Teacher Labor Markets, School Vouchers and Student Cognitive Achievement: Evidence from Chile

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Abstract

This paper uses administrative and survey data from Chile and a structural model to evaluate teacher policies in a market-based school system. The model accommodates equilibrium effects on parental sorting across school sectors (public or private), on the self-selection of individuals into teaching and across school sectors, and on teacher wages in private schools. Results indicate that the equilibrium effects are empirically relevant. The estimated model is used to simulate a reform that is planned to be implemented in Chile in 2023. Tying public school teacher wages to teacher skills and introducing minimum competency requirements for teaching is predicted to increase student test scores by 0.30 standard deviations and decrease the achievement gap between the poorest and richest 25 percent of students by a third. These impacts are ten times as large as the impact of a flat wage increase in public schools that induces the same average increase in public school wages. The key driver of policy outcomes is an improvement in the pool of teachers, amplified by equilibrium effects in the market for teachers.

1 Introduction

Teachers are one of the most important determinants of student achievement (Rivkin, Hanushek, and Kain 2005). Two key questions in education policy are how to attract good teachers into the teaching profession in a cost-effective way; and what impacts we can expect teacher policies to have on student achievement. The answers depend on the structure of the labor market for teachers, on how teacher quality combines with other inputs to produce achievement and, I argue in this paper, on the structure of the market for education.

I use administrative data from Chile and a structural model to empirically quantify the key forces behind teacher policy effectiveness in a market-based school system. Chile has a large-scale school voucher program and a large publicly subsidised private school sector. In this context, changes to teacher contracts in public schools generate equilibrium effects in private school wages and in the teacher-student match across school sectors. For example, suppose that teacher wages in the public sector become more tied to teacher quality. This changes the options available to individuals who are considering whether to teach, and in which school sector to teach. Private schools understand this and may decide to offer better wages to the best teachers, in response to the competitive pressure from public schools in the market for teachers. In turn, this equilibrium effect on wages feeds back into the labor supply decisions of potential teachers. Additionally, in an education system where parents choose with their feet, they may respond to the new allocation of teacher quality across sectors by changing their school choice. If the goal of policy evaluation is to estimate the impacts on student achievement, this parental response cannot be ignored.

I provide an estimable equilibrium model to analyse the response to teacher policies of private schools, potential teachers and parents. In counterfactual experiments using the estimated model, I quantify the relative importance of demand and supply side factors in determining teacher policy effectiveness. Finally, I provide an ex-ante evaluation of a merit-based teacher reform whose implementation is planned to complete in 2023, and compare it to a flat increase in public school wages which does not reward merit. I present predicted impacts on student achievement, and a welfare analysis of the reform. The advantage of estimating a structural model is that it can quantify equilibrium effects in impact and welfare calculations. By doing so, it identifies drivers of policy effectiveness that are not specific to the Chilean context, but apply more generally to any market-oriented school system.

In the model, parents choose between the municipal and the private subsidised school sectors. They care about consumption, which is lowered by tuition payments to private schools, about their child's achievement, and they have a direct preference for a school sector independent of its quality. Student achievement depends on student and household characteristics, on sector-specific school inputs, and on teacher quality. The latter is endogenously determined by the teacher labor supply, which is modeled as a Roy model, a workhorse theoretical framework in labor economics. Specifically, individuals with a college degree decide whether to teach, and if so in which sector, whether to work in the non-teaching sector, or whether to stay at home. They care about the wage and non-pecuniary aspects of the occupation.[1] In public schools, the wage is determined by rigid unionized wage formualae, while in private schools it is the product of the individual's teaching skills and the price of those skills. The latter, together with tuition fees (up to a legal cap), is endogenously determined within the model by a profit-maximising representative private school. The rules that determine public school contracts are determined ex-ante and taken as given by all agents in the model. Therefore, the public sector can be thought of as the first mover in the model.

When evaluating how teacher policies affect teacher quality across schools, many existing studies rely on teacher value added models to estimate teacher quality. This framework typically restricts teacher quality to be additively separable from student ability in the production of test scores. This assumption is problematic in a system with large school choice, because the teacher-student match is a potentially important margin of policy response. If this match matters for test scores, ignoring this interaction would bias aggregate predictions on test scores. In this paper, I do not assume additive separability. As a result, I cannot use test score data alone to estimate teacher quality, like in a teacher value added approach. Instead, I identify teaching skills using the Roy model and the labor supply part of the data. The estimation algorithm then plugs the inferred teaching skills into the cognitive achievement production function, and uses the test score data to identify the complementarity between inferred teaching skills and student ability.[2] The novelty of this equilibrium approach is that the estimated parameters that determine teaching skills and the complementarity between teaching skills and student ability *simultaneously* rationalize the teacher choices and the parental choices as utility maximizing.

The model determines endogenously various equilibrium objects that can be matched to the micro-level data: the distribution of student achievement, the parental school sector choices and tuition payments, and accepted wages and occupational choices of potential

[1] Non-pecuniary job characteristics have been found to be important determinants of teacher labor supply (Boyd, Lankford, Loeb, and Wyckoff (2005), Bonhomme, Jolivet, and Leuven (2016)).

[2] This approach is similar to studies of the impact of teacher wages on test scores (see, for example, Loeb and Page (2000)).

teachers. I use a number of Chilean datasets from 2006. Data on the pool of potential teachers, including their characteristics, occupational choices and wages, come from the CASEN (*Encuesta de Caracterización Socioeconómica Nacional*), a representative sample of all Chileans, and from the ELD (*Encuesta Longitudinal Docente*) a teacher survey. Data on students come from the SIMCE (*Sistema de Medición de Calidad de la Educación*), which provides administrative test scores and background information on 4^{th} and 10^{th} graders.[3]

The model is estimated on multiple markets. There are two steps. The first one uses the Method of Simulated Moments (McFadden 1989, Pakes and Pollard 1989) to estimate the technology, wage and preference parameters of households and of potential teachers, and to recover the skill prices that determine observed private school wages. The second step uses Nonparametric Simulated Maximum Likelihood (Laroque and Salanie 1989, Fermanian and Salanié 2004) to estimate the private school objective function parameters that rationalize the recovered skill prices as equilibrium prices. The good fit of the model helps build confidence about the lessons that we learn from the structural estimates and counterfactual experiments I perform.

The first set of results comes from the estimation of the structural parameters. First, the unionized public school wages overvalue degrees and certifications with respect to their impact on teacher quality. Second, outside options matter: worse teachers are found in markets with better non-teaching wages, and this is especially true for public sector teachers. Third, public schools attract lower quality teachers than private schools, confirming previous findings (Behrman, Tincani, Todd, and Wolpin 2016). Additionally, there is a pool of potentially highly skilled teachers not currently employed in teaching. Taken together, these results indicate that making public school wages more reflective of skills has the potential to improve not only the quality of teachers in public schools, but also the quality of the pool of teachers overall.

With regard to the demand for education side, parents care about education quality, but they also have a direct preference for the private voucher sector, independent of quality, that accounts for roughly a fifth of the enrolment share in private voucher schools. Finally, there is a student-teacher interaction in the production of test scores: the impact of teacher skills varies across students of different ability levels (unobserved types in the model). This empirical finding confirms the need for a policy evaluation that

[3]SIMCE administers each year standardized tests in Mathematics and Spanish that all students of selected grades are required to take. The school's average test results are published annually and parents can compare the performance of locally available schools. See Hastings and Weinstein (2008) for findings on the importance of information in parental school choice.

accommodates the reaction of both teacher and parental sorting across school sectors.

The first counterfactual experiment simulates the planned 2023 implementation of the merit-based reform of the teaching profession introduced by President Bachelet. Specifically, teacher wages in public schools are tied to their skills (so as to induce a 30 percent increase in wages on average), and individuals can enter the teaching profession only if their score on the PSU, the national university admission exam, is in the top 30 percent. The reform is predicted to increase test scores by 0.30 standard deviations (sd) on average, and to decrease the achievement gap between the richest and poorest 25 percent of students by a third.

The impact drivers are an improvement in the pool of teachers, a considerable reduction in the teacher quality gap between public and private voucher schools, and, to a lesser extent, the sorting of parents across school sectors. Specifically, teacher quality across school sectors is affected by two factors: first, merit-based pay in public schools attracts skilled individuals from outside of teaching and cream-skims the best teachers from the voucher sector. Second, private schools respond by increasing their wage offers, thus limiting their loss of teacher quality to public schools and also attracting skilled individuals from outside of teaching. These supply-side factors contribute more to policy impacts than parental sorting: they account for 70 percent of the treatment effects. A key lesson that we learn is that the existence of a large school choice program amplifies the positive impacts of merit reforms in the teacher labor market, thanks to equilibrium wage adjustments in the large non-public school sector which result in an even better self-selection of individuals into teaching compared to the selection that would have occurred in the absence of equilibrium effects.

The welfare analysis indicates that the reform increases the average utility of households, with larger gains accruing to the poorer households, who benefit from larger improvements in teacher quality in their schools of choice. Moreover, the policy pays for itself in the long run, because better teacher quality in the public sector attracts students back into public schools. Because the voucher that each student in the country receives can be used in private subsidized or public schools, the policy attracts voucher revenues back into the public sector, reducing the need for additional funds to cover public school running costs. Compared to the pre-reform system, the merit-based reform is more financially sustainable.

Finally, I simulate a flat increase to public sector wages that results in the same 30 percent average public sector wage increase as under the reform. The impacts on test scores and inequality are one tenth of those of the merit-based reform, because the flat bonus is not as successful at improving the pool of teachers. Moreover, it would require an increase in Government costs, because it fails to attract voucher revenues back into the public sector. Therefore, a merit-reform is more cost-effective at improving student outcomes than a flat increase to public school teacher wages in a market-oriented school system.

The closest paper to this one is Behrman, Tincani, Todd, and Wolpin (2016), which focuses on the dynamics of the teacher labor supply in Chile, but abstracts from equilibrium effects and from the demand side of the market.[4] By incorporating the demand side of the market, this paper can predict policy impacts on student test scores, the most relevant outcome for policy analysis.

This paper is related to an emerging literature using (static) market equilibrium frameworks to study education policy at the primary and secondary levels. Neilson (2017) models demand and supply of education quality to analyze the equilibrium implications of a Chilean targeted voucher reform. He models competition within the private sector, abstracting from competition across sectors. In this respect, it uses a complementary approach to this paper, which focuses on the response of private schools to competitive pressure from public schools in the market for teachers. While the objective of study in Neilson (2017) is different and, therefore, he does not model the teacher labor market, the conclusions regarding the drivers of policy impacts are similar: the largest margin of policy response comes from the supply side, with private schools improving their quality to attract larger voucher revenues. In particular, correlations between his estimates of school quality and observed measures of teacher quality suggest that it is precisely teacher quality that improves in response to policy, adding to the plausibility of the findings in this paper.

With respect to equilibrium studies of the teacher labor market, Boyd, Lankford, Loeb, and Wyckoff (2013) provide a matching model of teachers to jobs, and Biasi (2017) develops a model of teacher demand and supply, and estimates it using data from Wisconsin. Like in this paper, Biasi (2017) models teacher labor supply as a (static) Roy model, and compares unionized wage regimes to individual wage negotiations. There are two distinctions in this paper. First, teacher labor demand is derived from the parental demand for education (which enters private school profits). Analysing the

[4] Behrman, Tincani, Todd, and Wolpin (2016) estimate large costs of switching occupational sectors in Chile, indicating that the static model of teacher labor supply is an acceptable approximation in this context. See Stinebrickner (2001a) and Stinebrickner (2001b) for dynamic structural models of teacher labor supply estimated on data from the United States, and Rothstein (2015) for simulations from a dynamic model of teacher labor supply using parameters calibrated to the United States.

parental elasticity to teacher quality is more relevant in a market-based school system like the Chilean one than in the one studied by Biasi (2017). Second, the teacher labor supply includes the decision to enter teaching. This allows me to study not only the stratification of teachers across sectors, but also how the pool of teachers reacts to policy. In the context of Chile, existing research shows that this is an important margin of policy response (Behrman, Tincani, Todd, and Wolpin 2016).

The rest of the paper is organised as follows. Section 2 describes the Chilean school system and the data used in the analysis. Section 3 introduces the model, and section 4 discusses its key features and limitations. Section 5 describes the estimation technique and the identification strategy. Section 6 presents the model fit, and it is followed by the empirical results, in section 7. Section 8 concludes. The appendices follow.

2 Institutional Background and Data Description

2.1 Institutions

In 1981, Chile introduced a nationwide school voucher plan. Under the plan, each school-aged child receives a voucher that can be spent toward full coverage of tuition fees in a municipal (public) school or coverage (partial or full) in a private subsidized school. The value of the voucher was CLP $27,391.903$ ($\sim$ \$50) per month in 2006, the sample year. The voucher cannot be used in private unsubsidized schools, from which this paper abstracts. These schools enroll 6% of students and cater to the wealthiest families. Private voucher schools in the sample year were allowed to charge a fee that exceeds the value of the voucher, up to a legal cap of CLP $54,018.768$ per month ($\sim$ \$100).

Some children are eligible for a *beca*, a fellowship for private education, that partially or fully covers the tuition fees in excess of the voucher. According to the SIMCE dataset, in 2006 around 60% of all Chilean children enrolled in private subsidized schools received a fellowship. As a result of government guidelines for fellowship assignment, children of lower socioeconomic status and from larger families are eligible for larger fellowships.[5]

Teachers' wages in the municipal sector are determined by rigid formulae that are negotiated between the government and the national teachers' union, the *Colegio de Profesores*. Wages are subject to seniority increments and other adjustments, such as allowances for

[5]The value of the voucher and the cap on private school tuition can be found in the *Decreto con Fuerza de Ley N^o 2, De Education, De 20.08.98* and in the law on shared financing, *Financiamiento Compartido, Ley N^o 19.532.* The guidelines for fellowship assignment can be found in articles 24 and 27 of the *Ley de Subvenciones*, *Decreto con Fuerza de Ley N^o 2, 20.08.98.*

professional training and for working in difficult conditions. Teacher assignment to schools is centralized nationally. Public schools, therefore, do not have control over the quality of the incoming pool of teachers. Teachers in private schools, on the other hand, are subject to the Private Labor Code, and their wages can be individually negotiated with private schools. Private schools are allowed to tie wages to teacher quality to attract a high-quality pool of teachers.

2.2 Data Description

2.2.1 Data Sources

I combine three data sources from 2006, the only year for which detailed information on both students and teachers in primary and secondary schools is available. I use the *Encuesta de Caracterización Socioeconómica Nacional* (CASEN) dataset to identify the pool of potential entrants into the teaching profession through a representative sample of individuals holding a college degree, a requirement for teaching.[6] The CASEN survey is a nationally representative survey of the general population from which I extract a sample of $3,520$ individuals holding a college degree, tracking their occupational choices, accepted wages, and characteristics.

To augment the sample of teachers, I use a sample of $3,195$ teachers from the *Encuesta Longitudinal Docente* (ELD) dataset. I extract from ELD the same set of individual characteristics obtained from CASEN, as well as the choice of school sector and accepted wages. From ELD and CASEN, I drop idnividuals who live in the remote Aisén and Tarapacá areas, for sample size reasons.

On the students' side, I randomly select a sample of $100,000$ students from the *Sistema de Medición de Calidad de la Educación* (SIMCE) dataset, which contains information on all 4^{th} and 10^{th} graders in the country.[7] The dataset contains administrative information

[6] Individuals who want to become teachers must obtain a teaching certification. Although the teachers' statute, *Estatuto Docente*, *Ley N^o 10.070*, allows for four ways to become certified to teach, according to the 2006 teacher census (*Idoneidad Docentes*), 95% of all teachers (100% of all teachers in this paper's sample) get certified through one of two channels: i) a college degree in education, ii) a college degree in another area and a special degree in education (2-4 semesters). Importantly, anyone with a college degree can become a teacher, as long as they receive training in education if their college major was not education. Because in CASEN I do not observe the college major, in the model I let the non-pecuniary preference for teaching depend on an individual's unobserved characteristics. This captures, in a reduced form way, the fact that to accept an offer from the teaching sector, a college graduate without a major in education must pay the (financial and time) cost of obtaining training in education. Therefore, everything else being equal, the utility cost of teaching is higher for this individual.

[7] The sample size is approximately one third of the population size. Selecting a sample was necessary for computational tractability.

on students' test scores in Mathematics and Spanish, used to measure achievement, as well as information on the students' household, tuition fee payments net of financial aid, and choice of school.

