Competition and the Cannibalization of College Quality

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May 14, 2018

Abstract

The university system in Chile has dramatically expanded in the last 30 years as a result of deregulation and changes in government loan policies. This has resulted in intensified competition between institutions and rapid increase in enrollment. Deregulation can lead to substantial benefits, mostly by lowering tuitions and improving access to education. However, there are potentially negative effects on the quality of college education as quality of programs is partially determined by the quality of students. In this paper, we first document the growth in the supply and the change in quality of programs following the loan and grant reforms in 2006. Then we estimate a structural model of student sorting to measure the degree of substitution between programs. We use the elasticity of substitution between programs, implied by student preference estimates, to quantify the degree of cannibalization in program quality across colleges. In particular, we measure the degree to which marginal improvements in the attractiveness of each program reduces, through business stealing and peer effects, the perceived quality of programs at low, intermediate and high levels of selectivity. We find significant substitution between middle tier programs, whereas programs in the top quartile tend to substitute from other programs in that same category. Our results suggest that the entry and expansion of programs of intermediate quality levels likely led to sizable cannibalization and excess entry, as those programs are perceived as close-substitutes to other programs with lower and similar quality levels.

1 Introduction

Over the last 30 years, the Chilean government deregulated the higher education market. As a result, universities massively expanded their network of campuses, which intensified the competition between institutions and rapidly increased enrollment. In 1990, most Chilean universities were public, and concentrated their activity around one region. Over the following 20 years, the number of private campuses whose enrollees were eligible for government financial aid nearly doubled, while the fraction of college students enrolled in private universities increased from 25% to 54.3%. At the same time, traditional universities diversified their operation, and now cover on average two regions through multiple campuses. From 2001-2010 the average number of campuses increased from 1.57 to 2.56 for public universities, and from 1.25 to 3.9 for private universities. On average, 84% of students enrolled at a public university are affiliated with its main campus, compared to nearly 100% in the early 1990s. This trend is even more pronounced among private universities: 58% of their students are affiliated with the main campus (compared to 97% in 1992), and an average private university is present in four regions (compared to one in 1992).

Much of this growth from private colleges was caused by a reform on the student loan program in 2006, which gave access to governmental loans to students enrolled in accredited private universities and lifted an important barrier to entry into the higher-education market. As a result of reforms of this kind, the Chilean higher education system became highly decentralized and competitive, like the one in the U.S.

This decentralization can lead to substantial benefits for students, mostly by lowering tuitions and improving access to education. However, there is a potentially negative effect on the quality of college education that we point out in this project. By independently choosing the optimal size and characteristics of their own campuses, universities ignore the potentially adverse impact of their actions on competing universities. This stems from the fact that the quality of universities is in part determined by the quality of students who choose to enroll (see Epple et al. (2006) for a sorting model in which that is the case). For instance, the enrollment at new campuses is generated in part by attracting students who would otherwise be admitted at existing campuses serving the same population. This competition can in turn force incumbent colleges to reduce their admission thresholds and lower their quality levels.

This "cannibalization" of school quality caused by competition is analogous to the business stealing effect of price competition in oligopoly markets with product differentiation (see Bresnahan (1987) and Berry et al. (1995) for examples in the car market). The main difference in the education context is that this externality does not only reduces tuitions, but also affects the quality of colleges. This is in contrast with standard differentiated product framework, where quality is fixed in the short-run and determined by firms' investments only.

From a welfare point of view, it is well documented that free-entry into differentiated product industries can lead to excess entry relative to what a social planner, accounting for consumer and producer surplus, would choose. Excessive entry arises when new products are (imperfect) substitutes from existing products, and firms must incur important fixed-cost to operate (see Berry and Waldfogel (1999)). In the education context, this inefficiency is expected to be important if new programs are close-substitutes for existing options, and if the peer-effect externality associated with business-stealing is large. Moreover, the degree of substitutability between programs depends on the level of spatial and quality differentiation between colleges. The first originates from the fact that students tend to favor campuses located near their home locations, and the second is due the fact that universities differ substantially in the quality of their facilities and programs.

In this paper we take a first step towards quantifying the welfare consequences of free-entry into the Chilean higher education market. We have two specific objectives. First, we document the growth in the supply and the change in quality of programs following the loan and grant reforms in 2006, accounting for program capacity constraints and peer effects. Second, we measure the degree of substitution between programs using a structural model of student sorting. In particular, we recover the distribution of student preferences for different characteristics of college programs, including quality, costs, distance and student-college match. We further quantify the importance of peer quality in determining a college's overall quality.

We use the elasticity of substitution between programs, implied by student preference estimates, to quantify the degree of cannibalization in program quality across colleges. In particular, we measure the degree to which marginal improvements in the attractiveness of each program reduces, through business stealing and peer effects, the perceived quality of programs at low, intermediate and high levels of selectivity. By measuring the number and type of students that each program attracts when it improves its quality, we can provide a measure of "segmentation" of programs across different quality levels, low, intermediate and elite. This knowledge is valuable for the assessment of college market expansion: free-entry is less likely to cause significant efficiency loss if high quality programs are sufficiently segmented as new programs tend to enter with low selectivity level.

The results can be summarized as follows. Using growth decomposition techniques developed in the productivity literature (e.g. Foster et al. (2001)), we identify the various sources for the growth in college enrollment and change in quality. We show that a significant part of the growth in enrollment is explained by elite institutions expanding existing programs and private universities increasing the differentiation of programs offered, with significant entry and exit of programs. The exit and entry of new programs is mostly present in private universities.

Our second set of results relate to the degree of differentiation between programs. Our estimated model shows that students have considerable preference for geographically close programs, and that females have strong preferences for social sciences programs. We find significant substitution between middle tier programs, whereas programs in the top quartile tend to substitute from other programs in that same category. Since much of the growth in enrollment originated from low and intermediate quality programs, we therefore conclude that elite programs have been fairly immune to quality cannibalization. The same is not true however for programs with intermediate quality levels. Our results suggest that the entry and expansion of programs of intermediate quality levels likely led to sizable cannibalization and excess entry, as those programs are perceived as close-substitutes to other programs with lower and similar quality levels.

Our paper builds on the literature on college education. For example, Manski and Wise (1983) use a non-structural approach to study tuition setting, applications, admissions and enrollment in isolation. Arcidiacono (2005) estimates a structural individual choice model to address the effects of college admissions and financial aid rules on future earnings. In modeling student choices, we incorporate rich heterogeneity in student preferences for different college programs, which has been shown to be important in previous studies. For example, Manski and Wise (1983) find that applicants do not necessarily prefer the highest quality school. To systematically model factors underlying these heterogeneity, we share features in studies that have explicitly modeled the cost of distance (e.g., Kapor (2015)), the preference for staying in one's home state (e.g., Fu (2014), Kennan (2015)) and the preference for having peers with ability levels similar to one's own (e.g., Arcidiacono (2005), Bordon and Fu (2015)).

While the majority of the literature on college education focuses on individual choices, our paper is closer to papers that study the college market in an equilibrium setting. For example, Epple et al. (2006) model equilibrium admissions, financial aid and enrollment, where a college's quality depends on the average test score of its students. Fu (2014) models equilibrium tuition, applications, admissions and enrollment in a college market that is subject to information friction and application costs.

Finally, our paper is part of a growing literature in education using econometrics techniques developed in the I.O. literature to measure the perceived quality of schools, accounting for endogenous characteristics such as tuitions and peer effects (e.g. Bayer et al. (2007), Hastings et al. (2009), Neilson (2013), Ferreyra and Kosenok (2015), and Gazmuri (2015)).

The remainder of the paper is organized as follows. Section 2.2 provides a description of the trends in the Chilean college market. Section 2.3 describes the data used in this project. Section 2.4 provides a descriptive analysis of the growth in enrollment. Section 2.5 describes the sorting model with selective programs. Section 2.6 describes the estimation and identification strategies. Section 2.7 shows the estimation results, and Section 2.8 offers a summary and conclusions.

2 The Chilean College Market

Institutions Higher education in Chile went through a radical reform in the early 1980s. This reform modified the education system structure and its funding mechanisms, resulting in an expanded, more diverse and highly privatized system.

