College-Major Choice to College-Then-Major Choice*

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Abstract

Many countries use college-major-specific admissions policies that require a student to choose a college-major pair upon college enrollment. Motivated by potential student-major mismatches under such policies, we explore the equilibrium effects of postponing student choice of major. To do so, we develop an equilibrium model of college-major choices under the college-major-specific admissions regime and estimate its structural parameters using data from Chile. Then we introduce the counterfactual policy regime as a Stackelberg game in which a social planner chooses college-specific admissions policies and students make enrollment decisions, learn about their fits to various majors and then choose their majors. We compare outcomes under the current and the counterfactual policy regimes and provide bounds on potential welfare gains from adopting the latter.

1 Introduction

In countries such as Canada and the U.S., students are admitted to colleges without declaring their majors until later years in their college life.[1] Peer students in the

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[1] With the exception of Quebec province.

same classes during early college years may end up choosing very different majors later on. In contrast, many countries in Asia, Europe and Latin America (Chile as a leading example) use college-major-specific admissions rules. A student is admitted to a specific college-major pair and attends classes with peers (mostly) from his/her own major upon college enrollment. We label these two admissions systems by their representative countries as Sys. US and Sys. Chile, respectively.

To the extent that college education is aimed at providing the society with specialized personnel, Sys. Chile may be efficient if potential college enrollees have sufficient information about their suitability to different majors. Because it facilitates the allocation of resources across majors and maximizes the interaction among students with similar comparative advantages. However, if students are uncertain about their fits, such a system may lead to serious mismatch problems. Given the same population of students, efficiency comparison across these two admissions systems depends critically on the degree of uncertainty faced by students, the relative importance of peer effect, and student sorting behavior that determines equilibrium peer quality.

In this paper, we develop an equilibrium model of student sorting under Sys. Chile, allowing for post-enrollment uncertainties and peer effects. We apply it to the case of Chile, where we have obtained detailed micro-level data on college enrollment from the Chilean Department of Evaluation and Educational Testing Service, and on job market returns from the Ministry of Education of Chile. Our first goal is to recover the structural parameters underlying the observed equilibrium sorting among Chilean students. Based on the estimation result, our second goal is to examine changes in student welfare and the distribution of educational outcomes if, instead of college-major-specific admissions, Chile adopts college-specific admissions and allows students to learn about themselves before declaring majors. Although our empirical analysis focuses on the case of Chile, our framework is general enough to be applied to other countries with similar admissions systems.

In our model, students differ in their (multi-dimensional) abilities and educational preferences, and they face uncertainty about their suitability to various majors. The cost of and return to college education not only depends on one's own characteristics, but may also depend on the quality of one's peers attending the same program. In the baseline case (Sys. Chile), there are two decision periods. First, a student makes college-major enrollment decision, based on his/her expectations about peer quality across different academic programs and about how well suited he/she is to various majors. The choices of individual students, in turn, determine the equilibrium peer quality. In the second period, a college enrollee learns about his/her fit to the chosen major and decides whether or not to continue his/her studies.

In our counterfactual policy experiments (Sys. US), a planner chooses optimal college-specific, rather than college-major-specific, admissions policies; students make enrollment decisions and postpone their choices of majors until after they learn about their fits to various majors. Although individual students always maximize their own welfare, the eventual sorting need not be efficient due to the existence of peer effects. Using optimal admissions policies, the planner guides student sorting toward the maximization of their overall welfare.

Several factors have major implications on the changes in equilibrium outcomes as Sys. Chile switches into Sys. US. The first is the degree of uncertainty students face about their major-specific fits, which we find to be nontrivial. Indeed, a lot of college dropouts occur under the current Chilean system because of student-major mismatches: the overall college retention rate increases from 75% in the baseline to 90% in the counterfactual.

Second, in contrast to Sys. Chile, where peer students are from the same major upon college enrollment, Sys. US features a much broader student body in first-period classes. While students differ in their comparative advantages, some students have advantages over others in multiple majors, and some majors have superior student quality. With the switch from Sys. Chile to Sys. US, on the one hand, the quality of first-period peers in "elite" majors will decline; on the other hand, "non-elite" majors will benefit from having "elite" students in their first-period classes. The overall efficiency depends on, among other factors, which of the two effects dominates. Our estimation results show that for "elite" majors, such as medicine, law and engineering, own ability is more important than peer ability in determining one's market return, while the opposite is true for "non-elite" majors such as education. Combining this fact with the improvement in student-major match quality, we find that the average productivity of college graduates improves in all majors when Sys. US is adopted.

Finally, as students spend time trying out different majors, their specialized training is postponed as the price. Welfare comparisons vary with how high this price is. We find that average student welfare will increase by a monetary equivalent of 4.6 million pesos or 5%, if delayed specialization under Sys. US does not reduce the amount of marketable skills one obtains in college compared to Sys. Chile.[2] At the other extreme, if the first period in college contributes zero to one's skills under Sys. US, and if a student has to make up for this loss by extending his/her college life accordingly, a 0.9% loss in mean welfare will result. In an alternative design, instead of extending the duration of college education for all majors, we allow students in most majors to graduate in time and spend only their upper college years specializing. Under this framework, if the shortened specific training causes a 20% loss of human capital ceteris paribus, average student welfare will keep the same as the Sys. Chile switches into Sys. US.

Our paper is closely related to studies that treat education as a sequential choice made under uncertainty and stress the importance of specificity of human capital.[3] For example, Altonji (1993) introduces a model where students learn their preferences and probabilities of completion in two fields of study during college years. Arcidiacono (2004) estimates a structural dynamic model of college and major choice in the U.S., where students learn about their abilities via test scores in college before settling down to their majors. As in our paper, he allows peer quality to affect one's market return as well as utility in college.[4] Given his focus on individual decisions, peer quality is treated as exogenous.[5]

While this literature has been focusing on individual decision problems, our goal is to study the educational and labor market outcomes for the population of students, and to provide predictions about these outcomes under counterfactual policy regimes. One cannot achieve this goal without modeling student sorting in an equilibrium framework, because peer quality may change as students re-sort themselves under different policy regimes.

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[2] 1 USD is about 484 Chilean Pesos.

[3] Examples of theoretical papers in this regard include Manski (1989) and Comay, Melnick, and Pollachek (1973).

[4] There is a large and controversial literature on peer effects. Methodological issues are discussed in Manski (1993), Moffitt (2001), and Brock and Durlauf (2001). Limiting discussion to recent research on peer effects in higher education, Sacerdote (2001) and Zimmerman (2003) find peer effects between roommates on grade point averages. Betts and Morell (1999) find that high-school peer groups affect college grade point average. Arcidiacono and Nicholson (2005) find no peer effects among medical students. Dale and Krueger (1998) have mixed findings.

[5] For a comprehensive survey of the literature on the demand for and return to education by field of study in the U.S., see Altonji, Blom and Meghir (2011). As an example of non-U.S. studies, Malamud (2010) compares the labor market consequences across the English (Sys. Chile) and Scottish (Sys. US) undergraduate systems using a regression approach and finds that the average earnings are not significantly different between the two countries.

In its emphasis on equilibrium structure, our paper is related to Epple, Romano and Sieg (2006) and Fu (2011). Both papers study college enrollment in a decentralized market, where colleges compete for better students.[6] Given our goal of addressing efficiency-related issues, and the fact that colleges in Sys. Chile countries are often coordinated, we study a different type of equilibrium, where the players include students and a single planner. In this centralized environment, we abstract from the determination of tuition, which is likely to be more important in decentralized market equilibria studied by Epple, Romano and Sieg (2006) and Fu (2011); instead, we emphasize some other aspects of college education that are absent in these two previous studies but are more essential to our purpose. In particular, we emphasize the multi-dimensionality of abilities and uncertainties over major-student fits, and relate college education to job market outcomes.

The rest of the paper is organized as follows: Section 2 provides some background information about education in Chile. Section 3 lays out the model. Section 4 describes our data. Section 5 describes our estimation followed by the empirical results. Section 7 conducts counterfactual policy experiments. The last section concludes the paper. The appendix contains additional details and tables.

2 Background: Education in Chile

There are three types of high schools in Chile: scientific-humanist (regular), technical-professional (vocational) and artistic. Most students who want to pursue a college degree attend the first type. In their 11th grade, students choose to follow a certain academic track based on their broad interests, where a track can be humanities, sciences or arts. From then on, students receive more advanced training in subjects corresponding to their chosen tracks.

The higher education system in Chile consists of three types of institutions: universities, professional institutes, and technical formation centers. Universities provide the highest degree of learning, combining teaching, research and outreach activities. They offer licentiate degree programs and award academic degrees. In 2011, for example, total enrollment in universities accounts for over 60% of all Chilean stu-

[6] Epple, Romano and Sieg (2006) model equilibrium admissions, financial aid and enrollment. Fu (2011) models equilibrium tuition, applications, admissions and enrollment.

dents enrolled in the higher education system.[7] There are two main categories of universities: the 25 traditional universities and the over 30 non-traditional private universities. Traditional universities comprise the oldest and most prestigious universities, and institutions derived from these old universities. They are coordinated by the Council of Chancellors of Chilean Universities (CRUCH), and are eligible to obtain partial funding from the state. In 2011, traditional universities accommodate about 50% of all college students pursuing a bachelor's degree.

The traditional universities employ a single admission process: the University Selection Test (PSU), which is very similar to the United States' SAT Reasoning Test. The test consists of two mandatory exams, one in Mathematics and one in Language. There are also two additional specific exams, Sciences and Social Sciences. Taking the PSU involves a fixed fee but the marginal cost of each exam is zero.[8] Students following different academic tracks in high school will take either one or both specific exam(s). Together with the cumulative grade point average achieved during high school, the various PSU test scores are the only components of an index used in the admissions process. This index is formed by taking a weighted average of its components, where the weights differ across college programs. A student is admitted to a specific college-major pair if his/her index, calculated using the relevant weights, is above the cutoff index required by this program. That is, college admissions are college-major specific. A student must choose a college-major pair in making his/her enrollment decision.

In our analysis, colleges refer only to the traditional universities for several reasons. First, our final goal is to examine the consequences of a centralized reform to the Chilean admissions process. This experiment is more applicable to the traditional universities, which are coordinated and state-funded, and follow a single admissions process. Second, although non-traditional private universities are growing in numbers, they are usually considered inferior to the traditional universities. Moreover, most of these private colleges follow (almost) open-admissions policies; and we consider it more appropriate to treat them as part of the outside option for students in our model. Finally, we have detailed enrollment data only for traditional universities.

[7] Enrollments in professional institutes and technical formation centers account for 25.7% and 13.7% respectively.

[8] In 2011, the fee was 23,500 pesos, or 45 USD.