The model is estimated on 18 local labor and education markets. The market boundaries were determined so as to strike a balance between sample size within markets, number of markets, and market closed-ness (see Appendix A). Markets are closed, with 98.8% of teachers working in the market in which they reside, and 99.0% of parents choosing a school in the market in which they reside. Nationally, the voucher sector accounts for 52.99% of student enrollment and 45.16% of teacher employment. However, there is across-market variation in these shares in part due to different local market conditions affecting demand for private education and teacher supply.

2.2.2 Descriptive Statistics

In private schools, there are students with higher socioeconomic status (SES) and less experienced teachers with higher measures of cognitive skills.

Children in the top 25 percent of the income distribution score, on average, 0.68 standard deviations (sd) higher than children in the bottom 25 percent. There is also a sizable test score gap between public and voucher school students. The difference in test score means is equal to 0.36 sd, which is larger than the gap between charter and traditional public schools in the U.S. A third of this gap remains after controlling for student characteristics.

As documented also in previous studies (e.g., McEwan, Urquiola, Vegas, Fernandes, and Gallego (2008), Hsieh and Urquiola (2006), Urquiola (2005)), in the Chilean education system there is considerable school-sector stratification by students' SES. This is true also in my dataset. Table 1 shows average household characteristics by school sector. Parents of students in private subsidized schools earn roughly 60 percent more than parents of students in municipal schools. Similar patterns are present among virtually all the household characteristics available in the data.

Teachers in the private voucher sector are on average 8.2 years younger and have 9.0 fewer years of teaching experience than teachers in the municipal sector. They score 0.27 standard deviations higher on the PAA test, the Chilean equivalent of the SAT, a measure of cognitive skills.[8]

[8] Private voucher school teachers also score 0.19 standard deviations higher on the AEP test (*Asignación Excelencia Pedagógica*), which evaluates teaching ability. However, taking the AEP test is voluntary and only 1.5 percent of teachers take it. Thus, this figure must be taken with caution.

Table 1: Household Characteristics by School Sector

Household's characteristics	Public	Voucher
Avg parents' educ (yrs)	9.78	11.52
Mother's educ (yrs)	9.60	11.84
Hh monthly income (CLP)	205,123	337,898
Hh head not working	9.08%	4.68%
Hh head low-skilled job	44.50%	22.21%

Source: SIMCE 2006. 1 USD = 604.8 CLP.

Table 2: Average Monthly Teaching Wages by Teaching Experience and School Sector (2006 CLP)

Teaching Experience (years)	Public	Voucher
$\leq$ 10	368,816	423,418
11-20	472,502	472,967
21-30	540,992	544,537
31+	585,683	583,353

Source: ELD 2006. 1 USD=604.8 CLP.

Private school wages correlate with cognitive skills, while public school wages do not. In the ELD dataset, an estimated panel data regression of log wages in public schools on teaching experience, teaching experience squared, nonteaching experience, and standardized PAA scores gives an insignificant coefficient on the PAA score (p-value=0.169). The same regression estimated for voucher schools indicates that a one standard deviation increase in the PAA score is associated with 4.0 percent higher wages in private schools (p-value=0.009). Similar results have been reported in Bravo, Flores, Medrano, and Santiago (2010), who, additionally, show that teacher PAA scores are positively correlated with student test scores in Chile. This suggests that the individually negotiated private school wages reward teaching skills.

Wages of teachers with up to ten years of teaching experience are 14% higher in private voucher schools than in public schools. This wage difference disappears for more experienced teachers as can be seen in Table 2.

Finally, non-teaching wages are on average 62.3% higher in the non-teaching sector for equally educated individuals. A college graduate employed in a non-teaching occupation earns monthly, on average, CLP $777,396$ ($\sim$ \$$1,550$), while a college graduate employed in teaching earns on average CLP $479,041$ ($\sim$ \$960). A wage difference persists at all ages, reaching peaks of over 80% for individuals younger than 45. In terms of hourly wages, the gap reduces to 18.7%, reflecting the fact that individuals in the non-teaching sector work more hours. Perhaps because of the higher flexibility of the teaching time schedule, around 70 percent of teachers in Chile are women.

2.3 Reduced-form evidence

2.3.1 Labor Supply

In a related paper (Behrman, Tincani, Todd, and Wolpin 2016) we show that the existence of the private voucher sector in Chile draws higher-productivity individuals into the teaching profession. Therefore, the choice to enter the teaching profession is an important margin to study, in addition to the sorting across school sectors within teaching. The CASEN dataset allows me to identify the pool of college graduates and examine the self-selection into teaching and non-teaching occupations.[9]

As shown in Table 7 in Appendix B, females are 25 percentage points (p.p.) less likely to work, however, conditional on working, they are 47 p.p. more likely to choose teaching over non-teaching. Females with children are less likely to work than females without children and than men with children, however, conditional on working, they are more likely to work in teaching. Given that females represent 70 percent of the teacher labor force in Chile, this indicates that it is important to jointly study the decision to enter the labor force and to enter the teaching profession.

Focusing on the choice of school sector within teaching, older individuals are more likely to work in public schools, There are no other significant differences in terms of observed individual characteristics. However, there are significant differences across markets. Probit regressions augmented with market dummies indicate that the residual difference in the probability of choosing teaching conditional on working ranges across markets from -22 p.p to +18 p.p.. This may reflect differences across markets in the relative remuneration of teaching and non-teaching jobs, due to differences in local labor market conditions

[9]Studying the selection into teaching is a point of departure from Biasi (2017), who studies sorting of teachers across schools under different counterfactual experiments abstracting from teacher entry. She finds that a large scale individual wage negotiation policy for teachers would not improve teacher quality, but acknowledges that this result may change in a model that allows for teacher entry.

as well as in the demand for teachers. The structural model disentangles teacher labor demand from teacher labor supply factors.

2.3.2 Wages

Wage regressions indicate substantially larger unexplained wage variation in private schools than in public schools. The residual variance is 22.5 percent higher in private schools, where individual negotiations limit the wage compression observed in public schools. In genetal, unobserved heterogeneity plays an important role in explaining wage variation. For this reason, it is incorporated into the structural model.

Graduate degrees and certifications appear to be valued more in voucher schools (and in non-teaching) than in public schools according to the reduced-form estimates in Table 8. This contradicts what would be expected, given that the rigid negotiated formulae in public schools explicitly reward professional training, while the individually negotiated wages in private schools (and in the non-teaching sector) need not. However, these reduced-form coefficients do not necessarily reflect true wage offer functions. The structural model aims to uncover the true wage offer functions by accounting for unobserved heterogeneity and self-selection into occupations. Indeed, the structural wage parameters are of the expected signs.

Age, a (noisy) proxy for experience, is positively correlated with wages in both teaching sectors. In public schools, this reflects the explicit rewards to seniority. In private schools, this may reflect a positive correlation of experience with skills. While some studies suggest that only the first few years of experience are correlated with teaching skills, Wiswall (2013) finds that experience improves teaching skills even in later career stages.

Estimates in Table 8 in Appendix B seem also to indicate that females' log-wages are disproportionately penalised in the non-teaching sector as compared to the two teaching sectors, with a negative dummy coefficient (-0.38) that is three times as large as in teaching (-0.10 and -0.14). However, these coefficients may be biased because of self-selection. The structural model explicitly accounts for self-selection into occupations that require different but potentially correlated skills to examine whether there exists a penalisation for women in wage offers, or whether other non-pecuniary factors explain the higher propensity of women to choose teaching.

Finally, like with occupational choices, there is substantial residual variation in sector-specific wages across markets. For example, market coefficients in log-wage regressions in voucher schools range from -0.39 to $+0.23$. This could reflect different patterns of self-selection into private school teaching, and/or different wage offer functions. Because the wage offered in private schools is an equilibrium object that depends on the alternatives available to potential teachers and on the demand for private school education in the local market, variation in both labor and education market conditions imply variation in wage offers across markets. The reduced-form parameters are uninformative on the distinct contributions of these sources to wage variation. One of the goals of the structural model is to disentangle how much of the residual variation in wages across markets is due to variation in self-selection and in skill prices (i.e., wage offers).

2.3.3 Demand for Public vs. Private Education

Confirming the well documented school sector stratification in Chile, Table 9 in Appendix B shows that parents with higher income and with higher education are more likely to choose the voucher sector. The public sector is selected more often at the primary level and in rural areas. In terms of variation across markets, probit regressions with market dummies indicate that the average (residual) probability of choosing the public sector ranges across markets from -22 p.p. to $+25$ p.p.. This may indicate different relative qualities of public versus private education due to, for example, differences across markets in relative teacher quality or in other aspects of school quality. One of the goals of the structural model is to estimate the elasticity of the parental school sector choice to teacher quality.

2.3.4 Achievement

Table 10 in Appendix B shows reduced-form estimates of the production of achievement as a function of individual student characteristics. First, if parents select into voucher schools based on unobservable characteristics that are correlated with the child's ability, these reduced-form coefficients are biased. Second, this simple model leaves substantial unexplained variation in outcomes. By accounting for unobservables of both teachers and students, the structural model identifies how variation in teacher and school quality and in student unobservables contribute to this unexplained variation in achievement.

3 Model

There are two stages in the model. In the first stage, wage rates (i.e., skill prices) and tuition fees in the private school sector are determined. In the second stage, the demand for public and private education and the supply of teachers to the two school sectors are determined. The model endogenously determines wages and fees in private schools, the supply of teachers of various skill levels across sectors, the allocation of students across sectors (and the resulting financial aid received by students in voucher schools), student achievement in both sectors, and Government costs.

Importantly, the private schools, parents, and individuals making occupational decisions (i.e., college graduates) take the public school sector policies as given. These are: the unionized teacher wages, the tuition cap for private school fees, and subsidies to households for private education. One could think of a stage zero in the model where such policies are determined. The counterfactual experiments simulate various public sector policies in stage zero, and the endogenous responses in stages one and two of all other agents in the model (potential teachers, parents and private schools).

The economy is comprised of M closed markets, in each market the model is solved separately.

3.1 First Stage: Tuition Fees and Wage Determination in the Private School Sector

There is a representative private school in each market which, following the existing literature, is assumed to maximise profits.[10] The private school takes as given wage offer functions in the public school sector and in the non-teaching sector, and it chooses teacher wages and tuition fees to maximize profits. Tuition fees p are subject to a legal cap $\bar{p}$. Wages are of the standard linear pricing type (Ben-Porath 1967): the private school chooses a wage rate/skill price r such that if a teacher possesses s_i units of teaching skills, his/her offered wage is equal to rs_i.

In the first stage, the private school anticipates the behaviour, in the second stage, of parents and potential teachers, who are price-takers. Therefore, it takes as given the student enrolment and teacher supply functions: $E(p, r; v)$, $T(p, r; v)$. They are indexed

[10] The only existing formal models of the Chilean market for education are in Urquiola and Verhoogen (2009) and Neilson (2017). Both studies assume that private schools are profit maximizing. Using data from the Ministry of Education, Elacqua (2006) documents that 73.60% of all Chilean voucher schools are for-profit. Finally, also McEwan, Urquiola, Vegas, Fernandes, and Gallego (2008) identify Chilean voucher schools as mostly profit maximizing.

by v, the voucher amount, and they depend also on other variables omitted by this simplified notation (for example, on the characteristics of the other options available to parents and to potential teachers). Thanks to the assumption that teachers' utility does not directly depend on student identify (see section 3.3), the expression for the teacher labor supply further simplifies to $T(r)$.

The profit function depends on school revenues and costs. Intuitively, revenues per student are determined by the per-student tuition fees, p, and total revenues are the product of per-student revenues and enrolment, $p \cdot E$. However, the law provides that revenues are adjusted according to two formulae.[11] First, private schools are required to offer fellowships to eligible students towards coverage of the portion of the tuition fee p that exceed the per capita voucher v. These fellowships are co-financed by the private schools and the Government. A formula determines the private schools' contribution to the financial aid budget, which decreases net revenues per student. Second, the size of the voucher subsidy v effectively received by private schools is adjusted according to a formula that penalises higher tuition charges. This adjustment reduces the rate at which the gross per-capita revenues increase as per-capita tuition fees increase. I incorporate both Government formulae into the calculation of profits and denote the adjusted total revenues by $\tilde{R}(p, r, E(p, r; v))$. The exact formulae can be found in Appendix C. Total costs are determined by the sum of a variable cost quadratic in enrolment, the total teacher wage bill, and other operating costs. Formally, the problem of the private subsidised school is:

$$
\begin{aligned}
\max_{(p,r)} \Pi \quad = \quad & \underbrace{\tilde{R}(p, r, E(p, r; v))}_{\text{Adjusted Revenues}} - \underbrace{((c_1 + \epsilon_{cost})E(p, r; v) + c_2 E(p, r; v)^2)}_{\text{Variable Cost}} \\
& - \underbrace{rT(r)}_{\text{Teacher Wage Bill}} - \underbrace{c_3 \frac{E(p, r; v)/NT(r)}{45}}_{\text{N Classes per Teacher}} - \underbrace{OC}_{\text{Fixed Operating Costs}} \\
& \text{s.t.} [\ E(p, r; v) \quad T(r) \quad NT(r)]' = [\ E^*(p, r; v) \quad T^*(r) \quad NT^*(r)]' \quad \forall p, r \\
& p \leq \bar{p}.
\end{aligned}
$$

The first constraint indicates that schools take as given the teacher labour supply function and the student enrolment function which result from utility maximizing behavior in the second stage of the model. The variable cost is subject to a shock ϵ_{cost} which is distributed according to a truncated log-normal distribution with parameters 0 and σ^2_{cost}, where the truncation guarantees that profits are non-negative, and that there is a private school

[11]See Article 25 of the *Decreto con Fuerza de Ley* N^0 *2, De Educacion, de 20.08.98.*

in the market.[12] The total wage bill is the total amount of teaching skills supplied to the sector, $T(r)$, multiplied by the unit price of those skills, r. The term $c_3 \frac{E(p,r;v)/NT(r)}{45}$, where $NT(r)$ is the number of teachers, is a cost proportional to the minimum average number of classes taught by the same teacher. This term captures a key data feature: schools do not hire very few highly skilled individuals and assign them to a large number of students. Therefore, c_3 allows the model to match student:teacher ratios.[13] Finally, if $E = 0$ or $NT = 0$, the private school does not operate.

At the estimated parameter value the profit function is well approximated ($R^2 = 0.96$) by a polynomial that admits only one maximum. Refer to Appendix D for details of this approximation.

3.2 Second Stage: Demand for Education and Supply of Teachers

In the second stage, parents choose a school sector and individuals with a college degree make labour supply decisions to maximize their utility. Parents choose between the public/municipal (M) and the private voucher (V) sector. Individuals with a college degree choose between private schools teaching (V), public school teaching (M), the non-teaching sector (NT), and home production (H).

3.2.1 Demand for Education

Parents, indexed by h, differ in terms of characteristics that are observed and unobserved to the econometrician. In estimation, the unobserved characteristics are modeled as types, in the spirit of Heckman and Singer (1984) and Keane and Wolpin (1997). A household's type k_h can be one of K, with type population proportions given by $\pi_1, ..., \pi_K$.

Parents care about consumption and their child's achievement. Moreover, they have a direct preference for a school sector that is independent of its effect on student achievement. For example, parents may sort on the basis of other amenities that aren't positively

[12] I choose a log-normal distribution to restrict the cost shock to be positive. The parameter c_1 is restricted to be non-negative. The fixed operating costs are normalised to zero in estimation.

[13] The legal cap on class size is 45 in Chile, so if there are x students per teacher, those students must be split into at least $x/45$ classes. An alternative way to match the student:teacher ratio in the data is to assume that either achievement or teachers' utility or both depend on class size in the second stage of the model. However, these modelling options introduce social interactions and a fixed point problem in the second stage that would substantially complicate the numerical tractability of the model.

correlated with educational gains (Rothstein 2006). Formally, the choice-specific utilities of household h in market m are:

$$\begin{aligned} u_{hmM} &= \tau(k_h)ln(c_h) + a_{hmM} + \eta(k_h) + \eta_1 primary_h + \eta_2 rural_h + \nu_{hm}^{pref} \\ u_{hmV} &= \tau(k_h)ln)(c_h) + a_{hmV}, \end{aligned} \quad (1)$$

where k_h is the household's type, a_{hmj} is achievement in sector $j = M, V$, and the η parameters capture the direct sectoral preferences. To capture key features of the data, the latter vary by the education level of the child (primary or secondary), and by whether the family resides in a rural or urban area. The shock ν_{hmM}^{pref} is a preference shock distributed as $N(0, \sigma^2_{pref})$. As is standard in discrete choice models, some normalizations are required. The coefficient on achievement is normalized to one because it is not separately identified from σ^2_{pref}. Moreover, because only the difference in utilities across choices is identified, in the voucher sector the direct preferences are normalized to zero and the shock is normalized to be a degenerate random variable equal to zero.

