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The effects of financial aid and returns information in selective and less selective schools: Experimental evidence from Chile[☆]

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ABSTRACT

Schools that provide higher education often belong to either a merit-based selective system or an open-access less selective system. We present the results of a field experiment that provided Grade 12 students in Chile with tailored information about financial aid and average earnings and employment probabilities for schools and careers in both types of schools. We find no effect on the extensive margins of enrollment in the selective or in the less selective sector. Treated students change their intensive margin decisions: they choose careers and schools with lower expected wages, lower employment probabilities, but with higher quality relative to their baseline preferences.

1. Introduction

In the standard framework modeling human capital investments, decision-makers have complete and accurate information about the costs and expected benefits of each schooling level. This enables them to make optimal schooling choices. Increasingly, new results from the development and economics of education literatures are challenging this assumption. For example, Jensen (2010) shows that providing children with basic information on average earnings increased education of treated students by 0.2 years. Other randomized controlled trials have shown that providing information to students or parents about the benefits and/or costs of investing in higher levels of education improves school attendance, grades, application choices and enrollment outcomes at different levels of schooling.[1]

Whether providing information affects human capital investments and what choices this information can affect may depend on context. In the case of higher education, students in many parts of the world encounter a two-tier structure comprised of a selective and a less

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[1] These experiments have taken different forms. For example, some provide application information to interested students (e.g. Carrell and Sacerdote, 2013; Hoxby and Turner, 2013), others provide information on economic returns (Nguyen, 2008; Jensen, 2010; Hastings et al., 2015) or on financial aid (Dinkelman and Martínez A, 2014; Dunn and Oreopoulos, 2013), while yet others supplement information interventions with targeted assistance in applying for financial aid or college (Bettinger et al., 2012; Brown et al., forthcoming), or with cash incentives or fee waivers for completing applications (Carrell and Sacerdote, 2013; Hoxby and Turner, 2013). Studies have been targeted at all levels of schooling (primary, secondary and tertiary), at different types of students (high achievers and more average students), and in high, middle-income and low-income countries such as the US, Chile, Madagascar, and Dominican Republic. Banerjee et al. (2013) and Lavecchia et al. (2014) present comprehensive reviews of much of this recent experimental evidence from studies in developed and developing country settings.

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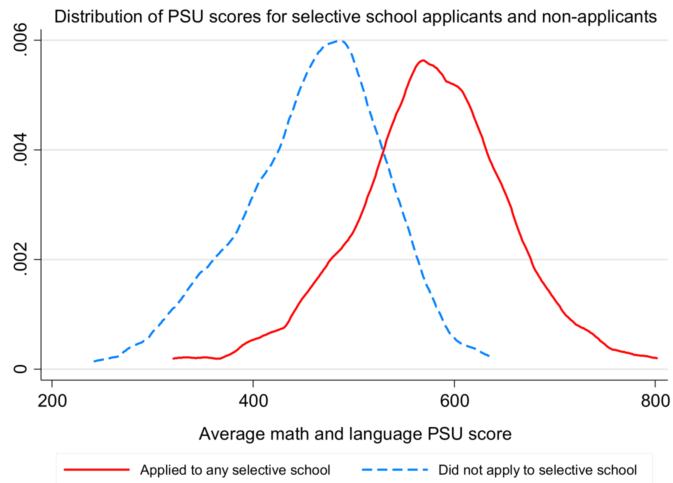

Fig. 1. PSU scores in the control group Note: PSU is the college entry examination.

selective system. The selective system includes a small number of schools of high and relatively homogeneous quality. Access to this system is merit-based, typically determined by performance on national tests, and usually managed through a centralized applications process.[2] In contrast, the less selective system is often populated by a larger number of new, for-profit schools of heterogeneous quality. Eligibility requirements are lower in these schools, and the application process decentralized. The role of information in helping students to make better choices in this environment is arguably more important for students considering the less selective sector.[3] So far, however, the literature has either focused on information interventions targeted at schools in the selective system (e.g. Hoxby and Turner, 2013) or does not differentiate between access to selective and less selective sectors (e.g. Hastings et al., 2015).[4]

In this paper, we describe the results of a randomized field experiment conducted with Grade 12 students in Chile that we designed to explore the effects of giving students tailored information about financial aid and economic returns in a context where selective and less selective systems of higher education coexist. Specifically, we tailored our information treatments to student preferences for careers and schools, collected at baseline. We measure the impacts of the treatments on the extensive margin of enrollment in each of the selective and less selective sectors and on the intensive margin of school choice, conditional on enrollment.

There are three distinguishing features of our study. First, we designed the intervention to be inexpensive and scalable: treated students receive information treatments by email at the time of the intervention, which coincides with the process of applications to post-secondary school and to financial aid for higher education. Several important studies analyze how information about higher education affects decisions in the US and find large positive effects on extensive margin outcomes of enrollment. However, these information treatments tend to be coupled with more expensive subsidies and/or guidance through the application process (e.g. Bettinger et al., 2012; Carrell and Sacerdote, 2013; and Hoxby and Turner, 2013). In contrast, our intervention involves only information.

Second, since preferences about careers and schools may significantly constrain student choices about where to enroll, our intervention accounts for preferences by providing students with tailored information. This differs from most of the literature, in which more general, aggregate information is provided.[5] We elicit student preferences regarding careers and schools at baseline. Then we provide them with information about financial aid, potential average wage returns, and expected employability for their specific preferred career-school combination as well as for alternative schools that offer the same or similar career paths.

Third, we provide students with information about career and school options in both the selective and less selective sectors. Our treatments include information on elite universities in the selective system and information regarding less selective universities, professional schools and technical/vocational colleges. We show that because there is substantial sorting of students across the selective and the less selective sectors based on college entry exam scores, information treatments have less room to – and in factor do not – impact access to the selective sector. Whether information treatments have larger impacts for students who are excluded from the selective school system is an empirical question, which we are also able to address.

Our first result is that delivering tailored information via email was a feasible and inexpensive method of reaching out to students at the time they were managing the transition to higher education. The downside of this delivery mechanism was low uptake. At most, half of the students received and opened our treatment emails. As a result, our study is underpowered to detect small impacts for many outcomes.

Turning to impacts, we find no evidence that exposure to tailored financial aid information affected applications to or enrollment in schools in the selective system.[6] This allows us to assess the impact of our treatments on the extensive and intensive margins of choice in the less selective sector, without concerns about sample selection. In the subsample of students not enrolling in any selective school, we find no statistically significant impacts of any information treatments on extensive margin choices about enrollment in the less selective schools. These extensive margin estimates are noisy, but small relative to control group means.

[2] Centralized admissions procedures for entry into selective public universities can be found in Australia, Brazil, Colombia, Hong Kong, India (universities may participate in one of several centralized admissions systems), Ireland, Nigeria, Norway, Thailand, and the United Kingdom. Similar systems exist for admission to prestigious public secondary schools in Kenya, Ghana, Malawi and Nigeria. In most of these countries, performance on a high-stakes qualifying exam, like the SAT in the US, is an important determinant of placement.

[3] Rodríguez et al. (2015) discuss issues around lack of information in postsecondary schooling in Chile, where the less selective sector has recently expanded.

[4] Kerr et al. (2014) find no impacts of an information intervention on applications or enrollment in the highly centralized system of higher education in Finland. They argue that information interventions may have little impact when preferences for specific careers have high consumption value, or when popular careers are heavily over-subscribed, as in the Finnish context.

[5] Recent exceptions are Hoxby and Turner (2013) and Hastings et al. (2015).

[6] Because of the timing of the intervention, we cannot estimate the impacts of exposure to the returns information on extensive margin choices in the selective sector. We discuss this issue in detail in Section 3.2.

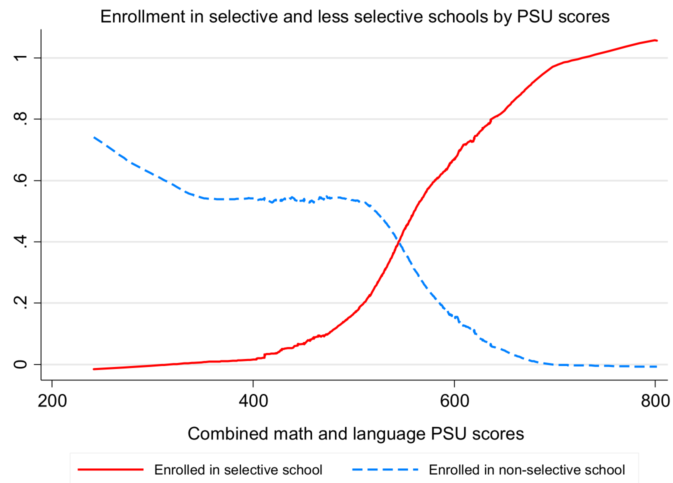

Fig. 2. Enrollment choices by PSU score - Control group Note: PSU is the college entry examination.

