of their schooling choices. In practice, we use measurements taken before the student makes the decisions relevant to our model.

In addition to the independence assumptions mentioned above, we assume that $\epsilon_{l} \Perp \epsilon_{l^{\prime}} \mid(Z, X)$ for any $l \neq l^{\prime}$, and that $\epsilon_{l} \Perp(Z, X, \theta, \nu, \eta)$.

### 4.4 Identification

The main argument for identification of our model uses a version of matching, and follows Heckman et al. (2016a). If $\theta$ were observed, then we could condition on $(Z, X, \theta)$, and identify all parts of the model. Since $\theta$ is not observed, we use the measurement system to proxy $\theta$, and allow for measurement error captured by $\epsilon=\left(\epsilon_{1}, \ldots, \epsilon_{L}\right)$. Using the conditions presented in Heckman et al. (2016a), we can nonparametrically identify our model, including the distributions of $\theta$ and $\epsilon$. This last part in the identification requires that we have at least three measurement equations for a one-dimensional factor structure. ${ }^{19}$ In practice, we use four measurements.

The factor loadings are identified up to a normalization. We set one of the loadings in the measurement system to be equal to one, which anchors the scale of the factor.

We also benefit from the use of instruments, that is, variables that shift the schooling decisions but that do not enter the outcome equations. This identification argument works even without imposing a factor structure in the error terms or invoking the independence conditional on ( $Z, X, \theta$ ) assumption. See Heckman et al. (2016a) and the papers cited therein for a formal proof of identification of a general version of a model that shares the characteristics of ours.

[^9]
### 4.5 Estimation

We estimate the model by maximum likelihood. The conditional on $(Z, X, \theta)$ independence of the error terms assumption is key when constructing the likelihood function, which is given by,

$$
\begin{aligned}
\mathcal{L} & =\prod_{i=1}^{N} \int f\left(Y_{i}, D_{i}, M_{i} \mid Z_{i}, X_{i}, \theta\right) f(\theta) d(\theta) \\
& =\prod_{i=1}^{N} \int f\left(Y_{i}, D_{i} \mid Z_{i}, X_{i}, \theta\right) f\left(M_{i} \mid X_{i}, \theta\right) f(\theta) d(\theta)
\end{aligned}
$$

where $f(\cdot)$ denotes a probability density function, and we integrate over the distribution of the unobserved factor. We assume mean zero normal distributions for the error terms, and approximate the distribution of the factor using a mixture of two normals. That is,

$$
\theta \sim p N\left(\mu_{1}, \sigma_{1}^{2}\right)+(1-p) N\left(\mu_{2}, \sigma_{2}^{2}\right),
$$

where we constrain the factor mean to be zero, and $p \in[0,1]$.
We perform the estimation in two stages. First, we estimate the measurement system and factor distribution parameters, using the following first-stage likelihood function,

$$
\mathcal{L}^{1}=\prod_{i=1}^{N} \int f\left(M_{i} \mid X_{i}, \theta\right) f(\theta) d(\theta)
$$

We obtain estimates $\hat{f}\left(M_{i} \mid X_{i}, \theta\right)$ and $\hat{f}(\theta)$, which we use to form the second-stage likelihood function,

$$
\mathcal{L}^{2}=\prod_{i=1}^{N} \int f\left(Y_{i}, D_{i} \mid Z_{i}, X_{i}, \theta\right) \hat{f}\left(M_{i} \mid X_{i}, \theta\right) \hat{f}(\theta) d(\theta) .
$$

By proceeding the estimation in two stages, we reduce the computational time, but also ensure that the estimation of the factor distribution is done using only the measurement system, which reinforces the interpretation of the unobserved factor as a proxy of the measurements. Moreover,
since the schooling decisions, $D$, and outcomes, $Y$, are independent of the measurement system, $M$, conditional on ( $Z, X, \theta$ ), we obtain consistent estimates.

We use the Gauss-Hermite quadrature for integration, and correct the second-stage standard errors following the procedure suggested by Murphy and Topel (1985). ${ }^{20}$

### 4.6 Definition of Treatment Effects

The model just described identifies distributions for counterfactual outcomes. We use these counterfactuals to construct treatment effect parameters. In our context, treatment is attending a private-voucher high school in lieu of a public high school. The relative gain an individual gets from attending a private-voucher school is $Y_{1}-Y_{0}$. Our model allows us to obtain the distribution of those gains over the entire population of students. We further define three different treatment effects by averaging those gains over different subsets of the population (Heckman et al., 2001; Aakvik et al., 2005).

The average treatment effect (ATE) is defined by averaging the treatment gains over the entire student population,

$$
A T E=\iint E\left(Y_{1}-Y_{0} \mid X=x, \theta=\bar{\theta}\right) d F_{X, \theta}(x, \bar{\theta}) .
$$

The average treatment effect on the treated (TT) is defined by averaging the treatment gains over the subset of students that actually choose to be treated,

$$
T T=\iint E\left(Y_{1}-Y_{0} \mid X=x, \theta=\bar{\theta}, D=1\right) d F_{X, \theta \mid D=1}(x, \bar{\theta}),
$$

where $D=1$ denotes receipt of the treatment. This treatment effect informs the average gain for students that endogenously choose to be treated, and it has particular policy relevance whenever a policymaker is interested in knowing the effect of a policy that has a strong self-selection component. That is the case of the voucher policy we study. Notice that this treatment effect

[^10]is generally different from what IV identifies in a context of heterogeneous treatment effects (i.e. LATE), but offers an arguably clearer interpretation (Heckman et al., 2001, 2006b; Heckman and Vytlacil, 2007).

The average treatment effect on the untreated (TUT) is defined by averaging the treatment gains over the subset of students that actually choose not to be treated,

$$
T U T=\iint E\left(Y_{1}-Y_{0} \mid X=x, \theta=\bar{\theta}, D=0\right) d F_{X, \theta \mid D=0}(x, \bar{\theta})
$$

where $D=0$ denotes non-receipt of the treatment. This treatment effect informs the average gain for students that endogenously choose not to be treated. It has particular policy relevance whenever a policymaker is, for example, considering an expansion of an existing policy, which is expected to cover a larger share of the population than it actually does.

## 5 Empirical Implementation

### 5.1 Schooling Decisions

As displayed in Figure 1, we model four levels of schooling choices the students make through the course of their education: enrolling in a private-voucher high school in lieu of a public high school, taking the college admission exams, enrolling in college, and graduating from college (for students enrolled in college). Table 1 displays summary statistics for the schooling choices observed in our sample (students that attended primary public schools offering only primary grades). About a third of students enroll in private-voucher high schools. $47 \%$ of students take the college admission exams. $57 \%$ of students enroll in a higher education institution. Notice that the higher share of individuals enrolling in college than taking the admission exams reflects the fact that most, but not all, higher education institutions require applicants to take the admission exams, and therefore there is a number of students that enroll in college even without taking the
exams. ${ }^{21}$ About a third of students in our sample earn a higher education degree. Lastly, there is a considerable number of students that drop out from college. More precisely, of the students ever enrolled in college, only $55 \%$ are able to graduate (i.e finish their degree).