The utility from consumption is equal to $\tau(k_h)ln(c_h)$, where $\tau(k_h)$ is a parameter that measures the trade-off between consumption and child achievement, and it determines parental willingness to pay for private education. Consumption is equal to household income Y_h if parents select a free public school, and it is equal to income net of tuition payments if they choose a private school. Tuition payments are given by the tuition charged by the school p, minus the voucher subsidy v, minus a fellowship f if the student is eligible for one according to Government guidelines. Formally:

$$c_{hmj} = \begin{cases} Y_h & \text{if j=M} \\ Y_h - (p - v - f(Z_h)) & \text{if j=V} \end{cases}$$

where Z_h are household characteristics determining the amount of fellowship the student is eligible for (which can be anywhere between 0 and $p - v$). The fellowship formula is:

$$f(Z_h) = b_o + b_1 primary_h + b_2 fam\_size_h + b_3 rural_h + b_4 Y_h$$

where fam_size_h is the family size.[14] To account for the fact that parents in the sample are never observed choosing the private sector when their income is lower than the tuition

[14] In estimation, I allow for the fellowship to be measured with error: $\tilde{f} = f + me$ with $me \sim N(0, \sigma^2_{me})$. This shock is independent of all other model shocks.

fees, I assume that parents are credit constrained. The utility from the voucher school is equal to $-\infty$ when tuition is above income, and it is never chosen.

Student achievement is determined by student characteristics, including type, and by the expected quality of the teachers in the school sector ($\bar{s}_{mj}$). There is no distinction between a household's and a student's type because their distributions would not be separately identified. Formally, for $j = M, V$:

$$a_{hmj} = \beta_{0j}(k_h) + \beta_{1j}(k_h)\bar{s}_{mj} + \beta_{2j}(k_h)peduc_h + \beta_{3j}(k_h)y_h + \beta_{4j}y_h^2 + \nu_{hj} \tag{2}$$

where $peduc_h$ is parental education in years (average between mother's and father's education) and y_h is household monthly income divided by household size. The productivity shocks ν_{hM} and ν_{hV} are distributed as independent mean-zero random variables with variances $\sigma^2_{\nu M}$ and $\sigma^2_{\nu V}$. They are independent of the preference shock ν^{pref}_{hm}, therefore, correlation between unobserved student ability and sectoral choice is captured by the type. The impact of parental characteristics on achievement may vary by household type and by school type, to allow for different propensities of observationally identical households to invest in educational inputs, and to capture sector-specific educational expenditures.

3.2.2 Supply of Teachers

Individuals who make labor supply decisions, indexed by i, differ in terms of characteristics that are observed and unobserved by the econometrician. Like in the demand side of the model, in estimation the unobserved characteristics are modeled as types. An individual's type l_i can be one of L, with type population proportions given by $\psi_1, ..., \psi_L$.

The labour supply part of the model is a Roy model of occupational choice augmented with a non-work option and with non-pecuniary preferences. First, the non-work option is important to capture the labour supply decisions of individuals with a high utility from not participating in the labour market, like, for example, women with young children. This is especially relevant in the study of the labour market for teachers in Chile, given the high share of women in the teaching profession. Second, it is important to consider non-pecuniary preferences because the teaching profession differs from non-teaching occupations in terms of job attributes such as flexibility of working arrangements, and because individuals may have an idiosyncratic taste or distaste for teaching. Moreover, within teaching, the private and public sectors differ in terms of non-pecuniary attributes such as job security.[15] Formally, the choice-specific utilities of individual i in market m from each choice $j \in \{M, V, NT, H\}$ are:

$$\begin{aligned}
u_{imM} &= ln(w_{imM}) + \mu_{0M}(l_i) + \mu_{0Teach} female_i \\
u_{imV} &= ln(w_{imV}) + \mu_{0V}(l_i) + \mu_{0Teach} female_i \\
u_{imNT} &= ln(w_{imNT}) \\
u_{imH} &= \mu_{0H}(l_i) + \mu_1 female_i + \mu_2 female_i * nki_i + \\
&\quad \mu_3 age_i + \mu_4 nk_i + \mu_5 nk0-2_i + \mu_6 nk3-6_i + \mu_7 age_i^2 + \epsilon_{iH}^{pref}
\end{aligned} \tag{3}$$

where w_{imj} is the wage offer from sector j to individual i in market m, the μ parameters capture choice and type specific non-pecuniary preferences, and $\epsilon_{iH}^{pref} \sim N(0, \sigma_H^2)$ is a preference shock to the home option. The non-pecuniary term for the non-teaching sector has been normalized to zero because only the differences in non-pecuniary values are identified.

Each individual, including those not observed teaching in the data, is endowed with a certain level of teaching skills, s_i, which would raise the achievement of students if they chose to teach. Teaching skills are a function of an individual's characteristics (both observed and unobserved by the econometrician):

$$s_i = exp\left(a_0(l_i) + a_1' X_i + \epsilon_i^{tech}\right) \tag{4}$$

where ϵ_i^{tech} is a technological shock, and $X_i = [age_i, age_i^2, female_i, cert_i, grad\_deg_i]$ where $cert_i$ is a dummy for whether the individual holds professional certificates and $grad\_deg_i$ is a dummy for graduate degrees (master's or Ph.D.).

The wage offers from the three work options depend on the individual's characteristics. Wage offers in public schools are determined by rigid governmental formulae, which are mostly seniority-based with some additional adjustments. Private school wages are a linear function of skills, as in the standard Ben-Porath/Roy model framework (Ben-Porath

[15]In a related paper (Behrman, Tincani, Todd, and Wolpin 2016), we fully specify a dynamic programming discrete choice model of teacher labor supply, including different future lay-off probabilities. In this paper, the non-pecuniary terms capture in a reduced form way the present discounted value of an occupational choice, including features of the dynamic environment such as lay-off probability.

1967, Roy 1951). Formally, wage offers in the three working sectors are:

$$w_{imj} = \begin{cases} exp\left(\alpha_{0mM}(l_i) + \alpha'_M X_i + \epsilon_{iM}\right) & \text{if j=M} \\ exp\left(\alpha_{0mNT}(l_i) + \alpha'_{NT} X_i + \epsilon_{iNT}\right) & \text{if j=NT} \\ r_m s_i = r_m exp\left(a_0(l_i) + a'_1 X_i + \epsilon_i^{tech}\right) & \text{if j=V} \end{cases}$$

where r_m is the price of teaching skills in market m (the wage rate), determined in the first stage of the model. The constant in the public school log-wage equation depends on an individual's type l_i to capture those individual characteristics entering the rigid wage formulae that are not observed in the data. The wage shocks $\epsilon_i = [\epsilon_{iM}, \epsilon_i^{tech}, \epsilon_{iNT}]'$ are i.i.d., independent of the preference shock, and distributed as $N(0, \Sigma)$, where Σ is a diagonal matrix with elements $\sigma^2_M, \sigma^2_V, \sigma^2_{NT}$. Non-teaching skills are not assumed to be identical to teaching skills. In the model, any correlation between teaching and non-teaching skills and between skills and occupational choices is captured by the distribution of types. These correlations determine how the wage elasticity of the teacher labor supply is affected by non-teaching opportunities.[16]

3.3 Equilibrium: Joint Determination of Demand for Education, Supply of Teachers and Prices

There is a co-dependence between parental school choice and the occupational choice of potential teachers that works through two channels. The direct channel is the dependence of payoffs on others' characteristics. The indirect channel is the mediation through the price mechanisms.

The choice of school sector that parents make depends on teacher labour supply directly and indirectly. First, parental school choice depends directly, among other things, on the expected quality of teachers in the two school sectors. This is endogenously determined within the model (see Appendix E for a derivation of equilibrium teaching skills by sector). Second, the wage elasticity of potential teachers determines the amount of resources needed by voucher schools to attract teachers of certain skills, therefore, it affects the tuition fees charged by private schools. This, in turn, affects parental choice of sector. This

[16] For example, if skilled teachers are also skilled in non-teaching occupations, they obtain high wage offers from outside of teaching and schools must offer higher wages to attract them.

chain of effects is endogenously generated within the model. Simulations of counterfactual teacher policies capture not only how the teacher labor supply varies across sectors, but also how parental school choice responds. It is important to consider this margin of policy response, especially when teacher and student ability are not assumed to be additively separable in the production of achievement. In this general case, the policy impact on test scores depends on the teacher-student match induced by the policy.

Conversely, the choice of occupation in the labor supply part of the model does not directly depend on the characteristics of students in the two school sectors. Because of this assumption, the teacher supply in the profit function in section 3.1 can be simplified as a function of the wage rate r only, and not also of tuition fees p. This assumption greatly simplifies the model solution and estimation. However, it still allows for occupational choices to be affected by student characteristics indirectly, through the price mechanism, because the wage rate r adjusts endogenously with school composition. The advantages of this assumption are that, first, it guarantees the existence and uniqueness of an equilibrium in the second stage of the model.[17] Without this restriction, solving the second stage of the model would require solving a fixed point problem. Not only existence of a solution would not be guaranteed in this case, but there would be the additional concern of multiplicity of the equilibria, which poses considerable challenges in estimation. Second, this assumption keeps the model tractable numerically. This assumption is less restrictive than it would initially appear, because the price mechanism captures the dependence of teacher labor supply on school composition.[18]

4 Discussion of Model Features

To be useful for policy analysis, the model makes a number of assumptions to obtain a reasonable and tractable approximation to how students and teachers choose school sectors.

[17] The second stage is equivalent to a sequential game where teachers move first. An equilibrium is attained when all parents and all potential teachers choose the option that maximizes their utility. An equilibrium exists because each potential teacher and each household have at least one most-preferred choice by construction: utilities are well defined. Moreover, because technology and preference shocks are continuously distributed in the population, no agent is indifferent between two options. Therefore, by backward induction the equilibrium is also unique.

[18] For example, a policy that increases the allocation of lower-SES students to private education would reduce the total net revenues of private schools through the financial aid mechanism, and this in turn would lower the price r that the private schools are able to offer to teachers. This would reduce the likelihood of teachers to choose private schools with lower SES students, a pattern uncovered in some previous studies (Hanushek, Kain, and Rivkin 1999).

The model abstracts from competition and stratification across schools within a sector. There are three reasons for this. First, understanding and tackling stratification across school sectors is a first-order objective of Chilean education policy (Epple, Romano, and Urquiola 2015). Second, this abstraction makes the equilibrium model tractable for two reasons. First, the private schools' pricing strategies can be obtained through the maximisation of a single profit function per market. This allows the model to abstract from the large set of potential strategies of competitors within each market, while still letting it capture the economic forces driving prices. The estimated prices implied by the model are found to correlate in a reasonable way with aggregate market characteristics not used in estimation (see section 7.1). Second, this assumption keeps the choice sets of parents and of teachers small. The third reason for this modelling choice is due to data limitations: in the teacher dataset, not all schools are sampled, and in sampled ones, on average there is a small number of teachers per school. A school-level analysis would not be informative because of large sampling noise.[19]

I use a Roy-model framework for the teacher supply part of the model because it allows me to predict the teaching skills of all individuals in the sample, including those who are not observed teaching in the data. The key parameters to identify teaching skills are those that enter equation (4) (the teaching skill production function) and that determine observed private school wages. Once these parameters are identified, teaching skills can be predicted for all potential teachers in the sample through equation (4). The estimation of a Roy model is made possible by the unique features of the Chilean labor market, where a large scale private school sector with individually negotiated wages co-exists alongside the more traditional public school sector with unionized wages.[20]

This paper focuses on teaching skills possessed by an individual, and it ignores teacher effort, following a stream of the teacher quality literature (Stinebrickner 2001a, Stinebrickner 2001b, Rothstein 2015, Hanushek, Rivkin, Rothstein, and Podgursky 2004, Biasi 2017, Rivkin, Hanushek, and Kain 2005). The reason for this is lack of data on teacher effort. Recent findings that separately identify the impact of teacher ability and effort

[19]See Neilson (2017) for a model of competition within the Chilean private school sector, which abstracts from competition across school sectors.

[20]Exploiting similar data variation, Biasi (2017) estimates a Roy model of teacher labor supply using data from Wisconsin, where the passage of Act 10 in 2011 changed teacher pay determination from collective bargaining (like in public schools in Chile) to individual negotiations (like in voucher schools in Chile).

suggest that ability has a considerably larger impact on student achievement than effort (Macartney, McMillan, and Petronijevic 2016). Therefore, it is an important margin to focus on as a first step. Complementing this study with endogenous teacher effort choices would be a valuable extension if adequate data become available.

The specification of the achievement production function is flexible in that it does not impose a specific type of complementarity between student ability and teaching skills. Moreover, it varies by school sector to capture differences in unobserved inputs across sectors (the constant in (2)) and in the productivity of teacher quality. This flexibility has the advantage that results of the counterfactual policy experiments are not driven by ex-ante arbitrary restrictions on key features of the technology such as the complementarity between teachers and students. For example, more standard value-added models rule out complementarity, making it difficult to predict the impact on test scores of policies that alter the student-teacher match..

A limitation of this specification is that it does not include peer effects. This modelling choice guarantees numerical tractability and uniqueness of the equilibrium.[21] A second reason for this restriction is that the identification of peer effects poses additional demands on the data which are not clearly met by the dataset (Manski 1993). For similar reasons, the only other existing models of the Chilean market for education equally abstract from peer effects (Urquiola and Verhoogen 2009, Neilson 2017). On the other hand, most studies of school choice that allow for peer effects abstract from teacher labor supply (see Altonji, Huang, and Taber (2015) and Epple and Romano (2008) for a structural approach and Dills (2005) for a non-structural one), and most studies of teacher labor supply abstract from parental school choice and peer effects.[22] Because there currently does not exist a modelling framework that simultaneously studies parental school choice, teacher supply and private school pricing with peer effects, the model presented here could be seen as a reasonable first step. Future studies could build on it to include peer effects.

Finally, the model assumes that residential sorting is exogenous. While a literature on location choices and public goods exists (Epple and Sieg 1999, Nechyba 2000, Ferreyra 2007), there is not yet a well developed literature on two-sided equilibrium models with

[21] Had there been peer effects, the solution to the parents' problem would have required solving for a fixed point with no guarantee of equilibrium existence or uniqueness (Brock and Durlauf 2001). This is the same reason why school composition does not enter the direct sectoral preference of parents, as already explained in section 3.3.

[22] Some studies examine the role that school choice programs play for teacher effectiveness, entry, turnover, and salaries (see, for example, Jackson (2012), Hensvik (2012) and Behrman, Tincani, Todd, and Wolpin (2016)), without explicitly analyzing parental school choice or peer effects.

two-sided residential sorting. The paper that is closest to this one in terms of modelling matching patterns of schools and teachers is Boyd, Lankford, Loeb, and Wyckoff (2013). As in this paper, they estimate their model on multiple markets and treat the allocation of teachers and schools to markets as exogenous.[23]

5 Estimation and Identification

5.1 Estimation

Estimation is performed on multiple markets, each of which is assumed to be in equilibrium. There are two estimation steps. The first step estimates the parameters from the second stage of the model, θ_{II}. These are the preference and technology parameters of households and of individuals making labor supply decisions and the fellowship formula parameters. This step recovers also the market-specific prices of teaching skills, r_m, $m = 1, ..., M$. The second estimation step treats the recovered skill prices as observations, and it uses them to estimate the parameters of the profit function in the private school sector, θ_I. The estimated θ_I parameters rationalize the prices p_m (tuition fees) and r_m (skill prices) as profit maximizing. Separation of the estimation in two steps is possible because the equilibrium of the second stage of the model depends on the profit function parameters only through their effect on tuition fees p_m and wage rate r_m.[24]

5.1.1 Step one of the estimation

The parameter vector θ_{II} is estimated by the method of simulated moments (MSM) (McFadden 1989, Pakes and Pollard 1989). The method minimizes the distance between observed outcomes and outcomes simulated from the model. The outcomes are occupational choices of potential teachers, school choices of parents, wages of potential teachers, test scores of children, and fellowship amounts. A list of the conditional moments used can be found in Appendix F.