3 Model

3.1 Primitives

There is a continuum of students with different gender, family income, abilities and academic interests. There are J colleges, each with M majors; and we denote each academic program as a pair (j, m). Admissions to these programs are subject to program-specific standards. There is also an outside option available to all students.

3.1.1 Student Characteristics

A student may come from one of the family income groups $In \in \{low, high\}$.[9] He/She has multi-dimensional knowledge in subjects such as math, language, social science and science, measured by $s = [s^1, s^2, ..., s^S]$, the vector of test scores.[10] Various elements of such knowledge are combined with major-specific weights to form major-specific ability

$$a_m = \sum_{l=1}^{S} \omega_m^l s^l,$$

where $\omega_m = [\omega_m^1, ..., \omega_m^S]$ is the vector of major–m-specific weights and $\sum_{l=1}^{S} \omega_m^l = 1$. ω_m's differ across majors: for example, an engineer uses math knowledge more and language knowledge less than a journalist. As one's multi-dimensional knowledge is used in various majors, although with different weights, one's major-specific abilities are correlated.

Given the different academic tracks they follow in high school, some students will consider only majors that emphasize knowledge in science subjects, some will consider only majors that emphasize knowledge in social science subjects, and some are open to all majors. Such broad interests are reflected in their test scores, hence in their abilities.[11] Let the observable characteristics of a student be $x = [a, In, g]$, where

[9] Empirically, a student is said to come from a low income family if his/her family income is lower than the median among Chilean households.

[10] In this paper, we treat as pre-determined the knowledge obtained by high school graduates as well as their tastes.

[11] Without increasing the test fee, taking both the science and the social science exams will only enlarge a student's opportunity set. For example, on the one hand, a student who does not take the science exam will not be considered by programs that require science scores; on the other, his/her admissions to programs that do not require science scores will not be affected even if he/she scores poorly in science. However, some students only take either science or social science exam, we view this as indication of their broad academic interest.

a is the vector of major-specific abilities, and g stands for gender. Denote the joint distribution by $F_x(\cdot)$.

3.1.2 Consumption Values and Costs

The consumption value of a particular major enters one's utility both in college and in workforce. This value depends on one's ability: an individual with higher ability a_m may find it more enjoyable (less costly) to study in major m and work in major$-m$ related jobs. We also allow for gender differences in major preferences: some majors may appeal more to an average female student than to an average male student.[12] In addition, each student has his/her own idiosyncratic tastes for majors, represented by a random vector $\epsilon^1 = \{\epsilon^1_m\}_m$.[13] In sum, the per-period consumption value of major m is

$$v_m(x, \epsilon^1_m) = \overline{v}_m I(female) + \beta_{1m} a_m + \beta_{2m} a^2_m + \epsilon^1_m,$$

where we have normalized the mean major-specific consumption values for males to zero, $\overline{v}_m$ is the mean major$-m$ value for females, and β_m's measure how one's consumption value in major m changes with one's major-specific ability.[14]

Besides the consumption value one attaches to his/her major, a student also derives consumption value provided by his/her academic program while in college. Net of cost, the per-period consumption value of attending program (j, m) is

$$v_{jm}(x, \epsilon, A_{jm}) = v_m(x, \epsilon^1_m) + \epsilon^2_{jm} - C_{jm}(x, A_{jm}),$$

where ϵ^2_{jm} is one's taste for program (j, m). Let $F_\epsilon(\cdot)$ denote the joint distribution of the unobserved idiosyncratic tastes for major and for academic programs $[\epsilon^1, \epsilon^2]$. An individual student's tastes are correlated across majors within a college, and across colleges given the same major. $C_{jm}(x, A_{jm})$ is the cost of attending program (j, m), which is a function of own characteristics x and peer quality A_{jm}, the average major$-m$ ability of enrollees in (j, m).[15] For example, it may be more challenging to

[12]Gender-specific preferences may arise from not only individual tastes, but also social norms and other channels. We label the combination of all these potential factors as "gender-specific tastes."

[13]We will adopt the convention that $\epsilon^1_m = -\infty$ if m is not in one's broad interest.

[14]In the estimation, we restrict β_{2m} to be the same across majors.

[15]Arguably, the entire distribution of peer ability may affect the cost of and return to education. For feasibility reasons, we follow the common practice in the literature and assume that only the average peer quality matters.

attend a class with high-ability peers because of direct peer pressure and/or because of curriculum designs that cater to average student ability. In either case, individuals with different own abilities are likely to feel this effect differently.

3.1.3 Skills and Wages

The level of skills one builds up in college depends on one's major specific ability (a_m), the quality of the one's peers (A_{jm}), and how efficient one is at his/her major.[16] The last determinant, the major-specific efficiency, reveals to a student only after he/she takes courses in that major. Denote one's major-specific efficiency levels as $\{\eta_m\}_m \,\tilde{}\, i.i.d. F_\eta(\cdot)$. The human capital production function reads[17]

$$h_m(a_m, \eta_m, A_{jm}) = a_m^{\gamma_{1m}} A_{jm}^{\gamma_{2m}} \eta_m.$$

Wage is major-specific and it is a stochastic function of one's human capital (hence of a_m, η_m, A_{jm}), work experience (τ) and one's other observable characteristics, where the randomness comes from a transitory wage shock ζ_τ. In particular, the wage rate for a graduate from program (j, m) is given by $w_m(\tau, x, \eta_m, A_{jm}, \zeta_\tau)$.

3.1.4 Timing:

There are three stages in this model.
Stage 1: Students make college-major enrollment decisions, subject to admissions policies.
Stage 2: A college enrollee in major m observes his/her major-specific efficiency η_m, and chooses to stay or to drop out at the end the first period in college.[18,19]

[16] There are different channels through which peer ability affects one's market return, including direct effects on human capital production, statistical discrimination on the labor market, social network, etc. Our data does not allow us to distinguish among various channels. For ease of illustration, we will label peer effect as if it affects one's human capital production.

[17] Notice that $h_m(\cdot)$ represents the total amount of marketable skills. As such, $h_m(\cdot)$ may be a combination of pure major-specific skill and general skill.

[18] We assume that an enrollee fully observes her efficiency in her major by the end of Stage 2. It will be interesting to allow for partial learning. Given the lack of information on student performance in college, we leave such extensions to future work.

[19] Transfers across programs are rare in Chile. "..., students must choose an academic field at the inception of their studies. With a few exceptions, lateral mobility between academic programmes is not permitted, even within institutions." (*Reviews of National Policies for Education: Tertiary Education in Chile* (2009) OECD, page 146)

Stage 3: Students who chose to stay in Stage 2 stay one more period in college and then enter the labor market.[20]

3.2 Student Problem

This subsection solves the student's problem backwards.

3.2.1 Continuation Decision

After his/her first period in college, an enrollee in (j, m) observes his/her major-specific efficiency level η_m, and decides whether to continue studying or to drop out, given peer quality A_{jm}. Let $V_d(x)$ be the value of dropping out for student x.[21] A student's second-period problem reads

$$u_{jm}(x, \epsilon, \eta_m | A_{jm}) =$$
$$\max \left\{ v_{jm}(x, \epsilon, A_{jm}) + \sum_{\tau'=3}^{T} \delta^{\tau'-2} \left[E_\zeta \left(w_m(\tau - 3, x, \eta_m, A_{jm}, \zeta) \right) + v_m(x, \epsilon) \right], V_d(x) \right\}.$$

If the student chooses to continue his/her education, he/she will stay one more period in college, obtaining the net consumption value $v_{jm}(x, \epsilon, A_{jm})$, and then enjoy the monetary and consumption value of his/her major after college from period 3 to retirement period $T = 45$, discounted at rate δ. Let $y^2_{jm}(x, \epsilon, \eta_m) = 1$ if an enrollee in program (j, m) chooses to continue his/her study.

3.2.2 College-Major Choice

Denote $\psi_{jm}(a) = 1$ if a student of ability a is admitted to program (j, m). Under the Chilean system, $\psi_{jm}(a) = 1$ if only if $a_m \geq a^*_{jm}$, where a^*_{jm} is the (j, m)-specific cutoff. Given the peer quality of each program $\{A_{jm}\}_{jm}$, a student chooses the best among the programs he/she is admitted to and the outside option with value $V_0(x)$.

$$\begin{aligned} U(x, \epsilon | \psi(a)) &= \max \left\{ \max_{(j,m)} \{ \delta E_{\eta_m} (u_{jm}(x, \epsilon, \eta_m | A_{jm})) + v_{jm}(x, \epsilon, A_{jm}) \}, V_0(x) \right\} \\ & \quad s.t.\ E_{\eta_m}(u_{jm}(x, \epsilon, \eta_m | A_{jm})) = -\infty \text{ if } \psi_{jm}(a) = 0. \end{aligned}$$

[20] We treat the first two years in college as the first college period in the model, and the rest of college years as the second period, which differs across majors. Student value functions are adjusted accordingly.

[21] See Appendix A1 for specific functional form assumptions on $V_d(x)$ and $V_0(x)$.

Let $y^1_{jm}(x,\epsilon|\psi(a)) = 1$ if program (j,m) is chosen.[22]

3.3 Equilibrium

Definition 1 *Given the admissions rule* $\left\{\psi_{jm}(a)\right\}_{jm}$*, an equilibrium consists of a set of student enrollment and continuation strategies* $\left\{y^1_{jm}(x,\epsilon), y^2_{jm}(x,\epsilon,\eta_m)\right\}_{jm}$*, and the enrollment and peer quality of each academic program* $\{\kappa_{jm}, A_{jm}\}_{jm}$*, such that*
(a) Given A_{jm}*,* $y^2_{jm}(x,\epsilon,\eta_m)$ *is an optimal continuation decision for every* (x,ϵ,η_m)*;*
(b) Given $\left\{A_{jm}, \psi_{jm}(a)\right\}_{jm}$*,* $\left\{y^1_{jm}(x,\epsilon|\psi(a))\right\}_{jm}$ *is an optimal enrollment decision for every* (x,ϵ)*;*
(c) Consistency condition holds: $\{\kappa_{jm}, A_{jm}\}_{jm}$ *is consistent with individual decisions such that*

$$\begin{aligned}\kappa_{jm} &= \int_x\int_\epsilon \psi_{jm}(a) y^1_{jm}(x,\epsilon|\psi(a)) dF_\epsilon(\epsilon)\, dF_x(x), \\ A_{jm} &= \frac{\int_x\int_\epsilon \psi_{jm}(a) y^1_{jm}(x,\epsilon|\psi(a)) a_m dF_\epsilon(\epsilon)\, dF_x(x)}{\kappa_{jm}}.\end{aligned}$$

An equilibrium of this model can be viewed as a classical fixed-point of an equilibrium correspondence that maps the support of $\{\kappa_{jm}, A_{jm}\}_{jm}$ onto itself. Such a fixed point exists under suitable regularity conditions. In the appendix, we outline the algorithm we use to search for equilibria, which we always find in practice.