The number of higher education institutions and enrollment in higher education programs increased significantly following this reform. In 1980, before this reform, approximately one out of four people graduating from high school enrolled in some type of higher education, by 2012 this proportion has increased to more than one out of two.

Currently, the Chilean higher education system is organized in three types of institutions: universities, professional learning institutes, and technical training centers. By 2012, there were 60 universities, 45 professional institutes, and 73 technical training centers. Among the group of universities, 25 form a council of universities that were created before the 1980 reform (also called CRUCH), and 35 are private universities that were created between 1980 and 2006.

Most of our analysis is focused on the group of *selective universities* that participate in the centralized admission system. This group includes the 25 traditional CRUCH universities plus eight (8) out of the other 35 private universities. We focus on explaining the enrollment of students in one of the 33 universities regulated by the same admission system. The remaining higher-education options correspond to the outside option of students (i.e. private non-selective universities, professional institutes, technical training centers, and work).

The colleges that do not participate in the admission system are typically of lower quality and use open admissions policies. One of the requirements of the institutions that participate in the centralized admission system is that they cannot accept students with less than 500 points. Table 2 reports the average characteristics of students choosing the outside option. We can see that the average test score is significantly lower than the average test scores if students choosing one of the selective college. In 2012, around 65% of the programs in the outside option do not report a minimum PSU score in the data. For the ones that do report the minimum test score of enrolled students, the average is 450.

Depending on the year the students attending these 33 universities are between 27% and 38% of the total students that took the admission test. The share of students going to other universities beside these 33, are about 25% of the total (between 22% and 28%). These 33 institutions have between 53% and 64% of the students attending some university.

In the empirical analysis, we also group universities in three categories, based on their degree of selectivity and age. Group 1 correspond to *Elite institutions*, that usually appear in international rankings: Pontificia Universidad Catolica de Chile, Universidad de Chile, Universidad de Concepcion, Universidad Tecnica Federico Santa Maria, Pontificia Universidad Catolica de Valparaiso, and Universidad de Santiago. Group 2 is an intermediate group corresponding to other traditional universities (or CRUCH) that are not included in the first group (i.e. *Other CRUCH*). Finally, group 3 universities include the eight private non-CRUCH universities that participate in the centralized admission process, and that entered after the 1980 reform. We label those institutions *Private Non-CRUCH.*

Admission system Schools participating in the centralized admission system report an admission score calculated from a nationwide admission test (PSU) and high school grades.

The PSU test consists of several parts. Everyone has to take math and language tests, but social sciences and science tests are optional. Each program has different requirements in terms of what parts of the test the applicant must take to be able to apply. Each of these 33 universities that participates of the centralized admission process, publicly announces the number of seats available and the weights to calculate the admission score for each program. Students apply to up to eight programs ordered by preference, after knowing their scores. Admission to each program is managed in a centralized way, where each program is filled by the students with the best scores that applied to that program until the number of seats are filled.

Financial aid In the 1990s, higher education policies carried out two major changes in terms of financial aid programs for postsecondary education. A means-tested loan scheme (FSCU) to cover tuition fees in one of the traditional universities with a fixed interest rate of two percent and income contingent repayment. Second, a scholarship scheme for students coming from low income families was set up to cover partial or total payment of tuition fees. Financial aid programs have recently expanded. In 2006, a new law established a need-based student loan system for all accredited institutions (including private institutions that were not part of traditional universities), complementing existing privately funded scholarships. The new loan scheme provides qualified students with government backed student loans to cover their tuition fees.

Also, in 2010 there was an expansion in the generosity of the government grants to include eligible students up to the third income quintile. As a result, almost half of students enrolled in higher education receive some type of financial aid, with the majority of this aid being in the form of loans.

3 Data

The empirical analysis rely on two data sets. Micro data on student college applications together with student sociodemographic characteristics for 2012, and aggregate data for university enrollment from 2005 to 2014, for every university that participates in the centralized admission process.

The 2012 data set on student applications contains the universe of students that applied to some program in one of the 33 universities (25 traditional plus 8 private non-traditional) that participate in the centralized admission process, even if the student was not admitted. The aggregate data set for the institutions, includes total enrollment and admission thresholds for every major.

There are more than 2000 majors offered by these 33 universities. We grouped these majors in 21 categories, so each category is a collection of programs with comparable academic requirements (weights for each of the admission tests). There are 54 campuses that are part of these 33 universities. Overall, students have access to 428 choices (campus/category combination).

The total universe of students considered is every student that took the admission test each year, about 180,000 student per year.

Table 1 shows the growth in the number of majors and campuses by institution. There is a large growth in the number of majors offered during this period, mostly in private non-traditional universities. On average these institutions have approximately 3 campuses in different regions.

Table 2 shows descriptive statistics for student characteristics in each type of institution for 2012. Students attending elite institutions are on average comparable to student going to private universities in family income and mother's education, but with significantly better scores and more likely to have a government scholarship.

4 Growth decomposition

During our sample period, there is a significant increase in the share of students enrolling in higher education and the number of programs offered by universities.

Figure 1 shows the share of students enrolling in one of the 33 selective university from 2005 to 2014, where there is a sharp increase, especially after 2011. Furthermore, Figure 2 shows that this growth is mostly coming from private universities.

To understand whether the growth in the number of programs is similar across institutions, we contrast the growth experienced by the three type of universities: (1) Elite, (2) Other CRUCH, and (3) Private Non-CRUCH.

Panel A in Table 3 shows the trends in number of programs for each group. It is apparent that growth in the number of programs is mostly coming from new private entrants, with an average annual growth in number of programs of 5.9% in group 3.

Second, we look at enrollment for these same groups (Table 3, columns 4 to 6). Enrollment has increased by about 50% in elite institutions (group 1), and considering that they did not increase significantly the number of programs offered, this means that existing programs are becoming larger on average in these institutions. Enrollment in the intermediate universities (group 2), was decreasing significantly from 2005- 2009 and started increasing again in 2010 probably due to the increase in generosity of government grants. The largest growth in enrollment comes from private non-CRUCH universities (group 3) that almost doubled their enrollment in 10 years, with an average annual growth of 6.32%.

Next, we divide the sample in two periods: before and after the second important financial-aid reform. Specifically, Period 1 from 2005-2009 and period 2 from 2010-2015, and we decompose total growth in the growth of incumbent programs, the entry of new programs, and exit of programs.

Table 4 shows this decomposition of growth in total enrollment for each of the two periods. Total growth corresponds to 10.4% in the first period and 17.9% in the second one. In total, incumbent programs decreased in enrollment and most of the growth is explained by entry of programs. This decomposition differs across institutions. For elite institutions, more than 50% of the growth arose from the expansion of incumbent programs (56% in period 1 and 54% in period 2), whereas for the rest, most of the growth arose from entry, especially in the second period.

We decompose the growth in average program size following Foster et al. (2001) into a growth in incumbent programs and the relative size of entering and exiting programs.

Program growth is calculated as the average growth in the number of students in a major for each of the three groups of institutions. The average growth is decomposed into the average growth of incumbent programs, growth explained by entry of programs larger than the average, and exit of programs smaller than the average. That is, the growth in average program size is given by:

$$\begin{aligned}\Delta\bar{q} =& \sum_{j\in C}\frac{q_{jt}-q_{jt-1}}{N_{t-1}} + \left(\frac{1}{N_t}-\frac{1}{N_{t-1}}\right)(q_{jt}-\bar{q}_{t-1}) + \left(\frac{1}{N_t}-\frac{1}{N_{t-1}}\right)(q_{j,t}-q_{j,t-1}) \\ &+ \sum_{j\in E}\frac{q_{jt}-\bar{q}_{t-1}}{N_t} - \sum_{j\in X}\frac{q_{j,t-1}-\bar{q}_{t-1}}{N_{t-1}}\end{aligned} \tag{1}$$

This equation decompose the growth in average program size. q_{jt} is the size of program j in year t, and N_t is the number of programs in year t. $\bar{q}_t$ is the average size in year t. The first 3 terms in the equation are the growth in program size of incumbents, the fourth term is the growth in average size due to entry of larger than average programs, and the fifth term is the growth due to exit of smaller than average programs.

Table 5 shows this decomposition where the three terms for the incumbents are summed together. Incumbent programs in elite and private universities seem to have grown during both periods. On the other hand, for all institutions, new programs are smaller than the average and the programs existing are also smaller than the average.