[23]In Biasi (2017), the district choice of teachers coincides with their labor supply choice. That is, teachers choose among districts that differ in terms of whether wages are unionized or individually negotiated. While the initial residential location of teachers is assumed to be exogenous, the labor supply choice generates a positive correlation between districts that use individual wage negotiation and teacher skills.

[24]This method is similar in spirit to Moro (2003), who uses the first step to estimate an equilibrium object, and the second step to estimate the model parameters that rationalize the equilibrium.

Because I use multiple data sources, I adjust the criterion function of the estimator and the parameter standard errors to account for the relative sizes of the samples and of their populations of reference. I follow the method developed in Bhattacharya (2005), details of which can be found in appendix G. This Appendix includes also technical details of the estimation, the asymptotic properties of the estimator, as well as details of the estimation of the asymptotic variance of the estimates.

5.1.2 Step two of the estimation

This step estimates the voucher sector cost parameters $\theta_I = [c_1, c_2, c_3, \sigma_{cost}]$. Estimation is by Nonparametric Simulated Maximum Likelihood (NPSML) (Laroque and Salanie 1989, Fermanian and Salanié 2004). All private schools are observed pricing at the tuition cap, hence, there is no variation across markets in this variable. Therefore, I use variation across markets in the wage rates r_m to estimate θ_I. The observation that the price cap is binding in all markets is treated as an over-identifying restriction.

The likelihood function does not have a closed-form expression, because the profit maximizing r_m in each market is an unknown function of the random cost shock, which does not admit a closed form. For this reason, the density of r_m, which enters the likelihood function, cannot be analytically derived. The NPSML method approximates the unknown likelihood function with a kernel-based nonparametric estimator based on simulations of the choice variable r_m. Under regularity conditions the estimator is consistent, asymptotically normal and asymptotically efficient when the number of simulations and observations go to infinity and the bandwidth goes to zero. For a formal description of how the NPSML method is implemented here, refer to Appendix H.
Given a realisation of the cost shock, the model holds predictions not only for the skill price r_m in each market, but also for tuition fees p_m, which are not used in estimation. I use this predictions to test the model's first stage. Simulated tuition fees p_m at the estimated parameter values are binding at the tuition fee cap, as observed in the data. Therefore, the model is able to match a key feature of the data that is not matched by construction. I other words, the first step of the model is falsifiable but not falsified by the data, a desirable property for a model.

5.2 Identification

5.2.1 Teaching Skills and Market-Specific Teaching Skill Prices

Self-selection of potential teachers into occupations based on unobservables could bias estimates of wage parameters. To account for this, I frame teacher sorting within a Roy model (Roy 1951) of self-selection into occupations, a workhorse model in labor economics.[25] For a formal proof of identification of the wage and non-pecuniary preference parameters in this class of models see, for example, Heckman and Honore (1990). Intuitively, self-selection bias is accounted for through an adjustment term generated by the structural model, which measures average unobserved ability conditional on an occupational choice, in the spirit of a control function approach (Heckman and Navarro 2004).[26] However, for the case of private school wages, unexplained wage variation is not only due to self-selection based on unobservables, but also to variation in market specific skill prices (which are unobserved). The self-selection correction method cannot separately identify prices from unobserved teacher ability in the constant of log-wages. For this, an additional identification strategy is needed.

Specifically, I exploit across market variation in private school wages, following closely the identification strategy in Heckman and Sedlacek (1985) (see note 17 in that paper). Markets in this paper play the role of years in Heckman and Sedlacek (1985). A key identifying assumption is that teaching skill prices vary across markets, but not within markets. Imagine estimating a regression model of log-wages in private schools which includes market dummies. Their coefficients are the sum of two terms: average unobserved ability of private school teachers in that market (a market-specific self-selection term), and the unobserved price of teaching skills in that market. The self-selection control function identifies unobserved ability in private schools up to scale, off of within-market data variation. Under the identifying assumption of exogenous residential location of potential teachers, normalizing the price of skills in one market sets the scale of the self-selection terms in all markets. The prices in the other markets are identified by subtracting the market-specific self-selection term from the market dummy.[27]

[25] It has been used to study self-selection in a number of contexts, for example, immigration and residential choice (Borjas 1987), occupational and industrial choice (Heckman and Sedlacek 1985, Heckman and Sedlacek 1990), optimal taxation with self-selection (Rothschild and Scheuer 2012) and employment in the private and public sectors (Borjas 2002).

[26] Exclusion restrictions are not needed for parametric identification. However, in the model fertility variables affect the labour supply decision but not the wage conditional on working.

[27] Teaching skills are identified only up to scale. This does not affect any of the counterfactual experiments presented, because the choice of normalizing constant does not affect the estimated impact of teaching skills on achievement. To see why, notice that the latter is given by the product $\beta_{1j}(k)\bar{s}_{jm}$ in

5.2.2 Demand for Private Education and Unobserved Student Ability

Self-selection of parents into school sectors could bias the parameters of the achievement production technology and of the preferences for a school sector. First, the structural model explicitly accounts for this source of bias, and in so doing, it corrects for it parametrically in the spirit of a control functions approach. In the model, self-selection into school sectors is governed by the price elasticity of parents, which is determined by parental willingness to trade off child achievement for consumption ($\tau(k_h)$ in equation (1)). This is correlated with students' unobserved ability through the unobserved type k_h. Therefore, private and public school students may have different unobserved abilities.

However, I do not rely only on the model for identification, I also use exclusion restrictions naturally occurring in the Chilean setting. I exploit variation in tuition fees due to the assignment of the fellowship, which is mandatory by law and depends on Government guidelines. Intuitively, fellowships generate observations where families with identical preferences and expected gains from private and public education make different school choices because they face different tuition fee requests. As long as at least one of the variables entering the fellowship formula is uncorrelated with unobserved student ability, (non-parametric) identification of price elasticities is possible. I find that two of the variables in the formula correlate significantly with the fellowship received by the student, but not with his/her test scores. Specifically, in an achievement regression that controls for income per capita and parental education, the coefficient on the school level has a p-value of 0.260, and on rurality of 0.744. Conversely, these variables are highly significant in predicting fellowship amounts (the p-values are 0.000).

This is not surprising, because national guidelines limit the ability of schools in Chile to perfectly price-discriminate through the fellowship. For this reason, other studies use Chilean school fellowships for identification (see Anand, Mizala, and Repetto (2009)). Similar variation in tuition discounts due to family size has been used in the U.S. setting to identify price elasticities of parents and unobserved student ability (Dynarski, Li, and Gruber 2015, Altonji, Elder, and Taber 2005).

5.2.3 Productivity of teaching skills

An important question in this paper is how teaching skills and student characteristics combine to produce achievement in the two school sectors. To identify the parameters of the production of achievement, one must observe variation in teacher skills and in

equation (2), which is identified as a residual in the test score equation and, therefore, its identification is independent of the choice of scale for the average skills, $\bar{s}_{jm}$.

student characteristics and relate them to variation in student outcomes. However, not all teacher and student characteristics are directly observed. To overcome this, I model unobserved heterogeneity on both sides of the education market, and estimate both sides simultaneously on a linked dataset. The key insight is that I use private school wage data (and an appropriate correction for self-selection on unobservables) to build a measure of teaching skills that combines observed and unobserved teacher characteristics. This measure of teacher quality is then inserted into the achievement production function in estimation.

Specifically, teaching skills are identified for all individuals in the sample, including those not observed teaching, because the parameters of the teaching skill equation (4) are identified, as explained in section 5.2.1. The estimated parameters from this equation can be used to predict teaching skills for all individuals. At each parameter iteration in the estimation algorithm, an inner loop solves for the supply of teaching skills to each school and inserts these simulated teaching skills into the achievement production function. Therefore, at each parameter iteration, it is *as if* teaching skills were observed. As a result, it is possible to estimate their impact on achievement and their effect heterogeneity across students. The latter would not be possible if teacher ability were estimated as a value-added from test score data only, because in this case teacher quality would have to be modelled as additively separable from student characteristics. Details of the algorithm can be found in appendix I.

5.2.4 Profit function parameters

The profit function parameters are identified from variation in skill prices r_m across markets. From the first order condition of the private school's problem, skill prices r_m are a function of the supply of teachers to private schools and demand from parents for private schools. These are functions of market characteristics that are identified in the first step of the estimation. To simplify the exposition of the identification argument, I present a linear version of the model. To further simplify, I do not include tuition fees p_m in the following equations, because this variable does not vary across markets. Consider the first order condition for skill prices:

$$r_m = \gamma_0 + \gamma_1 SV(r_m; \alpha_m) + \gamma_2 DV(r_m; \beta_m) + \epsilon_m, \tag{5}$$

where ϵ_m is the cost shock. The functions $SV(r_m; \alpha_m)$ and $DV(r_m; \beta_m)$ represent the supply of teachers to and demand from parents for voucher schools. To simplify further, assume they are linear: $SV_m = \alpha_{0m}+\alpha_1 r_m$ and $DV_m = \beta_{0m}+\beta_1 r_m$. The constants, indexed by m, represent idiosyncratic market conditions. For example, in the full structural model, markets differ in terms of the population distribution of parental characteristics and of potential teacher characteristics, moreover, wage rates in the non-teaching sector may vary across markets. The parameters of these functions are identified and estimated in the first step of the estimation. Plugging these estimates into equation (5) and rearranging:

$$r_m = \frac{\gamma_0}{1-\gamma_1\hat{\alpha}_1-\gamma_2\hat{\beta}_1} + \frac{\gamma_1}{1-\gamma_1\hat{\alpha}_1-\gamma_2\hat{\beta}_1}\hat{\alpha}_{0m} + \frac{\gamma_2}{1-\gamma_1\hat{\alpha}_1-\gamma_2\hat{\beta}_1}\hat{\beta}_{0m} + \epsilon_m. \tag{6}$$

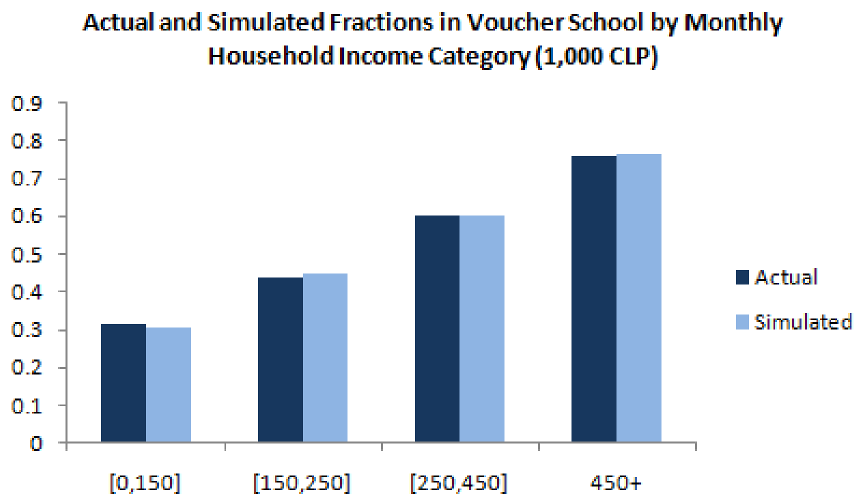
From this equation, it is clear that the identifying assumption is that the private schools' cost shock ϵ_m is independent of the idiosyncratic market conditions $\hat{\alpha}_{0m}$ and $\hat{\beta}_{0m}$. For example, as wage rates in the non-teaching sector vary, private school wage rates r_m are allowed to strategically respond. However, there should not be a correlation between wage rates in the non-teaching sector and the private school cost shock. When this is the case, variation in wage rates in the non-teaching sector generates variation in the supply of teachers to private schools that helps identify the private school's demand for teachers.[28]

6 Model Fit

Table 3 shows the model fit. Simulations of the choice distributions of parents and potential teachers are very close to the data, within, respectively, 0.9 and 1.1 percentage points. Figures 1 and 2 show visually how accurate the model predictions are for the choice distributions of parents (by income) and potential teachers (by gender). The fit is equally good when conditioning on other characteristics beyond gender and income. Figure 4 in the Appendix shows the accuracy of the model in predicting tuition payments (net of the voucher and fellowship) in private schools, which depend on the endogenous selection of households into private schools because different households are eligible for different fellowship amounts. Wages simulated from the model are within 6 percent of actual wages. Mean test scores are under-predicted by 0.025 standard deviations. The simulated test score gap by school type is close to the actual one, and the gap by income is within 6.5 percent of the actual one. Figure 5 in the Appendix shows that the distributions of actual and simulated test scores by school type are close, especially for public schools.

[28]Labor market opportunities outside of teaching have been found to be important determinants of teacher labor supply (Corcoran, Evans, and Schwab 2004a, Dolton and Klaauw 1999).

Figure 1: Model fit: parental sorting



The fit is similar within markets. An example of a within market fit is presented in Figure 6.

7 Empirical results

7.1 Estimation results

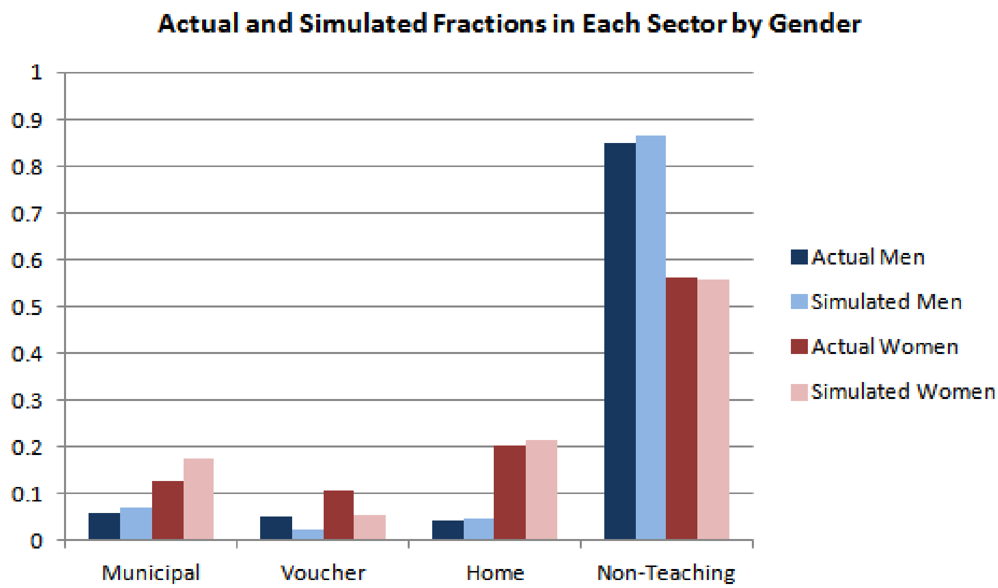
Parameter estimates of wage offers and potential teacher utility are reported in Tables 12 and 13. The reduced-form wage parameters suggested, surprisingly, that graduate degrees and certifications are valued more in private schools and the non-teaching sector than in public schools. By accounting for selection bias, structural estimates reveal that the opposite is true. Degrees and certifications are valued more in public schools, where wages are unionized and follow rigid formulae.[29] This gives me confidence in the goodness of the selection-correction provided by the structural model. A second finding is that women's wages in Chile are not penalized more in non-teaching occupations than in teaching, as would be suggested by reduced-form estimates. In fact, the wage penalisation for females in non-teaching jobs is the same as that in the voucher school sector, and

[29]The log-wage structural coefficients on certifications and on graduate degrees in public school, voucher schools, and the non-teaching sector are, respectively: public schools $0.425, 0.403$, voucher schools $0.36, 0.27$, non-teaching sector $-0.031, 0.11$.