We do find that exposure to financial aid and returns information affects intensive margin decisions in the less selective sector, for the subsample of students choosing to enroll in the less selective sector. We show that our treatment nudges students to enroll in schools suggested in the treatment emails, and to enroll in suggested schools of a quality higher than their baseline preferences. Treated students switch away from for-profit universities and towards professional institutes. They enroll in schools with lower average expected wages and lower expected employment probabilities, but offering shorter degree programs at lower tuition cost (although these last impacts are not estimated precisely). Using college entry exam scores as a proxy for the baseline level of information a student has about expected returns, we show that our information treatment changed the school choices of the lowest scoring (most misinformed) students the most.[7]

Our results on the lack of impacts on access to the selective sector are in line with results from a recent study by Hastings et al. (2015) who analyze the impacts of a similar information experiment in a sample of higher education loan applicants in Chile. In that study, loan applicants receive information via email and the web about returns (expected wages and tuition) to different programs of study at different schools, according to their baseline preferences. Similar to our estimates but in a different sample, they find that their treatment has no impacts on the extensive margin of enrollment in higher education overall and small positive impacts on their calculations of expected net value from enrolling in a program of higher education. Our study is complementary to theirs in highlighting the feasibility, and relevance, of providing tailored information to students seeking to enter higher education.

Our results have two broad implications. First, although we demonstrate that it is possible to scale up even highly tailored information interventions at low cost, such interventions are likely to have small effects on access to selective schools when the process for applying to these universities is well-known, centralized, and coordinated as is the case in Chile. If the selective system is already oversubscribed by the best students – those with the highest entry-level test scores and high school grades – there is little room for affecting the distribution of slots across students using an information intervention at the end of high school. Information at this point is unlikely to level the playing field for lower scoring students from disadvantaged backgrounds. Moreover, information interventions of this type are also unlikely to have large impacts on access to the less selective school system.

The second more novel implication of our results is that governments may still have a role to play in changing the allocation of students to schools in the less selective system by providing inexpensive and targeted information about the costs and benefits of post-secondary schooling. Such information will be relevant for the majority of students who do not gain access to the most selective schools and who must decide where it is worthwhile to invest in tertiary education. It is also likely to be important in any educational system in which the number of for-profit schools has recently expanded and where information about their quality is limited.

Section 2 provides some background on the higher education sector in Chile, distinguishing between the selective and less selective systems, while Section 3 describes the details of our experiment. Section 4 describes our data, Section 5 outlines the empirical strategy and Section 6 presents the main results. Section 7 discusses the results and the costs of the intervention, and concludes.

2. Post-secondary schooling in Chile

There are three main types of post-secondary institutions in Chile: universities (public, private, and public-private) that offer traditional five-year degree programs, professional institutes that offer some traditional and some technical degrees, and technical/vocational training colleges that focus on shorter, two to three year programs with technical training. Graduating high school seniors apply to a specific career in a specific school, for example, engineering at the University of Chile or mechanics at a technical college.[8] The most prestigious institutions are part of the selective school system, while other schools are less selective on applicants.

The selective school system consists of about 33 schools, including the oldest, traditional public universities, and some universities with private and combined public-private funding. To enroll in one of these schools, students must apply to and be accepted by the centralized DEMRE (*Departamento de Evaluación, Medición y Registro Educacional*) system at the end of their final year in high school. DEMRE (selective) schools, are considered selective because eligible students typically need to have high GPA scores during high school and high minimum scores on the college entry examination (the *Prueba de Selección Universitaria* – PSU— which is like the SAT for US

[7] In our experimental sample, 64% of students do not report any information about an expected wage for their preferred career and school, and those who do report an expected wage overestimate wages by an average 24%. The correlation between college entry exam score and item nonresponse on the expected wage question is -0.17 and the correlation between entry exam score and expected wage response is -0.3.

[8] Specialization occurs early in Chile, where schools admit students to specific degree programs for a specific career and where switching careers later on is almost impossible. This implies considerable "lock in" to enrollment decisions.

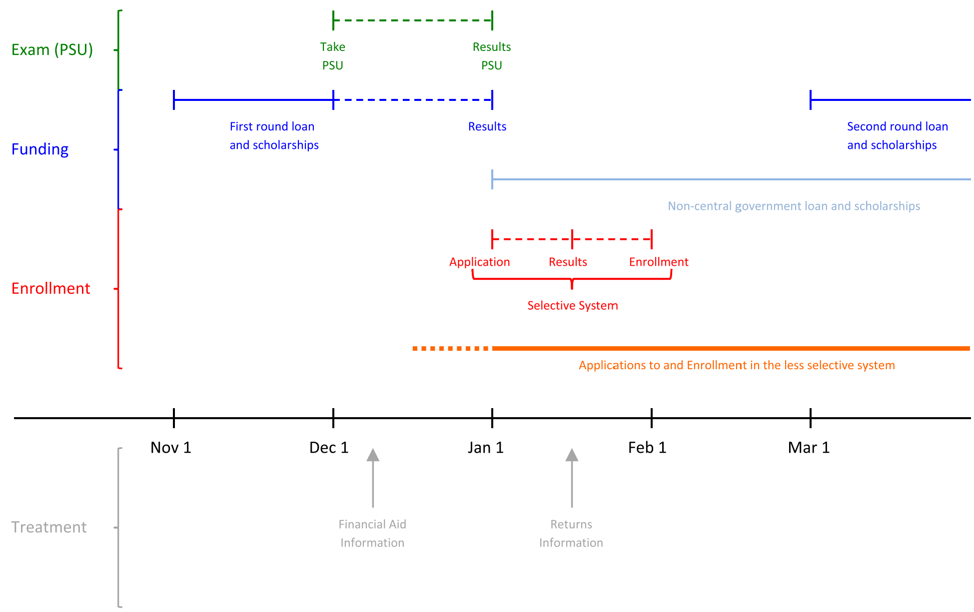

Fig. 3. Timeline of treatments relative to applications deadlines. Note: Solid lines represent times during which students could take actions (e.g. to apply for scholarships, to apply or enroll in a higher education institution). Dotted lines represent times in which students could take actions but this action was unlikely to have happened. For instance, in late December students have just finished high school and have not learned yet their PSU results or the results from the first round of scholarships run by the central government. It is therefore unlikely that they have already applied to a less selective institution. Dashed lines represent waiting times.

students).[9] Schools in this system are oversubscribed: in 2014, there were 1.25 applications for each available slot (DEMRE, 2015).

In contrast, applications to the remaining 129 non-DEMRE (less selective) schools (SIES, 2014) – some private universities, the majority of professional institutes, and all technical colleges – are decentralized, and entry requirements are lower. For example, PSU eligibility cut-off scores are lower on average relative to cut-offs for schools in the selective system. In some less selective schools, students do not require a PSU score to gain entry.

The quality of institutions varies both across and within the selective and less selective school systems. For example, the Chilean government certifies the quality of many degree programs and institutions by awarding them “accreditation status” from 1 (lowest quality) to 7 (highest quality) years. Schools choose to be accredited, and only 52% of institutions have an accreditation score (SIES, 2014). On average, schools in the less selective system have lower accreditation scores and many of them have no accreditation score at all. However, there is a range in quality measures within each system. Within the selective system, accreditation scores range from 2 to 7 while within the less selective system, in schools that are accredited, scores range from 1 to 7.

The majority of growth in enrollment in higher education in Chile since the early 1990s has been in this less selective sector, particularly in professional schools and private universities (OECD, 2012). By 2012, 27% of all students in higher education attended schools in the selective system, 33.2% in less selective universities, 26.2% in professional schools and 12.4% in less selective vocational schools. The decision to enter into higher education through less selective institutions has therefore become much more salient among recent high school graduates.