Table 1: Summary Statistics - Endogenous Variables

|  | mean | std. dev. | $\min$ | $\max$ |
| ---: | :---: | :---: | :---: | :---: |
| schooling decisions: |  |  |  |  |
| voucher high school | 0.36 | 0.48 | 0.00 | 1.00 |
| take college admission exams | 0.47 | 0.50 | 0.00 | 1.00 |
| college enrollment | 0.57 | 0.49 | 0.00 | 1.00 |
| college degree $^{a}$ | 0.32 | 0.46 | 0.00 | 1.00 |
| college graduation $^{b}$ | 0.55 | 0.50 | 0.00 | 1.00 |
|  |  |  |  |  |
| college admission exams: $^{\text {a }}$ verbal | -0.42 | 0.88 | -3.13 | 2.90 |
| math | -0.43 | 0.86 | -3.18 | 3.17 |
|  |  |  |  |  |
| measurement system: |  |  |  |  |
|  | verbal | -0.11 | 0.91 | -2.81 |
| math | -0.11 | 0.91 | -2.68 | 2.63 |
| social sciences | -0.11 | 0.92 | -2.79 | 3.06 |
| natural sciences | -0.11 | 0.92 | -2.76 | 2.81 |

Notes: This table displays summary statistics for the set of endogenous variables used in the empirical implementation of our model. Test scores, both from college admission exams and the measurement system, are normalized to have mean zero and standard deviation one in the entire population of test takers. ${ }^{a}$ College degree is a dummy for earning a college degree, unconditional on college enrollment. ${ }^{b}$ College graduation is a dummy for graduating from college, conditional on having enrolled in college.

### 5.2 Outcomes

We consider the following outcomes: college admission test scores, college enrollment, and college graduation (conditional on having enrolled in college). The college admission tests are not mandatory, but are key in determining students' chances of attending college, and therefore the majority of students willing to pursue higher education take them. The battery of admission

[^11]exams consist of two obligatory tests, verbal and mathematics, and two optative tests, social sciences, and sciences (biology, chemistry, physics). We consider only verbal and mathematics exams in our analysis, and normalize the scores in each subject to have mean zero and standard deviation one among all test takers (including students that are not part of our sample). Table 1 displays summary statistics for the college admission test scores in our sample. Both verbal and math distributions have negative means, $-0.42 \sigma$ and $-0.43 \sigma$, respectively, indicating that the students in our sample perform on average worse than the average student in the entire population of test takers.

The outcomes of enrolling in college, and graduating from college are part of the schooling choices in our model, and were analyzed above.

### 5.3 Measurement System

For the measurement system, we use the 8 th grade national standardized exams taken in 2000, which was the first year these tests were administered. ${ }^{22}$ The exams are mandatory for all students in 8th grade, and evaluate knowledge in four subjects: verbal, mathematics, social sciences, and natural sciences. We include all four tests as part of our measurement system. These tests help us identify the distribution of the unobserved heterogeneity in our model, and allow us to interpret the unobserved factor as a combination of student's inherent scholastic abilities. In the remainder of the paper, we also refer to the unobserved heterogeneity as ability.

We normalize each test score distribution to have mean zero and standard deviation one in the entire population of test takers. Table 1 displays summary statistics for the tests that are part of the measurement system. All four tests have a sample mean of $-0.11 \sigma$, which tell us that on average the students in our sample perform worse than the students in the entire population.

[^12]
### 5.4 Covariates

The exogenous variables we use in our model's equations mostly reflect socio-economic characteristics, and are common in the related education/labor literature (see, e.g., Altonji (1993), Heckman et al. (2006a), Heckman et al. (2016b), Walters (2017)). Table 2 lists the covariates we use, and displays summary statistics for each of them. The variables for gender, parents' education, and broken home are measured when the students is 14 years old. The variable for broken home is a dummy that takes the value of one if no parent or only one of them resides in the student's home, and zero otherwise. Income per capita variables are measured at the household level, represent monthly figures, and are in US\$ as of the year 2000. Half of our sample consists in male students. Both mothers and fathers have on average 9 years of schooling, which represents having graduated from primary but not from secondary education. Average monthly income per capita is around US\$42-62. Lastly, about a fifth of the students in our sample reside in the country's Northern region, and about half of the students reside in the Central region. The rest reside in the South. Notice that we observe income per capita and region of residence at ages 14 and 18.

Table 2: Summary Statistics - Exogenous Variables

|  |  | mean | std. dev. | min | max |
| ---: | :---: | :---: | :---: | :---: | :---: |
| covariates: |  |  |  |  |  |
| mother's education | 0.50 | 0.50 | 0.00 | 1.00 |  |
| father's education | 9.4 | 3.3 | 0.0 | 22.0 |  |
| broken home | 0.26 | 0.44 | 0.0 | 22.0 |  |
| log income per capita (age 14) | 3.73 | 0.84 | 1.06 | 1.00 |  |
| log income per capita (age 18) | 4.13 | 0.58 | 1.92 | 7.47 |  |
| region: north (age 14) | 0.18 | 0.38 | 0.00 | 1.00 |  |
| region: center (age 14) | 0.48 | 0.50 | 0.00 | 1.00 |  |
| region: north (age 18) | 0.18 | 0.38 | 0.00 | 1.00 |  |
| region: center (age 18) | 0.48 | 0.50 | 0.00 | 1.00 |  |
|  |  |  |  |  |  |
| \% voucher schools in municipality | 0.54 | 0.24 | 0.00 | 1.00 |  |
| exclusion restrictions: |  |  |  |  |  |
| $\Delta$ local unemployment (high-low skill, age 17) | -0.05 | 0.06 | -0.27 | 0.26 |  |
| $\Delta$ local log wage (high-low skill, age 17) | 0.74 | 0.31 | -0.39 | 2.55 |  |
| $\Delta$ local unemployment (high-low skill, age 20) | -0.03 | 0.06 | -0.30 | 0.46 |  |
| $\Delta$ local log wage (high-low skill, age 20) | 0.74 | 0.28 | -0.21 | 2.13 |  |
| $\Delta$ local unemployment (high-low skill, age 23) | -0.04 | 0.06 | -0.30 | 0.33 |  |
| $\Delta$ local log wage (high-low skill, age 23) | 0.69 | 0.27 | -0.13 | 2.15 |  |
| college in municipality (age 21) | 0.61 | 0.49 | 0.00 | 1.00 |  |

Notes: This table displays summary statistics for the covariates used in our model. The variables for gender, parents' education, broken home, and $\%$ of voucher schools in the municipality are measured when the students is 14 years old. The variable for broken home is a dummy that takes the value of one if no parent or only one of them resides in the student's home, and zero otherwise. Income per capita variables are measured at the household level, represent monthly figures, and are in $\log$ US\$ as of the year 2000. The variable for $\%$ of voucher schools in the municipality refers to the local availability of private-voucher high schools, and the reported figure is calculated taking into account private-non-voucher high schools. The variables for local unemployment and wages are differences in averages between high-skilled workers and low-skilled workers. The variable for presence of a college in the municipality is a dummy that is equal to one if there is one or more colleges in the student's municipality of residence, and zero otherwise.

### 5.5 Exclusion Restrictions

As stated in Section 4.4, our model is nonparametrically identified without the need of exclusion restrictions, and invoking a form of conditional independence assumption on mismeasured variables. However, we could also identify all parameters in our model with the use of node-specific
instruments, or variables that shift the schooling choices but that do not enter the outcome equations. With instruments, identification is secured even without relying on the matching-like assumption just mentioned.