Together with Table 4, Table 5 suggests that private non-traditional universities opened a significant number of small programs and at the same time expanded the size of incumbent programs. The overall enrollment decreased in non-elite traditional universities, with incumbent programs becoming smaller, but nevertheless opening a large number of small programs.

Table 6 shows changes in the minimum and average test score in programs in each of the three groups, where the minimum test scores can be viewed as the admissions thresholds. Thresholds (Table 6, columns 1-3) were growing in the first half of the sample period and then started decreasing for programs in the first two groups (all traditional universities). Given the large increase in the size of programs in institutions in group 1, it is expected that admission thresholds decrease in this group. Institutions in group 2 also increased enrollment during the second half or the period. The trend of thresholds in private non-CRUCH universities was divided into two parts, with significantly higher thresholds from 2010 onwards. This is most likely explained by the fact that when joining the centralized admission process, they are not allowed to admit students with less than 500 points. This is even more impressive considering that they have almost doubled their enrollment over this period. Table 6 (columns 4-6) show average test scores for each group. From 2005-2010, average PSU increased for all programs, with the largest increase for private non-traditional universities. During 2011-2015, average PSU decreased for all types of institutions.

Next, we decompose the improvement in average PSU from incumbent, exiting, and entry programs. The change in the average test scores can be decomposed into five terms:

$$
\begin{aligned}
\Delta T_t =& \sum_{j \in C} s_{jt}(t_{jt} - t_{jt-1}) + (t_{jt} - T_{t-1})(s_{jt} - s_{j,t-1}) + (t_{jt} - t_{j,t-1})(s_{j,t} - s_{j,t-1}) \\
&+ \sum_{j \in E} t_{jt} - T_{t-1} s_{jt} - \sum_{j \in X} (t_{j,t-1} - T_{t-1}) s_{t-1}
\end{aligned}
\tag{2}
$$

here T_t is the weighted average PSU in period t, t_{jt} is the average PSU for program j in year t, s_{jt} is the share of program j in year t .

Table 7 shows the total improvement on average PSU score over the whole period, and each of the five components of the decomposition. For institutions in Groups 1 and 2, most of the improvement came from the reallocation term (second term in equation (2)), meaning that programs better than average were increasing their shares. For programs in group 3 (private universities), most of the improvement is explained by increasing average test scores of incumbent programs (first term in equation (2)). The entry term (fourth term in equation (2)) is negative for the first two groups, meaning that the average PSU in entry programs was lower than the overall average in the previous period, contributing negatively to the improvement in average PSU. The exit term (fifth term in equation (2)) is positive for all three groups meaning that exiting programs had lower PSU scores than the average.

5 Sorting Patterns

The higher education system in Chile is characterized by strong assortative matching in terms of test scores. 80% of the students in the top quartile of the admission test go to programs in the top quartile ranked by admission cutoffs (see top panel in Table 8). This is not surprising and since cutoffs are determined by the students enrolled in each program, some level of sorting is expected.

More interestingly, the level of sorting decreases as family income decreases. The bottom three panels in Table 8 divides students by family income. High-achieving students from high income families are significantly more likely to go to top programs, compared to similar quality students from middle and low income groups. About 25% of students in the top quartile of scores coming from middle and low income families, choose to go to lower tier programs (versus just 10% of top students from high income families).

Furthermore, if we divide students by geographic regions, students from Santiago show significantly higher levels of sorting compared to students coming from other regions. Students in regions outside of Santiago seem more likely to sacrifice quality than students in Santiago. This could be related to preferences for staying in their home region but could also be affected by the lower variety of programs available outside of the capital.

In order to understand what determines student sorting, we need to estimate students preferences to be able to predict how students are substituting between programs when quality changes. In the next section, we estimate a model of students choice of a program considering the characteristics of the admission process.

6 A Sorting Model of College Enrollment

We develop a short-run model describing the allocation of students across campuses, and the endogenous determination of admission thresholds. The model has three components: (i) students preferences, (ii) the admission process, and (iii) market clearing conditions. We describe each in turn.

6.1 Admission Process

Let $\mathcal{J}$ denotes the set of programs available to students, where we define each program as a (university, major category) pair. As discussed in section 3, the total number of options varies over time, and was equal to 428 in 2012. In addition, an outside option is also available to all students. This option includes non-selective universities, professional schools, and the option of not attending a higher-education institution.

A student's choice of a college program is constrained by the admissions. The Chilean admission process is very transparent, and we use the admission thresholds and weights used by each campus to determine the set of available options for each student. Under the Chilean system, a program j is in a student's choice set if only if $t_{ij} \geq \bar{t}_j$, the institution-category-specific admissions threshold. The student test-sores and program thresholds are defined as follows.

A student has multi-dimensional knowledge in subjects such as math, language, social sciences and science, summarized by $s = [s_1, s_2, ..., s_S]$, the vector of test scores. Various elements of such knowledge are combined with the publicly known category-specific weights to form category-university-specific application test score,

$$t_{ij} = \sum_{l=1}^{S} \omega_{jl} s_{il},$$

where $\omega_j = [\omega_{j1}, ..., \omega_{jS}]$ is the vector of weights for option j, and $\sum_{l=1}^{S} \omega_{jl} = 1$. Given the different academic tracks they follow in high school, some students will consider only majors that emphasize knowledge in certain subjects, while some are open to all majors. Such general interests are reflected in their abilities and choices of which tests to take.[1] We assign a test result of ∞ to tests that students do not take.

The admission threshold of major j is determined by the score of the marginal admitted student:

$$\bar{t}_j = \sum_{l=1}^{S} \omega_{jl} \tilde{s}_{il}, \tag{3}$$

where $l = 1, \ldots, S$ indexes the required tests (i.e. language, math, high-school GPA, etc), $\tilde{s}_{il}$ is the result of the marginal student in campus/major j to test l.

Importantly, schools and programs can use different weighting scheme to determine the admission threshold, including weights of zero on tests that are not required for certain

[1] Without increasing the test fee, taking both the science and the social science exams will only enlarge a student's opportunity set. A student who does not take the science exam will not be considered by programs that require science scores, but her admissions to programs that do not require science scores will not be affected even if she scores poorly in science. However, some students only take either the science or the social science exam, we view this as indication of their general academic interests. We treat students' preferences and abilities as pre-determined.

majors. For example, an engineer uses math knowledge more and language knowledge less than a journalist. Programs differ both in terms of which tests are required (i.e. $\omega_{jl} \geq 0$), and in the importance that they assign to the required tests. Every student submitting an application to the centralized system must takes at least the math and language tests, and every program assigns positive weights to these two tests: $\omega_{j,\text{math}} > 0$ and $\omega_{j,\text{language}} > 0$. Information about each program weights is easily available to students, and we assume that students know perfectly their admission score associated with each program. In addition, we treat these weights as exogenously given parameters that may reflect how different programs combine test-score-measured knowledge to produce human capital. We make two important assumptions to simplify the model. First we assume that students have rational expectations over the admission thresholds for each option. Therefore, the admission thresholds determine the choice-set of each student, and there is no uncertainty about the probability of getting admitted to a particular program. Let $\mathcal{J}_i$ denotes the set of available options to student i:

$$\mathcal{J}_i = \{j \in \mathcal{J} | t_{ij} \geq \bar{t}_j\}.$$

Second, to reduce the number of options available, we aggregate the 400 individual programs into 21 major categories based on the type of entry exam required and profession. An option j is defined as a university/category pair. The admission threshold for each option is defined as the **smallest** admission threshold of the programs included in that category. We then assign students to the most selective program in each available option, defined as the program with largest **available** admission threshold.

For instance health category at Universidad de Chile contains 7 programs with thresholds ranging from 635 to 686. Under our admission assumption a student with a test score of 640 would get admitted in this major category, but enroll in the lowest-qualify program; as measured by the admission score of 635. In contrast, a student with a test score of 700, would enroll into the best program, associated with the score 686.

Using this procedure, we can construct the admission threshold of the best major available to student i in program j, denoted by $\tau_{ij}^{\max}$. By construction $\tau_{ij}^{\max} = \bar{t}_j$ if i is the marginal student admitted to program j. We interpret this variable as a student-specific measure of program quality. In the model, we will use this variable to differentiate between programs within the same major category.