Figs. 1 and 2 illustrate how students sort across selective and less selective school systems based on PSU scores. The first graph shows the (kernel-smoothed) distribution of PSU test scores of students in our control group who applied to any selective school, and a separate distribution for those who choose not to apply to any selective school. There is some overlap in the distributions but the figure also suggests a high degree of sorting by PSU score. Below a score of 400, almost nobody applies to the selective system. Above 600, almost nobody applies to a less selective school. This sorting continues into the enrollment stage. Fig. 2 shows the share of control group students who enroll in any selective school (solid line), any non-selective school (dashed line), or who chose not to enroll in any higher education at all (dotted line) by PSU score. The lines cross at a score of 540. Among students with scores higher than 540, 40% or more enroll in a selective school and with scores above 600, 60% or more enroll. Less than 10% of students with scores of 600 or more enroll in the less selective system. At the other end of the score distribution, about half of students with PSU scores between 300 and 540 enroll in some less selective institution. Most other students scoring in this low range do not enroll anywhere.

PSU scores are also important in qualifying for many forms of government aid, and for some types of privately provided financial aid. Scores above 475 are particularly salient, since they qualify a student to receive one of the two largest government loans. These loans are not restricted to specific programs of study and can be used for study in selective and less selective schools. There is good evidence that Chilean students are credit constrained in Chile (average tuition fees were almost half of median family income in 2009, Solis, forthcoming).[10] Access to financial aid has expanded dramatically since the mid-2000s, and currently, 65% of students currently use some combination of scholarships/grants and government loans for higher education (CASEN, 2013).[11]

The top part of Fig. 3 shows the timeline facing students who want to enter into higher education. Students first apply for the major

[9] The PSU is offered once per year in December and is free for students in any high school with public funding. Once students find out their PSU scores in late December, they have a two-day window in which to apply to their top six choices of selective schools through the centralized DEMRE application system. Solis (forthcoming) describes how, unlike the US, entry to the selective tier of tertiary education in Chile depends only on high school and PSU scores. Extra-curriculars and other aspects of a candidate do not affect probabilities of acceptance.

[10] Solis (forthcoming) uses a regression discontinuity design to show that getting access to a government loan doubles college enrollment in Chile.

[11] The two large government-sponsored programs are the loan program (*Crédito con Aval del Estado*) and a scholarship program (*Bicentenario*, among others).

sources of general financial aid (state scholarships and loans) administered centrally, before writing the PSU and learning their scores. After learning the results of the PSU test, students may apply to selective schools, supplying a maximum of eight choices to the centralized selective system. This system allocates students to spots in career-school combinations based on their PSU and high school GPA scores; The central government allocates financial aid to students conditional on their PSU scores meeting eligibility cut-offs, their financial need and the accreditation of the institution of higher education.[12] Throughout this period, students may also apply to other sources of financial aid not allocated by the central government. Information about these other sources is decentralized, often down to the level of the school and program and deadlines for applications are idiosyncratic.

Students find out the outcomes of these centralized university and financial aid applications by early/mid-January. Students not admitted to a selective school, as well as those who choose not to apply to or enroll in a selective school can then choose to apply to one of the less selective institutions. They may also choose not to enroll in any higher education after the end of high school. Applications to less selective institutions continue into late February when students also have a second chance to apply for remaining government-sponsored scholarships and other decentralized sources of financial aid. By early March, when the new school year starts, the market in each of the selective and less selective systems has mostly cleared.

Applications to and decisions for the selective and less selective systems occur almost sequentially. This allows us to examine student choices in two distinct stages of their transition to higher education. In Stage 1, we look at choices of our entire sample during the early part of the admissions process that focuses on selective schools. In Stage 2, the later part of the admissions process, we examine subsequent decisions of students who do not enter into a selective school over their remaining alternatives in the less selective system.

3. Experimental design

3.1. Sample: recruitment and randomization

We worked with a Chilean NGO, *Por Una Carrera* (PUC), to visit over 300 school career fairs in the greater Santiago region between July 2013 and November 2013. At the PUC booths, we collected over 10,000 emails from Grade 12 students, along with their preferences about post-secondary careers and institutions. Our sampling frame is more geographically targeted than the sampling frame used in Hastings et al. (2015). We use relatively poor neighborhoods in Santiago while they use the universe of government loan applicants. Another difference between our sample and theirs is that ours includes both students who will, and those who will not, go on to apply for government loans. We invited students to participate in our study by sending them a web link to our baseline survey; respondents had two weeks to complete the online survey.

We stratified the sample using baseline information on gender and on whether a student's parents had completed any tertiary education, or not, or had missing education information. Between October and December 2013, we randomized students into an information treatment and control group on a rolling basis, following a re-randomization protocol to maintain cumulative balance in the combined sample.[13] All treated students received the financial aid treatment: information about financial aid possibilities tailored to their baseline career-school preferences. Half of the treated students also received a returns treatment: information about expected returns related to their baseline preferences.[14]

3.2. Description of treatments and timeline of intervention

We sent our emails close to the time of decision-making (November-February). This was to ensure that students had given some thought to their desired program of study, and to prevent the loss of too much information between the time of the treatment and the time of actual choices.[15]

3.2.1. Control group

The control group received one email inviting them to learn about possible careers at www.eligecarrera.cl. This publicly accessible official website contains general information on types of careers, loans and scholarships available at different schools, eligibility criteria for these programs and financing options. Students in the treatment group also received a link to the same website in their treatment emails.[16]

3.2.2. Financial aid treatment

All treatment students received information about how to access general types of financial aid offered through the centrally administered public loan and scholarship programs. The distinguishing feature of our financial aid treatment was that every student also received personalized information about alternative specific financial aid opportunities linked to their baseline preferences or background characteristics. They received information about specific scholarships or loans offered by private schools or firms, by certain municipalities, and by specific programs and career tracks within certain schools. Because these alternative types of financial aid are not centrally administered, it is typically more costly to learn about them. Our financial aid treatment sought to reduce this learning cost. Volunteers searched for each student's personalized information about alternative sources of loans and scholarships, and provided this to them in an email.[17]

Table 1 describes the types of information provided in the financial aid treatment. Appendix 1 presents the full the email template (in English and Spanish) designed for this treatment. In some cases, the information provided was specific to the preferred career, or sub-area or area of study if no career preference was given, and relevant for multiple institutions. In other cases, the information was specific to an institution. Where socio-economic status or PSU score and high school GPA was relevant for eligibility, the PUC volunteers tailored their advice to these characteristics. For example: a student who had a PSU score that was not high enough to attend the top public institutions in Chile would not have received information on scholarships or loans specific to these institutions, but instead would have been given information for schools that were feasible targets of application given their scores.

We administered the financial aid treatment to students in December 2013, after applications to the government-sponsored general loan and scholarship programs had closed and after writing the

[12] In 2014, 89% of all state loans and scholarships are awarded in this first round.

[13] The re-randomization procedure followed Morgan and Rubin (2012). We re-randomized to achieve baseline balance on a set of covariates that included student characteristics in Panel A of Table 3, information on student academic performance listed in Panel B of Table 3, expected wage, expected probability of employment and expected probability of getting a scholarship. We used a simple Euclidean distance function to map the differences between treated and control means across covariates and across treatment arms to a scalar. We selected the pseudo-random number generator seed (from a set of 10,000 randomly generated seeds) that minimized that distance function.

[14] We did not have a sufficiently large sample to implement a pure returns-only treatment.

[15] Dinkelman and Martínez A. (2014) show that Grade 8 students on their own retained very little information four months after they viewed a DVD providing them with information about how to prepare for successful financial aid applications at the end of high school. In results not shown in that paper, student recall of information immediately after watching the DVD was significantly greater than recall four months after the treatment.

[16] The website is maintained by the *Consejo Nacional de Educación*.

[17] We did not design the content of the financial aid treatment emails; we designed the structure of the email, and relied on the expertise in the NGO to fill in the relevant cells from their database.

Table 1
Summary of financial aid treatment information for a given career preference.

Types of Financial Aid Information	*Description of information provided*
General	Links to application for central government financial aid (scholarships and loans) and YouTube video on how to complete
Specific: Loans	Links to other loan programs for which a student is eligible based on socio-economic status and expected PSU score. More than one link may have been provided.
Specific: Private scholarships offered by an institution for specific expenses (fees, boarding etc)	Links to scholarships from student's preferred institution and one other related institution
Specific: Private scholarships for certain careers	Links to up to two different scholarships targeted towards student's preferred career (may or may not be linked to a school)
Specific: Private scholarships (foundations and municipalities) for students meeting eligibility criteria	Links to any private scholarships for students meeting eligibility criteria e.g. age, duration of degree program, first or second year student, living in a particular municipality

Note: Table shows information provided in the financial aid treatment. Specific information is tailored to student career-school preferences at baseline.