Table 3: Model Fit

		Actual	Model
Parents			
Proportion Enrolled in Voucher Schools			
	Overall	52.99%	52.38%
	Primary	51.27%	50.99%
	Secondary	55.09%	54.08%
	Urban	55.06%	54.36%
	Rural	29.46%	29.84%
Mean Tuition (1,000 CLP)		15.25	15.52
Mean Test Scores			
	Overall	-0.003	-0.028
	Municipal Schools	-0.191	-0.219
	Voucher Schools	0.164	0.146
	Gap Municipal-Voucher	0.355	0.365
	Gap by Income (top-bottom quartile)	0.681	0.725
Potential Teachers			
Proportion Enrolled in			
	Municipal Schools	9.48%	10.65%
	Voucher Schools	7.81%	7.28%
	Non-Teaching Occupations	70.28%	68.97%
	Home	12.44%	13.10%
Mean Accepted Wages (1,000 CLP) in			
	Teaching	4790	4564
	Municipal Schools	5095	4828
	Voucher Schools	4415	4178
	Non-Teaching Occupations	7774	8075

Figure 2: Model fit: occupational choices



larger than in the public school sector (see the coefficients on the female dummy in Table 12). Therefore, the higher propensity of females to choose the teaching profession is not due to wage penalisation (e.g. discrimination) outside of teaching, rather, it is due to non-pecuniary aspects of teaching like, for example, more flexible working arrangements. This is confirmed by the structural non-pecuniary preference parameters, indicating that females have a larger non-pecuniary preference for teaching, as well as for choosing to not work, especially when there are children in the household.[30]

The structural model separately identifies the price that voucher schools offer for teacher quality, from teacher quality itself.[31] About half (50.8%) of the unexplained variation in private school teacher wages across markets is explained by variation in skill prices, and the remaining half by variation in unobserved teacher quality in private schools.[32] Therefore, unobserved teacher quality and the price that voucher schools offer for teacher quality are both important determinants of wages.

Estimated skill prices (reported in Table 14) respond to market forces in the expected direction. For example, they correlate negatively with the unemployment rate in the

[30]Similarly, using U.S. teacher data and a structural model, Stinebrickner (2001b) finds that women who are married or who have children have a higher non-pecuniary preference from staying at home.

[31]See Heckman, Lochner, and Taber (1998) for a discussion of the advantages of separately identifying unobserved skills from unobserved skill prices in wages.

[32]This is computed by dividing the variance in optimal skill prices across markets in the baseline simulation by the variance in market fixed effects estimated on simulated accepted log-wages in voucher schools.

market (correlation coefficient: -0.31), which is a determinant of reservation wages. They also correlate positively (albeit with a smaller magnitude) with aggregate factors that affect the parental demand for private education, such as various aggregate SES indicators of the parents in the market. These correlations are not matched by the estimation nor are they true by construction. They (informally) validate the model's ability to capture key features of the economic forces operating in the teacher labor market.

Although skill prices adjust to market conditions, in markets with more appealing non-teaching options teachers are of lower ability. The correlation between simulated teaching skills and simulated non-teaching wage offers is negative in both sectors, and more negative for public schools (-0.37) than private schools (-0.10). Private schools are better able to retain highly skilled teachers when appealing non-teaching options exist, a finding consistent with evidence from the United Kingdom and the United States.[33] More generally, teachers in public schools have lower skills than teachers in private schools, as can be seen in the top left panel of Figure 3. This is consistent with prior evidence in the literature that uses data not used in this paper.

Parameter estimates of the achievement production function and of parental preferences are reported in Tables 15 and 16. First, the reduced form estimate of the constant in the production of test scores was lower in municipal than in voucher schools. However,these estimates confound the impact of all unobserved inputs, including teacher quality. The structural estimates net out teacher effects through the equilibrium of the model, and yield a lower constant in voucher schools (for all student types). Therefore, other than a lower teacher quality, which drives the reduced form result, municipal schools do not have worse unobserved inputs than private schools.

Second, there is a teacher-student complementarity: the coefficient on teacher quality varies among student types in a statistically significant way. Hence, to evaluate teacher policies that change the allocation of teachers and/or students across school sectors, it is not sufficient to use a teacher value added approach. Rather, one needs to simultaneously analyse teacher and student allocation across schools, and how the teacher-student match affects achievement.

Finally, parents have, on average, a larger direct utility for private schools than for public school. This is a preference that is independent of the school's impact on student outcomes. Simulations indicate that if parents did not have this direct preference for the

[33] Dolton and Klaauw (1999) show that "higher opportunity wages increase the tendency among teachers to switch careers and leave the profession voluntarily," while Corcoran, Evans, and Schwab (2004b) find that the rise in employment opportunities for talented women in the United States is responsible for the decline in the quality of the teacher labor force.

private school sector, enrolment in private schools would be lower by 10 percentage points.

7.2 Counterfactual experiments

7.2.1 Ex ante evaluation of the Chilean merit-based teaching reform

In 2017, the Chilean Government introduced a teaching reform which will be implemented gradually until 2023 (law *N. 20.903*). The reform has two key elements: new hires will be compensated based on their merit (measured through numerous competency assessments), and there will be minimum competency requirements for new teachers. These requirements are set to gradually increase between 2017 and 2023.

This counterfactual simulates the long-term equilibrium of the reform, after the introduction of the 2023 requirements.[34] It lets wage offers in public schools depend on teaching skills, and it introduces an entry requirement for teachers. It then simulates equilibrium outcomes, utilities and Government costs.

First, in the counterfactual simulations the wage offer in public schools of individual i with teaching skills s_i is set to $r_M s_i$, where r_M solves

$$r_M = \frac{1.30\frac{\sum_{i\in M_b} w_{iM}}{n_{Mb}}}{\frac{\sum_{i\in M_c} s_i}{n_{Mc}}}.$$

In other words, r_M is such that average teacher wages in public schools would increase by 30 percent under the reform, the stated Government goal (Sanchez 2016).[35] Second, simulations introduce the minimum competency requirement that will be implemented in 2023, requiring that teachers have a test score on the PSU, the national university entry exam, equal to the 70^{th} percentile or higher.[36]

Simulation results are reported in the second column of Table 4. The reform is

[34] In the transition to the new rules, current teachers in Chile are not subject to the minimum competency requirements. In the long-term equilibrium, minimum competency requirements apply to all individuals wanting to teach.

[35] At the numerator, there is the average of public school wages at baseline (before the reform), while at the denominator there is the average of teaching skills in public schools under the counterfactual policy.

[36] I translate the cutoff in terms of the model's teaching skills, using the known distributions of the university entry exam scores for the entire population and for teachers pre-reform. Specifically, in the population the 70^{th} percentile corresponds to a score of 558.3. Using the statistics in Bravo, Flores, Medrano, and Santiago (2010), I calculate that among public school teachers before the reform, this cutoff corresponds to the 41^{st} percentile of the distribution of entry exam scores. Assuming that teaching skills are monotonically increasing in the entry exam score, the 41^{st} percentile in the university entry exam corresponds to the 41^{st} percentile in the teaching skills distribution among public school teachers. From model simulations at baseline (pre-reform), I obtain the value of this cutoff in terms of teaching skills, and impose it as an entry requirement for teaching in all sectors in the policy simulations.

predicted to increase test scores on average by 30 percent of a standard deviation (sd), and to decrease inequality in test scores by family income by around a third. Specifically, the difference in test scores between students in the top and in the bottom quarters of the income distribution decreases from 0.725 to 0.487 sd (fourth row of the top panel).

The quality of the pool of teachers improves: simulated teaching skills increase on average by 0.639 sd across both sectors.[37] Moreover, the teacher quality gap reverses, with better teachers in public schools than in private schools, and it reduces in size considerably, by 80 percent. The merit-based wages in public schools attract skilled individuals from outside of teaching, and cream skim good teachers from the voucher sector. As a result, average teaching skills increase in the public sector by 1.267 standard deviations, and they decrease in voucher schools and in the non-teaching sector by 0.549 sd and 0.097 sd respectively. However, average test scores do not decrease in voucher schools because because of a pure compositional effect due to the outflow of lower SES students into public schools.[38]

Voucher schools face more competitive pressure from the public sector to attract high quality teachers. As a result, they increase their wage rate offers on average by 27 percent, but they cannot match the higher wage rate offered in public schools, leading to the aforementioned decrease in teaching skills. Therefore, average accepted wages in private schools increase only by 7 percent (because they are the product of the offered wage rate and the skills of those who accept the wage offer).

The last two columns explore channels of policy effectiveness. Column four shows that ignoring the response of private schools to the reform would result in an underestimation of the quality of teachers in both school sectors, resulting in an underestimation of the positive effects of the reform on test scores. Column five shows that the reaction of parents reduces the test score gap between public and voucher schools that would prevail if they

[37] There is a distinction between teaching skills, an ordinal measure of skills, and the impact of those skills on student test scores. Because teaching skills in the model are allowed to have heterogeneous impacts on test scores across students and schools, model estimation does not yield a simple value-added measure of teaching skills that does not depend on students or schools. For this reason, I present impacts both on the ordinal measure of teaching skills, to analyze teacher quality across schools, and on test scores, which are the outcome of interest. The Table's fifth column can be used to benchmark the ordinal teaching skills in terms of student test scores: a decrease of about half a standard deviation in teacher skills in private schools results in a decrease by about 0.10 sd in test scores, keeping student composition fixed, while an increase in teacher skills in public schools of 1.3 sd results in an increase in test scores of about 0.60 sd, keeping student composition fixed.

[38] The reform does not induce any movement of students out of the public sector. New enrollees in public schools come, on average, from the lower tail of the SES-distribution of baseline voucher sector students. As a result, the reform improves the average SES in both school sectors, without changing considerably the gap in SES, as seen in Table 11 in the Appendix.

Table 4: Simulation of the 2023 merit-based reform and of a flat increase in Municipal wage offers

Outcome	**Baseline**	**2023 reform**	**Flat bonus**	**Reform without reaction of: Voucher schools**	**Parents**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
			Demand for education side		
Mean test scores (standardized)					
Entire population	-0.028	0.275	-0.004	0.025	0.183
Municipal schools	-0.219	0.272	-0.180	0.011	0.350
Voucher schools	0.146	0.280	0.172	0.235	0.019
Gap by income	0.725	0.487	0.704	0.144	0.480
Enrolment share in M	0.476	0.612	0.483	0.944	0.476
			Supply of education side		
Mean teaching skills (standardized)					
Municipal schools	-0.058	1.209	0.011	1.092	1.209
Voucher schools	1.441	0.892	1.558	0.850	0.890
Non-teaching	-0.129	-0.226	-0.139	-0.222	-0.226
Home	0.198	0.198	0.198	0.198	0.198
Teacher wages (baseline=1)					
Municipal schools	1.00	1.30	1.31	1.25	1.30
Voucher schools	1.00	1.07	1.11	1.15	1.08
Teaching skill prices (baseline=1)					
Voucher schools	1.00	1.27	1.09	1.00	1.27

Policy impacts are obtained by comparing columns 2 and 3 to the first one. For teacher wages and skill prices, impacts are in terms of percent increases from baseline. For example, Municipal school wages increase by 30 percent under the merit reform (1.30-1.00=0.30). For standardized test scores and teaching skills, impacts are expressed in standard deviations. The last two columns report impacts of the 2023 merit reform when private schools are not allowed to change the wage rates they offer (column 4); and when parents cannot change their school choice (column 5).

were not allowed to move. A key lesson that we learn is that the existence of a large school choice program amplifies the positive impacts of merit reforms in the teacher labor market, thanks to equilibrium wage adjustments in the large non-public school sector which result in a better self-selection of individuals into teaching and across school sectors.[39]

What are the individual contributions of demand and supply factors? Allowing for only the parental response but not the voucher schools' response would explain about 10 percent of the treatment effect on mean test scores (row one, column four), while allowing for only the voucher schools' reaction but not the parental reaction would explain almost 70 percent of the treatment effect (row one, column five). Therefore, the policy reactions on the supply side of the market contribute relatively more to overall impacts than demand side reactions. A lesson that we learn is that in a context with a large subsidised private school sector, private school reactions are an important driver of the effects of public policies in the teacher labor market. This result is in line with Neilson (2017), who finds that also in the case of reforms of the subsidy structure, policy impacts are driven by the supply side response of private schools rather than by parental sorting when there exists a large private subsidised school sector.

Finally, Table 5 contains a cost-benefit welfare analysis of the reform. There are positive impacts on the average utility of households, with poorer families enjoying higher gains. There are fairly large positive impacts on those college graduates who before the introduction of the reform would have chosen to work in the voucher sector: these are skilled individuals who enjoy teaching. On average, those who would have chosen to work in public schools at baseline are made worse off by the reform. This result is driven by the low skilled public school teachers who, before the reform, enjoyed high wages relative to their skills. Importantly, the reform pays for itself in the long run, so that Government costs are unchanged. At baseline, the voucher revenues are not sufficient to cover municipal school running costs: the Government needs to inject additional funds into public schools. Under the reform, voucher revenues in public schools increase by a quarter, reducing the need for additional, non-voucher funds by 90 percent.[40] The merit reform is more sustainable financially than the baseline scenario, because in a context where parents choose with their feet, better teachers induce higher voucher revenues.

The results of this counterfactual policy analysis indicate that the merit-based reform introduced in Chile in 2017 and whose implementation is planned to complete in 2023

[39] Column three does not allow private schools to change the wage rates they offer in response to the policy. Most private schools would be unable to fill their teaching posts and almost all enrollment would be in public schools.

[40] Simulations of detailed cost break-down are available from the author upon request.

Table 5: Welfare analysis of the 2023 merit-based reform

Outcome	**Baseline**	**Reform**	**Effect**
Mean parental utility (standardized at baseline)			
Entire population	0.000	0.079	0.079
Above median income	0.471	0.525	0.054
Below median income	-0.452	-0.349	0.103
Mean utility of college graduates in the labour market (standardized at baseline)			
Entire population of college graduates	0.000	-0.002	-0.002
Public school teachers at baseline	-0.740	-1.131	-0.391
Voucher school teachers at baseline	-0.757	-0.209	0.548
Non-teaching sector at baseline	0.162	0.179	0.017
Private school profits			
Baseline=1	1.00	1.23	+0.23
Cost to the Government			
Baseline=1	1.00	1.00	0.00

Utilities are standardized using the baseline mean and standard deviation, therefore, the last column contains policy effects in terms of standard deviations. Because individuals who do not work at baseline do not work under the reform and viceversa, I analyse the welfare impacts on those who at baseline are in the labour market because these are the only college graduates who are affected by the reform. The impacts on private school profits and Government costs are expressed in percentage terms (e.g., private school profits increase by 23 percent under the reform).

will increase student test scores by around 0.30 sd, and it will reduce the achievement gap between the poorest and the richest 25 percent of students by a third.[41] This result is driven by a stark improvement in the quality of the pool of teachers due to two factors: public school wages that better reflect skills in public schools, and an increase in wage rates in the large private-subsidised school sector in response to the reform. Additionally, the policy will benefit the welfare of households (as measured by their simulated utility functions) by 0.08 sd, with higher positive impacts on the poorer families. Finally, the policy will pay for itself in the long run because it is financially more sustainable than the status quo pre-reform. Specifically, the improved quality of teachers in the public sector attracts voucher revenues back into the public sector. This reduces the need for additional, non-voucher funds to cover costs in public schools.

7.2.2 Flat wage increase in Municipal schools

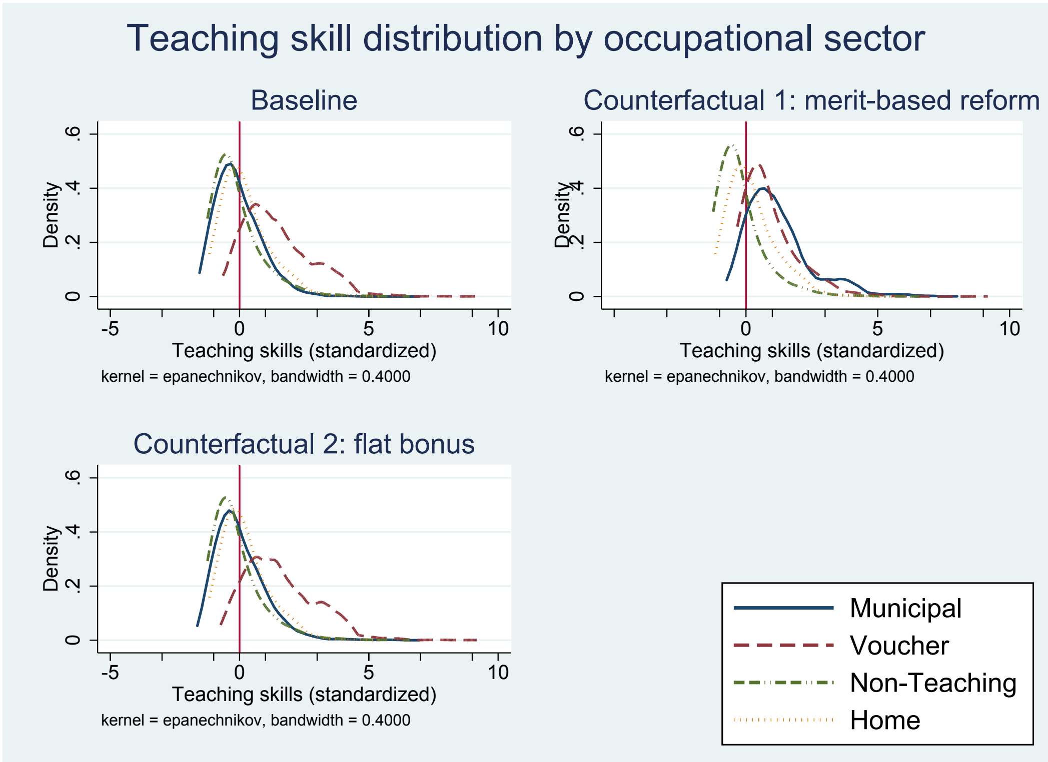
This experiment simulates an across the board increase in public school wage offers. To make it comparable to the merit-reform, the bonus is such that, in equilibrium, it results in a 30 percent increase in average wages in public schools, the Government target under the merit reform.