6.2 Student Preferences

When deciding which college to attend, we assume that students trade-off the convenience of each option, with the quality and cost of the education provided.

6.2.1 Student and Program Characteristics

Students are characterized by different gender (g) family income (y), home location (l), abilities (a) and academic interests.

Program characteristics are given by admission thresholds $\bar{t}_j$, the vector of weights on the different test scores ω_j, tuition p_j , municipality location, and average peer ability $\bar{A}_j$. Recall that admissions are subject to program-specific standards, and the program weights reflect those differences.

We define the *ability* of students and peers using the average of math and language tests:

$$\begin{aligned} a_i &= (s_{i,\text{math}} + s_{i,\text{language}})/2 \\ \bar{A}_j &= \frac{\sum_i 1(i \to j) a_i}{\sum_i 1(i \to j)}, \end{aligned}$$

where $1(i \to j)$ is an indicator function equal to one if student i enrolled in program j.

Denote student characteristics that are observable to the researcher, i.e., the vector of test scores, family income and gender by the vector $x \equiv [t, y, g]$, and its distribution conditional on location l by $F_x(\cdot|l)$.

6.2.2 Utility

We model the indirect utility of enrolling into a program j using a characteristic model. In particular the value of a program is a linear function of its perceived quality, distance to parents' municipality d_{ij}, out-of-pocket expenses $g(p_j, y_i, t_i)$, and an idiosyncratic utility shock:

$$u_{ij} = \begin{cases} \text{Quality}_{ij} - \alpha_i g(p_j, y_i, t_i) - \lambda d_{ij} + \varepsilon_{ij} & \text{If } j > 0 \\ \varepsilon_{i0} & \text{else.} \end{cases} \tag{4}$$

The degree of spatial differentiation is measured by the distance vector d_{ij}, and the i.i.d. shock ε_{ij}. Distance is measured using two variables: the Euclidian distance between the student and the campus municipalities, and an indicator for whether the campus j is located in a different administrative region to the student. The residual utility term is distributed according to a type-1 extreme value distribution. Next, we describe the construction of the two remaining terms.

Note that we omit the time subscript in equation (4) to simplify the notation. The choice-set and program characteristics all vary over time. In contrast, the distribution of student attributes is assumed to be fixed over time.

College quality The quality term in equation (4) measures the perceived value of option j relative to the value of not attending one of the selective colleges. To account for differences in the outside option across students, we allow the intercept to vary across students based on gender, family education, income and family size. This student-specific intercept is denoted by μ_{i0}.

The perceived quality of a program is further decomposed into an idiosyncratic component μ_{ij} and average component δ_j:

$$\text{Quality}_{ij} = \mu_{i0} + \delta_j + \mu_{ij}.$$

The idiosyncratic component account for differences across students in the perceived value of observed characteristics. We use the following functional form to measure the idiosyncratic valuation of student i:

$$\mu_{ij} = \mu^0 x_i + \mu^1 x_i \mathbb{1}(private) + \mu^2 w_i \cdot \omega_j^{\text{math+science}}$$

where,

$$x_i = \{\text{Test score}_i, \text{Family education}_i, \text{Income}_i/\text{ Family Size}_i\}$$
$$w_i = \{\text{Gender}_i, t_i^{\text{math}}\}$$

The parameter μ^1 allows students from different socioeconomic backgrounds to have a different preference for private universities. The rational behind this functional form is twofold. First, private schools are more likely to offer private grants to students. We account for some of the private grants, but we do not fully observe them in detail. Therefore, we need to allow for good students to have different preferences for private versus public institutions. Second, this functional form allow the measured out-of-pocket tuition to differentially affect the enrollment decision of students with different family income. Finally, μ^3 allows female students and students with stronger math score, to have different preferences for programs requiring relatively stronger math test (measured by the weight assigned on math and science).

The average quality of each college/category option is measured by the fixed-effect parameter δ_{jt}, and is function of the average peer quality in the program, and an unobserved (to the econometrician) measure ξ_{jt}:

$$\delta_j = \gamma \bar{A}_j + \xi_j, \tag{5}$$

Importantly, γ is a peer-effect parameter determining the extent to which students value the average ability of their peers when enrolling into a program. We assume that students have rational expectation over the admission process, and correctly anticipated the average ability of students enrolled in each program.[2]

Tuition sensitivity parameter In equation (4), we assume the cost of attending college is strictly function of the out-of-pocket expense, denoted by $g(p_j, y_i, t_i)$. The shape of this function reflects the tuition charged by program j (p_j), as well as the structure of the governmental loan and grant program. Eligibility to loans is function of parental income (y_i), while eligibility to grants is also function of students test score results (t_i) and college char-

[2]Peer quality may affect market returns via different channels, such as human capital production, statistical discrimination, social networks, etc. Our data does not allow us to distinguish among various channels. For ease of illustration, we describe peer quality in the framework of human capital production.

acteristics. As we mentioned above, the Chilean government expanded the grant program in 2010 to include eligible students in to the third income quintile.

The price sensitivity parameter α_{ij} is allowed to vary by student's family income and ability:

$$\alpha_{ij} = \alpha_0 + \alpha_1 y_i + \alpha_2 a_i$$

6.2.3 Program choice

Given the different academic tracks they follow in high school, some students will consider only majors that emphasize knowledge in certain subjects, while some are open to all majors. Such general interests are reflected in their abilities and choices of which tests to take.[3] We assign a test result of $-\infty$ to tests that students do not take. Given the admissions thresholds and the vector of peer quality, a student solves the following discrete-choice problem

$$U(x, \varepsilon | \bar{t}_j, A) = \max \left\{ \max_{j \in \mathcal{J}_i} \{u_j(x, \varepsilon, A_j)\}, \varepsilon_0 \right\}.$$

The probability of choosing option j is given by the following multinomial logit model:

$$\sigma_j(\boldsymbol{\delta}, \bar{\boldsymbol{t}} | x_i) = \frac{\exp\left(\mu_{i,0} + \delta_j + \mu_{ij} + \alpha_{ij} g_{ij} + \lambda d_{ij}\right)}{1 + \sum_{k \in \mathcal{J}(t_i)} \exp\left(\mu_{i,0} + \delta_k + \mu_{ik} + \alpha_{ij} g_{ik} + \lambda d_{ik}\right)} \tag{6}$$

To calculate the market-share and enrollment of each campus/major, we integrate over the empirical distribution of student attributes using Monte-Carlo integration methods:

$$\begin{aligned} \sigma_j(\boldsymbol{\delta}, \bar{\boldsymbol{t}}) &= \sum_{l=1,\dots,L} \int \sigma_j(\boldsymbol{\delta} | x_i) dF(t_i, y_i | l) \phi(l) \\ &\approx \frac{1}{S} \sum_{i=1}^{S} \int \sigma_j(\boldsymbol{\delta} | x_i) \end{aligned} \tag{7}$$

where $F(t_i, y_i | l)$ is the conditional distribution of student test-score and family income in municipality l, and $\phi(l)$ is the density of applicants in location l. In practice, we sample

[3] Without increasing the test fee, taking both the science and the social science exams will only enlarge a student's opportunity set. A student who does not take the science exam will not be considered by programs that require science scores, but her admissions to programs that do not require science scores will not be affected even if she scores poorly in science. However, some students only take either the science or the social science exam, we view this as indication of their general academic interests. We treat students' preferences and abilities as pre-determined.

10,000 students from the population of students who took the admission test in 2012. The population of applicants is defined as the set of students taking the required qualifying exams to enter college, and includes about 40% of students who chose either to work or attend a technical college.

Similarly, the average test-score of students enrolled in program j is implicitly defined as:

$$\bar{t}_j = \sum_{l=1,\ldots,L} \int t_i \frac{\sigma_j(\boldsymbol{\delta}, \bar{\boldsymbol{t}}|x_i)}{\sigma_j(\boldsymbol{\delta}, \bar{\boldsymbol{t}})} dF(t_i, y_i|l)\phi(l) \tag{8}$$

where t_i is the average test-score of student i, and δ_j is function of $\bar{t}_j$ through the effect of peers on school quality in equation 5.

