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Abstract

In labor markets where disadvantaged students are discriminated against, merit-based college scholarships targeting these students could convey two opposing signals to employers. There is a positive signal reflecting the candidate's cognitive ability (talented in high-school and able to maintain a high GPA in college) as well as her soft skills (overcoming poverty). There is also a possible negative signal as the targeting of the scholarship indicates that the beneficiary comes from a disadvantaged household. We conduct a correspondence study to analyze the labor market impact of an inclusive education program. *Beca 18* provides merit-based scholarships to talented poor students admitted to 3-year and 5-year colleges in Peru. We find that the positive signal dominates. Including information of being a scholarship recipient increases the likelihood of getting a callback for a job interview by 20%. However, the effect is much smaller in jobs and careers where the poor are under-represented, suggesting that the negative signal of the scholarship is not zero.

Key words: Employment, inclusive education, correspondence study, discrimination.

JEL Codes: C93, I23, J7, J15.

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1. Introduction

Worldwide, students from disadvantaged backgrounds are largely under-represented in higher education (UNESCO, 2020; Ferreyra et al., 2017), despite the documented high skill earnings premium (Patrinos and Psacharopoulos, 2020; Goldin and Katz, 2008). This is more salient in developing countries, where returns to postsecondary education are higher and credit constraints are more pronounced than in advanced economies. New work has started to emerge on the role of financial aid and student loan programs on access to college for high-achieving low-income students in middle-income countries (e.g., Londoño-Vélez et al., 2020; Solis, 2017).[1] Yet, little is known about the labor market returns of these merit-based scholarships.

To address this gap, we study the labor market impact of a scholarship for talented but disadvantaged students in Peru. This program, called *Beca 18* ("Scholarship 18"), was created in 2011, and is the largest public program financing higher education in the country. *Beca 18* is a highly competitive scholarship. Only five percent of applicants receive it every year. It is also a very generous scholarship to attend selected public or private colleges in the country. It covers full tuition costs plus all living expenses, books, moving costs, a laptop, health insurance and academic tutors, if needed. To satisfy its mandate to reduce the socioeconomic gap in access to higher education in Peru, *Beca 18* targets students from the bottom two quintiles of the country's poverty assessment, in which indigenous groups are severely over-represented.

However, in labor markets where indigenous groups are discriminated against as in the case of Peru (e.g., Galarza and Yamada, 2014, 2017), a merit-based scholarship for disadvantaged students

[1] For research on these programs in advanced economies see for example Angrist et al. (2014), Bettinger et al. (2019), Fack and Grenet (2015).

could convey two possible signals to employers. First, there is a positive signal in terms of ability. A *Beca 18* beneficiary had to be a top student in high school to become eligible and to score very well in a qualifying standardized test and be admitted to a selective college to be awarded the scholarship. She had to maintain a high GPA during college as well. All these sends a signal of strong cognitive skills. Beneficiaries also had to overcome poverty, showing resilience as well as important "soft" skills. Second, there is a negative signal due to poverty and ethnicity. The targeting of the scholarship clearly indicates that the recipient comes from a disadvantaged household, which correlates with a lower social status and indigenous background. Thus, the impact of *Beca 18* to employers would depend on how the market values these two competing signals. If the ability signal is larger than the poverty signal, *Beca 18* will have a positive impact on employment. Otherwise, it would hurt candidates.

If beneficiaries *perceive* that the poverty signal dominates, they will avoid listing *Beca 18* in their resumes. We found evidence supporting this view. From a sample of resumes from actual beneficiaries, less than 5% listed the scholarship. Those who did it, place it as the last item in their resumes and without highlighting it. However, not including this award in their resume could be an inefficient behavior if employers value the ability signal much more than the poverty signal. Thus, we need to test how the labor market reacts to the *Beca 18* signal.

We implement a correspondence audit study to examine the impact of *Beca 18* on employment opportunities for technical (for 3-year college graduates) and professional occupations (5-year college graduates).[2] Nearly 3500 fictitious resumes were sent in response to 877 job ads in Lima,

[2] As explained below, Peru's high school education ends in grade 11 (not 12) and the higher education system has 3-year (technical) and 5-year (professional) colleges.

Peru's capital and largest labor market (concentrating 44% of the country's labor force). For each job we sent four resumes, randomly assigning all elements of the resumes, including the listing of *Beca 18*. These resumes mimicked those from true beneficiaries of *Beca 18* in terms of style and structure, except that we make the information about the scholarship salient. We find that listing *Beca 18* in the resume increases the likelihood to be called back for a job interview by 20%. This finding implies that the ability signal exceeds the poverty signal. Beneficiaries of *Beca 18* are leaving "money on the table" by not listing the scholarship in their resumes.