4 Data

4.1 Data Sources and Sample Selection

Our first data source is the Chilean Department of Evaluation and Educational Testing Service, which records the PSU scores and high school GPA of all test takers and the college-major enrollment information if a student was enrolled in one of the 25 traditional universities. Although macro-level information is available for multiple years, we obtained micro-level information only for the 2011 freshmen cohort. There are $247,360$ PSU test takers in 2011. We focus on the $159,365$ students, who met the minimum requirement for admission to at least one college-major program

[22] For a student, the enrollment choice is generically unique.

and who were not admitted based on special talents such as athletes.[23] From the $159,265$ students, we draw $10,000$ students as our final sample due to computational considerations.[24,25]

Our second data source is Futuro Laboral, a project of the Ministry of Education that follows a random sample of college graduates (classes 1995, 1998, 2000 and 2001). This panel data set matches tax returns with students' college admissions information, so we observe the worker's annual earnings, months worked, high school GPA, PSU scores, and the college-major he/she graduated from. For each cohort, earnings information is available from graduation until 2005. We calculated the monthly real wage based on annual earnings and months worked, then we calculated the annual wage as 12 times the monthly wage, measured in thousands of pesos.[26] For each major, we trimmed our wage data at the $2nd$ and the $98th$ percentiles. The two most recent cohorts have the largest numbers of observations without missing information, and they have very similar observable characteristics. We combined these two cohorts to obtain our measures of abilities and annual wage levels among graduates from different college-major pairs. We also use the wage information from the two earlier cohorts to obtain information on major-specific wage growth at higher work experience levels. In our final sample, there are $19,201$ individuals from the combined 2000-2001 cohorts, and $10,618$ from the earlier cohorts.

The enrollment data provides us with measures of individual ability, enrollment and peer quality, but not the market return to college education. The wage data, on the other hand, contains wages for college graduates, but not the quality of their peers while in college. We combine these two data sets in our empirical analysis. We standardized the test scores according to the cohort-specific mean and standard deviation to make the test scores comparable across cohorts. As such, we have created a synthetic cohort, the empirical counterpart of students in our model.[27]

[23] Ineligible students can only choose the outside option and will not contribute to the estimation of the model.

[24] For each parameter configuration, we have to solve for equilibrium via an iterative procedure as discussed in the appendix. Each iteration involves solving every student's problem, since each of them has a different set of observables x, and there is no analytical solution to student problem. Moreover, we have to numerically integrate out the unobserved tastes for each student.

[25] Some options are chosen by students at much lower frequency than others. To improve efficiency, we conduct choice-based sampling with weights calculated from the distribution of choices in the population of $159,365$ students. The weighted sample is representative. See Manski and McFadden (1981).

[26] Student utility is also measured in thousands of pesos.

[27] Given data availability, we have to make the assumption that there exists no systematic difference

Our graduate wage data only allows us to observe one's wage path in the early stage of his/her career. In order to obtain information on wage growth at higher experience levels, we resort to the cross-sectional data from the Chilean Characterization Socioeconomic Survey (CASEN), which is similar to the Current Population Survey in the U.S. We compare the average wages across different cohorts of college graduates to obtain measures of wage growth at different experience levels. Although not ideal, such measures restrict the model from predicting unrealistic wage paths in one's later career in order to fit other aspects of the data.

Our last data source is the Indices database from the Ministry of Education of Chile. In this data set, we obtain information on college-major-specific tuition, weights $\left(\{\omega_m^l\}\right)$ used to form the admission score index, the admission cutoffs $\left(\{a_{jm}^*\}\right)$, as well as enrollment sizes in consecutive years.

4.2 Aggregation of Academic Programs

For both sample size and computational reasons, we have aggregated the specific majors into 8 categories according to the area of study, coursework, PSU requirements and average wage levels. The 8 aggregated majors are: Business, Education, Arts and Social Sciences, Sciences, Engineering, Health, Medicine and Law.[28] We also aggregated individual traditional universities into 3 tiers based on admissions criteria, student quality and university prestige. As such, students are faced with 25 options, including the outside option, in making their enrollment decisions.

The first column in Table 1 shows the number of colleges in each tier. The second column shows the quality of students within each tier, measured by the average of math and language scores. In the parentheses, we show the cross-college standard deviations of the within-college mean scores. In columns 3 and 4, we show similar statistics for total enrollment and tuition. Cross-tier differences are clear: higher-ranked colleges have better students, larger enrollment and higher tuition.

across cohorts conditional on comparable test scores. This assumption rules out, for example, the possibility that different cohorts may face different degrees of uncertainties.

[28] All these majors, including law and medicine, are offered as undergraduate majors in Chile.

Table 1 Aggregation of Colleges

Tier	No. Colleges	Mean Score[a]	Total Enrollment	Tuition[b]
1	2	702 (4.2)	21440 (2171)	3609 (568.7)
2	10	616 (17.7)	10239 (4416)	2560 (337.2)
3	13	568 (7.2)	5276 (2043)	2219 (304.2)

[a]The average of $\frac{math+language}{2}$ across freshmen within a college.

[b]The average tuition (in 1000 pesos) across majors within a college.

[c]Cross-college std. deviation shown in parenthesis.

4.3 Summary Statistics

In this subsection, we provide summary statistics for the aggregated tier-major categories based on our final sample. Table 2 shows summary statistics by student enrollment status. The first three columns show that both test scores and graduate wage levels are consistently ranked across tiers. The next two columns show the fractions of students who chose the correpsonding options among, respectively, all students and females. Over 71% of students in the sample were not enrolled in any of the traditional universities and only 5% were enrolled in the top tier.[29] Compared to males, females are less likely than males to enroll in college and even less so in better colleges.[30]

Table 2 Summary Statistics By Tier (All Students)

	Math[a]	Language	Log Wage[b]	Dist. for All (%)	Dist. for Female (%)
Tier 1	709 (80.9)	692 (58.5)	8.91 (0.59)	5.1	4.5
Tier 2	624 (69.0)	611 (68.9)	8.57 (0.66)	14.1	12.2
Tier 3	572 (58.8)	570 (62.4)	8.32 (0.69)	9.0	9.1
Outside	533 (67.5)	532 (67.4)	-	71.8	74.2

[a]The maximum score for each subject is 850. Std. deviation among students is in parenthesis.

[b]Log of starting wage in 1000 pesos. We only have wage info for CRUCH college grads.

Table 3 shows the characteristics of enrollees by major. We list the majors in the order of average starting wages as we observe in the data.[31] This rank is also roughly

[29]For students not enrolled in the traditional universities, we have no information on where they went.

[30]53.2% of the sample are females.

[31]See Figures 1 to 8 for wage paths by major.

consistent with the rank of average test scores across majors. For example, medical students have absolute advantages over all other students, while education students are at the other extreme. Comparative advantages differ across majors. For example, law and social science majors have clear comparative advantage in language, while the opposite is true for engineering and science majors. The last two columns show the fraction of students in each major among, respectively, all enrollees and female enrollees. Females are significantly more likely to major in education and health but much less likely to major in engineering. Different enrollment patterns across genders may arise both from unobserved tastes and from comparative advantages, which will be illustrated later.

Table 3 Summary Statistics By Major (Conditional on Enrollment)

	Math	Language	Dist. for All (%)	Dist. for Female (%)
Medicine	750 (66.0)	719 (55.5)	3.4	3.2
Law	607 (74.2)	671 (72.1)	4.6	4.8
Engineering	644 (79.7)	597 (75.4)	36.6	23.4
Business	620 (87.3)	605 (73.9)	9.9	10.5
Health	628 (58.3)	632 (64.3)	11.7	17.1
Science	631 (78.2)	606 (82.1)	8.5	8.3
Arts&Social	578 (70.7)	624 (72.4)	11.2	14.1
Education	569 (59.5)	593 (664.2)	14.0	18.6

5 Estimation

We estimate the structural parameters of the model via simulated generalized method of moment (SGMM).[32] For each parameter configuration, we solve for the equilibrium and compute the model-predicted moments. The parameter estimates minimize the distance between the model-predicted moments $(M(X,\theta))$ and the data moments $\left(M^d(X)\right)$:

$$\widehat{\theta} = \arg\min_{\theta} \left\{ \left(M(X,\theta) - M^d(X)\right)' W \left(M(X,\theta) - M^d(X)\right) \right\},$$

where W is a positive-definite weighting matrix.

[32] Given that we do not observe the same cohort from enrollment to labor market outcomes, we choose not to use maximum likelihood estimation method.

5.1 Target Moments

The moments we target come from different data sources and capture various key predictions from the model. Although all model predictions are joint outcomes from the equilibrium model, different moments contain different amounts of information on various subsets of model parameters. The PSU data allows us to compute enrollment and peer quality, the key variables that summarize equilibrium student sorting. It also provides other information critical for the identification of students' preferences. For example, to pursue the same major, some students chose to attend a lower-ranked college while others chose to attend a higher-ranked one although they have similar observables. This informs us about students' dispersed preferences for colleges. Similarly, the fraction of students who chose a less lucrative major although they could get in a more lucrative one informs us about the dispersion of tastes for majors. The wage data provides key information about major-specific market returns, human capital production technology, as well as the quality of college graduates. In total, we estimate 88 free parameters by matching the following 448 moments.

5.1.1 PSU Data and College Data

(1) Enrollment status:

Fractions of students across tier-major (j, m) pairs overall, for females and for low income group.

(2) Ability by enrollment status:

First and second moments of major-m ability (a_m) by (j, m).

Mean test scores among students who chose the outside option.

(3) Taste dispersion:

Fractions of students enrolled in (j, m) with $a_m \geq a^*_{j'm}$ where j' is a tier ranked higher than j.

Fractions of students enrolled in j with $a_m \geq a^*_{jm}$ by (j, m).

(4) Retention rate by (j, m) calculated from aggregated enrollments in the college data.

5.1.2 Wage Data

(1) Graduate ability:

First and second moments of major-m ability among graduates by (j, m).

(2) Starting wage:

First and second moments of log starting wage by (j, m).

First moments of log starting wage by (j, m) for females.

Cross moments of log starting wage and major-specific ability by (j, m).

(3) Wage growth:

Mean of the first differences of log wage by major for experience level $t = 1, ..., 9$.

From the CASEN data: first difference of the mean log wage at experience level $t = 10, ..., 40$.