This policy is less effective at attracting skilled teachers into public schools than a merit-based reform. Figure 3 shows the simulated distributions of teaching skills by occupational sectors at baseline, under the merit reform, and under the flat bonus experiment. The merit-based reform causes the mass of highly skilled teachers to increase in public schools, but under the flat bonus the teaching skill distribution in public schools does not experience such a considerable shift to the right. The distribution of skills in the voucher sector remains close to baseline under the flat bonus, indicating that there is no cream skimming of the best voucher school teachers into public schools, which instead occurs under the merit-based reform. Finally, unlike the merit-based reform, highly skilled individuals are not attracted from the non-teaching sector either (the distribution of skills among non-teachers does not shift to the left like it does under the merit-based reform).

Simulation results are reported in column three of Table 4. Average teaching skills

[41] A *caveat* to this result is that the model does not include the potential effects of class-size. Under the reform, the average size of classes in public schools is projected to increase by 10 from 12, and in private subsidised schools to decrease by 10 from 27. Therefore, the results may be underestimating (overestimating) the positive impacts in voucher (municipal) schools. Estimates of class size impacts among the highest available in the literature (Krueger 2003) suggest that a 10 pupil increase (decrease) would decrease (increase) test scores by roughly 0.10 sd. These magnitudes are not enough to change the main conclusion that the reform is predicted to improve mean test scores.

Figure 3: Teaching skills: baseline and counterfactual



of Municipal school teachers increase by 0.069 sd, ten times less than under the merit reform. In private schools, teaching skills improve by 0.117 sd, because of the absence of cream skimming from public schools and because of the 9 percent increase in teaching skill prices in voucher schools. Average teaching skills improve (marginally) in both sectors because the worst voucher school teachers move to public schools, where they are, on average, more highly skilled than the incumbents. Test scores increase on average in both sectors, but by a much smaller amount than under the merit reform. Specifically, they increase by 0.039 sd in municipal schools and by 0.026 sd in voucher schools. Overall, test scores increase by 0.024 sd, only 8 percent of the treatment effect of the merit-based reform. The bonus does not improve inequality considerably, reducing the gap by income by only 3 percent, compared to a 33 percent reduction under the merit reform. Impacts on test score levels and inequality are about a tenth of those produced by the merit-based reform.

Government cost simulations indicate that this policy would require a 61 percent increase in spending compared to baseline. This is due in large part to a four-fold increase in the additional, non-voucher funds injected into public schools to cover their running costs. Because this policy increases the wage bill in municipal schools without substantially improving teaching skills, it fails to attract parents, and their vouchers, back into the public sector.

The results of this counterfactual analysis indicate that a flat increase to public school wages would be considerably less cost-effective at improving student achievement levels and inequality than the planned 2023 merit-based reform.

8 Conclusions

Discussions of school choice typically focus on competition in the market for the education output. I show that competition in the market for teachers (an input) is empirically important too. In the presence of a large-scale school choice program, public policies generate equilibrium effects not only on the sorting of parents, but also on private school wages and on the sorting of teachers across school sectors. A policy maker needs to take these reactions into account to correctly predict policy impacts.

This is one of the first papers to model both sides of the education market and of the market for teachers. The advantage of this approach is that it allows me to quantify the importance of different channels in driving teacher policy impacts. Simulations from the estimated model are used to perform an ex-ante evaluation of a planned teacher reform in Chile. They show that when merit is rewarded more in public schools, private schools have an increased incentive to reward merit. This induces an equilibrium adjustment in private school wages that improves the selection of teachers with respect to the selection that would have occurred in the absence of the adjustment. Empirically, these equilibrium effects in the market for teachers are important, accounting for 70 percent of estimated policy impacts. A lesson that we learn is that, in a market-based school choice system, competition in the market for teachers amplifies the positive impacts on student test scores of merit-based reforms.

A Markets

To design market boundaries I analyzed mobility of parents and teachers. The design balances the trade-off in terms of sample-size and mobility across markets: a large within-market sample size yields low mobility across markets but a small number of (large) markets, whereas a large number of markets is obtained by having small within-market sample sizes with large across-market mobility.

The unique geographical configuration of Chile aided in the identification of empirically closed or nearly closed markets: the country occupies a narrow but long coastal strip, where mobility between northern and southern regions is hindered.[42] The resulting number of nearly perfectly closed markets is 18. Table 6 reports the region in which each market lies, and the number of schools in each school sector and market, which correlates to within-market sample sizes.

B Additional Tables and Figures

Table 7: Labor supply: descriptive analysis

	Teach	Teach in public sector	Work
Female	0.467***	0.025	-0.245***
	(0.056)	(0.072)	(0.085)
Number of children	-0.148***	-0.030	0.125***
	(0.023)	(0.034)	(0.048)
Number of Children X Female	0.099***	0.058	-0.300***
	(0.031)	(0.041)	(0.053)
Age	0.083***	-0.042**	0.173***
	(0.017)	(0.022)	(0.022)

[42]With a total area of 291,933 square miles (756,102 km^2), Chile is larger than all US states except Alaska and larger than all countries in the European Union. Yet, it extends 2,653 miles (4,270 km) from north to south, and it averages only 110 miles (177 km) from east to west.

Age Squared	-0.001***	0.001***	-0.002***
	(0.000)	(0.000)	(0.000)
Constant	-2.036***	-0.031	-1.703***
	(0.340)	(0.444)	(0.445)
Observations	5,061	3,195	5,471
Pseudo R^2	0.067	0.057	0.067

Standard errors in parentheses. Marginal effects reported.

Samples restrictions by columns: (1): individuals who work, (2): individuals who teach, (3): full sample.

Table 8: Log-wage regressions: descriptive analysis

	Public	Voucher	Non-Teaching
Age	0.030**	0.052***	0.027
	(0.012)	(0.018)	(0.017)
Age Squared	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
Female	-0.102***	-0.142***	-0.384***
	(0.031)	(0.032)	(0.044)
Prof. Certifications	0.029	0.087***	0.073*
	(0.031)	(0.034)	(0.042)
Graduate Degree	0.051*	0.093**	0.204***
	(0.029)	(0.036)	(0.062)
Constant	11.948***	11.629***	12.810***
	(0.254)	(0.354)	(0.359)

Observations	1,186	1,217	1,806
R^2	0.181	0.123	0.103

Standard errors in parentheses. Dependent variable: logwage.

Table 9: Demand for public sector schooling: descriptive analysis

	Public School
Log income	-0.311***
	(0.006)
Primary	0.082***
	(0.008)
Rural	0.327***
	(0.016)
Parents' education	-0.082***
	(0.002)
Family size	0.042***
	(0.003)
Constant	4.363***
	(0.071)
Observations	100,000
Pseudo R^2	0.091

Standard errors in parentheses. Marginal effects reported

Table 6: Markets and Number of Schools

Market	Region	Municipal	Voucher
1	Arica and Parinacota	51.5	57.5
2	Coquimbo	171	99.5
3	Libertador G. B. O'Higgins	101	61.5
4	Atacama	27	15.5
5	Maule	286	93
6	Biobío	193.5	67.5
7	Biobío	110	84
8	Los Ríos	128.5	111.5
9	Los Lagos	201.5	71.5
10	Los Lagos	73.5	54.5
11	Antofagasta	46	31.5
12	Libertador G. B. O'Higgins	85	23.5
13	La Araucanía	170	198.5
14	La Araucanía	20	32.5
15	Región Metropolitana (Santiago)	377	747.5
16	Valparaíso	228	261
17	Biobío	153.5	41
18	Magallanes and Antártica	13	10
TOT		2,436	2,061.5
AVERAGE		135.3	114.5

The number of schools in each market and sector is an average between the number of primary and of secondary schools.

Table 10: Achievement by school sector, descriptive analysis

	Public	Voucher
Parents' education	0.079***	0.088***
	(0.002)	(0.002)
Income pro-capite	0.455***	0.354***
(100,000 CLP)	(0.020)	(0.015)
Squared income	-0.079***	-0.059***
pro-capite (100,000 CLP)	(0.007)	(0.004)
Constant	-1.184***	-1.105***
	(0.016)	(0.018)
Observations	47,007	52,993
R^2	0.104	0.118

Standard errors in parentheses.

Table 11: Socio-economic status of students by school sector, at baseline and under the merit-based teaching reform (first counterfactual)

Pre-reform (Baseline)

	Municipal	Voucher
Parental education (yrs)	9.78	11.54
Household income (CLP)	207,249	337,811

Post-reform (Counterfactual)

	Municipal	Voucher
Parental education (yrs)	10.08	11.64
Household income (CLP)	224.976	353,600

Baseline values computed at the simulated baseline choice.

B.1 Estimates of structural parameters

Table 12: Parameters of Log-Wage Offer Functions

	Public	Voucher	Non-Teaching
Intercept, type 1	0.0245	0.0642	1.38
		(6.33e-04***)	
Intercept type 2 minus type 1	0.0472	-1.04	-1.18
	(7.72e-04***)	(4.15e-05***)	
Intercept type 3 minus type 1	-0.0127	-0.0193	-2.04
	(3.09e-03***)	(2.47e-03***)	
Age	0.0399	0.0863	0.0101
	(1.08e-03***)	(4.20e-04***)	(3.66e-03***)
Age Squared	-0.000151	-0.00165	-0.000400
	(2.69e-01)	(2.42e-02)	(9.85e-02)
Female Dummy	-0.143	-0.171	-0.138

	(2.51e-04***)	(2.39e-04***)	(3.14e-04***)
Has Professional Certificates	0.425	0.361	-0.0313
	(9.41e-05***)	(1.24e-04***)	(1.19e-03***)
Graduate Degree	0.403	0.271	0.119
	(9.05e-05***)	(1.58e-04***)	(3.29e-04***)
$log(\sigma)$	-1.22	-0.809	-0.400
	(3.28e-05***)	(4.94e-05***)	(1.33e-04***)

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The parameters with no standard errors

vary by market, their mean across markets is reported.

Table 13: Parameters of Non-pecuniary Utility of Potential Teachers

	Home	Public	Voucher
Intercept type 1	-3300	-0.800	-0.959
	(1.45e-08***)	(5.54e-05***)	(4.52e-05***)
Intercept type 2 minus type 1	-2150	-0.105	0.512
	(1.64e-08***)	(3.26e-04***)	(8.56e-05***)
Intercept type 3 minus type 1	651	-0.155	0.340
	(5.70e-08***)	(2.25e-04***)	(1.35e-04***)
Female	1640		
	(2.33e-08***)		
Female×N children	361		
	(1.10e-07***)		
Age	-17.2		
	(2.17e-06***)		
N children	14.3		
	(2.44e-06***)		
Has children aged 0-2	-11.9		

	(3.21e-06***)
Has children aged 3-6	173
	(2.70e-07***)
Age squared	0.331
	(1.30e-04***)
Non-pecuniary utility from teaching if female	1.00
	(3.92e-05***)

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14: Log of Prices of Teaching Skills

Market	Log of Skill Price	Standard Error
2	-0.109***	4.32e-04
3	0.0395***	9.29e-04
4	-0.440***	9.94e-05
5	-0.0558***	5.82e-04
6	-0.532***	7.61e-05
7	-0.229***	1.66e-04
8	-0.374***	1.01e-04
9	-0.288***	1.14e-04
10	-0.227***	1.60e-04
11	-0.702***	6.28e-05
12	-0.0627***	6.39e-04
13	-0.0113***	3.30e-03
14	0.216***	2.01e-04
15	0.0371***	1.08e-03
16	-0.596***	6.81e-04
17	-0.456***	8.16e-05

18	-0.147***	2.90e-04

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Log of skill price normalised to 0.00 in market 1.

Table 15: Production of Achievement

	Municipal	Voucher
Intercept, type 1	-1.85	-1.88
Intercept, type 2 minus type 1	-0.0610*	-3.00***
	(3.58e-02)	(6.62e-04)
Intercept, type 3 minus type 1	0.571***	-1.13***
	(3.52e-03)	(1.75e-03)
Teachers' skills, type 1	0.340***	0.211***
	(5.89e-03)	(9.06e-03)
Type 2 minus type 1	0.0374	-0.195***
	(5.32e-02)	(1.08e-02e-02)
Type 3 minus type 1	-0.210***	-0.211***
	(8.34e-03)	(9.66e-03)
Parental education, type 1	0.0572*	0.103***
	(3.15e-02)	(2.05e-02)
Type 2 minus type 1	-0.0471	0.138***
	(4.44e-02)	(1.31e-02)
Type 3 minus type 1	0.0427	0.0119
	(5.36e-02)	(1.18e-01)
Income (monthly, per capita), type 1	0.155***	0.978***
	(1.56e-02)	(2.22e-03)
Type 2 minus type 1	0.00628	0.233***
	(2.93e-01)	(8.39e-03)

Type 3 minus type 1	-0.148***	0.281***
	(1.24e-02)	(7.60e-03)
Income squared (monthly, per capita)	-0.0467	-0.252***
	(4.07e-02)	(7.13e-03)
Log of shock standard deviation	-0.0322	-0.195***
	(6.69e-02)	(8.78e-03)

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The intercept parameters for type 1 have some geographical variation, only the mean is reported.