We use a variety of instruments that shift the schooling decisions. Table 2 lists these instruments, and provide summary statistics for each of them. The variable for the percentage of voucher high schools in the municipality is measured when the student is 14 years old. The variables for local unemployment and wages are differences between high-skilled and low-skilled municipality averages. The variable for presence of a college in the municipality is a dummy that is equal to one if there is one or more colleges in the student's municipality of residence, and zero otherwise. On average, students live in a municipality where $54 \%$ of high schools are privatevoucher. Local unemployment rates for high-skilled individuals are on average 3-4 percentage points lower than local unemployment rates for low-skilled workers. On average, local wages for high-skilled workers are about twice as high as the wages earned by low-skilled workers. Lastly, $61 \%$ of students at age 21 reside in a municipality where one or more colleges are present. Notice that we observe many of the instruments at different moments in the course of the student's education.

Finally, Table 3 displays the exact inclusion of the covariates and instruments in the various equations of our model.
Table 3: Variables Used in the Empirical Analysis

|  | measurement system | choices: |  |  |  | outcomes: test scores |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | $D_{1}$ | $D_{2}-D_{3}$ | $D_{4}-D_{7}$ | $D_{8}-D_{11}$ |  |
| covariates: |  |  |  |  |  |  |
| male | Y | Y | Y | Y | Y | Y |
| mother's education | Y | Y | Y | Y | Y | Y |
| father's education | Y | Y | Y | Y | Y | Y |
| broken home | Y | Y | Y | Y | Y | Y |
| log household income per capita (age 14) log household income per capita (age 18) | Y | Y | Y | Y | Y | Y |
| region: north (age 14) | Y | Y |  |  |  |  |
| region: center (age 14) | Y | Y |  |  |  |  |
| region: north (age 18) |  |  | Y | Y | Y | Y |
| region: center (age 18) |  |  | Y | Y | Y | Y |
| exclusion restrictions: |  |  |  |  |  |  |
| \% voucher schools in municipality |  | Y |  |  |  |  |
| $\Delta$ local unemployment (high-low skill, age 17) |  |  | Y |  |  |  |
| $\Delta$ local log wage (high-low skill, age 17) |  |  | Y |  |  |  |
| $\Delta$ local unemployment (high-low skill, age 20) |  |  |  | Y |  |  |
| $\Delta$ local log wage (high-low skill, age 20) |  |  |  | Y |  |  |
| $\Delta$ local unemployment (high-low skill, age 23) |  |  |  |  | Y |  |
| $\Delta$ local log wage (high-low skill, age 23) |  |  |  |  | Y |  |
| college in municipality (age 21) |  |  | Y | Y |  |  |
| unobserved heterogeneity: |  |  |  |  |  |  |
| factor | Y | Y | Y | Y | Y | Y |

Notes: This table shows the allocation of the covariates and exclusion restrictions used in the various equations of our model. The symbol Y means that the variable is included in the corresponding equations. The variables for gender, parents' education, broken home, and $\%$ of voucher schools in the municipality are measured when the students is 14 years old. The variable for broken home is a dummy that takes the value of one if no parent or only one of them resides in the student's home, and zero otherwise. Income per capita variables are measured at the household level, and represent monthly figures. The variable for $\%$ of voucher schools in the municipality refers to the local availability of private-voucher high schools, and the reported figure is calculated taking into account private-non-voucher high schools. The variables for local unemployment and wages are differences in averages between high-skilled workers and low-skilled workers. The variable for presence of a college in the municipality is a dummy that is equal to one if there is one or more colleges in the student's municipality of residence, and zero otherwise.

## 6 Results

### 6.1 Estimates

### 6.1.1 Distribution of the Unobserved Heterogeneity

Figure 2 displays the estimates for the distribution of the unobserved heterogeneity. It also plots the estimated distribution. A first look at the plotted distribution suggests its departure from the normal distribution. In particular, the estimated distribution presents two modes, one positive and one negative. This result confirms our approach of allowing for a degree of flexibility in the distribution of the factor.

Figure 2: Distribution of Ability


Notes: This figure displays the estimated distribution of the unobserved factor. Estimated parameters were obtained from a maximum likelihood procedure on the measurement system.

### 6.1.2 Measurement System

The estimates for the measurement system are reported in Table 4. Consistent with other studies for the case of Chile, we find that female students outperform males in verbal, but the opposite occurs in math. ${ }^{23}$ A gender effect also exists in social sciences, favoring males. Both mother's

[^13]and father's education are strong determinant of students' performance, although the effect of mother's education is estimated to be stronger in all subjects. Residing in a household without both parents being present does not affect test scores. That is not the case for household's income per capita, which increases students' performance. Residing in the Southern region also increases test scores. Finally, the unobserved ability factor is estimated to be a strong determinant of test scores, playing a comparable role in all subjects.

Table 4: Estimates - Measurement System

| subject: | verbal |  | math |  | social sciences |  | natural sciences |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | coef. | std. err. | coef. | std. err. | coef. | std. err. | coef. | std. err. |
| male | -0.226 | 0.007 | 0.055 | 0.007 | 0.154 | 0.007 | -0.003 | 0.007 |
| mother's education | 0.034 | 0.001 | 0.031 | 0.001 | 0.032 | 0.001 | 0.027 | 0.001 |
| father's education | 0.022 | 0.001 | 0.022 | 0.001 | 0.024 | 0.001 | 0.020 | 0.001 |
| broken home | 0.004 | 0.008 | -0.004 | 0.008 | 0.007 | 0.008 | 0.004 | 0.008 |
| log income per capita | 0.042 | 0.004 | 0.036 | 0.004 | 0.054 | 0.004 | 0.034 | 0.004 |
| region: north | -0.070 | 0.010 | -0.076 | 0.010 | -0.077 | 0.010 | -0.093 | 0.010 |
| region: center | -0.108 | 0.007 | -0.108 | 0.007 | -0.092 | 0.008 | -0.120 | 0.008 |
| constant | -0.592 | 0.017 | -0.687 | 0.017 | -0.845 | 0.017 | -0.594 | 0.018 |
| factor | 1.000 | - | 0.932 | 0.005 | 0.950 | 0.005 | 0.985 | 0.005 |
| $\log (\sigma)$ |  |  |  |  |  |  |  |  |
|  | -0.674 | 0.003 | -0.550 | 0.003 | -0.565 | 0.003 | -0.583 | 0.003 |
| observations |  |  |  |  |  |  |  | 66,009 |

Notes: This table reports the estimated coefficients of the maximum likelihood procedure on the measurement system. All variables are measured when the students is 14 years old. The variable for broken home is a dummy that takes the value of one if no parent or only one of them resides in the student's home, and zero otherwise. The variable for income per capita is measured at the household level, represents monthly figures, and is in $\log$ US $\$$ as of the year 2000 . The factor loading for verbal is normalized to be equal to one. All tests are taken in 8th grade, and are normalized to have mean zero and standard deviation one in the entire population of test takers. The variable $\log (\sigma)$ is the natural logarithm of the standard deviation of the corresponding test's distribution.

### 6.1.3 Schooling Decisions

Estimates for the decision of attending a private-voucher high school in lieu of a public high school are presented in Table 5. This decision corresponds to node $D_{1}$ in Figure 1. Males are more likely to enroll in a voucher high school. Higher levels of mother's education increases the likelihood
that a student attends a voucher high school. The effect of father's education is not statistically different from zero. Higher levels of household income also increase the likelihood of attending a voucher school. Residing in the Northern region decreases the chances of going to a private school, and the opposite occurs with residency in the Central region; all, relative to residing in the South. Notice that the exclusion restriction, which captures local availability of voucher high schools, is a strong determinant of the decision. Lastly, higher levels of the unobserved ability increase the likelihood of enrolling in a voucher school.