6 Results

6.1 Parameter Estimates

In this section, we report the estimates of parameters of major interests. The appendix reports the estimates for other parameters. The standard errors (in parentheses) are calculated via bootstrapping.[33]

Table 4 Human Capital Production

	Own Ability (γ_{1m})		Peer Ability (γ_{2m})	
Medicine	0.18	(0.007)	0.01	(0.002)
Law	1.26	(0.002)	0.58	(0.004)
Engineering	1.53	(0.001)	0.70	(0.001)
Business	1.52	(0.001)	1.48	(0.001)
Health	0.48	(0.003)	0.53	(0.003)
Science	1.62	(0.001)	1.44	(0.001)
Arts&Social	1.03	(0.003)	0.91	(0.002)
Education	0.55	(0.002)	1.08	(0.001)

Table 4 shows parameters governing the production of human capital, which also measure the elasticities of wage with respect to own ability and to peer ability.[34]

[33] Standard first-order Taylor expansions yield very small standard errors that might be problematic because we have to use numerical method to calculate the derivatives of our GMM objective function.

[34] Own ability refers to the major-specific ability a_m in the corresponding major m, not the whole vector a. Peer ability refers to the average major-specific ability among peers in the same program A_{jm}.

Focusing on the right panel first, we find significant differences in the importance of peer ability across majors: the elasticity of wage with respect to peer quality ranges from 0.01 in medicine to 1.48 in business.[35] Considering both the left and the right panels, we find that the relative importance of peer ability versus own ability differs systematically across majors although no restriction has been imposed in this respect. In particular, for majors with the highest average wages, medicine, law and engineering, the elasticity of wage with respect to peer ability is at most half of that with respect to own ability, while the opposite is true for education, the major with the lowest average wage. For the other four majors, peer ability is as important as one's own ability. This finding has major implications for welfare analysis as we switch from Sys. Chile to Sys. US, because the quality of first-period peers will decline for "elite" majors, while increase for "non-elite" majors. Table 4 suggests that the former negative effect is likely to be small, while the latter positive effect may be significant.

Another interesting finding from Table 4 is that wages are very inelastic to both own ability and peer ability in medicine. In other words, although medical students face a very high rental rate of their human capital (as shown in Table A2.4 in the appendix), their wages are concave in ability measures. This implies that although pre-college ability measures can largely distinguish bad doctors from mediocre doctors, it is individual suitability realized after enrollment that most effectively distinguishes mediocre doctors from good doctors. The former is consistent with the high admissions standards for medicine major; while the latter is consistent with the practice of internship and strict licensing in the medical profession.

Table 5 focuses on parameters that govern major-specific consumption values. The first two columns show how these values vary with own ability and peer ability. The three majors with highest average wages and social science major are the most satisfying for high ability individuals. Except for engineering, effort costs in these majors are also the most responsive to peer abilities. Relative to other majors, the consumption value of business major is not very responsive to one's own ability, however, high peer ability significantly increases the effort cost for business students. The last column of Table 5 shows that compared to average male students, average female students have higher tastes for the conventional "feminine" majors: health

[35] As mentioned earlier, our model is silent about why peer ability affects one's market return. These reasons are likely to differ across majors, for example, the high elasticity of peer ability in business major may arise because the social network one forms in college is highly valued in the business profession.

and education, but lower tastes for all the other majors.

Table 5 Consumption Value (Major-Specific Parameters)

Major	Own Ability		Peer Ability		Female	
Medicine	6.33	(0.37)	-6.11	(0.62)	-1982.2	(155.8)
Law	2.13	(0.14)	-17.46	(0.30)	-196.9	(63.8)
Engineering	2.22	(0.01)	-0.01	(0.002)	-1719.5	(29.7)
Business	0.004	(0.006)	-2.52	(0.02)	-196.6	(23.5)
Health	0.006	(0.004)	-0.24	(0.02)	1668.6	(16.6)
Science	0.001	(0.003)	-0.001	(0.0002)	-376.6	(20.6)
Arts&Social	1.50	(0.08)	-4.14	(0.16)	-393.3	(19.4)
Education	0.003	(0.008)	-0.001	(0.022)	1302.5	(17.9)

6.2 Model Fit

Overall, the model fits the data well. The first two columns of Table 6 show the fraction of all students enrolled in each tier. The model slightly under-predicts the enrollment in the top tier and over-predicts that in the other two tiers. The last two columns of Table 6 show the same statistics among females.[36]

Table 6 Enrollment by Tier (%)

	All		Females	
	Data	Model	Data	Model
Tier 1	5.1	4.5	4.5	3.4
Tier 2	14.1	14.7	12.2	12.1
Tier 3	9.0	9.9	9.1	8.8

Table 7 shows the distribution of enrollees across majors, where each column adds up to 100%. For all enrollees, the discrepancy is most obvious in the two smallest majors: the enrollment in medicine is over-predicted and that in law is under-predicted. For female enrollees, the model underpredicts the fraction of enrollees in social sciences and overpredicts that in education.

[36] The fits of enrollment patterns for students with low family income are in the appendix.

Table 7 Enrollee Distribution Across Majors (%)

	All		Females	
	Data	Model	Data	Model
Medicine	3.4	5.0	3.2	2.9
Law	4.6	3.9	4.8	3.6
Engineering	36.6	36.5	23.4	24.2
Business	9.9	9.9	10.5	10.6
Health	11.7	10.7	17.1	17.9
Science	8.5	9.0	8.3	8.0
Arts&Social	11.2	11.0	14.1	10.8
Education	14.0	14.1	18.6	21.8

Table 8 (Table 9) shows the fit of average student ability and retention rates by tier (major). By tier, the ability measures are closely matched but the retention rate for Tier 3 is overpredicted by about 5%. By major, ability is under-predicted for social science and retention rate is over-predicted for science.

Figures 1 to 8 show the fit of major-specific wage patterns. The biggest discrepancy occurs in health major, where the model consistently underpredicts the wage.

Table 8 Ability & Retention (by Tier)

	Ability[a]		Retention (%)	
Tier	Data	Model	Data	Model
1	701	701	79.3	79.6
2	624	626	76.5	75.5
3	581	583	68.1	73.2

[a]The average of major-specific ability across majors in each tier.

Table 9 Ability & Retention (by Major)

	Ability[a]		Retention (%)	
	Data	Model	Data	Model
Medicine	738	727	87.6	87.0
Law	658	649	81.3	80.8
Engineering	623	625	71.8	74.4
Business	619	619	74.6	73.4
Health	641	636	79.8	78.0
Science	622	614	63.7	72.0
Arts&Social	612	597	74.3	75.1
Education	590	592	77.1	73.8

[a]Average major-specific ability a_m in each major m.

6.3 Illustration: Gender Differences

In this subsection, we explore the importance of gender-specific preferences in explaining different enrollment patterns across genders.[37] We do so by comparing the baseline model prediction with a new equilibrium where females have the same preferences as males.[38] Table 10 shows the distribution of enrollees within each gender in the baseline equilibrium and the new equilibrium. When females share the same preferences as males, gender differences in the choice of majors almost disappear: there no longer exists a major that is obviously dominated by one gender. Differences between male and female choices still exist. For example, although college enrollment rate among females increases from 24.3% to 27.1% (not shown in the Table), it is still lower than that among males (35.9%) . Moreover, compared with males, females are still less likely to enroll in medicine and science and more likely to enroll in social science. One reason is that, on average, males have higher test scores than females; and they have comparative advantage in majors that uses one's math skill more than one's language skill.[39]

[37]The importance of gender-specific preferences has been noted in the literature. For example, Zafar (2009) finds that preferences play a strong role in the gender gap of major choices in the U.S.

[38]The purpose of this simulation is simply to understand the importance of preferences; the simulation ignores potential changes in admission cutoffs.

[39]The average math score for males (females) is 572 (547), and the average language score for males (females) is 557 (553).

Table 10 Female Enrollee Distribution

(%)	Baseline		New	
	Male	Female	Male	Female
Medicine	6.7	2.9	9.3	6.6
Law	4.0	3.6	3.9	3.6
Engineering	46.3	24.2	45.9	45.7
Business	9.2	10.6	9.2	9.7
Health	4.9	17.9	3.9	4.8
Science	9.8	8.0	9.1	8.4
Arts&Social	11.1	10.8	10.5	12.6
Education	8.0	21.8	8.1	8.5

7 Counterfactual Policy Experiments

In the counterfactual experiments, we introduce college-specific, rather than college-major-specific, admissions to Chile. Students choose their majors after they learn about their fits. We solve a planner's problem, who aims at maximizing total student welfare by making admission policies.[40] The constraints for the planner include: 1) a student admitted to a higher-tier college is also admitted to a lower-tier college, and 2) the planner can use only ability a to distinguish students. These two restrictions keep our counterfactual experiments closer to the current practice in Chile in dimensions other than the college-specific versus college-major-specific admissions. Restriction 1 prevents the planner from admitting a student to only the one college that the planner deems optimal, which is both far from the current Chilean practice and also may lead to mismatches due to the heterogeneity in student tastes. Restriction 2 rules out discrimination based on gender or family income.

7.1 New Model

There are four stages in this new environment:

Stage 1: The planner announces college-specific admissions policies.

Stage 2: Students make enrollment decisions.

[40]The planner takes into account the monetary cost of education via tuition, which differs across educational programs. If tuition reflects the cost of providing college education, the planner also maximizes total social welfare.

Stage 3: An enrollee in college j takes courses in majors within his/her broad academic interests and learn his/her efficiency levels in these majors. Then, he/she chooses one of these majors or to drop out.
Stage 4: Students who chose to stay in college in Stage 3 stay one more period studying in the major of choice and then enter the labor market.

The planner acts as the Stackelberg leader in this game, knowing that different admissions decisions would lead to different equilibrium outcomes in the following coordination game among students. Instead of simple unidimensional cutoffs, optimal admissions policies will be based on the whole vector of student ability a. In the following, we describe the model formally, readers not interested in the details may skip to the result section.

7.1.1 Student Problem

Denote M_a as the set of majors that are within the broad academic interest of a student with ability a, and $|M_a|$ as the number of majors in this set.

Continuation Decision After the first period, a student with ability a learn about his/her abilities within M_a. Given $\left(x, \epsilon, \{\eta_m\}_{m\in M_a}\right)$ and $A_j \equiv \{A_{jm}\}_m$, an enrollee in college j chooses one major of interest or to drop out:

$$u_j(x, \epsilon, \{\eta_m\}_{m\in M_a} | A_j) =$$
$$\max\left\{\max_{m\in M_a}\left\{v_{jm}(x, \epsilon, A_{jm}) + E\sum_{\tau'=3}^{T}\delta^{\tau'-2}\left(w_m(\tau-3, a_m, \eta_m, A_{jm}) + v_m(x, \epsilon)\right)\right\}, V_d\left(x\right)\right\}.$$

Let $y^2_{m|j}\left(x, \epsilon, \{\eta_m\}_{m\in M_a}\right) = 1$ if an enrollee in j with $\left(x, \epsilon, \{\eta_m\}_{m\in M_a}\right)$ chooses major m.