Table 2
Summary of returns treatment information for a given career preference.

School type	*Quality tier of school*	*Mean earnings, employability given for:*
Student preferred school: X (if listed)	Quality tier of X (high/medium/low)	X if preference given; else nothing
Selective school	Same quality tier as X/highest quality tier if no X	List of up to 3 schools
Selective school	Lower quality tier than X/medium quality tier if no X	List of up to 3 schools
Less selective school	Same quality tier as X/highest quality tier if no X	List of up to 3 schools
Less selective school	Lower quality tier as X/medium quality tier if no X	List of up to 3 schools

Note: Table shows information provided in the returns treatment based on student career-school preferences at baseline. X is the first choice preferred school at baseline. Quality tiers are defined over each of the selective and less selective systems, by grouping years of government accreditation into three roughly equal bins.

PSU, but before the deadlines for applying to selective and less selective schools and most other sources of specific financial aid. We monitored the first email from the NGO staff for treatment compliance, but did not monitor subsequent interactions between volunteers and students. We expect that the financial aid treatment could have affected student choices about applying to and enrolling in selective and less selective schools. It may also have affected the types of schools to which students apply. We examine all of these outcomes in our analyses. We also expect this treatment to affect their application to and receipt of non-state financial aid. Unfortunately, there are no centralized data available to measure these outcomes.

3.2.3. Returns treatment

To construct information for the returns treatment, we gathered data from the publicly accessible MiFuturo database (www.MiFuturo.cl) of 2013. This database reports average monthly earnings and average employability rates for recent graduates of specific career-school programs.[18]

Table 2 summarizes the types of information provided to students in the returns treatment, given their baseline career-school preferences. Appendix presents the full text of the email template (in English and Spanish) for this treatment. Students received returns information for their specific preference and for schools in four alternative categories offering their same career. Up to three schools in each of the selective and less selective systems were listed, for each of two quality tiers.[19] To define three quality tiers, we ranked schools within the selective and less selective systems based on their years of accreditation (high, medium, and low levels of accreditation). Students were given information on schools from each of the selective and less selective systems in the same quality tercile as their baseline preference, and in a lower quality tercile.[20] The rationale behind providing information on lower quality tier schools relative to baseline preferences was that if a student did not gain access to their first choice school, they might be successful at a lower quality institution. However, we did not label schools as selective or less selective. The email only listed a set of alternative schools along with associated average wages and employability data.

Half of the students in the financial aid treatment were randomized into receiving the returns treatment. Because of a delay in preparing the returns treatment, the treatment was administered after the deadline for applications to selective schools had passed but before the main period of applications to less selective schools. That is, the financial aid treatment was delivered after students had applied to the first round of central government funding and before the end of applications to selective schools. The returns treatment came after applications to selective schools had concluded but before results were released and before the second round of government funding closed. Both treatments were delivered before the process of applications for less selective schools closed, and while applications for decentralized sources of funding was still ongoing.

The returns treatment was sent via a University of Chile email account, and we had full control over the content of these emails. Because of the timing of the returns intervention, we cannot affect intensive margin choices of where to apply among those applying to selective schools. And, because an allocation algorithm manages how students are assigned to schools and programs within this selective

[18] Income and employment statistics are computed from IRS data, although it is not clear how the statistics are created. The *MiFuturo* data represent average returns rather than causal estimates of the impact of specific degree-school combinations for marginal students as in Hastings et al. (2015). We merged *MiFuturo* with the 2012 and 2013 National Council of Education databases (CNED) to identify schools and types of institutions.

[19] For students without career information, we used the preferred subarea or area at baseline to create average wage and employability measures for these more aggregate categories. We included information on schools chosen in the same way, e.g. schools offering programs in the preferred subarea or area. For students without a preferred institution, we provided information on schools from the first (highest) and second (medium) quality terciles.

[20] Although we listed the schools along with their associated returns, we did not specify to which quality tier each school belonged. In practice, students would have been able to infer something about quality (years of accreditation) using the information about returns and employability along with the type of institution (university/institute/technical college). This strategy is similar to Hastings and Weinstein (2008). In that study, parents were provided with information about school test scores that are potentially correlated with a host of other school quality measures.

Table 3
Baseline balance.

	Whole Sample				Sub-sample excluding selective school enrollees			
	Control Mean [s.d]	Financial Aid Treatment	Financial Aid plus Returns Treatment	N	Control Mean [s.d]	Financial Aid Treatment	Financial Aid plus Returns Treatment	N
Panel A: Student Characteristics								
Age	17.576	0.040	-0.042	1665	17.665	0.118	0.012	1085
	[1.574]	[0.105]	[0.098]		[1.609]	[0.147]	[0.137]	
Self-reported poor status	0.199	0.019	0.016	1513	0.231	0.017	0.032	972
	[0.400]	[0.025]	[0.025]		[0.422]	[0.033]	[0.034]	
% poor in municipality in 2009	12.132	-0.052	-0.103	1520	12.479	0.028	0.032	1021
	[4.988]	[0.309]	[0.309]		[5.007]	[0.370]	[0.398]	
Panel B: Academics and Grades								
Final high school grade, expected	58.089	0.150	-0.186	1463	56.549	0.245	-0.070	929
	[4.536]	[0.290]	[0.288]		[4.043]	[0.337]	[0.332]	
PSU Math and Language, expected	589.423	-5.373	2.567	1389	557.635	-11.468	3.475	869
	[96.707]	[6.492]	[6.210]		[93.895]	[8.138]	[7.995]	
Will take the PSU	0.945	-0.012	-0.006	1534	0.936	-0.019	-0.014	989
	[0.229]	[0.015]	[0.015]		[0.245]	[0.020]	[0.020]	
Prepare for PSU > 6 months	0.076	0.015	0.027	1426	0.056	-0.003	0.019	901
	[0.265]	[0.018]	[0.018]		[0.230]	[0.018]	[0.020]	
Panel C: Baseline Preferences and Expectations								
At least one selective school listed	0.759	-0.018	-0.016	1298	0.639	-0.052	-0.041	817
	[0.428]	[0.029]	[0.029]		[0.481]	[0.041]	[0.040]	
At least one less selective school listed	0.928	-0.015	0.017	1298	0.964	-0.011	0.019	817
	[0.259]	[0.018]	[0.016]		[0.187]	[0.017]	[0.014]	
Probability get a state or private scholarship (%)	58.946	0.979	2.622	1331	56.129	-0.863	4.204*	831
	[26.829]	[1.828]	[1.799]		[26.013]	[2.279]	[2.237]	
Without a scholarship, I will study using a loan	0.559	0.000	-0.009	1366	0.512	0.011	0.000	856
	[0.497]	[0.033]	[0.033]		[0.501]	[0.041]	[0.042]	
Without a scholarship, I will postpone	0.190	0.018	-0.008	1366	0.235	0.005	-0.023	856
	[0.393]	[0.026]	[0.026]		[0.425]	[0.035]	[0.035]	
Without a scholarship, I do not know what I will do	0.236	-0.021	0.013	1366	0.239	-0.029	0.010	856
	[0.425]	[0.028]	[0.028]		[0.427]	[0.035]	[0.036]	
Probability of being employed after study (%)	73.314	-1.768	-1.421	789	69.164	-1.192	0.187	486
	[23.829]	[2.198]	[2.155]		[25.713]	[2.933]	[2.828]	
Average expected wage: $200K to $600K	0.259	-0.004	-0.002	816	0.351	-0.033	-0.026	507
	[0.439]	[0.038]	[0.037]		[0.479]	[0.051]	[0.052]	
Average expected wage: over $600K	0.741	0.004	0.002	816	0.649	0.033	0.026	507
	[0.439]	[0.038]	[0.037]		[0.479]	[0.051]	[0.052]	

Note: Variables in this table were collected from students at career fairs and from the online survey administered at baseline. Selective school is defined as a school belonging to the DEMRE group, for which application must be made through the centralized application system. PSU is the college entry examination. All balance regressions contain stratum fixed effects. Missing values are balanced across experimental group. Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

system, there is almost no flexibility for students to make intensive margin changes in the type of selective school in which they enroll, in response to our information treatment. Therefore, we expect that the returns treatment may affect extensive margin enrollment choices into the less selective school system, and may also change intensive margin choices about the types of less selective schools which students enroll in.