To understand better the role of each signal, we conducted a heterogeneity analysis dividing the sample by jobs, careers and place of residence. The intuition is that the negative signal from poverty will be less (more) salient in the subgroups where the poor are (under-) over-represented. We find evidence supporting this prediction. For example, we show that gains from listing *Beca 18* in the resume is concentrated among 3-year college graduates, where the poor are more likely to graduate from. The gains in callback rates increases to 39% in this subsample. For graduates from 5-year colleges, where the poor are under-represented, the effect is just 6% and not statistically different from zero. These findings suggest that the negative signal is not zero when the poor are underrepresented.

One potentially additional impact of *Beca 18* is the reduction of ethnic gaps, not only in terms of college enrollment and graduation rates, but also in labor market outcomes, a topic over which the literature is particularly scarce. Using surnames as an ethnic signal, we find that the return to *Beca 18* is the largest among job applicants with paternal *and* maternal indigenous surnames, a result suggesting a greater ethnic equality in the access to the labor market.

We contribute to two strands of the literature. First, the literature on the impact of financial aid and loan programs for higher education has largely focused on enrollment (see, e.g., Angrist et al. 2014; Bettinger et al. 2019, and Fack and Grenet 2015, for developed countries, and Londoño-Velez et al., 2020; Laajaj et al., 2018 and Solis, 2017, for developing countries). We contribute to this area of study, by examining how the labor market responds to a merit-based and need-based scholarship program. That is, we extend the analysis of the impact of these type of programs beyond college graduation, a topic over which the literature in developing countries is particularly scant.

Second, the fast-growing literature on correspondence studies (CS) has been widely used to detect ethnic and gender discrimination in the labor market, both in developed and developing countries (see Neumark, 2018 and Baert, 2018 for recent reviews). While their results are revealing, it is unclear from existing CS which policy prescription to use to increase employment opportunities for disadvantaged groups. This is particularly relevant since anonymous job applications do not seem to help as much, as Behaghel et al. (2015) shows for France. We evaluate the effect of an inclusive education policy on higher access to the labor market, as an alternative to using anonymous resumes. We posit that, while an affirmative action policy could reinforce discrimination (Coates and Loury, 1993), sending a signal of ability could address, at least partly, the issue, depending on how the poverty and ability signals are perceived in the labor market.[3] We are not aware of other CS examining this labor market effect of similar programs.

[3] We focus on hiring because this program is too young as to analyze other labor market outcomes, such as its impact on wages. This extension to analyze the human capital impact of the program is an important topic for future research.

The remainder of the paper proceeds as follows. Section 2 provides information about the *Beca 18* program (coverage, requirements, and outreach). Section 3 presents our experimental design. Section 4 introduces our data. Section 5 discusses our results and section 6 concludes.

2. *Beca 18* program

Created in late 2011, *Beca 18* began to operate the following year as the first full scholarship program for higher education funded by the national government in Peru.[4] With the aim to reduce the poor's unequal access to higher education, *Beca 18* funds full tuition and related expenses of young talented students coming from poor households who have been admitted to selective private and public universities (5-year college degrees) and technical institutions (3-year college degrees). *Beca 18* granted 65.826 scholarships from 2012 to 2019, with some changes in administrative issues of the application but keeping its focus on talented students from disadvantaged backgrounds. About two thirds of the scholarships were granted to fund 3-year technical degrees.

All Peruvian nationals attending—or graduated from—a public high school, interested in applying for a scholarship need to pass a pre-selection process, summarized in Appendix Figure 1. The eligibility criteria is based on age (under 22), household poverty condition (verified by SISFOH, the national system of household targeting for social programs), and academic merit (top third in GPA in the last two years prior to their application).[5] In addition, *Beca 18* pre-candidates must take a national test of math and reading comprehension, in order to qualify for the final round. The final ranking considers test scores plus some bonus points awarded to applicants in priority

[4] Prior to *Beca 18*, PRONABEC, the Ministry of Education office in charge of administering the program, had only had short-term loans financing tuition expenses for less than a year.
[5] Students can apply during their senior year (11^{th} grade) but also after high school graduation as long as they are younger than 22.

situations including indigenous groups.[6] As shown in Appendix Figure 1, using numbers from the 2019 process, only about one tenth of applicants (4,539 out of 43,906) made it to this stage, given the budget constraint of the program. An additional third of applicants were eliminated in the final round of the process, considering admission and quality of the colleges and careers chosen.[7] Only 3,139 scholarships were ultimately granted that year, yielding a success rate of 5.19%.