Enrollment Decision We assume that in the first period of college, an enrollee pays the average cost for and derives the average consumption value from majors within his/her broad academic interest.[41] At the enrollment stage, a student chooses

[41] We assume that in the first period students do not choose from which majors to take courses. Presumably, there will be greater welfare gains if such choices are allowed. Our estimates provides a lower benchmark for potential welfare gains from the switch of the admissions system. We leave the extension for future work.

the best among colleges he/she is admitted to and the outside option:

$$U(x,\epsilon|q(a),A) =$$
$$\max\left\{\max_j\{\delta E_\eta u_j(x,\epsilon,\{\eta_m\}_{m\in M_a}|A_j) + \frac{1}{|M_a|}\sum_{m\in M_a} v_{jm}(x,\epsilon,A_{jm})\}, V_0(x)\right\}$$
$$s.t.\ E_\eta u_j(x,\epsilon,\{\eta_m\}_{m\in M_a}|A_j) = -\infty \text{ if } \psi_j(q(a)) = 0,$$

where $q(a)$ is the planner's admissions rule toward student with ability a, and $\psi_j(q(a)) = 1$ if such a student is admitted to college j. Let $y_j^1(x,\epsilon|q(a)) = 1$ if a student with characteristics (x,ϵ) chooses college j under the admissions rule $q(a)$.

7.1.2 Planner's Problem

One can show that in this environment, it is not optimal to use simple unidimensional cutoffs as admissions criteria. Instead, the whole vector of student ability a should be taken into consideration. To calculate the benefit of applying some $q(a)$ to a student of ability a, the planner has to consider the expected individual value for this student, as well as his/her expected effect on peer quality. Peer quality matters both because it affects the market return via the human capital production and because it affects student effort cost. Both the student's individual value and his/her effect on other students' welfare may differ with $q(a)$ because his/her choices may change with $q(a)$. Comparing across all possible $q(a)$ toward student a, the planner chooses the best one. Overall, planner's optimal admissions policies lead student sorting toward the maximization of total student welfare. Formal discussions are provided in the appendix.

7.1.3 Equilibrium

Definition 2 *An equilibrium in this new system consists of a set of student enrollment and continuation strategies* $\left\{y_j^1(x,\epsilon|q(a)), \left\{y_{m|j}^2(x,\epsilon,\{\eta_m\}_{m\in M_a})\right\}_m\right\}_j$, *a set of admissions policies* $\{q(a)\}$, *and the characteristics of academic programs* $\{\Omega_{jm}\}$, *including enrollment and average student ability* $A = \{A_{jm}\}_{jm}$, *such that*
(a) Given A, $\left\{y_{m|j}^2(x,\epsilon,\{\eta_m\}_{m\in M_a})\right\}_m$ *is an optimal choice of major for every* $(x,\epsilon,\{\eta_m\}_{m\in M_a})$;
(b) Given $(A,q(a))$, $\{y_j^1(x,\epsilon|q(a))\}_j$ *is an optimal enrollment decision for every* (x,ϵ);

(c) $q(a)$ *is an optimal admissions policy for every* a;
(d) *Consistency condition holds:* $\{\Omega_{jm}\}$ *is consistent with* $\{q(a)\}$ *and individual student decisions.*

In the appendix, we provide formal theoretical details and describe our algorithms to compute local equilibria and verify global optimality.

7.2 Results

7.2.1 Welfare

One of our major goals is to compare welfare under different admissions systems.[42] One factor that deserves special attention is the amount of major-specific human capital that may be lost when specialized training is postponed.[43] We consider various possible scenarios and provide bounds on welfare gains under the counterfactual admissions system.[44] To this end, we conduct two sets of experiments, solve for new equilibria to compare with the equilibrium under the baseline.

In the first set of experiments, we assume that to make up for the first period (2 years) of college spent without specialization, students have to spend, respectively, 0, 1 and 2 extra year(s) in college. Table C1 shows the equilibrium enrollment, retention and student welfare under the baseline and the new admissions system with different lengths of college life. In all cases, postponing major choices until after students learn about their fits increases the overall retention rate from 75% to around 90% : a significant fraction of dropouts occur in the current system because of student-major mismatches. In the first counterfactual case, enrollment increases from 29% to 39%, and the mean student welfare increases by about 4.6 million pesos or 5%. When one has to spend one more year in college, college enrollment decreases sharply to 28% but welfare is still 1.2 million pesos higher than the baseline case. In the third case where a student accumulates zero marketable human capital in the first period, the new system causes a 0.9% welfare loss relative to the baseline case. However, we believe the last case to be overly pessimistic.

[42] As a caveat, our policy experiment assumes an open economy and holds the wage functions unchanged. A more comprehensive model would consider the reactions of labor demand to the new regime, which is beyond the scope of this paper.

[43] On the other hand, if the labor market values the width of one's skill sets, one would expect greater gains from the new system than those predicted in this paper.

[44] The data we have does not allow us to predict the exact change in human capital associated with the shift of admissions regimes.

Table C1 Different Lengths of College Life

	Baseline	0 Extra Year	1 Extra Year	2 Extra Years
Enrollment (%)	29.1	39.1	27.5	19.2
Retention (%)	75.3	91.1	89.2	90.2
Mean Welfare (1000 Peso)	93931	98574	95185	93093

In the second set of experiments, instead of extending college life for all majors, we take an arguably more realistic approach and treat majors differently.[45] For the two most specialized and prestigious majors, law and medicine, students have to spend extra time in college to make up for the non-specializing first period. For other majors, the lengths of studies keep unchanged at the cost of potential losses of human capital due to reduced years of specialization. Specifically, we assume that under the new system, for a major other than law and medicine, the amount of human capital achieved in college is given by $(1-\phi)\, h_m(a_m, A_{jm}, \eta_m)$, where ϕ is the fraction of human capital lost ceteris paribus. Given this framework, we seek the combinations of the number of extra years (up to two years) in law and medicine and the fraction ϕ for other majors that equalize student welfare between the old system and the new system. The two combinations that satisfy this condition are either 1) law and medicine majors extend for 1 year, and $\phi = 23\%$ for other majors; or 2) law and medicine majors extend for 2 years, and $\phi = 19.5\%$ for other majors.

The first two rows of Table C2 show different configurations of year requirement and ϕ; the next two rows show the corresponding equilibrium enrollment and welfare. Although by construction the average welfare under Combinations 1 and 2 is the same as the baseline, enrollment rates under both combinations are about 7% lower than the baseline. It follows that under Combinations 1 and 2, some former enrollees choose the outside option and experience welfare loss. In contrast, average enrollees in the new system gain because they are able to choose the best match after learning about their fits.

[45] For example, in the U.S., for most majors, students receive specialized training only in upper college years. For law and medicine, specialization usually starts after one has received more general college training and lasts another 3 to 6 years.

Table C2 Different Treatments Across Majors

	Baseline	Combination 1	Combination 2	Combination 3
Extra Years in Law & Med	-	1	2	1
ϕ: Loss in Other Majors (%)	-	23.0	19.5	8.5
Enrollment (%)	29.1	22.7	22.3	29.1
Mean Welfare (1000 Peso)	93931	93934	93935	96312

The last column of Table C2 shows results from a third (year, ϕ) combination such that the overall enrollment rate in the new system equals that in the baseline. Arguably, it is overly pessimistic to think that the first two years are totally unproductive for law and medical students, we therefore examine the medium case, where these students have to spend one more year in college to finish their specialized training. Given this time line, we find that a reduction $\phi = 8.5\%$ in other majors will keep enrollment at the baseline level. Given the same total enrollment, the following subsection compares the distribution of students under the baseline and the new system Combination 3.

7.2.2 Enrollment and Major Choice Distribution

Table C3 displays enrollment and retention rates by tier. Compared to the baseline case, the new system features more students enrolled in both the top tier (Tier 1) and the bottom tier (Tier 3), and fewer in the middle tier. What explains the growth of Tier 1 relative to Tier 2? Under the old system, a nontrivial fraction of students were eligible to enroll in Tier 1 but only for majors other than their ex-ante most desirable ones. Among these students, some opted for their favorite majors in Tier 2 rather than a different major in Tier 1. Under the new system, the planner still deem (some of) these students suitable for Tier 1, and some of them will matriculate.[46] This is because, regardless whether or not these students eventually choose their ex-ante favorite majors, given their relatively high ability, enrolling them in Tier 1 does not have a significant negative effect on peer quality, while the improved match quality significantly increases the net benefits of doing so.

What explains the growth of Tier 3 relative to Tier 2? Although the total enrollment remains the same, the composition of enrollees changes as the system shifts. On the one hand, some former outsiders choose to enroll given the prospect of a better

[46] Some of these students will opt for a lower-ranked tier due to tastes.

match. A large fraction of them are students with relatively low ability, whom are deemed suitable only for hence admitted only to Tier 3 by the planner. On the other hand, some former enrollees choose the outside option because of the potential loss of either time or human capital embedded in Combination 3. Since one's outside value increases with one's ability, a lot of students in this group are former Tier 2 enrollees who have middle-level abilities.

Table C3 Enrollment and Retention (%)

	Baseline		Combination 3	
	Enrollment	Retention	Enrollment	Retention
Tier 1	4.5	79.6	5.1	93.6
Tier 2	14.7	75.5	12.2	92.5
Tier 3	9.9	73.2	11.7	89.3
All	29.1	75.3	29.1	91.4

Table C3 also shows that retention rates in all three tiers improve significantly with the change of the system. In fact, even the worst case under the new system (Tier 3) features a retention rate that is 10% higher than the best case under the old system (Tier 1).

Table C4 displays the distribution of students across majors in the first and second period in college.[47] Focusing on the first four columns, we see some changes that might have been expected. For example, without major-specific barriers to enrollment, the fraction of students increases in law and medicine, the two most prestigious majors; while both social science and education majors lose students. Some changes are, however, less expected. For example, the fraction in engineering decreases and that in science increases, both of which use similar combinations of skills. This arises because some former engineering students opt for even more lucrative majors even if they are suitable for engineering, and some find out that they are not suitable for engineering. It is also related to the human capital production technology: the market return to science major is very responsive to both own ability and peer ability (see Table 4). In the new system, the first-period peers for a would-be science student include some of the best students who have very high science ability although whose final best choices may not be science. The enhanced peer quality, reinforced by the

[47] For the first period in college, the distribution across majors is defined only for the baseline case, since in the new system students do not declare majors until the second period.

strong complementarity between own ability and peer ability for science major, makes it a more attractive major.