4. Data

4.1. Survey data

We collected baseline survey data from 1727 Grade 12 students between October 2013 and December 2013. These students responded to our initial email invitation to be part of the study and filled out an online survey, providing basic demographic information and confirming their preferences reported at career fairs about specific career, subarea or area of study and preferred institution of study. Respondents reported on measures of their own ability (expected high school GPA and expected score on the PSU exam) and their expectations about access to finance for higher education, future earnings and future employment probabilities in their preferred careers.

Appendix Table 1 compares students in our experimental sample with the larger sample of career fair students. Our sample students expect to achieve higher high school grades and scores on the PSU relative to career fair students. They are also more likely to list at least one selective school in a baseline preference, and significantly less likely to list at least one less selective school. However, they resemble the larger sample of students on most other dimensions, e.g. demographics, on self-reported poverty score, and the distribution of preferences for careers.[21] Appendix Table 2 compares the demographics of our experimental sample to the universe of PSU exam takers. Our sample is relatively more female, with lower high school GPA, and somewhat higher household income, but from similar family backgrounds as measured by mother and father education.

The majority of students enter our study with "complete preferences", meaning that they have a well-defined idea of what they want to study, and where. About 95% of the experimental sample provided information about a specific career preference and 80% provided both a preferred career and preferred school, although not all students had accurate information (e.g. some provided a career-school preference that did not exist at a particular school). Most of the remaining 5% without any career information provided some general preference information (e.g. the subarea or area of preferred study) and a minority expressed that they had "no idea" about what to study.

4.2. Administrative data

We matched our experimental sample to administrative databases using unique national identification numbers from the Chilean Ministry of Education. The data include PSU scores, applications to the selective school system and the outcome of that application at the end of 2013 (acceptance into and enrollment in a selective school-career or not), enrollment in any less selective school-career, characteristics (type of institution, measures of school quality) of the school in which the student eventually enrolled in 2014, and receipt of government financial aid.[22] We can also tell whether a student graduated from high school in 2013; we exclude 59 students who failed to graduate from our final analysis sample of 1668 students. Summary statistics for the administrative data outcomes are in Appendix Table 3.

Almost everyone (1602 students, 96% of the sample) wrote the PSU exam and of those students, 879 (or 53%) chose to apply to at least one selective school. By March 2014, 1206 students were enrolled in some higher education (72% of the sample), with 48% enrolling in selective universities, 17% enrolling in less selective universities, 23% in professional schools and 10% in technical schools. Receipt of centrally allocated financial aid from the government is highly prevalent. Three quarters of all enrollees have some form of government aid (scholarship or loan), 60% of enrolled students have some government scholarship, and 43% have a government-backed loan. These sources of financial aid are not mutually exclusive: 22% of enrollees have both a government-backed loan and a scholarship (not shown). As noted above, we have no data on the share of enrolled students that also receive financial aid from non-federal government sources.

It is worth noting that the 73% enrollment rate in our sample is quite a bit higher than national enrollment rates for young adults. In 2013, the share of 18 to 20 year olds enrolled in school was 46% (CASEN, 2013). Likewise, the share of our sample with access to financial aid through loans and scholarships is slightly higher than rates of access in national data, in which 65% of enrollees (ages 18 to 20) have some government loan or scholarship (CASEN, 2013). These higher shares make sense, given that we recruited from among the policy-relevant group of Grade 12 students who attended career fairs and expressed interest in wanting information about post-secondary schooling.

5. Empirical strategy

We proceed in three steps. First, we use the full analysis sample to examine the impacts of exposure to the financial aid treatment relative to the control group. We focus on impacts on the extensive margin of applications and acceptance into, and enrollment in, selective schools. We estimate intent to treat effects (a_1) using student-level data (i) and regressions of the following sort:

$$Y_i = a_0 + a_1F_i + k_i + GPA_i + PSU_i + e_i \tag{1}$$

where F_i is an indicator variable equal to one if student i received the financial aid treatment at all, k_i is a set of six stratum fixed effects for gender and level of parent education (less than tertiary education, some tertiary education, or missing education information), e_i is an idiosyncratic error term and we estimate robust standard errors. We also control for baseline expected high school GPA score and expected PSU score, GPA_i and PSU_i.

We do not find large impacts on margins related to the selective school system. That is, the financial aid information treatment had no statistically significant impact on who applies to, gets accepted into, or enrolls in, a selective schools. This implies suggests that our treatment does not affect selection into, or out of the selective school system. To proceed we shrink our sample to the subset of students who do not enroll in the selective school system. We show that treatment and control groups in this subsample have balanced characteristics at baseline.

In the second step, we then use this sample of students (non-enrollees in the selective system) to analyze the impact of the two information treatments (F_i alone, and R_i for returns plus financial aid) on extensive margin choices about schools in the less selective sector. This subsample includes all those who choose not to apply to selective schools (about half of the full sample), those who are not accepted into the selective system (9.5% of the full sample), and those who choose not to enroll in selective schools conditional on acceptance (about 8.8% of the full sample). These students are overwhelmingly middle- and low-PSU scoring students.

Within this sample, we estimate (2):

$$Y_i = b_0 + b_1F_i + b_2R_i + k_i + GPA_i + PSU_i + e_i \tag{2}$$

for enrollment in less selective schools (relative to no enrollment). This enrollment variable summarizes the outcome of extensive margin choices in the less selective system, since administrative data on applications to and acceptance into less selective schools does not exist. If we assume that the effects of each treatment are additive, then the difference between b_2 and b_1 captures the additional impact of providing only the returns information.

In the third and final step, we investigate whether the information treatments changed the characteristics of the less selective schools in which students enrolled. Again, because we find no evidence of either treatment changing extensive margin choices into enrollment in the less selective sector, we restrict our analysis to the subsample of those who enroll in any less selective school. Again, this sample is balanced on observables at baseline. In this subsample, we ask whether students responded to the specific information provided in the returns treatment. Then, we ask whether students chose different types of schools (e.g. non-college versus college, programs with different wages, employability, tuition and duration) in response to the treatments. Our results provide insight into how information provision affects the intensive margin of school choice, among those constrained to select schools within the less selective sector.

[21] About one fifth of the sample is interested in careers in technology or social sciences, law and teaching; the rest are distributed across management and business (16%), health sciences (28%) and remaining categories like humanities, architecture, and natural sciences (13%).

[22] Note that because the less selective school system is decentralized, we cannot measure applications to schools in this system; we also cannot measure receipt of one of the many sources of private scholarship and loan programs.

Table 4
Treatment compliance and take up.

Experimental group	N	*Financial Aid Treatment*			*Returns Treatment*	
		Emails Sent	Emails did not bounce	Emails received and answered	Emails Sent	Emails Opened
Control	556	8 [1.44%]	8 [1.44%]	0 [0%]	4 [0.72%]	2 [0.36%]
Financial Aid Treatment	553	548 [99.10%]	547 [98.92%]	60 [10.85%]	3 [0.54%]	2 [0.36%]
Financial Aid and Returns Treatment	559	556 [99.46%]	553 [98.93%]	79 [14.13%]	539 [96.42%]	301 [53.85%]

Note: We are able to verify whether financial aid emails bounced or not, and whether any students replied to the email sent by PUC. We can verify whether returns emails were opened at all, since we administered the treatment from a single University of Chile email address.

6. Results

6.1. Baseline characteristics and balance

Table 3 shows that the experimental treatment and control groups are balanced across a range of observable characteristics at baseline. For each variable, we show the control mean (and standard deviation), the coefficients (and standard errors) on each indicator of treatment group – financial aid treatment and financial aid plus returns treatment – and the sample size with non-missing data.[23] We estimate the coefficients of the balance regressions including stratum fixed effects (k_i) and report robust standard errors. All variables are balanced at baseline.