Table 5 also reports the estimates for the decision of taking the college admission exams, which corresponds to the nodes $D_{2}$ and $D_{3}$ in Figure 1. Female students are more likely to take the admission exams. Both mother's and father's education increase the likelihood of taking the exams. Not having both parents at home reduces such chances. Higher levels of household's income increase the likelihood of taking the exams. The regional dummies estimates are statistically significant, with a positive sign for students in voucher high schools and a negative sign for students in public high schools. We use three exclusion restrictions in these schooling choices. The first one is the difference between the local unemployment rate of high-skilled workers and the local unemployment rate of low-skilled workers. The corresponding estimated coefficients are not too precise, but are of negative sign, meaning that higher rates of high-skilled unemployment (relative to low-skilled unemployment) lead to fewer individuals to take the college admission exams. The second instrument we use in these equations is the difference between the local log wage of high-skilled workers and the local log wage of low-skilled workers. The estimated coefficients are statistically significant, and negative for students in voucher high schools and positive for students in public high schools. A positive coefficient indicates that a higher wage differential increases student's likelihood of taking the college admission exams. Our third instrument is the local availability of a higher education institution. The corresponding estimated coefficients are statistically significant, and positive for students in voucher high schools and negative for students in public high schools. A positive coefficient indicates that local availability of college increases the likelihood of taking the college admission exams. Lastly, the loading for the unobserved abil-
ity factor is strongly positive, meaning that higher levels of ability increase the chances of taking the admission exams.

Table 5: Estimates - Schooling Decisions $D_{1}, D_{2}, D_{3}$

| conditional on: decision node: | $D_{1}$ : voucher school |  | $D_{1}=1$ <br> $D_{2}$ : take exams |  | $\overline{D_{1}=0}$ <br> $D_{3}$ : take exams |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | coef. | std. err. | coef. | std. err. | coef. | std. err. |
| male | 0.084 | 0.010 | -0.233 | 0.018 | -0.278 | 0.014 |
| mother's education | 0.008 | 0.002 | 0.090 | 0.003 | 0.093 | 0.003 |
| father's education | 0.001 | 0.002 | 0.071 | 0.003 | 0.066 | 0.002 |
| broken home | -0.012 | 0.012 | -0.093 | 0.021 | -0.055 | 0.015 |
| log household income per capita (age 14) | 0.107 | 0.007 | - | - | - | - |
| log household income per capita (age 18) | - | - | 0.147 | 0.017 | 0.050 | 0.013 |
| region: north (age 14) | -0.475 | 0.016 | - | - | - | - |
| region: center (age 14) | 0.191 | 0.012 | - | - | - | - |
| region: north (age 18) | - | - | 0.190 | 0.036 | -0.042 | 0.019 |
| region: center (age 18) | - | - | 0.057 | 0.021 | -0.122 | 0.016 |
| \% voucher schools in municipality | 0.947 | 0.022 | - | - | - | - |
| $\Delta$ local unemployment (high-low skill, age 17) | - | - | -0.021 | 0.165 | -0.148 | 0.110 |
| $\Delta$ local log wage (high-low skill, age 17) | - | - | -0.116 | 0.029 | 0.039 | 0.022 |
| college in municipality (age 21) | - | - | 0.065 | 0.019 | -0.121 | 0.014 |
| constant | -1.429 | 0.027 | -2.064 | 0.076 | -1.469 | 0.057 |
| factor | 0.040 | 0.008 | 0.643 | 0.014 | 0.691 | 0.011 |
| observations |  | 711 |  | 582 | 42 | ,427 |

Notes: This table reports the estimated coefficients for the schooling decision nodes $D_{2}$ and $D_{3}$ in Figure 1. The estimates were obtained by maximum likelihood. The variables for gender, parents' education, broken home, and $\%$ of voucher schools in the municipality are measured when the students is 14 years old. The variable for broken home is a dummy that takes the value of one if no parent or only one of them resides in the student's home, and zero otherwise. The variable for income per capita is measured at the household level, represents monthly figures, and is in log US\$ as of the year 2000. The variables for local unemployment and wages are differences in averages between high-skilled workers and low-skilled workers. The variable for presence of a college in the municipality is a dummy that is equal to one if there is one or more colleges in the student's municipality of residence, and zero otherwise.

Estimates for the decision of enrolling in college are presented in Table 6. This decision corresponds to the nodes $D_{4}-D_{7}$ in Figure 1. Similar to the results for the decision of taking the college admission exams, female students are more likely to enroll in college. Family observable endowments, i.e. parents' education and household's income, strongly increase the likelihood
that a student enrolls in college. Residing in a household without both parents being present decreases the chances of attending college. Regional dummies are mostly significant, and all negative, meaning that residing in the South increases the chances of enrolling in college. We use the same instruments as for the decision of taking the college exams, with the difference that local labor market conditions are measured when the student is 20 years old. The instrument for the relative unemployment rate of high-skilled workers is not precisely estimated, and of negative sign for students taking the college admission exams and of positive sign for student not taking the exams. The instrument for the relative wage of high-skilled workers is negative in all equations, but only significant for students in public high schools. The instrument for local college availability is mostly positive and significant, indicating that having a college in the municipality of residence increases the likelihood of attending college. Lastly, the loading for the unobserved ability factor is strongly positive and significant, meaning that higher levels of ability increase the likelihood of pursuing higher education. This is in line with the related existing evidence from Chile (Rau et al., 2013; Rodríguez et al., 2016) and the U.S. (Heckman et al., 2006a, 2016b).
Table 6: Estimates - Schooling Decisions $D_{4}, D_{5}, D_{6}, D_{7}$

| conditional on: decision node: | $\begin{array}{r} D \\ D_{4}: \mathrm{en} \end{array}$ | $=1$ <br> oll college | $\begin{array}{r} D \\ D_{5}: \text { en } \end{array}$ | $=0$ <br> ll college | $D_{6}: \text { en }$ | $=1$ <br> oll college | $D_{7}: \text { enr }$ | $=0$ <br> oll college |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | coef. | std. err. | coef. | std. err. | coef. | std. err. | coef. | std. err. |
| male | -0.057 | 0.031 | -0.082 | 0.024 | -0.085 | 0.023 | -0.197 | 0.018 |
| mother's education | 0.055 | 0.006 | 0.044 | 0.004 | 0.060 | 0.004 | 0.047 | 0.003 |
| father's education | 0.044 | 0.006 | 0.042 | 0.004 | 0.050 | 0.004 | 0.039 | 0.003 |
| broken home | -0.136 | 0.035 | -0.096 | 0.027 | -0.126 | 0.025 | -0.082 | 0.020 |
| log household income per capita (age 18) | 0.219 | 0.025 | 0.229 | 0.027 | 0.168 | 0.020 | 0.228 | 0.020 |
| region: north (age 18) | -0.066 | 0.061 | -0.233 | 0.051 | -0.252 | 0.031 | -0.154 | 0.026 |
| region: center (age 18) | -0.214 | 0.037 | -0.028 | 0.027 | -0.296 | 0.026 | -0.174 | 0.021 |
| $\Delta$ local unemployment (high-low skill, age 20) | -0.127 | 0.288 | 0.353 | 0.204 | -0.072 | 0.186 | 0.076 | 0.144 |
| $\Delta$ local log wage (high-low skill, age 20) | -0.036 | 0.060 | -0.069 | 0.044 | -0.090 | 0.040 | -0.075 | 0.032 |
| college in municipality (age 21) | 0.059 | 0.032 | -0.002 | 0.024 | 0.125 | 0.024 | 0.061 | 0.019 |
| constant | -0.740 | 0.120 | -1.742 | 0.113 | -0.633 | 0.088 | -1.751 | 0.083 |
| factor | 0.480 | 0.025 | 0.400 | 0.020 | 0.510 | 0.018 | 0.389 | 0.015 |
| observations | 11,158 |  | 12,424 |  | 19,872 |  | 22,555 |  |