Table C4 Distribution Across Majors (%)

	Baseline		Combination 3		Rationed Combination 3	
	1st Period	2nd Period	1st Period	2nd Period	1st Period	2nd Period
Medicine	1.5	1.3	-	3.3	-	1.5
Law	1.1	0.9	-	1.6	-	1.1
Engineering	10.6	7.9	-	7.3	-	7.2
Business	2.9	2.1	-	3.4	-	3.5
Health	3.1	2.4	-	2.8	-	2.6
Science	2.6	1.9	-	3.6	-	3.5
Arts&Social	3.2	2.4	-	2.1	-	2.1
Education	4.1	3.0	-	2.5	-	2.5
All	29.1	21.9	29.1	26.6	26.5	24.1

7.2.3 Rationing

Without constraints on student major choices, the new system leads to a large increase in the number of students majoring in law and medicine. However, enrollment in these two majors are often strictly rationed regardless of the admissions system. In the following experiment, we mimic such rationing by adding one more constraint to the new system Combination 3. In particular, among all enrollees in college j, only those with law-specific (medicine-specific) ability that meets a certain cutoff have the option to major in law (medicine).[48] We conduct a series of experiments with different cutoffs and report results from the one where the final number of students in each law (medicine) program equals the number of available slots as proxied by the enrollment size of the corresponding program under the baseline.

The last two columns of Table C4 show the equilibrium enrollment with rationing.[49] By construction, the fraction of students majoring in law (medicine) is cut down to its capacity. It is not clear a priori how enrollment in unrationed majors

[48] These cutoffs are taken as given by both the planner and the students. An interesting and ambitious extension is to endogenize these cutoffs.

[49] Compared to the unrationed case, rationing decreases student welfare by 132 thousand pesos, or 0.1%.

may change because two conflicting effects coexist. On the one hand, given total enrollment, enrollments in unrationed majors should increase as rationed-out students reallocate themselves. On the other hand, some students who would enroll without rationing may be discouraged from enrolling at all as they are denied of the option to major in law and medicine. Indeed, as shown in the last row of Table C4, 2.7% fewer students are enrolled in the first period when rationing is imposed. Due to the domination of this second effect, engineering, health and science majors all become smaller. The only major where the first effect dominates is business, which becomes slightly larger.

Table C5 Log Starting Wage

	Baseline	Combination 3	Rationed Combination 3
Medicine	9.10	9.17	9.18
Law	9.20	9.59	9.63
Engineering	8.97	9.03	9.03
Business	8.51	8.74	8.76
Health	8.38	8.89	8.90
Science	8.36	9.07	9.08
Arts&Social	8.32	8.79	8.80
Education	8.06	8.35	8.35

Table C5 shows the mean log starting wages (in 1000 pesos) by major, which also reflects the average productivity by major. With or without rationing, allowing students to learn their fits before choosing their majors improves the quality of matches and hence productivity in all majors compared to the baseline case. This is true even though Combination 3 assumes a 8.5% loss of human capital ceteris paribus for majors other than law and medicine.

When enrollment in law and medicine is rationed, the average productivity increases even further in both majors, which consist of only the very best students. As students who are rationed out of law and medicine reallocate themselves, two conflicting effects occur for the average productivity in other majors. On the one hand, some rationed-out students have higher abilities in multiple majors over an average student; even if their comparative advantages are in law or medicine, they will improve the average productivity in the majors they flow into. On the other hand, some rationed-out students are ill suited for other majors and they will drag down the average productivity in the majors they flow into. Comparing the last two columns of

Table C5, we see that the resulting changes in the productivity of unrationed majors are marginal. However, at least in one major we can clearly see the dominance of the second effect: the major of business gains not only in size (shown in Table C4), but also in average productivity due to the inflow of high-ability students.

8 Conclusion

In many countries, college admissions are college-major-specific: a student has to choose a college-major pair in making his/her enrollment decision. When students are uncertain about their fits across majors, serious mismatches may occur. We explore the equilibrium effects of postponing students' choices of majors until after they have learned about their fits. To do so, we develop an equilibrium college-major choice model under the college-major-specific admissions system, allowing for uncertainty and peer effects. We apply our model to the case of Chile and recover the structural parameters underlying the equilibrium sorting among Chilean students. Our model is able to capture most of the patterns observed in the data.

We model our counterfactual policy regime as a Stackelberg game in which a social planner chooses college-specific admissions policies and students make enrollment decisions, learn about their fits to various majors and then choose their majors. We have showed changes in the distribution of student educational outcomes and provided bounds on potential welfare gains from adopting the new system.

Although our empirical application is based on the case of Chile, our framework is general enough to be applied to other countries with similar admissions systems. We view the methods developed in this paper and our main empirical results as promising for future research. One interesting extension is to model human capital production explicitly as a cumulative process and to measure achievement at each stage of one's college life, so as to provide a more precise estimate of the impacts on student welfare when the admissions system changes. This extension requires information on student performance in college and/or market returns to partial college training.

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Appendix

A1 Detailed Functional Form and Distributional Assumptions

A1.1 Cost of college for students:

$$C_{jm}(x, A_{jm}) = p_{jm} + c_1 p_{jm} I(In = low) + c_2 p_{jm}^2 I(In = low) + c_{3m} A_{jm} + c_4 (A_{jm} - a_m)^2,$$

where p_{jm} is the tuition and fee for attending program (j, m). c_1 and c_2 allow tuition to have different impacts on students from low-income families. c_{3m} and c_4 measure the effect of peer quality on effort cost.

A1.2 The value of the outside option and that of dropout depend on one's test scores as well as one's family income. We assume that the intercepts of outside values differ across income groups, and that the value of dropout is proportional to the value of the outside option, with

$$\begin{aligned} V_0(x) &= \sum_{l=1}^{L} \theta_l s^l + \theta_{01}(1 - I(In = low)) + \theta_{01}\theta_{02} I(In = low), \\ V_d(x) &= \rho V_0(x). \end{aligned}$$

A1.3 Idiosyncratic tastes:
For major: each element in ϵ^1 is independent and ϵ^1_m˜$i.i.d.N(0,\sigma^2_{\text{major}})$.
For academic programs: $\epsilon^2_{jm}=\varepsilon_j+\varepsilon_{jm}$, where ε_j˜$i.i.d.N(\overline{\upsilon}_j,\sigma^2_{\text{col}})$ and ε_{jm}˜$i.i.d.N(0,\sigma^2_{\text{prog}})$.
$\overline{\upsilon}_j$ is the consumption value of college j for an average student.

A1.4 Log wage function:

$$\begin{aligned}\ln\left(w_m\left(\tau,x,\eta_m,A_{jm},\zeta_\tau\right)\right) &= \alpha_{0m}+\alpha_{1m}\tau-\alpha_{2m}\tau^2+\alpha_{3m}I(female)+\ln(h_m\left(a_m,\eta_m,A_{jm}\right))+\zeta_\tau,\\ h_m\left(a_m,\eta_m,A_{jm}\right) &= a_m^{\gamma_{1m}}A_{jm}^{\gamma_{2m}}\eta_m.\end{aligned}$$

Elements in the vector η are independent and each element η_m˜$i.i.d.\ln N(-0.5\sigma^2_\eta,\sigma^2_\eta)$.
ζ_τ˜$N\left(-0.5\sigma^2_\zeta,\sigma^2_\zeta\right)$ is an i.i.d. transitory wage shock.

A2 Estimation and Equilibrium-Searching Algorithm

Without analytical solutions to student problem, we resort to numerical procedure to integrate out their unobserved tastes: for every student with observable characteristics x, we draw R sets of taste vectors ϵ, which are fixed throughout. The estimation involves an outer loop searching over the parameter space and an inner loop searching for equilibrium. Finding a local equilibrium can be viewed as a classical fixed-point problem of an equilibrium correspondence $\Gamma:O\Rightarrow O$, where $O=\left([0,1]\times\left[0,\overline{A}\right]\right)^{JM}$, $o=\{\kappa_{jm},A_{jm}\}_{jm}$. Such a mapping exists, based on this mapping, we design the following algorithm to compute equilibria numerically.
0) For each parameter configuration, set the initial guess of o at the level we observe from the data, which is the realized equilibrium.
1) Given o, solve student problem backwards for every (x,ϵ) pair, and obtain enrollment decision $\left\{y^1_{jm}\left(x,\epsilon|\psi\left(a\right)\right)\right\}_{jm}$.[50]
2) Integrate over ϵ to calculate the expected enrollment for each student x.
4) Integrate over all students to calculate the aggregate $\{\kappa_{jm},A_{jm}\}_{jm}$, yielding o^{new}.
5) If $\|o^{new}-o\|<\upsilon$, where υ is a small number, step out of the inner loop. Otherwise, set $o=o^{new}$ and go to step 1).

A3 Counterfactual Model

A3.1 Planner's Problem

[50]Conditional on enrollment in (j,m), the solution to a student's continuation problem follows a cutoff rule on the level of efficiency shock η_m, which yields closed-form expressions for $E_{\eta_m}(u_{jm}(x,\epsilon,\eta_m))$.