The first four columns pertain to the full sample. The average student in our sample is 17.5 years old. Almost one in five respondents reports being in one of the bottom two quintiles of household income and on average, 12% of people are poor in the municipalities represented in our sample. Almost everyone expects to take the PSU exam, and one in four respondents spends more than four hours per week studying for the exam. 75% of the sample lists at least one school from the selective system in their baseline preferences (we asked about first and second choice at baseline), and over 90% of respondents lists at least one school from the less selective system. Students place reasonably high probabilities on getting state or private (59%) scholarships for further study, and 55% of the students anticipate being able to use a loan if they do not get scholarship funding. However, almost one quarter of the sample has no plan about how to finance higher education without scholarship funding.

Students come into the applications process with relatively poor information about future returns. Expectations about predicted future returns (wages and employment probabilities) for people with their preferred degree are missing for a large share of the sample, suggesting that students had a difficult time answering these questions. Among those who do answer these survey questions, 73% expect that graduates with their preferred degree find a job, which is an underestimate relative to actual employment rates among cohorts age 25-35 with any further education (the employment rate among these cohorts is 84%, CASEN, 2013). At the same time, students tend to overestimate wages for people with their preferred degree. Three quarters of respondents with non-missing data expect that monthly wages are over 600,000 pesos. This is 1.6 times the median monthly wage for similarly educated young adults in 2013.[24]

[23] Appendix Table 4 shows that missing data are balanced across each of the treatment and control groups for the full sample. Appendix Table 5 shows the same balance regressions for the subsample of individuals who do not enroll in any selective schools.

[24] This median is calculated over the sample of employed adults ages 20-29, who have some level of higher education. The data source is the 2013 CASEN, a standard labor force survey conducted each year in Chile.

Table 5
Extensive margin impacts on access to selective schools (Whole sample).

	Control mean [s.d]	Any Financial Aid Treatment	MDE	N
Applied to selective school	0.522 [0.500]	0.015 [0.022]	0.07	1668
Accepted into selective school	0.412 [0.493]	0.018 [0.022]	0.07	1668
Enrolled in selective school	0.340 [0.474]	0.018 [0.021]	0.08	1668

Note: All regressions include stratum fixed effects (for gender and parental education). The set of controls include baseline variables: expected PSU score and high school GPA. MDE is the minimum detectable effect size for each outcome, given sample design. Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Combining stated student preferences for being in the selective school system with the high expectations over PSU score (the average expected score is 589; we calculate that 82% of our sample over-estimates their actual performance on the PSU) and high wage expectations, we can see this sample is optimistic about their prospects in higher education. Other work has shown that students routinely overestimate their prospects (e.g. Bobba and Frisancho, 2015).

6.2. Treatment compliance and take-up

Table 4 shows that treatment compliance was high in both treatment groups, but take-up was low. For each of the Control, the financial aid Only Treatment, and the financial aid plus returns treatment groups, we show the number [percent] of the group to whom we sent financial aid (first three columns) and returns (last two columns) emails. We also show the number [percent] of financial aid emails that did not bounce, the number [percent] that received an answer from a respondent, and the number [percent] of returns emails that we can verify were opened.[25]

Compliance was high in each of the treatment groups. 98% of financial aid emails did not bounce, and 96% of the returns emails were sent out to the assigned respondents. In only a handful of cases (a

[25] We worked with a programmer to develop a program that assembled, delivered, and kept track of opened and bounced emails.

Table 6
Extensive margin impacts on access to less selective schools (Sub-sample of students not enrolled in selected schools).

	Control mean [s.d]	Any Financial Aid Treatment	Financial Aid Only Treatment	Financial Aid plus Returns	P-value of difference in treatment coefficients	MDE	N
Enrolled in less selective school	0.556 [0.498]	0.037 [0.032]	0.045 [0.037]	0.029 [0.036]	0.652	0.109	1088

Note: The regression includes stratum fixed effects (for gender and parental education). Column (2) presents coefficients from the pooled treatment; columns (3) and (4) present coefficients for the separate treatments. The set of controls include baseline variables: expected PSU score and high school GPA. MDE is the minimum detectable effect size for each outcome, given sample design. Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

maximum of 8 students in any one group) did non-assigned individuals receive any treatment email. Our measures of take-up are much lower. We verify that 10–14% of students treated with the financial aid treatment responded to their PUC volunteer, as was requested in the first contact email. This measure of take-up is imperfect though, since it is likely that more treated students actually read their email than responded to their PUC volunteer. However, even when we can verify that students received the treatment, as in the case of the returns treatment that we directly administered, only 53% of students opened their emails.[26]

These rates of take-up clearly limit the potential impact the treatment could have on choices and outcomes. We report Intent to Treat (ITT) results instead of instrumenting for treatment using take up rates. These estimates represent the average effects we can expect when scaling up these information treatments in a population of similar students. Alongside each outcome in our main results tables, we also report minimum detectable effect (MDE) sizes given our sample size and take-up.

6.3. Effects of information treatments on extensive margin outcomes

Table 5 shows how providing financial aid information affects behavior on the extensive margin of entry into the selective school system. The control group mean appears in the first column, and the impact estimate of a_1 in Eq. (1) is shown in the second column. We present three sets of outcomes: application to any selective school, acceptance into a selective school, and enrollment in a selective school.

Over half of the control group applied to a selective school, and 78% of them were accepted (.41/.52). In the entire control group, 34% enrolled in a selective school, or about 82% of those accepted. The second column shows that the financial aid information treatment had no statistically significant impacts on any of these outcomes. The treatment effects are all positive, but relatively small and not statistically significantly different than zero. Low take up rates in a small sample make it difficult to estimate any small effects precisely: we could only reject fairly large MDEs on these access variables (columns 3), given our experimental set up. Nonetheless, despite the specificity and targeting of the financial aid treatment to student preferences, we can say our information treatment does not have meaningfully large impacts on access to the selective school system.

These results make sense. Selective schools are already oversubscribed and schools can choose from the highest PSU scorers. Students with high enough scores seem to know they are eligible for these schools: they apply, are accepted, and enroll. Lower scoring students cannot meet the high PSU cut-off scores required for selective school eligibility, and middle scoring students (i.e. those between 400 and 600) generally cannot compete with the highest scoring students for the limited spots allocated by the centralized process.

Next, we restrict the analysis sample to those students who did not enroll in a selective school. This subsample consists of 1088 students who did not apply to any selective school (781 respondents), to students who applied but were not offered a place in the selective system (159 students), and to students who applied to and were accepted into the selective system but chose not to enroll (148 respondents). This represents 65% of the full sample. Restricting the sample in this way makes sense, because Table 5 gave no strong evidence of extensive margin adjustments into selective schools. The fact that average baseline characteristics are balanced across treatment and control groups in this subsample (see Table 3, columns 5–8) further reassures us that restricting the sample in this way is reasonable.

Table 6 examines how our information treatments impact extensive margin outcomes in the less selective school system. The only outcome we can measure here is whether a student chose to enroll in any less selective school by March 2014. To compare with Table 5, we show the control mean and treatment effect coefficients for any financial aid treatment in the first two columns. Over half of the control group enrolls in a less selective school, and while the coefficient on the Any financial aid treatment is positive and slightly larger than the similar coefficients in Table 5, it is not statistically significant. Columns (3) and (4) of Table 6 split out the treatment effects into the effect of the financial aid only treatment and the effect of the financial aid in combination with returns treatment. We show the p value of the difference in these coefficients in column (5). Again, the MDE is large (0.109). We are unable to find any large impacts of the information treatment on the extensive margin of enrollment into less selective schools.[27]

6.4. Effects of information treatments on intensive margins of choice among less selective school enrollees

In Table 7, we provide evidence that our information treatments affected intensive margin choices among the subsample of students who were constrained to choose enrollment in schools in the less selective sector and who chose to enroll. We present control means in the first column, an estimate of the impact of Any financial aid treatment (F_i or R_i) in column (2), and then estimates of each of the financial aid only and the combined financial aid and returns treatments in columns (3) and (4). Under the assumption that the effects of each information treatment are additive, the difference between the two treatment effects tells us the impact of exposure to the returns treatment. The p value for this difference is given in column (5). The

[26] Compared with other recent experiments that evaluate the role of information and mentoring for college applications and enrollment in the USA, our measurable take-up rate for the financial aid treatment is lower, while the take-up rate for the returns treatment is on par with these other studies. For example, in Carrell and Sacerdote's (2014) college application mentoring program in New Hampshire high schools, the take up rate was around 50%. Take-up in this study meant that students actually attended the offered mentoring program. Hoxby and Turner's (2013) information intervention targeted at low-income, high achieving high school graduates, measured take-up in a subsample of the experimental sample at 23–48%. In Hastings et al. (2015), less than 50% of the treatment group used the searchable information database provided in the intervention.