[^14]The decision of graduating from college is estimated only for students that enroll in college, and its estimates are presented in Table 7. This decision corresponds to the nodes $D_{8}-D_{11}$ in Figure 1. Female students are more likely than males to graduate from college. Mother's education is a significant determinant of college graduation, where higher levels of education increase the likelihood of earning a college degree. That is not the case of father's education, that has a small and mostly insignificant effect on college graduation. Growing up in a household without both parents being present decreases the chances of obtaining a college degree. The coefficients for household's income are only significant for students that take the college admission exams, and indicate that higher levels of income translate into higher chances of graduating from college. Regional dummies' effects indicate that residing in the South increases college graduation. We use only local labor market instruments, measured when the individual is 23 years old. The coefficients for the relative rate of unemployment for high-skilled workers are mostly insignificant. Same is the case of the coefficients for the relative wage of high-skilled workers. Lastly, the loadings for the unobserved ability factor are strongly positive, meaning that higher levels of ability increase the chances of earning a college degree. This is, again, in line with the related evidence (Heckman et al., 2006a, 2016b; Rau et al., 2013; Rodríguez et al., 2016).
Table 7: Estimates - Schooling Decisions $D_{8}, D_{9}, D_{10}, D_{11}$

| conditional on: decision node: | $D_{4}=1$ <br> $D_{8}$ : college degree |  | $D_{5}=1$ <br> $D_{9}$ : college degree |  | $\begin{gathered} D_{6}=1 \\ D_{10}: \text { college degree } \end{gathered}$ |  | $D_{7}=1$ <br> $D_{11}$ : college degree |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | coef. | std. err. | coef. | std. err. | coef. | std. err. | coef. | std. err. |
| male | -0.329 | 0.027 | -0.372 | 0.038 | -0.379 | 0.021 | -0.356 | 0.030 |
| mother's education | 0.016 | 0.005 | 0.021 | 0.007 | 0.015 | 0.004 | 0.011 | 0.006 |
| father's education | 0.009 | 0.005 | -0.004 | 0.007 | 0.007 | 0.004 | -0.006 | 0.006 |
| broken home | -0.162 | 0.031 | -0.157 | 0.044 | -0.089 | 0.023 | -0.098 | 0.035 |
| log household income per capita (age 18) | 0.057 | 0.020 | -0.003 | 0.042 | 0.079 | 0.016 | 0.023 | 0.033 |
| region: north (age 18) | -0.271 | 0.048 | -0.313 | 0.087 | -0.227 | 0.028 | -0.184 | 0.041 |
| region: center (age 18) | -0.284 | 0.032 | -0.188 | 0.042 | -0.204 | 0.024 | -0.164 | 0.034 |
| $\Delta$ local unemployment (high-low skill, age 23) | 0.036 | 0.263 | -0.356 | 0.366 | -0.713 | 0.173 | 0.032 | 0.255 |
| $\Delta$ local log wage (high-low skill, age 23) | 0.010 | 0.051 | 0.035 | 0.067 | -0.074 | 0.041 | -0.051 | 0.060 |
| constant | 0.084 | 0.098 | $-0.095$ | $0.174$ | $0.051$ | 0.075 | -0.071 | 0.137 |
| factor | 0.349 | 0.021 | 0.222 | 0.031 | 0.286 | 0.016 | 0.221 | 0.026 |
| observations |  | 504 |  | 722 |  | ,380 |  | 346 |

Notes: This table reports the estimated coefficients for the schooling decision nodes $D_{8}-D_{11}$ in Figure 1. The estimates were obtained by
maximum likelihood. The variables for gender, parents' education, and broken home are measured when the students is 14 years old. The
variable for broken home is a dummy that takes the value of one if no parent or only one of them resides in the student's home, and zero
otherwise. The variable for income per capita is measured at the household level, represents monthly figures, and is in log US $\$$ as of the year
2000 . The variables for local unemployment and wages are differences in averages between high-skilled workers and low-skilled workers.

### 6.1.4 Outcomes: College Admission Exams

We include performance in the college admission exams as outcomes in our model. The corresponding scores are observed only for individuals taking the exams, that is, students that reach the nodes $D_{4}$ and $D_{6}$ in Figure 1 (or, that choose $D_{2}=1$ and $D_{3}=1$ in the same figure). The estimated coefficients for verbal and math scores are presented in Table 8. Analogous to the results we obtained for the measurement system, we observe that females outperform males in verbal, and that the opposite occurs in math. Observable family endowments, i.e. parents' education and household's income, are strong determinants of students' performance, with higher levels of family endowments increasing test scores. Growing up in a household without both parents being present has a negative effect on performance. The coefficients for the regional dummies indicate that residing in the South increases test scores. Lastly, the unobserved ability factor is a strong and positive determinant of students' performance in college admission exams.

Table 8: Estimates - College Admission Exams Scores

| conditional on: <br> subject: | $D_{2}=1$ <br> verbal |  | $D_{2}=1$ <br> math |  | $D_{3}=1$ <br> verbal |  | $D_{3}=1$ <br> math |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | coef. | std. err. | coef. | std. err. | coef. | std. err. | coef. | std. err. |
| male | -0.039 | 0.012 | 0.223 | 0.013 | -0.058 | 0.010 | 0.193 | 0.010 |
| mother's education | 0.037 | 0.002 | 0.033 | 0.002 | 0.040 | 0.002 | 0.035 | 0.002 |
| father's education | 0.031 | 0.002 | 0.025 | 0.002 | 0.034 | 0.002 | 0.030 | 0.002 |
| broken home | -0.031 | 0.014 | -0.053 | 0.015 | -0.020 | 0.011 | -0.052 | 0.011 |
| log income per capita (age 18) | 0.078 | 0.009 | 0.067 | 0.009 | 0.049 | 0.007 | 0.052 | 0.008 |
| region: north (age 18) | -0.136 | 0.021 | -0.047 | 0.022 | -0.206 | 0.013 | -0.131 | 0.013 |
| region: center (age 18) | -0.164 | 0.014 | -0.174 | 0.015 | -0.098 | 0.011 | -0.116 | 0.011 |
| constant | -1.492 | 0.040 | -1.497 | 0.042 | -1.515 | 0.031 | -1.498 | 0.033 |
| factor | 0.929 | 0.009 | 0.806 | 0.009 | 0.943 | 0.007 | 0.798 | 0.007 |
|  |  |  |  |  |  |  |  |  |
| $\log (\sigma)$ | -0.613 | 0.007 | -0.497 | 0.007 | -0.620 | 0.005 | -0.494 | 0.005 |
| observations |  |  |  |  |  |  | 19,872 | 19,872 |

Notes: This table reports the estimated coefficients for the college admission exams, and were obtained by maximum likelihood. The variables for gender, parents' education, and broken home are measured when the students is 14 years old. The variable for broken home is a dummy that takes the value of one if no parent or only one of them resides in the student's home, and zero otherwise. The variable for income per capita is measured at the household level, represents monthly figures, and is in $\log$ US\$ as of the year 2000 . The tests are normalized to have mean zero and standard deviation one in the entire population of test takers. The variable $\log (\sigma)$ is the natural logarithm of the standard deviation of the corresponding test's distribution.