Beca 18 covers full tuition costs of attending a public or private 3-year or 5-year colleges. It also covers course materials, tuition to study English (only for 5-year colleges), academic tutoring, and a laptop, in addition to health insurance, living expenses (food, housing), local transportation, and a round-trip ticket to the place of residence, if applicable.[8]

Merit-based higher education scholarships targeting to the poor are also available in other Latin American countries, such as Brazil, Chile, Colombia, and Costa Rica, though we are not aware of studies of the effect of those scholarship programs on labor market access. Table 1 summarizes the characteristics of relatively large public programs for higher education scholarships in the region. With 84.8 U.S. million dollars of budget spent in 2019, *Beca 18* ranks first in terms of relative fiscal effort devoted to finance the program (0.27% of central government budget), though

[6] Other criteria rising eligibility are disability, active firefighter (or children of firefighter), volunteers registered by the Ministry of Women and Vulnerable Populations, farmers, and Afro-descendant population.

[7] Quality indicators include the college ranking (which is based on scientific production, faculty with undergraduate or graduate degrees, and instructor/student ratio), graduation rates, and average wages of graduates. All these indicators are used to construct a list of prioritized colleges, whose ranking is used to award the bonus points for college quality. In terms of careers, bonus points are awarded in direct relationship to their economic returns, and to whether those careers belong to areas of science and technology prioritized in the 2006-2021 National Strategic Plan of Science, Technology, and Innovation for the Competitiveness and Human Development (life sciences, biotechnology, material technology and science, information and communication technologies, environmental science, and basic sciences—mathematics, chemistry physics, biology, geology, and geophysics).

[8] A significant proportion of the scholarship recipients are born in a rural place and choose to migrate and study in a college located in Lima. As of 2016, only 13% of the recipients reside in Lima but 53% of all recipients chose to attend a college in Lima.

it is the smallest program in the sample, both, in terms of absolute numbers of beneficiaries (15.619 in 2019) and relative to total enrollment in higher education (0.87%).

Table 1: A Sample of Government-Funded Higher Education Scholarship Programs in Latin America

Program	Country	General Qualification Requirements	Number of Beneficiaries (Latest Year Available)	Number of Beneficiaries / Total Higher Education Students (%)[a]	Annual Government Expenditure on the Program (millions of U.S. dollars)	Program Expenditure / Central Government Expenditure (%)
ProUni	Brazil	1) Gross family income of up to 3 minimum wages. 2) Minimum score in the Exame Nacional do Ensino Médio.	224,921 (2019)	2.66	549.4	0.09[b]
Beca Bicentenario	Chile	1) Belong to bottom 70% of household income distribution. 2) Minimum score in the University Selection Test. 3) Be enrolled in an eligible institution and educational field.	34,755 (2017)	5.27	140.5	0.22
Ser Pilo Paga	Colombia	1) Be registered in the System of Selection of Beneficiaries for Social Programs (SISBEN). 2) Minimum score in the national test "Saber 11". 3) Be admitted in an eligible institution.	40,000[c] (2018)	1.79	253.9	0.04
Beca Universitaria	Costa Rica	1) Poverty or extreme poverty condition accredited by SINIRUBE. 2) High academic performance (last period grades). 3) Be enrolled in an institution and in a career recognized by CONESUP.	4,522 (2019)	2.17	5.9	0.15
Beca 18	Peru	1) Poverty or extreme poverty condition accredited by SISFOH. 2) Top third in GPA in last two years of secondary education and minimum score in the pre-selection test. 3) Be admitted in an eligible institution and educational field.	15,619 (2019)	0.87	84.8	0.27

Sources: Banco Central do Brasil, Ministério da Educação (Brazil), Ministério da Economia (Brazil), Banco Central de Chile, Ministerio de Educación (Chile), Consejo Nacional de Educación (Chile), Ministerio de Hacienda (Chile), Superintendencia Financiera de Colombia, Ministerio de Educación (Colombia), Ministerio de Hacienda y Crédito Público (Colombia), Banco Central de Costa Rica, FONABE, Programa Estado de la Nación (Costa Rica), Ministerio de Hacienda (Costa Rica), SBS, Ministerio de Economía y Finanzas (Peru), PRONABEC, SUNEDU, Ministerio de Educación (Peru), and World Bank (2019).

Notes:

[a] In the case of Brazil, Costa Rica and Peru, the figures for total student population are of 2018, 2015 and 2016, respectively.

[b] The central government expenditure figure is of 2018. In the first three quarters, spending in 2018 is similar to that of 2019.

[c] Target number according to government announcements.