[27] For each outcome, MDEs for each of the treatments differ in the third or higher decimal place. To be conservative and to save space, we report only the maximum of the MDEs across both treatments in Tables 6–8.

Table 7
Intensive margin impacts of exposure to Information Treatments (Sub-sample of enrollees in less selective schools).

	Control mean [s.d]	Any financial aid treatment	Financial Aid Only Treatment	Financial Aid plus Returns	P-value of difference in treatment coefficients	MDE	N
Panel A: Nudge effects - enrolled in a school that would have been:							
Suggested by Returns Treatment	0.113	0.059**	0.035	0.083**	0.196	0.092	626
	[0.317]	[0.029]	[0.034]	[0.036]			
Suggested by Returns Treatment, and higher quality than student's baseline preference	0.618	0.060	0.021	0.099**	0.082	0.141	626
	[0.487]	[0.040]	[0.047]	[0.046]			
Panel B: Type of school							
Private University	0.358	-0.062	-0.058	-0.066	0.857	0.140	626
	[0.481]	[0.038]	[0.044]	[0.044]			
Professional Institute	0.441	0.064	0.088*	0.04	0.327	0.145	626
	[0.498]	[0.042]	[0.048]	[0.049]			
Vocational training school	0.201	-0.002	-0.03	0.026	0.149	0.117	626
	[0.402]	[0.034]	[0.039]	[0.040]			
Panel C: Measures of returns for enrollment outcomes							
Log of wage bracket (midpoint)	13.325	-0.091***	-0.094**	-0.088**	0.875	0.126	624
	[0.434]	[0.035]	[0.041]	[0.040]			
Average employability	0.842	-0.011	-0.004	-0.018*	0.146	0.029	622
	[0.099]	[0.008]	[0.009]	[0.010]			
Years the program-career has existed	4.315	0.064	-0.002	0.129	0.449	0.512	624
	[1.760]	[0.148]	[0.169]	[0.174]			
Panel D: Cost of enrollment outcomes							
Log annual tuition	14.265	-0.026	-0.032	-0.019	0.719	0.110	624
	[0.379]	[0.031]	[0.037]	[0.035]			
Semesters duration	7.089	-0.157	-0.104	-0.211	0.631	0.663	624
	[2.278]	[0.188]	[0.220]	[0.217]			

Note: All regressions include stratum fixed effects (for gender and parental education). Column (2) presents coefficients from the pooled treatment; columns (3) and (4) present coefficients for the separate treatments. The set of controls include different baseline variables: expected PSU score and high school GPA. MDE is the minimum detectable effect size for each outcome, given sample design. In this case, MDE is the maximum MDE across both treatments; MDEs only differ in the third or higher decimal place for each outcome. Robust standard errors in parentheses.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$,

final two columns show the largest MDE associated with each of the separate ITT estimates and the sample size in each regression.

We first check to see whether our treatments nudged students towards choosing schools suggested in the emails. We know the names of the schools suggested in each respondent's returns treatment, and we can construct similar data for the other experimental groups who did not receive the returns treatment. We construct an indicator for whether the respondent enrolled in one of the schools that was (for the returns group) or would have been (for all other groups) suggested by the returns treatment. We construct another indicator that captures whether a student enrolls in a school that was (or would have been) suggested in the returns treatment and was of a higher quality than their preferred school at baseline. Recall, students did not know which quality tier the suggested schools came from, they only received a list of schools and associated average wages and employability.

Panel A shows that our returns treatment in particular nudged students in the direction of enrolling in schools suggested in the treatment emails. Among control students, 61% would have enrolled in a less selective school that would have been a good match for them in the returns treatment. Exposure to our information treatments raises this share by 6 percentage points. And, it is the returns treatment specifically that raises the share of students enrolled in a suggested school. Returns treatment students are also more likely to choose suggested schools of higher quality than their baseline preference, relative to the control group. The information about alternative schools seems to have stuck with students, despite low take-up rates.

Panels B, C and D present further evidence that the information treatments changed the types of schools chosen by students constrained to the less selective sector. In Panel B, we show that the information treatment (overall) appears to move students away from private universities and towards professional schools, although these effects in column (2) are not statistically significantly different than zero. Splitting up the treatment effects, we see that the financial aid only treatment moves students towards professional institutes. One potential explanation for this is that the personalized information on decentralized financial aid provided more information about funding in professional institutes, and therefore opened up opportunities in these schools, relative to private universities.

Panel C shows that exposure to both information treatments causes students to choose schools and careers offering around 9% lower expected average wages. They also tend to choose schools with lower average employability, although this effect is driven by the interaction of the returns and financial aid treatments. Results for tuition costs and duration of program in Panel D suggest that information treatment students choose shorter, cheaper programs, although these estimates are not statistically significant at conventional levels. The signs of the

Table 8
Heterogeneity in intensive margin impacts (Sub-sample of enrollees in less selective schools).

	Control mean [s.d]	Any financial aid treatment	Financial Aid Only Treatment	Financial Aid plus Returns	P-value of difference in treatment coefficients	MDE	N
Panel A: Low PSU < 475							
Enrolled in school that would have been	0.048	0.121***	0.093**	0.150***	0.277	0.094	287
suggested by Returns treatment	[0.214]	[0.037]	[0.044]	[0.047]			
Enrolled in school that would have been	0.643	0.102*	0.064	0.140**	0.226	0.213	287
suggested in Returns Treatment; higher quality	[0.482]	[0.062]	[0.070]	[0.068]			
Private University	0.226	-0.070	-0.046	-0.094*	0.378	0.186	287
	[0.421]	[0.052]	[0.061]	[0.056]			
Professional Institute	0.500	0.116*	0.148**	0.083	0.358	0.222	287
	[0.503]	[0.065]	[0.074]	[0.074]			
Vocational training school	0.274	-0.046	-0.101	0.010	0.063	0.198	287
	[0.449]	[0.059]	[0.064]	[0.068]			
Panel B: High PSU > 475							
Enrolled in institution that would have been	0.149	0.053	0.046	0.060	0.819	0.148	295
suggested in Returns Treatment	[0.358]	[0.047]	[0.057]	[0.056]			
Enrolled in school that would have been	0.608	0.008	-0.041	0.058	0.167	0.202	295
suggested in Returns Treatment; higher quality	[0.491]	[0.059]	[0.069]	[0.069]			
Private University	0.467	-0.002	-0.012	0.009	0.778	0.206	295
	[0.501]	[0.060]	[0.069]	[0.071]			
Professional Institute	0.383	0.028	0.058	-0.001	0.409	0.201	295
	[0.488]	[0.058]	[0.068]	[0.069]			
Vocational training school	0.149	-0.027	-0.046	-0.007	0.410	0.148	295
	[0.358]	[0.042]	[0.047]	[0.049]			

Note: All regressions include stratum fixed effects (for gender and parental education). Column (2) presents coefficients from the pooled treatment; columns (3) and (4) present coefficients for the separate treatments. The set of controls include different baseline variables: expected PSU score and high school GPA. MDE is the minimum detectable effect size for each outcome, given sample design. In this case, MDE is the maximum MDE across both treatments; MDEs only differ in the third or higher decimal place for each outcome. Robust standard errors in parentheses.

* $p < 0.1$.

** $p < 0.05$

*** $p < 0.01$

impact estimates for the expected returns and cost of enrollment outcomes make sense, given that exposure to the information treatments caused students to change enrollment patterns away from private universities towards professional schools (Table 7, Panel B). Professional schools tend to offer shorter degree programs, and result in lower average wages compared with similar programs in universities.

6.5. Who was nudged by the information treatments?

To understand more about how information is working to cause these intensive margin shifts, we would like to know whether students with the greatest misperceptions about earnings, and those with the least information about financial aid opportunities, respond the most to our treatments. Unfortunately, because of high item non-response rates in our baseline survey, we do not have good data on baseline earnings expectations or loan and scholarship probabilities for all students in the subsample of less selective school enrollees. This means we cannot explore heterogeneous effects with respect to baseline expectations/information.