### 6.2 Goodness of Fit

Using the model and its estimates, we simulate 500,000 observations. We test the ability of our model to reproduce the actual data. Tables 9-11 compare our model's predictions with the data. Table 9 reports comparisons for the measurement system. Table 10 reports comparisons for schooling decisions. Table 11 does analogously for college admission exams. In general, our model fits the data satisfactorily well, which allows us to use the model to compute counterfactuals, treatment effects, and learn more about the consequences of schooling decisions (in particular, attending a voucher high school).

Table 9: Goodness of Fit - Measurement System

|  | mean |  | std. |  |
| :--- | :---: | :---: | :---: | :---: |
|  | actual | model | actual | model |
| verbal | -0.105 | -0.106 | 0.912 | 0.908 |
| math | -0.108 | -0.108 | 0.907 | 0.902 |
| social sciences | -0.112 | -0.111 | 0.918 | 0.912 |
| natural sciences | -0.112 | -0.112 | 0.920 | 0.916 |

Notes: This table compares our simulated model with the actual data. Simulations consist in 500,000 draws taken from the model and its estimates.

Table 10: Goodness of Fit - Schooling Decisions

|  | actual | model |
| :---: | :---: | :---: |
| $D_{1}$ | 0.357 | 0.358 |
| $D_{2}$ | 0.473 | 0.475 |
| $D_{3}$ | 0.468 | 0.473 |
| $D_{4}$ | 0.852 | 0.851 |
| $D_{5}$ | 0.380 | 0.382 |
| $D_{6}$ | 0.824 | 0.825 |
| $D_{7}$ | 0.326 | 0.330 |
| $D_{8}$ | 0.616 | 0.617 |
| $D_{9}$ | 0.382 | 0.383 |
| $D_{10}$ | 0.632 | 0.632 |
| $D_{11}$ | 0.387 | 0.389 |

Notes: This table compares our simulated model with the actual data. Simulations consist in 500,000 draws taken from the model and its estimates.

| Table 11: Goodness of Fit - College Admission Exams |  |  |  |  |  |
| ---: | ---: | ---: | :---: | :---: | :---: |
|  | mean <br> actual | model | std. dev. |  |  |
| actual | model |  |  |  |  |
| voucher high school: |  |  |  |  |  |
| verbal | -0.347 | -0.362 | 0.874 | 0.861 |  |
| math | -0.400 | -0.413 | 0.866 | 0.851 |  |
|  |  |  |  |  |  |
| public high school: |  |  |  |  |  |
| verbal | -0.459 | -0.466 | 0.882 | 0.863 |  |
| math | -0.444 | -0.451 | 0.860 | 0.844 |  |

Notes: This table compares our simulated model with the actual data. Simulations consist in 500,000 draws taken from the model and its estimates.

### 6.3 Effects of and Sorting on Ability

Using our simulated model, we investigate the effects of ability on outcomes. We are interested in the outcomes of college admission exams, college enrollment, and college graduation (conditional on having enrolled in college). Figure 3 plots the effects of ability on each of the outcomes. Higher levels of ability strongly determine higher test scores and higher chances of college enrollment and graduation. These results, previewed by the analysis of estimates in Section 6.1, and confirmed with the analysis from the simulations, underscore the key role that inherent abilities have on socio-economic outcomes. They also connect this paper with a growing literature on the effects of skills (Heckman et al., 2006a, 2016b; Sarzosa and Urzúa, 2015; Prada and Urzúa, 2017; Sarzosa, 2017), and call for the importance of policies aimed at developing those skills, especially in early stages of children's development (Cunha and Heckman, 2007, 2008; Cunha et al., 2010; NoboaHidalgo and Urzúa, 2012; Campbell et al., 2014; Heckman and Mosso, 2014).

Figure 3: The Effects of Ability on Outcomes


Notes: This figure plots nonparametric relationships between abilities and outcomes. The nonparametric estimations are performed using the simulations from the model. College graduation is conditional on having enrolled in college.

We also investigate how ability determines the sorting of students into intermediate and final schooling levels. In particular, we are interested in the sorting effect of ability on students' decision to attend a private-voucher high school, and on final schooling levels (i.e. high school degree, college dropout, college degree). Figure 4 plots distributions of ability for students deciding to attend a private-voucher school and for students deciding to attend a public school. The two
distributions are very similar one from another. If anything, students in voucher schools have somewhat higher levels of ability, but the differences are almost negligible. We conclude that students of similar ability enroll in private-voucher schools and in public schools.

Figure 4: Distribution of Ability by Voucher/Public High School


Notes: This figure plots distributions of ability for students attending private-voucher schools and for students attending public schools. The distributions are nonparametrically estimated using the simulations from the model.

Figure 5 plots distributions of ability for students attaining the following final schooling levels: high school degree, college dropout (i.e. enrolling in college but not earning the degree), and college degree. The sorting on ability is clear. Individuals earning a college degree have higher levels of ability than individuals dropping out from college, who in turn have higher levels of ability than individuals earning a high school diploma. These results are in line with the existing evidence on the role of skills in educational attainment (Heckman et al., 2006a, 2016b; Rodríguez et al., 2016; Prada and Urzúa, 2017), and, again, highlight the key role of ability in educational success.

Figure 5: Distribution of Ability by Final Schooling Level


Notes: This figure plots distributions of ability for individuals attaining three different levels of schooling: high school degree, college dropout, and college degree. The distributions are nonparametrically estimated using the simulations from the model.

### 6.4 The Effects of Vouchers

We investigate the effects of attending a private-voucher high school in lieu of a public high school on the performance in college admission exams, the likelihood of enrolling in college, and the likelihood of graduating from college (conditional on having enrolled in college). To that aim, we use simulated counterfactuals from our model to construct the treatment effect parameters defined in Section 4.6. More precisely, we compute the gains of attending a private-voucher school, $Y_{1}-Y_{0}$, for each of our simulated individuals, and then compute averages that correspond to the definition of the treatment effects.

Table 12 reports the estimated treatment effects. It displays estimates for the average treatment effect (ATE), the average treatment effect on the treated (TT), and the average treatment
effect on the untreated (TUT). The statistical significance of the treatment effects is tested by using a $t$-test in means. The estimated effects on test scores are all significant, and are all but one positive. On average, attending a voucher school increases verbal scores by $0.07 \sigma$. This effect is somewhat smaller for the subsample of students actually attending voucher high schools, or treated individuals $(0.06 \sigma)$, and larger for students attending public schools, or untreated individuals $(0.08 \sigma)$. The effect sizes are in the mid-range of the existing evidence, and are higher than many of the voucher effects reported in the literature (Epple et al., 2017). The effects found for math are somewhat smaller. The average treatment effect is $0.01 \sigma$. Moreover, students actually deciding to attend voucher high schools see their math scores slightly decrease by $0.004 \sigma$. On the contrary, the voucher effect is positive and significant for students that attend public high schools. The estimated TUT effect is $0.02 \sigma$. These estimated effects lie in the mid- to low-range in the existing literature.