Table 16: Parental Preference Parameters

	Value	Standard Error
Intercept of preference for Municipal, type 1	-1.12***	1.53e-03
Types 2 minus type 1	0.753***	2.33e-03
Types 3 minus type 1	-0.0758***	2.56e-02
primaria in preference for Municipal	0.502***	4.21e-03
rural in preference for Municipal	0.373***	5.65e-03
Weight on consumption, type 1	0.118***	1.70e-02
Type 2 minus 1	0.187***	9.04e-03
Types 3 minus type 1	5.57***	3.26e-04
Log of preference shock standard deviation	-4.52***	4.85e-04

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 17: Fellowship Assignment

	Value	Standard Error

Intercept	0.448***	4.99e-03
p, price charged by school net of voucher	0.186***	2.45e-03
primaria	0.0667***	3.07e-03
Family size	0.105***	1.64e-02
rural	-0.325***	5.96e-03
Monthly income	-0.0542	3.56e-02
Log of measurement error standard deviation	-5.91***	3.21e-04

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 18: Profit Function of Voucher Schools

	Value	Standard Error
Variable cost c_1: enrollment	1.097e-02	6.61e-01
Variable cost c_2: enrollment squared	2.928e-06	9.24e-04
N classes per teacher, c_3	4.099e+03	2.87e+07
Log of standard deviation of shock σ_{cost}	-3.212	4.53e+02

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 4: Model fit: tuition payments net of financial aid

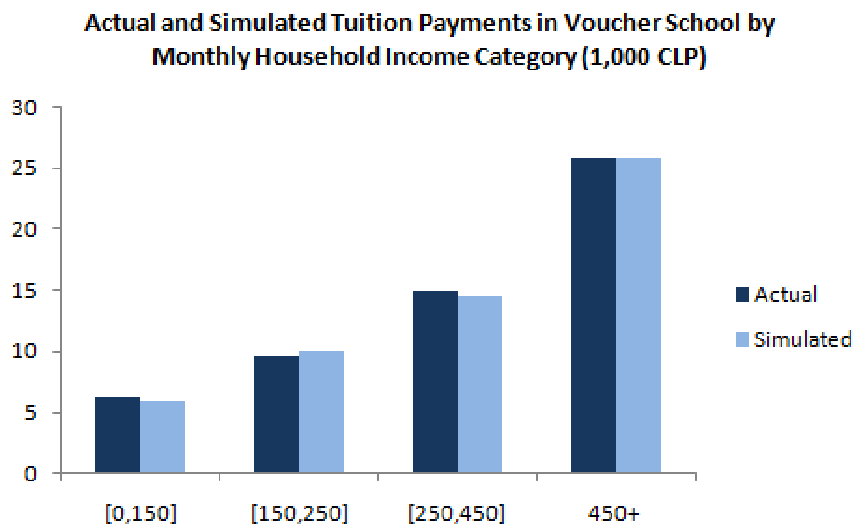
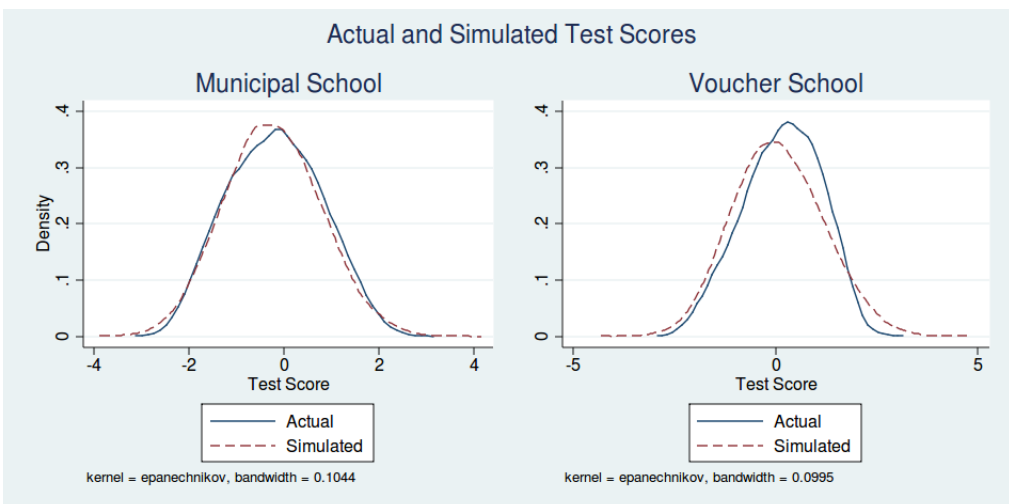


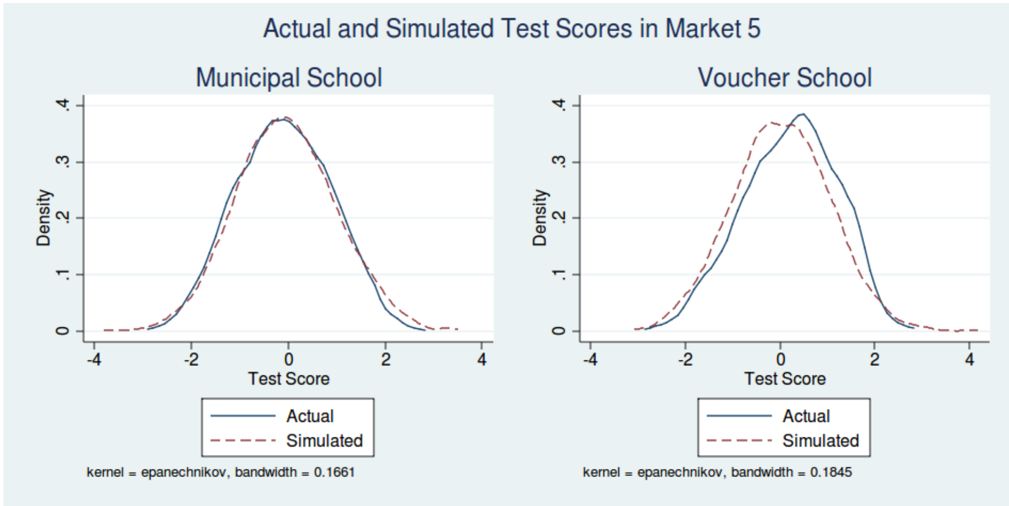
Figure 5: Model fit: test scores by school sector



C Governmental Formulae for Private School Revenues

This appendix reports the formulae in article 25 of the law *Decreto con Fuerza de Ley N^o 2, De Educacion, de 20.08.98*, fully incorporated into the model. Let p denote the tuition charged by the school, and let v be the voucher. Each household choosing the voucher sector is responsible for the payment of $p - v - f(Z_h)$ where $0 \leq f(Z_h) \leq (p - v)$ is the

Figure 6: Model fit: test scores by school sector, market number 5



amount of fellowship received by the family if the voucher sector is chosen. However, the amount of the per-pupil subsidy that is effectively received by the private school is not necessarily v. It decreases as the average tuition payments in the school increase. The latter depend on the tuition fee charged by the school, and on the composition of the households at the school, which determines the amount of financial aid received by the student body at the school. Formally, let $EPV(p,r)$ denote the mean tuition payments in the voucher school sector:

$$EPV(p,r) = \int \big(p - v - f(z)\big) g^z(z| \text{ V chosen}; p, v)dz \tag{7}$$

where the conditional density $g^z(z| \text{ V chosen}; p,r)$ is indexed by (p,r) because it depends on parental school choice, which is a function of the prices (p,r). Below, I drop the dependence of EPV on (p,r) for simplicity. The first Government formula adjusts the amount of per-pupil voucher subsidy effectively received by the school. Accordingly, the adjusted per-pupil gross revenues $(R^g(EPV))$ in the private school sector are:

$$
R^g(EPV) = \begin{cases} p & \text{if } EPV \leq 0.5 \\ p - 10\%(EPV - 0.5USE) & \text{if } 0.5 < EPV \leq 1USE \\ p - 10\%(EPV - 0.5USE) - 20\%(EPV - 1USE) & \text{if } 1USE < EPV \leq 2USE \\ p - 10\%(EPV - 0.5USE) - 20\%(EPV - 1USE) & \\ -35\%(EPV - 2USE) & \text{if } 2USE < EPV. \end{cases}
$$

where *USE* stands for *Unidad de Subvención Educacional*.

Adjusted per-pupil net revenues are different from adjusted per-pupil gross revenues because the school is also required to contribute to the financial aid budget. That is, private schools partially cover the fellowship expenses. The law provides that the per-pupil contribution to financial aid due by the private schools be:

$$
R^f(EPV) = \begin{cases} 5\%EPV & \text{if } EPV \leq 1USE \\ 5\%EPV + 7\%(EPV - 1USE) & \text{if } 1USE < EPV \leq 2USE \\ 5\%EPV + 7\%(EPV - 1USE) & \\ +10\%(EPV - 2USE) & \text{if } 2USE < EPV. \end{cases}
$$

Therefore, the adjusted net per-pupil revenues are $\tilde{R}(p, r, E(p, r)) = R^g(EPV) - R^f(EPV)$.

D Constrained Maximization of Approximated Profits

Because cumulative normal distribution functions enter the expression for profits, the function Π and its first and second derivative functions do not admit a closed form; hence, Π's critical points and curvature properties can't be derived analytically. In estimation, I approximate profits with a function with a known closed form and I solve the constrained maximization of approximated profits at each candidate parameter value. To perform the approximation, I first evaluate numerically the true profit function at a large number of points $(p^{(s)}, r^{(s)})$. To evaluate the true profit function I derive numerically the vector $OS = [E^*, T^*, NT^*]$ at each evaluation point $(p^{(s)}, r^{(s)})$ by solving the second stage of the model, and I plug OS into the profit function. I then approximate the profit function using an interpolating regression. Notice that the approximation is conditional on a realization of the variable cost shock ϵ_{cost}. For simplicity, in the following formulae I drop the dependence of the estimated regression coefficients on the cost shock. Approximation is by Ordinary Least Squares using a cubic interpolating polynomial:

$$\hat{\Pi} = \hat{a}_1 + \hat{a}_2 p + \hat{a}_3 p^2 + \hat{a}_4 r + \hat{a}_5 r^2 + \hat{a}_6 pr + \hat{a}_7 p^3 + \hat{a}_8 r^3 + \hat{a}_9 p^2 r + \hat{a}_{10} pr^2. \tag{8}$$

I solve the constrained maximization of approximated profits subject to the legal cap on tuition. I derive the points that satisfy the Kuhn-Tucker conditions, and then verify that at those critical points the second-order conditions are satisfied. To find the critical points I use a combination of analytical and numerical methods. I solve for the school's choice variables (p, r) and for the Kuhn-Tucker-Lagrange multiplier λ.

The approximated problem of the firm is the following:

$$\max_{(p,r)} \hat{\Pi}$$

$$p \leq \bar{p} \quad \text{w/ multiplier} \quad \lambda$$

or equivalently:

$$\max_{(p,r)} \hat{a}_1 + \hat{a}_2 p + \hat{a}_3 p^2 + \hat{a}_4 r + \hat{a}_5 r^2 + \hat{a}_6 pr + \hat{a}_7 p^3 + \hat{a}_8 r^3 + \hat{a}_9 p^2 r + \hat{a}_{10} pr^2$$

$$p \leq \bar{p} \quad \text{w/ multiplier} \quad \lambda$$

I solve for the optimal (p^*, r^*) and for the Kuhn-Tucker-Lagrange multiplier λ^* following the procedure described in Judd (1998), Ch. 4, p.122. At the optimum, the inequality constraint is either binding or not binding. I find the set of solutions to the Kuhn-Tucker conditions under both configurations. Among the feasible solutions thus found, I select the one with the highest value of approximated profits. The first-order conditions are:

$$\begin{aligned}
\frac{\partial L}{\partial p} &= \hat{a}_2 + 2\hat{a}_3 p + \hat{a}_6 r + 3\hat{a}_7 p^2 + 2\hat{a}_9 pr + \hat{a}_{10} r^2 - \lambda = 0 \\
\frac{\partial L}{\partial r} &= \hat{a}_4 + 2\hat{a}_5 r + \hat{a}_6 p + 3\hat{a}_8 r^2 + \hat{a}_9 p^2 + 2\hat{a}_{10} pr = 0
\end{aligned}$$

Case i): when the constraint is not binding at the optimum, the Kuhn-Tucker-Lagrange multiplier is equal to zero. I set $\lambda = 0$ and I use Newton method to solve numerically the following system of two equations in the two unknowns (p, r):

$$\begin{cases} \hat{a}_2 + 2\hat{a}_3 p + \hat{a}_6 r + 3\hat{a}_7 p^2 + 2\hat{a}_9 pr + \hat{a}_{10} r^2 = 0 \\ \hat{a}_4 + 2\hat{a}_5 r + \hat{a}_6 p + 3\hat{a}_8 r^2 + \hat{a}_9 p^2 + 2\hat{a}_{10} pr = 0 \end{cases}$$

Case ii): when the constraint on p is binding at the optimum, $p = \bar{p}$. I use Newton method to solve numerically the following system of two equations in the two unknowns (r, λ):

$$\begin{cases} \hat{a}_2 + 2\hat{a}_3 \bar{p} + \hat{a}_6 r + 3\hat{a}_7 \bar{p}^2 + 2\hat{a}_9 \bar{p} r + \hat{a}_{10} r^2 - \lambda = 0 \\ \hat{a}_4 + 2\hat{a}_5 r + \hat{a}_6 \bar{p} + 3\hat{a}_8 r^2 + \hat{a}_9 \bar{p}^2 + 2\hat{a}_{10} \bar{p} r = 0 \end{cases}$$

It is important that the approximation be good in order for the solution of the approximated problem to be close to the solution of the real problem. The R^2 of the approximation depends on the vector of model parameters. At the parameter estimates, the average of the R^2 across markets is 96.14%.

E Derivation of Equilibrium Teacher Quality by School Sector

To compute the mean teaching skills supplied to the voucher sector in each m, I derive the density of teaching skills conditional on the voucher school being chosen, which in general is different from the population density of teaching skills. Recall that the teaching skills of individual i are:

$$s_i = exp\left(a_0(l_i) + a_1^{'} X_i + \epsilon_i^{tech}\right) \tag{9}$$

with $\epsilon_i^{tech} \sim N(0, \sigma_V^2)$. That is, conditional on type, skills are log-normally distributed. Conditional on $X_i = x$, the density of teaching skills depends both on the density of the shock ϵ_i^{tech} and on the type probability ψ_{l_i}:[43]

$$f^s(s_i|x) = \frac{\psi_{l_i}}{s_i\sigma_V\sqrt{2\pi}}exp\left\{-\frac{(lns_i - a_0(l) - a^{'}x)^2}{2\sigma_V^2}\right\}.$$

The population density is obtained by integrating over the distribution of x in market m, $f_m^x(x)$:

$$f_m^s(s_i) = \int \frac{\psi_{l_i}}{s_i\sigma_V\sqrt{2\pi}}exp\left\{-\frac{(lns_i - a_0(l) - a^{'}x)^2}{2\sigma_V^2}\right\}f_m^x(x)dx.$$

To derive the density of teaching skills in the voucher school, define $A(q,\epsilon_i^{tech},l_i)$ to be the subset of R^3 that is such that if $\epsilon_i^{-tech} = [\epsilon_i^M \quad \epsilon_i^{NT} \quad \epsilon_i^H]' \in A(q,\epsilon_i^{tech},l_i)$, an individual with characteristics q, shock realization ϵ_i^{tech}, and type realization l_i chooses the voucher school. Letting $Pr_m(V)$ denote the proportion of individuals choosing sector V in market m, the density of teaching skills in sector V may be written as:

$$g_m^V(s_i|\text{sector V chosen}) = \frac{1}{Pr_m(V)}\psi_{l_i}\int_{\epsilon_i^{-tech}\in A} f_m^s(s_i)f^{-tech}\left(\epsilon_i^{-tech}\right)d\epsilon_i^{-tech}$$

where I let $\int_{\epsilon_i^{-tech}\in A}$ denote multiple integration with respect to $\epsilon_i^M,\epsilon_i^{NT},\epsilon_i^H$ over the area $\epsilon_i^{-tech} \in A(q,\epsilon_i^{tech},l_i)$ and where the joint density of the shocks in sectors M, NT and H is:

$$f^{-tech}\left(\epsilon_i^{-tech}\right) = \frac{1}{\sigma_M\sigma_{NT}\sigma_H}\phi\left(\frac{\epsilon_i^M}{\sigma_M}\right)\phi\left(\frac{\epsilon_i^{NT}}{\sigma_{NT}}\right)\phi\left(\frac{\epsilon_i^H}{\sigma_H}\right).$$

The density of teaching skills in the municipal school, $g_m^M(s_i|\text{sector M chosen})$, can be derived in a similar way.[44]

The mean skills supplied to each sector in market m are obtained using the conditional densities g_m^M, g_m^V:

$$\begin{aligned}\bar{s}_{Mm} &= \sum_{l_i}\psi_{l_i}\int s_i g_m^M(s_i|\text{sector M chosen})d\epsilon_i^{tech}\\ \bar{s}_{Vm} &= \sum_{l_i}\psi_{l_i}\int s_i g_m^V(s_i|\text{sector V chosen})d\epsilon_i^{tech}.\end{aligned} \tag{10}$$

[43]If $ln(x) \sim N(0,\sigma^2)$, x has density $\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{(lnx-\mu)^2}{2\sigma^2}}$ with $x \geq 0$.

[44]First define the proportion of potential teachers choosing the municipal school in market m, $Pr_m(M)$. Then define the area $B(q,\epsilon_i^{tech},l_i)$ that is such that if $[\epsilon_i^M \quad \epsilon_i^{NT} \quad \epsilon_i^H]' \in B(q,\epsilon_i^{tech},l_i)$, an individual with characteristics q, shock realization ϵ_i^{tech}, and type realization l_i chooses the municipal school.

F List of Moment Conditions

I compute 607 moments, 321 pertaining to parents and 286 to potential teachers.