To formalize the constraint on the planner's strategy space, we introduce the following notation. Let $\Xi \equiv \{\chi_1, \chi_2, \chi_3, \chi_4\} = \{[1,1,1], [0,1,1], [0,0,1], [0,0,0]\}$, where the j-th component of each χ_n represents the admissions to college j, i.e., $\chi_{nj} = 1$ if a student is admitted to college j. Denote the planner's admissions policy for student with ability a as $q(a)$, we restrict the planner's strategy space to be probabilities over Ξ. That is, for all a, $q(a) \in Q \equiv \Delta([1,1,1], [0,1,1], [0,0,1], [0,0,0])$. As such, the probability that a student is admitted to college j, denoted as $\psi_j(q(a))$, is given by

$$\psi_j(q(a)) = \sum_{n=1}^{4} q_n(a)\chi_{nj}.$$

Consistent with the assumptions on student course taking, we assume that in the first period in college, a student with interest set M_a will take $\frac{1}{|M_a|}$ slot in each $m \in M_a$, and that in the second period in college, he/she will take one slot in his/her chosen major and zero slot in other majors. Let $z = [In, g]$ be the part of x that is not observable to the planner, the planner's problem reads:

$$\pi = \max_{\{q(a) \in Q\}} \left\{ \int_a \widetilde{U}(a|q(a), A) f_a(a) da \right\}$$

where $\widetilde{U}(a|q(a), A) = \int_z \int_\epsilon U(x, \epsilon|q(a), A) dF_\epsilon(\epsilon) dF_z(z|a)$ is the expected utility of student with ability a, integrating out student characteristics that are unobservable to the planner.[51]

For each a, one can take the first order conditions with respect to $\{q_n(a)\}_{n=1}^4$, subject to the constraint that $q(a) \in Q$. Given the nature of this model, the solution is generically at a corner with one of the $q_n(a)$'s being one. As such, we use the following algorithm to solve the planner's problem. For each student a, we check the net benefit of each of the four pure strategies $([1,1,1], [0,1,1], [0,0,1], [0,0,0])$. The (generically unique) strategy that generates the highest net benefit is the optimal admissions policy for this student. Let "$\cdot$" stand for $(q(a), A)$, it can be shown that

[51] Given that test scores are continuous variables, we nonparametrically approximate $F_{z|a}(z)$ by discretizing test scores and calculating the data distribution of z conditional on discretized scores. In particular, we divide math and language test scores each into n narrowly defined ranges and hence generate n^2 bins of test scores. All a's in the same bin share the same $F_{z|a}(z)$.

the net benefit of applying some $q(a)$ to student with ability a is:

$$
\begin{aligned}
& f_a(a)\int_z\int_\epsilon U(x,\epsilon|\cdot)\,dF_\epsilon(\epsilon)dF_{z|a}(z) \\
& +f_a(a)\sum_j \psi_j(\cdot)y_j^1(a|\cdot)\sum_{m\in M_a}\frac{(a_m-A_{jm})}{|M_a|}b_m\gamma_{2m}A_{jm}^{\gamma_{2m}-1}K_{jm} \\
& -f_a(a)\sum_j \psi_j(\cdot)y_j^1(a|\cdot)\sum_{m\in M_a}\frac{(a_m-A_{jm})}{|M_a|}\begin{pmatrix} c_{3m}(1+\sum_{\tau'=1}^{2}\delta^{\tau'-1}\frac{\mu_{jm}^2}{\mu_{jm}^1}) \\ +2c_4\sum_{\tau'=1}^{2}\delta^{\tau'-1}\frac{\mu_{jm}^2}{\mu_{jm}^1}(A_{jm}-A'_{jm})\end{pmatrix}.
\end{aligned}
\tag{1}
$$

The first line of (1) is the expected individual net benefit for student a. An individual student has effect on his/her peer's net benefits because of his/her effect on peer quality: the second line calculates his/her effect on his/her peers' market return; the third line calculates his/her effect on his/her peers effort costs. Peers of student a are those who study in the programs he/she takes courses in. Student a's effect on his/her peers is weighted by his/her course-taking intensity $\frac{1}{|M_a|}$.

To be more specific, $y_j^1(a|\cdot)=\int_z\int_\epsilon y_j^1(x,\epsilon|\cdot)dF_\epsilon(\epsilon)dF_{z|a}(z)$ is the probability that a student with ability a matriculates in college j. $\psi_j(\cdot)y_j^1(a|\cdot)$ is the probability that student a is enrolled in college j. μ_{jm}^1 is the size of program (j,m) in the first period, where each student a takes $\frac{1}{|M_a|}$ seat in major $m\in M_a$. A_{jm} is the average ability among these students.

$$
\begin{aligned}
\mu_{jm}^1 &= \int_a y_j^1(a|\cdot)\psi_j(\cdot)I(m\in M_a)\frac{1}{|M_a|}f_a(a)da, \\
A_{jm} &= \frac{\int_a \psi_j(\cdot)y_j^1(a|\cdot)I(m\in M_a)\frac{1}{|M_a|}a_m f_a(a)da}{\mu_{jm}^1}.
\end{aligned}
$$

The second line of (1) relates to market return. b_m is the part of expected lifetime income that is common to all graduates from major m.[52] K_{jm} is the average individual

[52] $b_m = E\left(e^{\zeta}\right)\sum_{\tau'=3}^{T}\delta^{\tau'-1}e^{\left(\alpha_{0m}+\alpha_{1m}(\tau'-3)-\alpha_{2m}(\tau'-3)^2\right)}$, so that the expected major-m market value of student with ability a can be written as

$$
\begin{aligned}
& b_m\int_z e^{\alpha_{3m}I(female)}\int_\epsilon y_j^1(x,\epsilon|\cdot)\int_\eta y_{m|j}^2(x,\epsilon,\eta)\,h(a_m,A_{jm},\eta)\,dF_\eta(\eta)\,dF_\epsilon(\epsilon)dF_{z|a}(z) \\
= & \; b_m\int_z e^{\alpha_{3m}I(female)}\int_\epsilon y_j^1(x,\epsilon|\cdot)\int_\eta y_{m|j}^2(x,\epsilon,\eta)\,a_m^{\gamma_{1m}}A_{jm}^{\gamma_{2m}}\eta_m dF_\eta(\eta)\,dF_\epsilon(\epsilon)dF_{z|a}(z) \\
= & \; b_m A_{jm}^{\gamma_{2m}}\int_z e^{\alpha_{3m}I(female)}\int_\epsilon y_j^1(x,\epsilon|\cdot)\int_\eta y_{m|j}^2(x,\epsilon,\eta)\,a_m^{\gamma_{1m}}\eta_m dF_\eta(\eta)\,dF_\epsilon(\epsilon)dF_{z|a}(z).
\end{aligned}
$$

contribution to the total market return among students who take courses in (j,m) :

$$K_{jm} \equiv \frac{\int_a \psi_j(\cdot) I\left(m \in M_a\right) k_{jm}\left(a\right) f_a(a) da}{\mu^1_{jm}},$$
$$\text{where } k_{jm}\left(a\right) = \int_z e^{\alpha_{3m} I(female)} \int_\epsilon y^1_j(x,\epsilon|\cdot) \int_\eta y^2_{m|j}\left(x,\epsilon,\eta\right) a_m^{\gamma_{1m}} \eta_m dF_\eta\left(\eta\right) dF_\epsilon(\epsilon) dF_{z|a}\left(z\right).$$

The higher a_m is relative to A_{jm}, the bigger one's marginal contribution to the total market return of one's peers.

The third line of (1) relates to effort cost. μ^2_{jm} is the size of program (j,m) in the second period. $A^{'}_{jm}$ is the average ability among students enrolled in (j,m) in the second period. Formally,

$$\mu^2_{jm} = \int_a y^1_j(a|\cdot)\psi_j(\cdot) y^2_{m|j}\left(a|\cdot\right) f_a(a) da,$$
$$A'_{jm} = \frac{\int_a \psi_j(\cdot) y^1_j(a|\cdot) y^2_{m|j}\left(a|\cdot\right) a_m f_a(a) da}{\mu^2_{jm}},$$

where $y^2_{m|j}\left(a|\cdot\right) = \frac{\int_z \int_\epsilon y^1_j(x,\epsilon|\cdot) \int_\eta y^2_{m|j}(x,\epsilon,\eta) dF_\eta(\eta) dF_\epsilon(\epsilon) dF_{z|a}(z)}{y^1_j(a|\cdot)}$ is the probability that student a will take a full slot in (j,m) in the second period conditional on enrollment in j.

A3.2 Counterfactual Model: Equilibrium

A3.2.1 The characteristics of each program is

$$\Omega_{jm} = \left\{\mu^1_{jm}, \mu^2_{jm}, K_{jm}, A_{jm}, A^{'}_{jm}\right\},$$

where the components of Ω_{jm} are as defined in A3.1.

A3.2.2 Equilibrium-Searching Algorithm:

To integrate over unobserved tastes, we use the same random taste vectors ϵ for each student as we did for the estimation. In the new model, student continuation problem does not have analytical solution, so we also draw K sets of random efficiency vectors η, fixed throughout.

Finding a local equilibrium can be viewed as a classical fixed-point problem of a correspondence $\Gamma : O \rightrightarrows O$, where $O = \left([0,1] \times [0,1] \times \left[0, \overline{A}\right] \times \left[0, \overline{A}\right] \times \left[0, \overline{K}\right]\right)^{JM}$,

$o = \left\{\mu^1_{jm}, \mu^2_{jm}, K_{jm}, A_{jm}, A'_{jm}\right\}_{jm} \in O$. Such a mapping exists, based on this mapping, we design the following algorithm to compute equilibria numerically.
0) Guess $o = \left\{\mu^1_{jm}, \mu^2_{jm}, K_{jm}, A_{jm}, A'_{jm}\right\}_{jm}$.
1) Given o, for every (x, ϵ) and every pure strategy $q(a)$, solve the student problem backwards, where the continuation decision involves numerical integration over efficiency shocks η. Obtain $y^2_{m|j}(x, \epsilon|q(a))$ and $y^1_j(x, \epsilon|q(a))$.
2) Integrate over (ϵ, z) to obtain $y^2_{m|j}(a|q(a))$, $y^1_j(a|q(a))$ and $\widetilde{U}(a|q(a), A)$.
3) Compute the net benefit of each $q(a)$, and pick the best $q(a)$ and the associated student strategies, yielding o^{new}.
4) If $\|o^{new} - o\| < \upsilon$, where υ is a small number, stop. Otherwise, set $o = o^{new}$ and go to step 1).

A3.3.3 Global Optimality:[53]

After finding the local equilibrium, we verify ex post that the planner's decisions satisfy global optimality. Since it is infeasible to check all possible deviations, we use the following algorithm to check global optimality. Given an old local equilibrium $o = \left\{\mu^1_{jm}, \mu^2_{jm}, K_{jm}, A_{jm}, A'_{jm}\right\}_{jm}$, we perturb o by changing its components for a random program (j, m) and search for a new equilibrium using the algorithm described in A3.2.2. If the algorithm converges to a new equilibrium with higher welfare, global optimality is violated. After a substantial random perturbations with different magnitudes, we have not found a new equilibrium. This suggests that our local equilibrium is a true equilibrium.

Additional Tables

1. Data

[53] Epple, Romano and Sieg (2006) use a similar method to verify global optimality ex post.

Table A1.1 Score Weights (ω) and Length of Study

	Weights[a] (%)						Length
	Language	Math	GPA	Social Sc	Science	max(Social Sc., Science)[b]	(years)
Medicine	22	30	25	0	23	0	7
Law	33	19	27	21	0	0	5
Engineering	18	40	27	0	15	0	6
Business	21	36	31	0	0	12	5
Health	23	29	28	0	20	0	5
Science	19	36	30	0	15	0	5
Arts&Social	31	23	28	18	0	0	5
Education	30	25	30	0	0	15	5

[a]Weights used to form the index in admissions decisions, weights on the six components add to 100%.
[b]Business and education majors allow student to use either social science or science scores to form their indices, students use the higher score if they took both tests.