6.3 Market Clearing Conditions

We assume that the capacity and tuition of each program are fixed in the short-run, and that schools adjust the admission thresholds in order to fill every available seat. If κ_{jm} denotes the capacity of option j (expressed as a fraction of the applicant population), the equilibrium allocation is implicitly defined by the following condition:

$$\xi_j = \sigma_j^{-1}(\boldsymbol{\kappa}, \bar{\boldsymbol{t}}) - \gamma \bar{A}_j, \forall j \tag{9}$$

where $\bar{t}_j$ defined in equation 8, and σ_j^{-1} is the inverse-demand function. From Berry et al. (1995), there exists a unique inverse demand that rationalizes the observed capacities, conditional on the admission thresholds. However, due to the presence of the peer effects, existence and uniqueness of a sorting equilibrium is not guaranteed. This will have consequences on our ability to solve for equilibrium allocations under alternative policy environments, but, as we discuss below, will not prevent us to obtain consistent estimates of college quality.

7 Estimation and Identification Strategy

Our objective is to construct a measure of college quality that accounts for students endogenous sorting and college admission policies. To do so, we follow a revealed-preference approach, in which we estimate students' preferences, conditional on a perceived quality index that is consistent both with schools admission policies and students equilibrium sorting decisions. In other words, we estimate a vector of perceived quality δ_j such that the market satisfies the sorting equilibrium described above.

We impose the equilibrium conditions on the data in two stages. First, we estimate by maximum likelihood the preference of students for convenience and price sensitivity parameters, without decomposing the perceived quality of colleges into a pre-determined and peer effect components. Then in a second stage, we estimate the quality of colleges by imposing additional assumptions on the distribution of the unobserved quality of programs. We describe both stages in the next two sections.

7.1 Student Preferences

The parameter vector can be divided in two parts: $\theta_1 = \{\mu, \alpha, \lambda\}$ determines the choice-probability of each student, and $\theta_2 = \{\bar{\xi}, \gamma\}$ determine the average quality of programs. In the first stage of our estimation strategy, we estimate θ_1 only, by treating the net quality index δ_j as a fixed-effect. This leads to a constrained maximum-likelihood estimator similar to the one used in Goolsbee and Petrin (2004) and Bayer et al. (2007).

Our sample corresponds to the population of high-school students taking the admission tests in 2012. Let c_i denotes the choice of campus/program made by student i. The maximum likelihood estimator can be written as follows:

$$\max_{\theta_1} \sum_i \log \sigma_{c_i}(\boldsymbol{\delta}, \boldsymbol{t} | t_i, y_i, l_i) \tag{10}$$

$$\text{s.t.} \delta_j = \sigma_j^{-1}(\boldsymbol{\kappa}, \boldsymbol{t}) \tag{11}$$

7.2 Quality Decomposition

The presence of the quality of peers enrolled in each program creates a standard simultaneity problem, since we assume that students sort across schools after observing the quality of each option, and while holding rational expectations about the quality of programs. This simultaneity problem is akin to the endogenous of prices in differentiated product settings.

To get around this simultaneity problem, we will combine standard panel-data techniques with an instrumental variable approach. In particular, assuming that preference parameters (θ_1) remained stable over time, we can recover an estimate of the combined quality of programs for every options available between 2001 and 2012:

$$\hat{\delta}_{js} = \sigma_{js}^{-1}(\boldsymbol{\kappa}_s, \boldsymbol{t}_s) \tag{12}$$

where $\boldsymbol{\kappa}_s, \boldsymbol{t}_s$ are the observed vector of enrollment capacity and admission thresholds for year $s \in \{2001, \dots, 2012\}$. Notice also that the inverse-demand system has a year subscript to capture the fact that the set and characteristics program available have been changing over time, as well as the generosity of the government loan and grant program. While we observe all of these changes, we do not observe micro-data on students enrollment choices for years prior to 2012. This prevents us from estimating time-varying preference parameters.

Treating the quality index as data, we obtain the following panel-data linear regression model:

$$\hat{\delta}_{jt} = \gamma \bar{A}_{jt} + \bar{\xi}_j + \bar{\xi}_t + \Delta\xi_{jt}, \tag{13}$$

where $\bar{\xi}_j$ is a major/campus fixed-effect, $\bar{\xi}_t$ is a year fixed-effect, and $\Delta\xi_{jt}$ is the time-varying component of the residual quality.

In order to identify the effect of peer characteristics on college quality, we construct an instrument for $\bar{A}_{jt}$. Since the characteristics of students enrolled naturally depends on the characteristics of alternative college options, we will construct instruments based on the time-varying characteristics of programs available at campuses that are close-substitutes to option j. Measures of "close-substitutes" can be obtained using spatial variation.

The main threat to the validity of this class of instruments is that the physical characteristics of competing colleges can be correlated with the unobserved college quality. This can be the case for instance if colleges invest in technologies that we fail to observe and are able to react to investments made by other colleges. Additionally, ξ_{jt} can proxy for time-varying omitted attributes that are spatially correlated.

The second threat can be addressed in part by incorporating time-varying region fixed-effects. The first threat on the other hand cannot be easily tested, and we must rely on a timing assumption. In particular, we assume that competing colleges react to ξ_{js} with a lag, due for instance to the presence of sunk adjustment costs. This an often invoked assumption in the production function literature (e.g. Ackerberg et al. (2006)).

8 Estimation Results

8.1 Preference parameters

Table 9 shows estimates for the taste parameters. The negative coefficient on the absolute difference between own ability and average peer ability suggests that students like being around with peers of similar ability as their own. The coefficient on the interaction between science weight ($\omega_j^{\text{math+science}}$) and gender, helps to fit the fact that females sort into social science majors that is not explained by their math test score. Additionally, students with high math score, tend to sort into programs with high science weight. The negative coefficients in distance and different region show a taste for geographic proximity: students are willing to pay between 0.8 and 1.2 million pesos (approximately 2000 US dollars) to attend a program in their region. The intercept on the price coefficient is significantly higher for public than private institutions, that could be explained by the fact that private institutions offer scholarships that are not included in the data.

These estimates can be used to calculate substitution patterns between different types of programs when there is an increase in average quality (δ_j) of a given program. Table 10 shows these patterns. Programs are arranged in four groups by average peer ability, and diversion ratios are calculated between each program and rival programs, including the outside option. In particular, it shows, when a program in each row increases its quality and hence attracts more students, where do these newly attracted students come from. For example, when a program in the lower quartile of peer ability increases its average quality, 55% of the new students come from the outside option and 32% from programs in the lowest two quartiles. The percentage of students coming from the outside option decreases as the average peer quality goes up. When a program in the top quartile improves its quality, 61% of the new students come from other programs in that same group, and only 20% from the outside option.

8.2 Quality decomposition

Table 11 shows the first stage using three sets of instruments for average peer ability and university-program fixed effects. For instruments we use measures of changes in competition in the region, either share of traditional programs, or share of highly ranked programs in the same category, or number of new programs. As expected, most of these variables are negatively correlated with average peer ability since the entry of new competitors or an increase in the share of competitors in the region should decrease the peer ability of a program in that region. The validity of these instruments is discussed in the previous section.

Table 12 shows the decomposition of college quality. The different IV specifications tend to increase the coefficient on average peer ability compared to the OLS estimation. This suggests that the error term is negatively correlated with the average peer quality. This could be explained by low quality programs in private institutions offering scholarships that we do not observe in the data to students that have high test scores.

Additionally, in all specifications, there seem to be an upward trend starting around 2011. This could be associated with an increase in investments that may influence perceptions of quality.

We can decompose the overall change in δ during the whole period according to equation 2. Table 13 shows the five terms of the decomposition of the overall change in quality and the change in the residual after accounting for peers:

$$\hat{\xi}_{jt} = \hat{\delta}_{jt} - \hat{\gamma}\bar{A}_{jt}$$

For both δ_{jt} and $\hat{\xi}_{jt}$ the biggest change is observed for categories in elite universities, and explained mostly by improvement of incumbent programs. The covariance term is positive in all cases, meaning that either programs that improved quality are growing or programs that decreased quality are shrinking. Entry is negative meaning that new programs have quality lower than the average, and same for exiting programs (exit term is positive).