F.1 Parents' Moments: Matching Choices, Test Scores and Fellowship Amounts

I use the following categories:

- family size $nfam_h$: $[2,3], [4,6], \geq 7$
- monthly income in terms of CLP100,000 Y_h: $[0, 0.5]$, $(0.5, 1.5]$, $(1.5, 2.5]$, $(2.5, 3.5]$, $(3.5, 4.5]$, $(4.5, 5.5]$, $(5.5, 7]$, $(7, 9]$, $(9, 11]$, > 11
- average parental education in years $peduc_h$: $[0 - 6.5]$, $(6.5, 8]$, $(8, 9.5]$, $(9.5, 10.5]$, $(10.5, 11.5]$, $(11.5, 12]$, $(12, 12.5]$, $(12.5, 13]$, $(13, 14]$, > 14
- monthly income in terms of CLP100,000 divided by family size, $\frac{Y_h}{nfam_h}$: $[0, 0.15]$, $(0.15, 0.25]$, $(0.25, 0.36]$, $(0.36, 0.45]$, $(0.45, 0.50]$, $(0.50, 0.70]$, $(0.70, 0.84]$, $(0.84, 1.13]$, $(1.13, 1.75]$, > 1.75

I partition the state of observable exogenous variables and build an indicator for whether an observation belongs to a certain element of the partition. The moment conditions are obtained by multiplying the difference between actual and predicted outcomes by this indicator. The moment conditions are built on the following outcomes (number of moment conditions in parentheses):

- Test scores by sector and by:
  - market (18x2=36)
  - monthly income per capita and parental education (10x10x2=200)
- Fraction choosing voucher school by:
  - market (18)
  - parental education (10)
  - monthly income (10)
  - number of individuals in the family (3)

- elementary school (2)
- rurality of the household's residence (2)

- Private school tuition payments made by parents by:
  - elementary school, number of individuals in the household, rurality of the residence (2x3x2=12)
  - monthly income (10)
  - market (18)

Total number of parents' moments: 321.

F.2 Potential Teachers' Moments: Matching Choices and Accepted Wages

I use the following categories:

- coarse age, age_i: $[20-30]$, $[31-40]$, $[41,50]$, ≥ 51
- fine age, age_i: $[20,31]$, $(31,36]$, $(36,39]$, $(39,45]$, $(45,48]$, $(48,52]$, $(52,56]$, > 56
- number of children in the household, $nkids_i$: 0,1,2,≥ 3
- number of children aged 0-2, $nkids2_i$: 0, ≥ 1
- number of children aged 3-6, $nkids3-6_i$: 0, ≥ 1

I partition the state of observable exogenous variables and build an indicator for whether an observation belongs to a certain element of the partition. The moment conditions build on the following outcomes (number of moment conditions in parentheses):

- Accepted wages by sector (3 working options) and by:
  - age, gender, professional certifications (3x4x2x2=48)
  - graduate degree (3x2=6)
  - market (3x18=54)
- Fractions in sector M, V and NT (exclude one sector to avoid multicollinearity and hence singularity of the variance-covariance matrix of the moment conditions) by:

- professional certifications (3x2=6)
- age, gender, graduate degree (3x4x2x2=48)
- market (3x18=54)
- gender, number of kids (3x2x4=24)
- number of kids up to 2 years of age, age (3x2x4=24)
- number of kids of age 3 to 6 (3x2=6)

- Accepted wages in the teaching occupations (2) by finer age category (2x8=16)

Total number of potential teachers' moments: 286.

G Details of the First Step of the Estimation

For simplicity, I drop the subscript from θ_{II}, and refer to the parameters of the second stage of the model, estimated in the first step of the estimation, as θ. Let y_i denote an observed outcome for individual i. Let $\Omega_i \times \{1, ..., L\}$ denote the state space of individual i with elements (ω_i, l_i) (where $l_i \in \{i, ..., L\}$ is the person's type). Vector ω_i contains, for example, degrees, age, gender, etc. Let $\hat{y}_i(\omega_i, \theta)$ denote the outcome predicted by the model. This outcome is replaced by the simulator:

$$\tilde{\hat{y}}_i(\omega_i, \theta) = \frac{1}{S} \sum_{s=1}^{S} \sum_{l=1}^{L} Pr(l_i|\theta) \tilde{\hat{y}}_i(\omega_i, l_i, s, \theta)$$

obtained by drawing S simulated shocks from the model's shock distribution under parameter θ and using the model to simulate behavior, and hence an outcome for each individual, simulation, and type: $\tilde{\hat{y}}_i(\omega_i, l_i, s, \theta)$.[45] The simulated outcomes are then averaged across simulations and types. Moment conditions are constructed by taking the difference between the actual and the simulated outcome: $m_i(\theta) = y_i - \tilde{\hat{y}}_i(\omega_i, \theta)$.

The MSM finds the vector θ that minimizes the weighted distance of the empirical moment conditions from zero:

$$\hat{\theta}_{MSM} = \arg\min_{\theta} m(\theta)'_n W_n m_n(\theta) \tag{11}$$

[45] S is set equal to 100.

where W_n is a symmetric positive definite weighting matrix such that as $n \to \infty$, $W_n \to W$ in probability with W symmetric and positive definite. Vector $m_n(\theta)$ is the sample average of the individual moment conditions $m_i(\theta)$.

Estimation fully accounts for the fact that multiple datasets of different sizes are used. Consider the population moment condition based on outcome y_i:

$$E\left[(y_i - \hat{y}_i(\omega_i, \theta))I_i(\omega_i, y_i \text{ non-missing})\right]$$

and suppose that there are M moment conditions $\{m_i^1, ..., m_i^M\}$ with

$$m_i^m = (y_i^m - \hat{y}_i^m(\omega_i^m, \theta))I_i(\omega_i^m, y_i^m \text{ non-missing}).$$

Let m_i be a vector that stacks all moment conditions for individual i. Assume that the population is divided in two strata: the stratum of students, with mass H_A, and the stratum of college graduates, with mass H_B. The M population moment conditions are:

$$H_A E_A[m_i] + H_B E_B[m_i]$$

where $E_A[\cdot]$ and $E_B[\cdot]$ represent within-stratum expectations.
Let n_A be the sample size of students and n_B be the sample size of potential teachers, and let $m_i(\theta)$ be the $M \times 1$ vector of empirical moment conditions computed at a parameter value θ. The sample analog of the population moment conditions is:

$$H_A \frac{1}{n_A} \sum_{i \in A} w_i m_i(\theta) + H_B \frac{1}{n_B} \sum_{i \in B} w_i m_i(\theta)$$

where w_i are weights provided with the datasets that are used to reweight the sample back to random sampling proportions, and that are normalized to sum to n_A and n_B.[46] Let $n = n_A + n_B$ and pre-multiply the sample moments by $\frac{n}{n}$. Denote the vector of empirical moments based on a sample of size n by $m_n(\theta)$:

$$m_n(\theta) = \frac{1}{n} \sum_{i=1}^{n} \left(H_A a_A w_i m_i(\theta) I(i \in A) + H_B a_B w_i m_i(\theta) I(i \in B)\right)$$

where $a_A = \frac{n}{n_A}$, $a_B = \frac{n}{n_B}$ and $I(\cdot)$ is an indicator function equal to 1 if the expression in parentheses is true.

The method of simulated moments finds the vector θ that minimizes the weighted

[46]For SIMCE observations the weights are all equal to one because the SIMCE sample is a simple random sample.

distance of the empirical moment conditions from zero:

$$\hat{\theta}_{MSM} = arg \min_{\theta} m_n(\theta)' W_n m_n(\theta) \tag{12}$$

where W_N is an $M \times M$ symmetric positive definite weighting matrix such that as $n \to \infty$, $W_n \to W$ in probability with W symmetric and positive definite.

To see the asymptotic properties of the estimator, let $n_A, n_B \to \infty$ with $\frac{n_A}{n} \to a_A < \infty$ and $\frac{n_B}{n} \to a_B < \infty$ as in Bhattacharya (2005), who derives the asymptotic properties of the generalized method of moments with a stratified sample. The MSM estimator defined in (12) is consistent and asymptotically normal:

$$\sqrt{n}(\hat{\theta} - \theta) \Rightarrow N(0, Q)$$

with $Q = (\Gamma' W_n \Gamma)^{-1} \Gamma' W_n V W_n \Gamma (\Gamma' W_n \Gamma)^{-1}$ and $\Gamma = E[\frac{\partial m(\theta)}{\partial \theta'}]$. V is the variance covariance matrix of the moment vector.[47]

To estimate consistently the asymptotic variance of the estimator, I substitute V with a consistent estimate $\hat{V}$ computed at $\hat{\theta}_{MSM}$. The estimator includes a stratum correction that accounts for the sampling design.[48] The estimator of the variance covariance matrix is:

$$\begin{aligned} \hat{V} &= \sum_{i \in A} \left(\frac{H_A}{n_A} w_i \right)^2 m_i(\hat{\theta}_{MSM}) m_i(\hat{\theta}_{MSM})' + \sum_{i \in B} \left(\frac{H_B}{n_B} w_i \right)^2 m_i(\hat{\theta}_{MSM}) m_i(\hat{\theta}_{MSM})' \\ & -\frac{1}{n_A} \left(\sum_{i \in A} \frac{H_A}{n_A} w_i m_i(\hat{\theta}_{MSM}) \right) \left(\sum_{i \in A} \frac{H_A}{n_A} w_i m_i(\hat{\theta}_{MSM}) \right)' \\ & -\frac{1}{n_B} \left(\sum_{i \in B} \frac{H_B}{n_B} w_i m_i(\hat{\theta}_{MSM}) \right) \left(\sum_{i \in B} \frac{H_B}{n_B} w_i m_i(\hat{\theta}_{MSM}) \right)' \end{aligned} \tag{13}$$

where $m_i(\hat{\theta}_{MSM})$ is the $M \times 1$ vector of individual-level moment conditions computed at $\hat{\theta}_{MSM}$. To estimate consistently the matrix of moments' partial derivatives, I use:

[47] The optimal weighting matrix is the inverse of the variance covariance matrix of the moment conditions, $W_n^* = V^{-1}$. The asymptotic variance reduces to $(\Gamma' V^{-1} \Gamma)^{-1}$ when the optimal weighting matrix is used. I cannot adopt the optimal weighting matrix because the variance covariance matrix is a high-order sparse matrix that cannot be numerically inverted. The inverse of the variance covariance matrix must be obtained to compute the standard errors of the efficient MSM estimator. This negative result is standard in numerical methods. I adopt a weighting matrix that contains the variances of the moments on the main diagonal and zeros elsewhere. This matrix is easily invertible.

[48] The correction term is derived and discussed in Bhattacharya (2005). Intuitively, ignoring the fact that observations come from two separate strata would over-estimate the between-strata variances.

$$\hat{\Gamma} = H_A \frac{1}{n_A} \sum_{i \in A}^{N} w_i \frac{\partial m_i}{\partial \theta'}|_{\hat{\theta}_{MSM}} + H_B \frac{1}{n_B} \sum_{i \in B}^{N} w_i \frac{\partial m_i}{\partial \theta'}|_{\hat{\theta}_{MSM}}$$

where the differentiation is numerical. Letting Δ_t denote a vector of the same size as the parameter vector with zeros everywhere and $\delta > 0$ as its t^{th} element, the derivative of the m^{th} element of $m_i(\theta)$ with respect to the t^{th} element of θ is computed as:

$$\frac{\partial \hat{m}_i^m(\theta)}{\partial \theta_t}|_{\theta=\hat{\theta}_{MSM}} = \frac{\hat{m}_i^m(\theta + \Delta_t) - \hat{m}_i^m(\theta)}{\delta}|_{\theta=\hat{\theta}_{MSM}}.$$

H Second Step of the Estimation: Implementing NPSML

Let $\theta_I = [c_1 \quad c_2 \quad c_3 \quad \sigma_{cost}]'$ denote the vector of parameters to be estimated in the second step (i.e., the parameters from the first stage of the model), $\hat{\theta}_{II}$ the vector of estimates of θ_{II} and $\hat{r}_m$ the vector of wage rates obtained in the first step of the estimation. Imagine obtaining a sample of markets, and suppose that for each sampled market, a sample of college graduates making labor supply decisions and of students is available. Denote by $X_m = \{x_1, ..., x_i, ..., x_{NS}\}_{i \in m}$ and $Q_m = \{q_1, ..., q_i, ..., q_{NC}\}_{i \in m}$ the within-market samples of students and of college graduates respectively. Let $(\hat{r}_m, X_m, Q_m)_{m=1,...,M}$ be an independently and identically distributed sample of markets. The true log-likelihood is:

$$L_M(\theta_I) = \sum_{m=1}^{M} \ln l_m(\theta_I)$$

where $l_m(\theta_I)$ is the market-contribution to the likelihood, i.e., the density of r computed at the observed value $\hat{r}_m$ conditional on the exogenous characteristics in the market, on θ_I and on $\hat{\theta}_{II}$: $l_m(\theta_I) = f(r|\theta_I, X_d, Q_d; \hat{\theta_{II}})|_{\hat{r}_m}$. The function $l_m(\theta_I)$ cannot be computed analytically, therefore, I approximate it using a kernel estimator based on an i.i.d. simulated sample $(\epsilon_{cost}^{ms})_{s=1,...,S}$ of draws from the log-normal distribution of ϵ_{cost}.

Denote by $\hat{r}_m^s(\theta_I)$ the simulated wage rate in market m given a value for θ_I, and conditional on $\hat{\theta}_{II}$, X_m, Q_m. The s superscript means that for every simulated draw s, the wage rate is derived as a solution to private school profit maximization. I estimate the likelihood $l_m(\theta_I)$ by:

$$\tilde{l}_S(\hat{r}_m|X_m, Q_m, \theta_I; \hat{\theta}_{II}) = \tilde{l}_{mS}(\theta_I) = \frac{1}{Sh} \sum_{s=1}^{S} \mathcal{K}\left(\frac{\hat{r}_m - \hat{r}_m^s(\theta_I)}{h}\right)$$

where $\mathcal{K}(\cdot)$ is the normal kernel and h is the optimal bandwidth that minimizes the approximate Integrated Mean Squared Error, and it is such that $h \to 0$ as $S \to \infty$.

The simulated log-likelihood is obtained by summing over markets:

$$\tilde{L}_{MS}(\theta_I) = \sum_{m=1}^{M} \ln \tilde{l}_{mS}(\theta_I)$$

and the NPSML estimator is defined as the global maximum of $\tilde{L}_{MS}(\theta_I)$:

$$\hat{\theta}_I(M, S) = \arg\max_{\theta_I \in \Theta_I} \tilde{L}_{MS}(\theta_I),$$

where Θ_I is assumed to be compact. Under regularity conditions, $\hat{\theta}_I(M, S)$ is asymptotically normal and asymptotically efficient:

$$\sqrt{D}(\hat{\theta}_I(M, S) - \theta_{I,0}) \underset{S,M \to \infty}{\Rightarrow} N(0, \Omega),$$

where Ω is the asymptotic variance-covariance matrix of the exact maximum likelihood estimator:

$$\Omega = \left(-E\left[\frac{\partial^2 L_M(\theta_{I,0})}{\partial \theta_2 \partial \theta_I'} \right] \right)^{-1} E\left[\frac{\partial L_M(\theta_{I,0})}{\partial \theta_I} \frac{\partial L_M(\theta_{I,0})}{\partial \theta_I'} \right] \left(-E\left[\frac{\partial^I L_M(\theta_{I,0})}{\partial \theta_I \partial \theta_I'} \right] \right)^{-1}. \qquad (14)$$

I Estimation Algorithm Embedding Equilibrium Restriction

This algorithm refers to the first step of the estimation. For simplicity, I drop the subscript II from θ_{II}.

- Choose an initial guess for the parameter: $\theta^{(0)}$.
- Draw unobserved types for each potential teacher and student.
- Use $a^{(0)} = [a_0^{(0)}(l_i) \quad a_1^{(0)}]'$ to compute teaching skills for each potential teacher i: $s_i\left(a^{(0)}\right)$.
- Calculate the optimal occupational choice of each teacher in each market and use these individual choices to calculate the mean skills supplied to each school sector $j \in \{M, V\}$ in each market m: $\bar{s}_{jm}$. This is the non-linear function of $a^{(0)}$ in equation (4). Simulate also accepted wages.

- Plug the values for mean teacher skills into the production functions for achievement in M and V.
- Simulate achievement of each student in each school, and simulate optimal parental choice of school.
- Compute value of objective function of the Method of Simulated Moments using simulated and real data.
- Update guess $\theta^{(0)}$ to $\theta^{(1)}$ (using the Generating Set Search optimization algorithm in HOPSPACK) and repeat until objective function is minimized.

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