Table A1.2 College-Major-Specific Cutoff Index

	Medicine	Law	Engineering	Business	Health	Science	Arts&Social	Education
Tier 1	716	679	597	609	640	597	578	602
Tier 2	663	546	449	494	520	442	459	468
Tier 3	643	475	444	450	469	438	447	460

The lowest admissible major-specific index across all programs within each tier-major category.

Table A1.3 College-Major-Specific Annual Tuition (1000 Peso)

	Medicine	Law	Engineering	Business	Health	Science	Arts&Social	Education
Tier 1	4546	3606	4000	3811	3085	3297	3086	3012
Tier 2	4066	2845	2869	2869	2547	2121	2292	1728
Tier 3	4229	2703	2366	2366	2391	2323	2032	1763

The average tuition and fee across all programs within each tier-major category.

2. Parameter Estimates

We fix the annual discount rate at 0.9.[54] Table A2.1 shows how the value of one's outside option varies with one's characteristics. The constant term of the outside value for a student from a low income family is only 70% of that for one from a high income family. Math and language scores increases one's outside value by about the

[54]Annual discount rates used in other Chilean studies range from 0.8 to 0.96.

same magnitude.[55] The last row of Table A2.1 shows that relative to the outside value a high school graduate faces, the outside value faced by a college dropout is about 3% higher.

Table A2.1 Outside Value

Constant (θ_{01})	8919.8	(98.1)
Low Income (θ_{02})	0.70	(0.01)
Language (θ_1)	131.2	(9.8)
Math (θ_2)	133.3	(17.0)
Dropout (ρ)	1.03	(0.01)

Table A2.2 displays major-independent parameters that govern one's consumption value. The left panel shows parameters for the consumption value one attaches to a college program and the right panel for the consumption value of majors. Relative to Tier 3 colleges, Tier 2 colleges are more attractive to an average student, while top-tier colleges are less attractive. One possible explanation is that the two top tier colleges are both located in the city of Santiago, where the living expenses are much higher than the rest of Chile. As shown by the standard deviations of student tastes, there exists substantial unobserved heterogeneity in student educational preferences.

Table A2.2 Consumption Value (Major-Independent Parameters)

College Value			Major Value		
Tier 1 ($\overline{v}_1$)	-3311.1	(248.8)	a_m^2 (β_{2m})	0.011	(0.0003)
Tier 2 ($\overline{v}_2$)	1126.7	(141.1)			
σ_{col}	3197.1	(386.0)	σ_{major}	2344.3	(86.1)
σ_{prog}	1618.5	(242.8)			

$\overline{v}_3$ is normalized to 0.

Table A2.3 shows major-independent parameters that govern the cost of college.

Table A2.3 College Cost (Major-Independent Parameters)

I(Low Inc)*Tuition (c_1)	3.68	(0.19)
I(Low Inc)*Tuition^2 (c_2)	-0.001	(0.00004)
$(a_m - A_{jm})^2$ (c_4)	6.74	(0.61)

[55] We cannot reject the hypothesis that the outside value depends only on math and language scores, therefore, we restrict θ_l for other test scores to be zero.

Table A2.4 shows other parameters entering the log wage function. The last two rows shows the dispersions of transitory wage shocks and permanent efficiency shocks realized after enrollment, each of which explains about 50% of log wage variance.

Table A2.4 Other Parameters in Log Wage Functions

	Constant (α_{0m})		Experience (α_{1m})		Experience^2 (α_{2m})		female (α_{3m})	
Medicine	7.78	(0.02)	0.09	(0.003)	-0.002	(0.0001)	-0.37	(0.09)
Law	-2.63	(0.03)	0.11	(0.004)	-0.007	(0.0002)	-0.08	(0.03)
Engineering	-5.38	(0.01)	0.10	(0.001)	-0.002	(0.0003)	-0.19	(0.01)
Business	-10.67	(0.02)	0.11	(0.001)	-0.003	(0.0001)	-0.19	(0.02)
Health	2.30	(0.02)	0.02	(0.002)	-0.0003	(0.0001)	-0.19	(0.02)
Science	-10.94	(0.01)	0.05	(0.001)	-0.0007	(0.0001)	-0.29	(0.03)
Arts&Social	-3.80	(0.01)	0.02	(0.001)	-0.0005	(0.0001)	-0.11	(0.02)
Education	-2.23	(0.02)	0.07	(0.002)	-0.001	(0.0001)	-0.30	(0.04)
Transitory Shock (σ_ζ)	0.683	(0.04)						
Efficiency Shock (σ_η)	0.602	(0.02)						

3. Model Fits

Table A3.1 Enrollment (Low Income) (%)

	Data	Model
Tier 1	2.3	2.6
Tier 2	12.6	12.4
Tier 3	9.7	9.7

Enrollment among students with low family income.

Table A3.2 Enrollee Distribution Across Majors (Low Income) (%)

	Data	Model
Medicine	1.7	3.0
Law	3.4	3.2
Engineering	35.1	34.8
Business	10.0	9.9
Health	12.2	10.4
Science	8.2	9.6
Arts&Social	11.0	12.6
Education	18.5	16.4

Distribution across majors among enrollees with low family income.

Table A3.3 Mean Test Scores Among Outsiders

	Data	Model
Math	533	531
Language	532	532
HS GPA	542	541
Max(Science, Soc Science)	531	530

Mean test scores among students who chose the outside option.

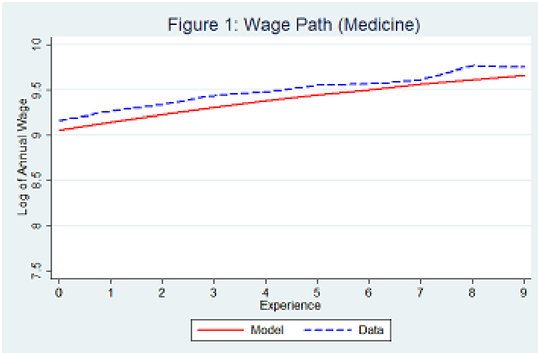

Figure 1: Wage Path (Medicine)

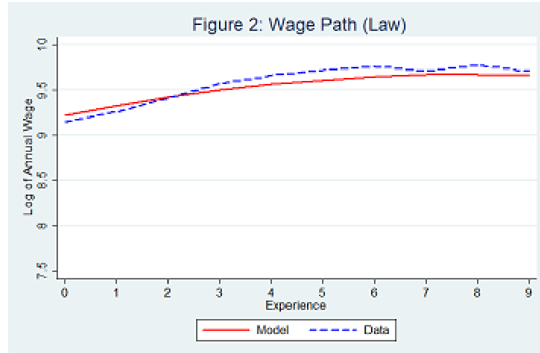

Figure 2: Wage Path (Law)

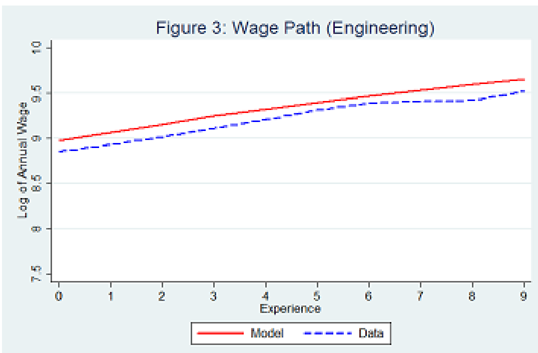

Figure 3: Wage Path (Engineering)

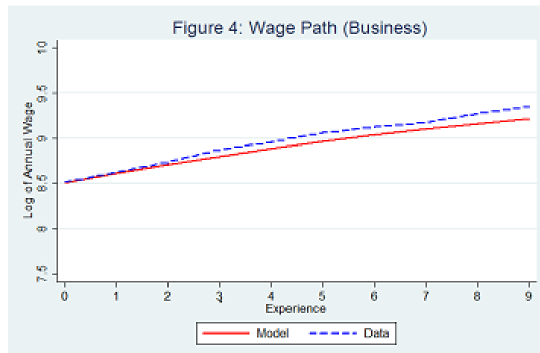

Figure 4: Wage Path (Business)

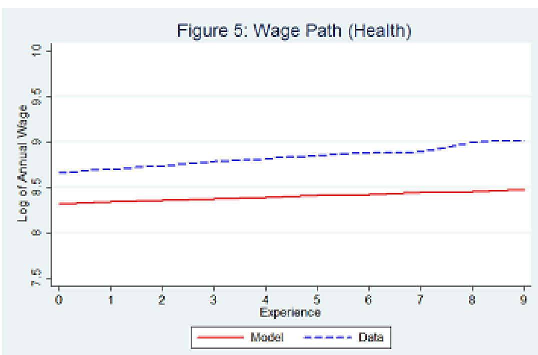

Figure 5: Wage Path (Health)

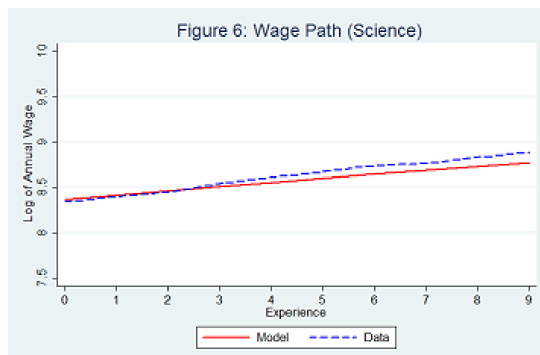

Figure 6: Wage Path (Science)

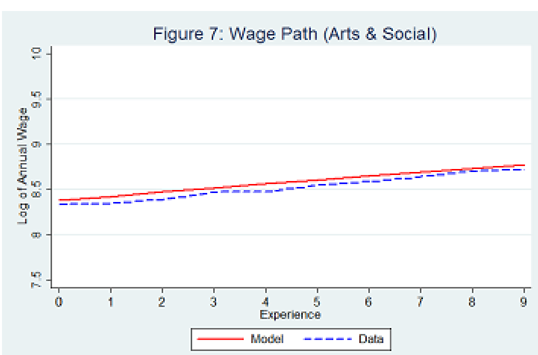

Figure 7: Wage Path (Arts & Social)

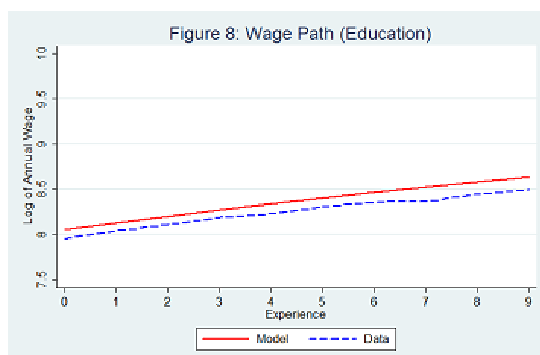

Figure 8: Wage Path (Education)