We can also calculate the effect of an increase in average quality (δ_{jm}) of a given program in the average peer ability of rival programs. The weighted average change of rival peer ability is calculated according to the following expression

$$\frac{\partial \bar{A}_j}{\partial \delta_k} = \frac{\partial \left(\frac{\sum_i P_{ij} a_i}{\sum_i P_{ij}} \right)}{\partial \delta_k} = \frac{\left(\sum_i P_{ij} \frac{\partial \sum_i a_i P_{ij}}{\partial \delta_k} - \sum_i a_i P_{ij} \frac{\partial \sum_i P_{ij}}{\partial \delta_k} \right)}{(\sum_i P_{ij})^2} \tag{14}$$

Since the scale of δ_k varies across programs, we report the effect of a 1% increase in δ_k on the average peer ability of students enrolled in programs j: $\frac{\partial \bar{A}_j}{\partial \delta_k} \cdot |\delta_k|$.

This statistic measures the effect of a 1% increase in the quality of school k, on the average peer ability in school j. As with the business-stealing effect, this is a partial equilibrium response since we are not allowing the admission threshold to adjust. We already know from Table 10 that the effect of an increase in the quality of j on the enrollment of k is negative (i.e. business stealing). It tells us how many students each program "steals" from others by improving its quality.

Table 14 illustrate the *composition effect* associated with the same quality improvement. When the estimate is negative, it tells us that students who move from program j to k are better than the average enrolled in j, and therefore the average ability at program j goes down (i.e. k "steals" the good students). If the estimate is positive, k steals the "bad" students, and the average ability of those that remain in j is larger. The effect can be negative or positive, because it depends on the ability of the marginal students enrolled in each program.

The first column reports the composition effect on the own average ability. The estimate is positive across all three groups of colleges, meaning that increasing the quality level of programs increases the average peer ability of students. This suggest that improving the average quality tends to attracts students with higher ability. Interestingly, the effect is stronger for less selective programs in groups 2 and 3.

The results show that the average composition effect on rival programs is negative for elite schools, and positive for the other two groups of schools. In other words, when elite schools increase their quality by 1%, they lower the average ability score of the other elite schools by 1.736. The decrease for the other two school types is lower, because those schools are not as close substitutes and because those schools tend to attract lower ability students. This is a form of "quality" cannibalization.

In contrast, we find an "adverse selection" effect when non-elite schools improve their quality. When type 2 and 3 schools improve their quality, the ability of all rival programs increases. In other words, these schools tend to steal students that have lower ability score than the average at the program that they "come from", which tends to help rival programs.

This is consistent with the idea that lower ranked schools tend to attract students that are on the margin more sensitive to non-academic characteristics of each program, such as distance, tuition, etc. In contrast, students enrolled in elite programs, put more weight on peer quality and other measure of program quality. In addition, since the composition effect on the own average peer ability is positive on average (column 1), we can conclude that type 2 and 3 three schools draw a large share of their students from the group of "high" ability students who tend to choose the outside option. This is consistent with the business stealing results we documented in Table 10.[4]

9 Conclusion

This paper studies the effects of increasing competition and differentiation on accessibility to higher education and quality of university programs. Between 2006 and 2011, the Chilean higher education system experienced major reforms on the access and generosity of government grants and loans. These changes led to a significant expansion and diversification of university programs, with institutions trying to meet the demand of a society with increased means to finance higher education.

We find that most of the growth in enrollment came from elite institutions that expanded the size of existing programs and private universities that almost doubled their enrollment and at the same time doubled the number of programs offered. Also, we find significant entry and exit of programs in private universities compared to public institutions.

We estimate a sorting model where we find that students have strong preference for geographically close programs, and that females have preferences for social sciences careers, even after controlling for math test scores. Using these estimates, we calculate substitution

[4]Notice that these results do not imply than the equilibrium effect of an improvement in quality would be positive on average for all schools in groups 2 and 3. This is because Table 14 and 10 do not account for the adjustment in admission thresholds. When school k increases its quality, it lowers the number of students interested in all rival programs. This forces those programs to lower their admission thresholds in order to fill their seats, and therefore lower the quality of the marginal students. The equilibrium net effect depends on the relative strength of the business stealing and composition effects. Investigating the equilibrium effect is our next step.

patterns to see where students come from when a program increase its quality. We find significant substitution between middle tier programs, whereas top tier universities tend to substitute mainly from other programs in that same range. For middle tier programs, about 40% of the increase in share associated with an increase in quality come from students who would otherwise choose the outside option, and about 60% from students in other programs.

We decompose the overall quality of a college program into program quality and peer quality, using the entry of competitors as an instrument for peer quality. There seems to be an improvement in average program quality of programs over this period, especially after 2011.

Further work is necessary to be able to use these results to simulate a counter-factual distribution of education quality under an alternative configuration in which the Chilean government would have limit the expansion of private colleges. This will allow us to shed light on the trade-off between the quality and accessibility of higher education.

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Table 1: Increase in Number of Programs

Year	Nb. Majors	Campus /Inst.	Majors per Institution Private	Majors per Institution Traditional
2005	1634	2.5	59.3	66.9
2006	1678	2.6	61.9	67.9
2007	1643	2.5	60.7	66.6
2008	1737	3.5	65.3	74.2
2009	1796	3.5	71.7	73.2
2010	1850	3.4	82.4	75.5
2011	1946	4.0	95.2	78.1
2012	1910	2.5	101.4	71.8
2013	2051	2.6	105.8	76.8
2014	2099	2.7	108.7	77.1
2015	2148	2.7	109.1	79.3

Note: This table presents the number of undergraduate programs and number of campuses in traditional and private universities. Source: DEMRE

Table 2: Average Student Characteristics across Types of Institutions

	Elite	Other CRUCH	Private Non-CRUCH	Outside Option
Avg. Family Income	8.99	5.42	9.98	4.58
Avg. Mother's Educ.	13.47	12.05	13.49	10.99
Avg. PSU Score	646.53	573.78	596.36	467.43
Prop. of Students w/ Scholarship	0.45	0.45	0.22	0.16
Prop. of Students w/ Loan	0.25	0.39	0.36	0.23
Prop. Of Students from Private School	0.31	0.10	0.38	0.12

Note: This table present average characteristics of students attending each type of higher education institution. Family income is annual income measured in millions of pesos. Mother's education is measured in years of education. The outside option includes any high-school graduate that applied to some program in these universities but either was not admitted or chose not to enroll in a program to which he was admitted.

Table 3: Growth by Type of Institution

	Total Number of Programs			Total Enrollment		
	Elite	Other CRUCH	Private Non-CRUCH	Elite	Other CRUCH	Private Non-CRUCH
2005	435	918	281	21,152	38,289	15,888
2006	447	942	296	22,618	36,218	19,133
2007	426	932	292	24,221	33,522	19,024
2008	427	1002	312	23,931	33,485	21,576
2009	447	1015	343	24,134	34,144	22,903
2010	452	1025	373	25,983	35,716	24,117
2011	453	1074	419	26,584	35,708	25,125
2012	462	1003	445	28,364	35,538	27,028
2013	489	1091	471	28,345	39,093	28,488
2014	479	1129	491	28,282	39,800	29,851
2015	488	1163	497	30,174	42,209	28,829
	1.20%	2.48%	5.94%	3.67%	1.10%	6.32%

Note: Columns 1-3 show the number of programs in each year by type of institution. Institutions are classified in three groups: Group 1 corresponds to six elite institutions, private or public that commonly appear in international rankings. Group 2 corresponds to the rest of CRUCH universities that are not in group 1. Type 3 corresponds to private non-CRUCH universities that participate in the centralized admission process. The last row shows the average yearly growth. Columns 4-6 present the total enrollment by type of institution and the last row shows the average yearly growth.