To make some headway on this, we use the full sample of students to show that PSU score is highly correlated with non-response to the baseline question about expected earnings in one's preferred career-school program (Appendix Fig. 1). The PSU score is also correlated with the size of the gap between expected earnings and actual average earnings in a given school-career, for the sample of students who responded to the question (Appendix Fig. 2). Therefore, we interpret PSU score as a proxy of how much information students have, with lower scores indicating less information. We split the sample of less selective school enrollees into above and below median PSU scores (median is 475), and estimate results for school choice in this sample for the high and low PSU scorers.

Table 8 presents the results for outcomes describing whether students responded to the information nudge, and what type of school students enrolled in. Panel A shows results for the subsample of low PSU scorers, that is, those with the lowest quality information about earnings in their preferred career. Panel B shows the results for the subsample of high PSU scorers. We see immediately that the intensive margin effects on school choice within the less selective sector are driven by the low PSU scorers. Any financial aid treatment raises the chances of enrolling in a school suggested in the returns treatment by 12 percentage points, and although this is driven by the returns treatment (column (4)), some of the effect is also coming from the financial aid alone treatment. This is most likely because the set of alternative schools and programs suggested in the returns treatment overlapped with decentralized sources of financial aid for schools and programs similar to student baseline preferences that were provided by PUC. The low PSU scorers are also the ones switching out of private universities and towards professional institutes, in response to our information treatments. Because most of the professional institutes and vocational schools have no PSU requirement, it makes sense that the low PSU scorers would be able to respond to the new information by changing their intensive margin choices.

6.6. Discussion of cost effectiveness

One of the innovations of our project was to test the impact of tailoring information to student preferences in a way that is easily scaled at low cost. The cost of our intervention had three components: the cost of collecting student contact details (emails) at baseline, along with their baseline school and career preferences; the cost of delivering the tailored returns information; and the cost of delivering the tailored financial aid information.

The first cost would be incurred by any intervention seeking to deliver information via email.[28] The cost of the returns treatment consisted of a fixed cost of designing an algorithm that uses publicly available data to provide the tailored information treatment, and a variable cost of delivering this information. In our experiment, the former amounted to 2.68USD per treated student while the latter was basically zero. The cost of the financial aid treatment also had two components. There was a fixed cost associated with building and updating a database of decentralized financial aid opportunities. Like the fixed costs of the returns treatment, this cost would become negligible the more students are included in the intervention. The only variable cost that is relevant is the cost of compensating workers to match student preferences with financial aid opportunities and send the personalized emails. The NGO used volunteers to perform this task. We compute an upper bound for the cost of employing recent high school graduates to perform this task. Assuming that it takes a worker 30 minutes to search the database on decentralized financial aid to find matches with student preferences and populate an email template with this information, the cost per treated student would be 1.5USD (using the average wage of recent high school graduates).

Overall, relative to other interventions that distribute only general information via email, the cost of personalizing returns information is low, as long as there is a public database on wages and employment outcomes for schools and careers. The cost of personalizing financial aid information is somewhat higher since it requires labor to tailor the information to students.

7. Conclusion

We designed our project to test whether an inexpensive and scalable information intervention could improve access to higher education and affect enrollment choices made by students in an education system with both selective and less selective schools. Two main findings emerge in our analysis. First, we find no evidence that providing tailored information about financial aid and returns to students at the end of high school changes decisions about application or enrollment to higher education. There are no meaningful extensive margin effects in either the selective system or the less selective system. Second, we find the information treatments changed the types and characteristics of the less selective schools in which students enroll. Treated respondents shift out of private universities, towards professional schools, with students significantly more likely to choose to enroll in institutions suggested in the returns treatment. We provide suggestive evidence that the information treatments (specifically, the returns treatment) changed school choice behavior the most for students with the worst quality information on average returns at baseline.

These intensive margin changes have ambiguous implications for student welfare. While we might be concerned that a shift into programs and schools offering lower wages and employability would reduce student welfare, a shift towards shorter programs that charge lower tuition could have positive or negative effects on predicted net returns. This is even more likely to be the case if treated students were able to access private sources of financial aid at higher rates because of the financial aid treatment, an outcome we are unable to measure because it does not exist in any centralized administrative dataset. Without better data, we are unable to make general statements about the welfare effects of this information intervention.

Despite the problems with statistical power that we face given our small sample size and low take-up rates, this experiment adds to what we know about how information about higher education affects individual choices and outcomes in settings where two tiers of higher education coexist. The insights we generate may be important in many countries where the supply of less selective institutions of higher education has recently grown and where there is great heterogeneity in the quality of these institutions. Governments could still play a role in providing inexpensive and targeted information interventions to help marginal students better understand quality gradients and cost-benefit trade-offs in schools in the less selective sector.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.labeco.2016.11.001.

References

Banerjee, Abhijit, Paul Glewwe, Shawn Powers, Melanie Wasserman, 2013 Expanding access and improving student learning in post-primary education in developing countries: A review of the evidence, Abdul Latif Jameel Poverty Action Lab (J-PAL) Post-Primary Education Initiative Review Paper.

Bettinger, Eric P., Bridget Terry Long, Phillip, Oreopoulos, Sanbonmatsu, Lisa, 2012. The role of simplification and information in college decisions: results from the H & R block FAFSA experiment. Q. J. Econ. 127, 3.

Bobba, M., Frisancho, V., 2016. Learning about oneself: the effects of signaling ability on school choice. Inter-Am. Dev. Bank, Discuss. Pap. 450.

Brown, R.S, Lavecchia, A., Oreopoulos, P., Pathways to education: an integrated approach to helping at-risk high school students, J. Polit. Econ., forthcoming.

Carrell, S. Sacerdote, B., 2013. Late interventions matter too: The case of college coaching in New Hampshire, NBER Working Paper No. 19031, May

CASEN, 2013. Encuesta de caracterización socioeconómica nacional. Ministerio de Desarrollo Social (MSD), Santiago Chile.

Departamento de Evaluación, Medición y Registro Educacional (DEMRE), 2015. Compendio Estadístico Proceso de Admisión Año Académico 2014. Santiago, Chile.

Dinkelman, Taryn, Claudia, Martínez A., 2014. Investing in schooling in Chile: the role of information about financial aid for higher education. Rev. Econ. Stat. 96 (2), 244–257.

Dunn, Ryan, Oreopoulos, Phillip, 2013. Information and college access: evidence from a randomized field experiment. Scand. J. Econ. 115 (1), 3–26.

Hastings, Justine S., Jeffrey, M. Weinstein, 2008. Information, school choice and academic achievement: evidence from two experiments. Q. J. Econ., (1373-141).

Hastings, J., Neilson, C., Zimmerman, S., 2015. The effects of earnings disclosure on college enrollment decisions, NBER Working Paper Number 21300, June

Hoxby, C.Turner, S., 2013. Expanding college opportunities for high-achieving, low income students, SIEPR Discussion Paper No. 12-014

Jensen, Robert, 2010. The perceived returns to education and the demand for schooling. Q. J. Econ..

Kerr, Sari, Pekkala, Tuomas, Pekkarin, Matti, Sarvimäki, Uusitalo, Roope, 2014. Educational choice and information on labour market prospects: a randomized field experiment. Work. Pap..

Lavecchia, Adam M., Liu, Heidi, Oreopoulos, Philip, 2014. Behavioral economics of education: progress and Possibilities. Work. Pap. Prep. Handb. Econ. Educ..

Morgan, K., Rubin, D., 2012. Rerandomization to improve covariate balance in experiments. Ann. Stat. 40 (2), 1263–1282.

Nguyen, Trang, 2008. Information, Role Models and Perceived returns to Education: experimental Evidence from Madagascar. Abdul Latif Jameel Poverty Action Lab (J-PAL).

OECD, 2012. Quality Assurance in Higher Education in Chile - Reviews of National Policies for Education. OECD Publishing, Paris.

Rodríguez, Jorge, Sergio, S. Urzúa, Loreto, Reyes, 2015. Heterogeneous Economic returns to Postsecondary Degrees: evidence from Chile. J. Hum. Resour..

SIES, 2014. Panorama de la Educación Superior en Chile 2014. División de Educación Superior, Ministerio de Educación, Chile.

Solis, Alex, Credit access and college enrollment J. Political Econ., forthcoming.

[28] In our case, this was done through student career fairs and cost 1.8USD per student. In other settings, this cost would be incurred by a government collecting student contact

(footnote continued)
details through, for example, a loan application form.