Table 12 also reports the estimated effects on the outcomes related to higher education, namely college enrollment and graduation. Attending a voucher high school increases the likelihood of enrolling in college by 1.9 percentage points (p.p.) on average. In contrast to what we observe for the effects on test scores, it is the subsample of treated students (i.e. that attend a voucher high school) that present the highest effects. The corresponding TT effect is 2.3 p.p., and the TUT effect is 1.6 p.p. Recall from Table 1 that the average college enrollment rate in the actual sample is $57 \%$. When compared to the existing small literature that looks at the effects of vouchers on college enrollment, our estimates are in line with what is found elsewhere (Chingos and Peterson, 2015; Chingos, 2018). An interesting result is found for the outcome of college graduation (conditional on having enrolled in college). On average, attending a voucher high school reduces the chances of graduating from college by 1.6 p.p. However, the estimated effect is highly heterogeneous among students. For students actually attending a voucher high school (treated group), the effect is positive and of about 1.2 p.p. For students actually attending a public high school (untreated group), the effect is negative and of about -3.3 p.p. An immediate question that arises is, what is driving these disparities? Our model as it is does not provide
an exact explanation of the actual mechanisms, but it does allow us to shed some light on the underlying factors. We conjecture that the large and positive effects of vouchers on test scores forcefully allow students not only to attend college with a higher probability, but also to attend "better" higher education institutions (e.g. higher-quality, more prestigious, more professional than vocational). ${ }^{24}$ But "better" institutions are also presumably more difficult to graduate from (e.g. stricter grading and passing rules, more competition from higher-ability peers). Thus, students attending public high schools may find it harder to complete their college degree in "better" colleges whenever they lack the endowments and family background that are necessary to avoid dropping out (see Table 7). That may not be the case of students actually attending voucher high schools, who on average have better endowments and family background (see Table 5). Thus, the positive TT and negative TUT effects.

Table 12: Estimated Treatment Effects of Attending a Voucher High School

|  | ATE | TT | TUT |
| :---: | :---: | :---: | :---: |
| college admission exams (std. dev.): <br> verbal math | $\begin{aligned} & 0.071^{* * *} \\ & 0.011^{* * *} \end{aligned}$ | $\begin{gathered} 0.058^{* * *} \\ -0.004^{* *} \end{gathered}$ | $\begin{aligned} & 0.079^{* * *} \\ & 0.019^{* * *} \end{aligned}$ |
| higher education (probability): <br> college enrollment college graduation | $\begin{gathered} 0.019^{* * *} \\ -0.016^{* * *} \end{gathered}$ | $\begin{aligned} & 0.023^{* * *} \\ & 0.012^{* * *} \end{aligned}$ | $\begin{gathered} 0.016^{* * *} \\ -0.033^{* * *} \end{gathered}$ |

Notes: This table presents the estimated treatment effects of attending a private-voucher high school in lieu of a public high school. We compute the treatment effects by using counterfactuals from our simulated model. The statistical significance of the treatment effects is tested by using a $t$-test in means. ATE refers to the average treatment effect, or $E\left[Y_{1}-Y_{0}\right]$. TT refers to the average treatment effect on the treated, or $E\left[Y_{1}-Y_{0} \mid D=1\right]$. TUT refers to the average treatment effect on the untreated, or $E\left[Y_{1}-Y_{0} \mid D=0\right] .{ }^{* *}$ and ${ }^{* * *}$ denote statistical significance at the 0.05 and 0.01 levels, respectively.

Our last exercise examines the heterogeneity of the voucher effects with respect to students' ability. Specifically, we use our simulated sample to estimate the statistical relation between the individual treatment gains, $Y_{1}-Y_{0}$, and ability. We call this relation the effect of ability on the treatment effect. Figure 6 plots this effect for all four outcomes we study. We observe a

[^15]negative relation between the treatment effect and ability for verbal scores and college enrollment (panels A and C). That is, low-ability individuals benefit more of attending a voucher high school than high-ability individuals. In particular, students with very low levels of ability experience a treatment effect of about $0.09 \sigma$ on verbal scores, which is almost three times as large as the effect experienced by high-ability students. Similarly, the treatment effect for college enrollment varies from about 3 p.p. for low-ability students to about 0 p.p. for high-ability students. A different pattern is found for math scores (panel B). Students with low levels of ability benefit less of attending a voucher high school than students with high levels of ability. The treatment effect varies from about 0 p.p. to about 3 p.p. Lastly, the treatment effect on the probability of graduating from college (conditional on having enrolled in college) is estimated to be fairly constant at -0.02 p.p. for individuals with low levels of ability, and then to be increasing in ability for individuals with high levels of ability. This is consistent with our above-mentioned conjecture that the ability endowment is an important factor driving positive treatment effects.

The analysis presented in Figure 6 is key to better understand how vouchers affect students. They show that the treatment effects are highly heterogeneous, and can certainly help policymakers better target the implementation of policies.

Figure 6: The Effect of Ability on Treatment Effects


Notes: This figure plots the statistical relation between the treatment effect, $Y_{1}-Y_{0}$, and ability, for the outcomes of verbal scores, math scores, college enrollment, and college degree attainment. The relations are estimated nonparametrically using simulations from the model.

## 7 Conclusions

We investigate the short and longer-term effects of attending a private-voucher high school in Chile. To that aim, we postulate a sequential model of schooling decisions and educational
outcomes, which we estimate using rich administrative panel data from Chile. We find that attending a private-voucher high school increases performance in high-stakes college admission exams, increases the probability of enrolling in college, and increases the probability of graduating from college (conditional on having enrolled in college) for students that actually attend voucher high schools, but decreases such probability for students that actually attend public high schools. We explain this last result by conjecturing that attending a voucher high school increases the likelihood of attending a higher-quality but also more academically challenging college. In such institutions, graduation strongly depends on endowments and family background, which students in public high schools usually lack. We also show important heterogeneity in the treatment effects, where in general low-ability students benefit more from attending a voucher high school than high-ability students.

Our results are novel, and show an advantage of private schools over public schools in many educational outcomes. They also suggest that some efficiency gains can be obtained by targeting voucher policies to low-performing and low-ability students.

Future research should build on our results and investigate the effects that vouchers ultimately have on labor market outcomes. Such evidence is nonexistent to the best of our knowledge, and can certainly increase our knowledge about the consequences of vouchers.

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## A Data

The following are the various administrative and survey data sets for Chile that we use in our analysis.

- National standardized exams (SIMCE) for 8th graders, student-level, 2000.

These data provide information on students' test scores for four different subjects: verbal, mathematics, social sciences, and natural sciences. They also provide information on students' gender and grade.

- 8 th grade SIMCE's questionnaire to parents and tutors, 2000.

These data consist in the responses to a survey that parents and tutors answer during the days when the national standardized tests are taken. The survey is voluntary, though about more than $90 \%$ of parents respond it. It provides information on students' household size, house amenities, and time use, total number of books available in the household, household total monthly income, parents and tutors' time use, education, indigenous identification, occupation, health insurance, participation in social programs, reasons for the choice of the school, beliefs on the student's future educational attainment, satisfaction with the school, knowledge of school's average performance in standardized tests, total monthly expenses related to the student's education other than tuition, and school's admission criteria, tuition, and fees.