Table 4: Growth Decomposition

	Total	Type 1	Type 2	Type 3
Period 1				
Incumbent	-1,132 (-14.4%)	2,559 (56.5%)	-7,376 (-167.0%)	3,685 (47.6%)
Entry	14,860 (189.3%)	2,257 (49.8%)	7,834 (177.3%)	4,769 (61.6%)
Exit	-5,878 (-74.8%)	-286 (-6.3%)	-4,876 (-110.4%)	-716 (-9.3%)
Total Growth	7,850 (10.4%)	4,530 (21.4%)	-4,418 (-11.5%)	7,738 (48.7%)
Period 2				
Incumbent	-36 (-0.23%)	2,282 (54.5%)	-2,077 (-32.0%)	-241 (-5.1%)
Entry	18,069 (117.36%)	2,210 (52.7%)	10,415 (160.4%)	5,444 (115.5%)
Exit	-2,637 (-17.13%)	-301(-7.2%)	-1,845 (-28.4%)	-491(-10.4%)
Total Growth	15,396 (17.9%)	4,191 (16.1%)	6,493 (18.2%)	4,712 (19.5%)

Note: This table shows a decomposition of enrollment growth between incumbent institutions, new entrants, and institutions that exited during that period for each type of institution. First period corresponds to 2005-2009, and the second period corresponds to 2010-2015. Institutions are classified in four groups: Type 1 corresponds to six elite institutions, private or public that commonly appear in international rankings. Type 2 corresponds to other CRUCH universities that are not in group 1. Type 3 to private non-CRUCH universities that participate in the centralized admission process.

Table 5: Decomposition of Growth in Program Size

	Type 1	Type 2	Type 3
Period 1			
Incumbents	8.12	-6.29	18.80
Entry	-0.53	-6.98	-2.73
Exit	0.26	1.92	1.61
Overall Change Period 1	7.84	-11.35	17.68
Period 2			
Incumbents	6.15	-2.32	12.04
Entry	-2.11	-2.47	-14.91
Exit	0.93	0.40	2.11
Overall Change Period 2	4.97	-4.40	-0.76
Average Program Size		46.27 students	

Note: This table shows a decomposition of program size growth between incumbent institutions, new entrants, and institutions that exited during that period for each type of institution. Each entry corresponds to the growth measured as the average number of students. For the entrants the size of the new programs is compared to the average size in the previous period and for exit programs, the size is compared to the average size that period. First period corresponds to 2005-2009, and the second period corresponds to 2010-2015. Institutions are classified in four groups: Type 1 corresponds to six elite institutions, private or public that commonly appear in international rankings. Type 2 corresponds to CRUCH public universities that are not in group 1. Type 3 corresponds to CRUCH private universities that are not in group 1. Type 4 corresponds to private non-CRUCH universities that participate in the centralized admission process.

Table 6: Changes in Test Scores

	Minimum PSU			Average PSU		
Year	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
2005	562.8	495.5	332.7	634.0	568.4	572.4
2006	567.6	497.9	339.9	634.7	561.9	573.5
2007	578.9	502.7	328	644.4	570.2	583.7
2008	575.2	500.9	328.6	643.6	566.6	585.8
2009	587.3	504.9	342.5	648.7	572.3	595.0
2010	582.2	505.9	563.6	649.5	573.5	611.1
2011	577.1	508.3	565.7	648.0	576.0	612.9
2012	572	496.9	518.6	643.4	569.2	595.8
2013	558.5	496.8	519	639.1	571.0	592.4
2014	548.4	491.5	514.7	637.4	567.5	589.0
2015	548.2	492.5	516.3	639.1	568.0	589.4

Note: Columns 1-3 show the average math and language score of the last student admitted in each type of institution each year. Institutions are classified in three groups: Type 1 corresponds to six elite institutions, private or public that commonly appear in international rankings. Type 2 corresponds to CRUCH universities that are not in group 1. Type 3 corresponds to private non-CRUCH universities that participate in the centralized admission process.

Table 7: Decomposition of Average PSU Growth

Type of Inst.	Incumb. Improv.	Reallocat.	Covariance	Entry	Exit	Total Growth	Percentage
Overall	1.816	4.034	0.095	-3.573	1.709	4.082	0.7%
1	-1.959	6.427	-1.158	-1.100	0.499	2.709	0.4%
2	-2.877	2.995	-0.693	-2.482	1.655	-1.403	-0.2%
3	15.298	-0.607	-1.329	0.911	0.778	15.050	2.6%

Note: This table presents the decomposition of the change in average PSU over the whole period for each type of institution. Type 1 corresponds to six elite institutions, private or public that commonly appear in international rankings. Type 2 corresponds to CRUCH universities that are not in group 1. Type 3 corresponds to private non-CRUCH universities that participate in the centralized admission process. The decomposition follows Foster et al. (2001).

Table 8: Student Sorting

Program Quartile	Student Quartile 1	2	3	4
	Overall			
1	81,5%	26,6%	3,3%	0,3%
2	15,0%	49,4%	33,0%	7,3%
3	2,9%	18,7%	42,3%	33,4%
4	0,6%	5,3%	21,4%	59,0%
	High Income Group			
1	88,2%	32,4%	4%	0,5%
2	9,7%	48,4%	38,5%	9,9%
3	1,8%	13,7%	36,7%	34,1%
4	0,4%	5,5%	20,7%	55,5%
	Middle Income Group			
1	77,7%	25,8%	3,4%	0,4%
2	18,3%	50,1%	33,54%	8,0%
3	3,2%	18,9%	42%	34%
4	0,8%	5,3%	21%	57,5%
	Low Income Group			
1	75,4%	24,5%	3,2%	0,3%
2	19,7%	49,5%	31,9%	7,0%
3	4,2%	20,7%	43,3%	33,3%
4	0,7%	5,3%	21,6%	59,5%

Note: This table presents the share of students in each score quartile that are enrolled in each program quartile determined by the admission cutoffs. The top table shows the sorting overall, and the bottom three tables show the sorting by income group. High income students correspond to students in the top 20% of the income distribution, middle income students correspond to the following 20%, and low income students correspond to the bottom 60%. It is not possible to divide students in equally sized groups because of the way income is defined in the data.

Table 9: Preference Parameters

		Coefficients	Std. Error
Intercept	Test Score	0.896*	0.091
	Income/Family size	−0.155*	0.025
	Education of parents	−0.049*	0.015
Sci+Math weight × Math score		0.521*	0.042
Sci+Math weight × Gender		−0.715*	0.143
Distance		−0.537	0.365
	Income/Family size	−0.043*	0.018
	Education of parents	0.013	0.014
Different region		−5.946*	0.695
	Test score	0.474*	0.029
	Income/Family size	0.158*	0.026
	Education of parents	0.069	0.121
Price		−1.068*	0.221
	Test score	0.211*	0.007
	Income/Family size	0.016	0.012
	Education of parents	0.004	0.039
LLF/N		−1.528	

Note: This table presents the estimated parameters and standard errors for the sorting model. Gender is an indicator variable equal to one for females and zero for males. Education of parents is measured in years of education, income in millions of pesos per year. Admission score is measured in thousands of points (same as ability, which is just the average of math and language test scores). Distance is measured in hundreds of miles, and different region is an indicator variable equal to one if the program is located in a region different to the student's home region. Prices are measured as out of pocket tuition after considering government grants and loans, in millions of pesos per year.

Table 10: Business Substitution when Quality Increases

Own Peer Ability	Outside Option	Rival Peer Ability $(\bar{A}_{\min}, \bar{A}_{.25})$	$(\bar{A}_{.25}, \bar{A}_{.5})$	$(\bar{A}_{.5}, \bar{A}_{.75})$	$(\bar{A}_{.75}, \bar{A}_{1})$
$(\bar{A}_{\min}, \bar{A}_{.25})$	0.55	0.14	0.18	0.10	0.03
$(\bar{A}_{.25}, \bar{A}_{.5})$	0.48	0.11	0.20	0.16	0.06
$(\bar{A}_{.5}, \bar{A}_{.75})$	0.36	0.06	0.16	0.24	0.18
$(\bar{A}_{.75}, \bar{A}_{1})$	0.20	0.01	0.05	0.13	0.61

Note: Programs are classified in four groups according to the average student ability. Each cell is the average fraction of new students going to *row* schools that come from the *column* schools, when a *row* school marginally increases its quality using the results from the estimation.

Table 11: College Quality Decomposition - First Stage

	Average Peer Ability		
Share of programs in region/category	-4.998***	-3.290**	-4.404***
	(1.181)	(1.113)	(1.166)
New programs in category	1.876***		-2.273**
	(0.537)		(0.852)
Share of top ten programs in region		-5.463**	-5.450**
		(1.678)	(1.671)
Share of old institutions in the region		-17.914*	
		(7.691)	
Ranking $\times$ New Programs in Region			0.285***
			(0.046)
F-test	11.60	8.70	17.72

Note: This table presents the first stage estimation using different sets of instruments for average peer ability in the program.