- National standardized exams (SIMCE), school-level, 8th grade in 2000, 10th grade in 1998. These data provide information on schools' average test scores for verbal, mathematics, and social and natural sciences, municipality, management type (public, private-voucher, private-non-voucher), socio-economic category of the population served by the school, urban status, and number of students taking the tests.
- Registry of students, 2004-2008.

These data provide information on students' gender, date of birth, age, municipality of residence, type and level of education, grade, class, grade repetition status, special educa-
tion status, and various characteristics of the school of attendance, such as municipality, management type, single/double shift schedule, and urban status.

- Registry of schools, 2000, 2004-2009.

These data provide information on schools' municipality, management type, urban status, address, and type and level of education offered.

- National standardized college admission exams (PSU), student-level, 2005-2010.

These data provide information on students' college admission test scores for four different subjects: verbal, mathematics, social sciences, and natural sciences. These exams are not mandatory, but are essential in determining students' chances of attending higher education. The data also provide information on students' birth date, home address, level of education of the parents, occupation of the parents, high school attended, high school GPA, preference ranking of higher education institutions-majors, among others.

- National socio-economic characterization household survey (CASEN), 2003, 2006, 2009. The CASEN series of household surveys corresponds to the most important piece of socioeconomic information in Chile. It is used to inform public polices, and contains extensive information on individuals' education, health, employment, etc. It is nationally representative at the municipality level.
- Registry of students in higher education institutions, 2007-2016.

These data provide detailed information on students' enrollment in higher education institutions, including the institution, major, geographical location where the classes are taken, as well as students' age, gender, and birth date.

- Registry of individuals completing a higher education degree, 2007-2016.

These data provide information on the students completing a higher education degree, by year. It also contains detailed information on the degree (major and higher education institution), the time needed to complete the degree, the official duration of the degree, the exact date when the degree was completed, as well as students' age, gender, and birth date.


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[^1]:    ${ }^{1}$ See Rouse (1998), Angrist et al. (2002), Mayer et al. (2002), Peterson et al. (2003), Wolf et al. (2010b), Lara et al. (2011), Muralidharan and Sundararaman (2015), Mills and Wolf (2017), Abdulkadiroglu et al. (2018), among others.
    ${ }^{2}$ There is a small, but growing, literature that has analyzed the effects of vouchers on longer-term educational outcomes, mainly high school graduation and college enrollment. These studies include Angrist et al. (2006), Wolf et al. (2010a), and Chingos and Peterson (2015).
    ${ }^{3}$ Gauri (1998) describes Chile's voucher system as "...perhaps the world's most ambitious attempt to design and implement a program of educational choice...".
    ${ }^{4}$ In 2008, the Chilean government introduced an important reform to its voucher system, that, among other things, created a differentiated voucher for low-income students. However, since my data covers a period that precedes this reform, I do not go into the details of the implied changes in the system's structure. See Correa et al. (2014), Gazmuri (2015), Feigenberg et al. (2017), Navarro-Palau (2017), Murnane et al. (2017), Neilson (2017), and Sánchez (2018a) for studies that analyze this reform.
    ${ }^{5}$ Public schools are mandated to be tuition-free. Subsidized private schools are allowed to charge tuition; however, only few of them charge any amount to its students (Gazmuri, 2015; Sánchez, 2018b).

[^2]:    ${ }^{6}$ See, also, Willis and Rosen (1979).
    ${ }^{7}$ This is in contrast to other approaches, such as instrumental variables, difference-in-difference, and regression discontinuity, from which one can only identify specific treatment parameters, but not their entire distribution. See the discussions in Heckman et al. (2006b), Heckman and Vytlacil (2007), and Heckman and Urzua (2010).
    ${ }^{8}$ Standard deviation units are represented by $\sigma$.

[^3]:    ${ }^{9}$ See Epple et al. (2017) for a comprehensive review of the theoretical and empirical literature on educational vouchers.
    ${ }^{10}$ The reported effect of 21 p.p. corresponds to the local average treatment effect (LATE), where random assignment of the voucher offer is used as an instrument for voucher school attendance. The intent-to-treat (ITT) effect is 12 p.p.
    ${ }^{11}$ Epple et al. (2017) interpret the evidence from the United States as being consistent with vouchers improving some types of skills more than others. In particular, they argue that it is possible that vouchers improve noncognitive skills, which may explain the positive effects on high school graduation (Heckman et al., 2006a, 2016b), while the lack of an effect on test scores may be the result of weaker impacts on cognitive skills. Though plausible, this interpretation falls short in explaining the zero effects on college enrollment and degree attainment.

[^4]:    ${ }^{12}$ It is worth noting that the authors are well aware of this aspect of their study, and are careful in attributing the effects they find to the school reform as a whole, and not only to its school choice component.
    ${ }^{13}$ Most notably, the country suffered a major economic crisis in 1982.

[^5]:    ${ }^{14}$ For a more detailed description of the universal voucher system in Chile, see Gauri (1998), and McEwan and Carnoy (2000).

[^6]:    ${ }^{15}$ See the discussion in Taber (2000), Cameron and Taber (2004), and Heckman et al. (2016b).
    ${ }^{16}$ See, also, Heckman et al. (2006a), Urzua (2008), Rau et al. (2013), and Rodríguez et al. (2016).

[^7]:    ${ }^{17}$ This is a common feature of the literature on dynamic discrete choice models. See, for example, Keane and Wolpin (1997), and Aguirregabiria and Mira (2010).

[^8]:    ${ }^{18}(Z, X)$ denotes the stacked vector of all observables.

[^9]:    ${ }^{19}$ See, also, Carneiro et al. (2003), Hansen et al. (2004), and Theorem 1 in Kotlarski (1967).

[^10]:    ${ }^{20}$ See, also, Greene (2008).

[^11]:    ${ }^{21}$ For a detailed description of the college admission exams, and the college admission process in Chile, see Rau et al. (2013), Espinoza et al. (2016), Hastings et al. (2016), Rodríguez et al. (2016), Espinoza (2017), and Bucarey (2018).

[^12]:    ${ }^{22}$ In 1999, a similar battery of tests were administered to 4 th graders. In subsequent years, different national standardized tests have been administered to students in $2 \mathrm{nd}, 4$ th, 6 th, 8 th, 10 th, and 11 th grades.

[^13]:    ${ }^{23}$ See Rau et al. (2013), and Rodríguez et al. (2016).

[^14]:    Notes: This table reports the estimated coefficients for the schooling decision nodes $D_{4}-D_{7}$ in Figure 1. The estimates were obtained by maximum likelihood. The variables for gender, parents' education, and broken home are measured when the students is 14 years old. The variable for broken home is a dummy that takes the value of one if no parent or only one of them resides in the student's home, and zero otherwise. The variable for income per capita is measured at the household level, represents monthly figures, and is in log US\$ as of the year 2000. The variables for local unemployment and wages are differences in averages between high-skilled workers and low-skilled workers. The variable for presence of a college in the municipality is a dummy that is equal to one if there is one or more colleges in the student's municipality of residence, and zero otherwise.

[^15]:    ${ }^{24}$ See Rodríguez et al. (2016).