Table 12: College Quality Decomposition

VARIABLES	(1) OLS	(2) IV 1	(3) IV 2	(4) IV 3
Avg. Peer	0.009***	0.035**	0.021	0.020*
	(0.001)	(0.013)	(0.012)	(0.009)
2006	-0.183***	-0.101	-0.147**	-0.146**
	(0.044)	(0.058)	(0.056)	(0.048)
2007	-0.031	-0.166	-0.096	-0.089
	(0.044)	(0.088)	(0.077)	(0.064)
2008	-0.181***	-0.311***	-0.235**	-0.233***
	(0.044)	(0.084)	(0.075)	(0.063)
2009	0.196***	-0.043	0.087	0.093
	(0.044)	(0.136)	(0.123)	(0.098)
2010	0.336***	-0.023	0.177	0.190
	(0.044)	(0.195)	(0.174)	(0.135)
2011	0.467***	0.156	0.331*	0.343**
	(0.044)	(0.176)	(0.152)	(0.123)
2012	0.300***	0.166	0.240**	0.249**
	(0.043)	(0.105)	(0.091)	(0.080)
2013	0.547***	0.421***	0.490***	0.479***
	(0.043)	(0.105)	(0.095)	(0.086)
2014	0.816***	0.745***	0.782***	0.769***
	(0.043)	(0.096)	(0.087)	(0.083)
Program FE		X	X	X
Weak IV		9.623	5.668	10.045
J-test (p-value)		0.668	0.106	0.065

Note: This table presents the quality decomposition by OLS and using the three different IV specifications shown in Table 11

Table 13: Decomposition of Quality Change

Delta Decomposition							
	Incumb. Improv.	Reallocat.	Covariance	Entry	Exit	Total Growth	Percentage
overall	0.189	-0.230	0.169	-0.141	0.065	0.052	4.28%
1	2.060	0.049	0.204	0.009	-0.051	2.271	51.65%
2	0.259	-0.268	0.420	-0.025	0.157	0.543	11.28%
3	-0.273	-0.459	0.333	-0.180	0.015	-0.565	-19.29%
Residual Decomposition							
	Incumb. Improv.	Reallocat.	Covariance	Entry	Exit	Total Growth	Percentage
overall	0.165	-1.049	0.163	-0.675	0.237	-1.158	-17.97%
1	1.976	0.056	0.205	0.007	-0.049	2.194	9.68%
2	0.178	-0.253	0.425	-0.041	0.154	0.463	2.00%
3	-0.360	-0.446	0.341	-0.198	0.015	-0.648	-3.05%

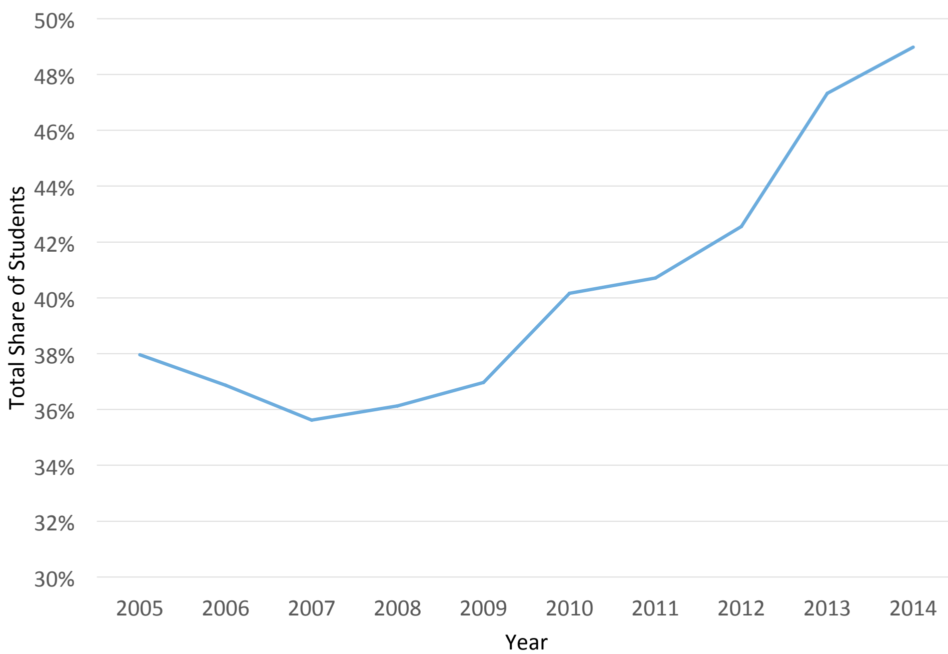
Note: This table presents the decomposition of the change in quality over the whole period for δ and the residual $r_{jt} = \hat{\delta}_{jt} - \rho \bar{t}_{jt}$ for each type of institution. Type 1 corresponds to six elite institutions, private or public that commonly appear in international rankings. Type 2 corresponds to CRUCH universities that are not in group 1. Type 3 corresponds to private non-CRUCH universities that participate in the centralized admission process.

Table 14: Effect on Average Peer Ability when Quality Increases

Own Quality	Own Peer Ability	Rival Peer Ability Type 1	Rival Peer Ability Type 2	Rival Peer Ability Type 3
Type 1	1.984	-0.413	-0.152	-1.736
Type 2	2.579	4.321	2.841	3.268
Type 3	2.215	1.386	0.423	3.483

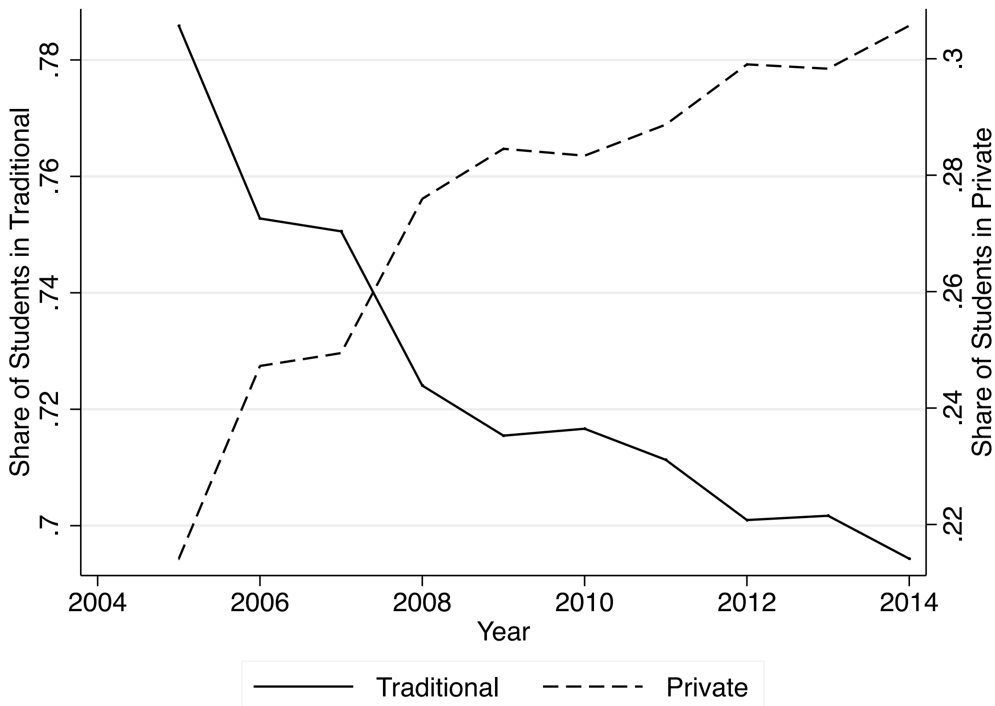
Note: Programs are classified in three groups according to the type of institution. Each cell is the change in average peer ability in a *column* schools when a *row* school marginally increases its quality using the results from the estimation. It corresponds to $\frac{\partial \bar{A}_j}{\partial \delta_k} \cdot |\delta_k|$.

Figure 1: Growth in College Enrollment in Chile 2005-2014



Note: This figure shows the total share of high-school graduates attending some type of higher education program each year from 2005 to 2014.

Figure 2: Growth in Enrollment by Type of Institution



Note: This figure shows the share of students in higher education attending a traditional institution and the share attending a private institution, each year from 2005 to 2014.