There are several potential effects that a scholarship program such as *Beca 18* can have. In the short-term, it can increase higher education enrollment rates for ethnic minorities (indigenous and afro-descendants) and it may also increase graduation rates (thus increasing human capital accumulation). In the medium-term, the program may increase access to the labor market for poor people. And in the long run, it may ultimately reduce the ethnic income gap. We study the effect of *Beca 18* on the increase in employment opportunities. As described before, we posit that being recipient of *Beca 18* sends (at least) two signals to the market: the job applicant is talented (positive signal) but poor (negative signal). In this framework, the impact of *Beca 18* on the labor market will depend on how employers read those signals: if the ability signal is stronger (weaker) than the poverty signal, *Beca 18* will have a positive (negative) effect on hiring chances.

3. Experimental design

We use a paired correspondence study design and sent four resumes in response to each selected job ad. We use the resume randomizer by Lahey and Beasley (2009), v.31, to construct all resumes, whose format and structure mirror those used by real *Beca 18* recipients obtained thanks to PRONABEC.[9] Two key variables for the experimental operation include the allocation of being recipient of *Beca 18* and surnames, our major ethnic signal. Randomly assigned, two resumes indicated the job applicant had received *Beca 18*, while the remaining two did not. In terms of the surnames, each full name in the resume included a paternal and maternal surname, as is common in Peru.

[9] We did not include photographs in our resumes, which is not uncommon in Peru.

As explained below in more detail, we have four equally likely combinations of paternal-maternal names by combining indigenous and mixed-race surnames: Indigenous-Indigenous (I-I), Mestizo-Indigenous (M-I), Indigenous-Mestizo (I-M), and Mestizo-Mestizo (M-M). In terms of gender, each resume had a 50% chance of listing a woman's name, from a common pool regardless of the type of surnames.[10] All selected jobs were either for technical (requiring a 3-year college degree) or professional (5-year degree) occupations. We did not select low-skilled occupations as we focus on college graduates.

3.1 Beca 18 and education

Half the resumes (per batch) sent to a job included the *Beca 18* signal. We did this by assigning two possible wordings (randomly). The first wording said verbatim "Premios: Beca 18 (PRONABEC)" (Awards: Beca 18 (PRONABEC)). The second said "Beneficiario del Programa Nacional de Beca18 – PRONABEC" (Beneficiary of the National Program Beca 18 – PRONABEC). We use the male variation for "becario" in all resumes. While not gender neutral, this is a common practice in Peru. The selected statement was listed right below the name of the college assigned to the resume. We used administrative data to select the 3-year colleges—called Institutos de Educación Superior, or *Institutos*, for short—and the 5-year colleges (called *universidades*). This selection, as well as that of the college majors, largely responded to the characteristics of the job vacancies posted.[11] We further gathered information about whether the college and/or major was prioritized or not prioritized by the National Program of Scholarships

[10] To our best knowledge, the performance of mestizos in labor access has not been analyzed elsewhere, with the only exception of Arceo-Gomez and Campos-Vasquez (2014) for Mexico.
[11] The set of majors financed by *Beca 18* is sufficiently broad as to not impose a constrain in the set of occupations matched with the job vacancies available every week.

and Education Loans (PRONABEC, for its acronym in Spanish), the public office from the Ministry of Education running the *Beca 18* Program.

3.2 Signaling indigenous status

In Peru, as in many other Latin American countries, the use of two surnames (paternal and maternal, in that order) is widespread, for official identification purposes and also for job applications. In the latest population census, around a quarter of the population self-identifies as indigenous, with Quechua and Aimara being the largest groups among them. These groups have distinctive surnames and have been used in the literature before (e.g., Galarza and Yamada, 2014, 2017).

We used two ways to signal indigenous status: surnames and whether the job applicant went to a high school in a province outside of Lima, which is more likely to be populated by a larger share of indigenous people. In the case of surnames, an innovation of our experiment is that we can assess different degrees of our indigenous status on callbacks. In particular, we selected Indigenous (I) and *mestizos* (mixed race) (M) surnames and created four combinations of paternal - maternal surnames: M-M, M-I, I-M, and I-I (See Figure 2). We thus can compare the *mestizo* job applicant (M-M) with an Indigenous job candidate of any of the three types (paternal only: I-M, maternal only: M-I, or both: I-I).

Our second signal is the high school graduation in an Indigenous/rural place (a province outside of Lima). Except for the M-M category, in the remaining three categories, each resume had a 2/3 chance of including the name of a high school located in a province, outside Lima. This signal may be considered a weaker signal of Indigenous status. To maximize our statistical power in the innovative aspect of our study, we sent four resumes for each job ad, each with one of the four combinations of surnames mentioned earlier.

Figure 2. Structure of the four resumes sent to a job ad

A Resume *Mestizo* *Address and contact information* *Brief personal statement* College signal (Beca 18/No Beca 18) High School signal (Lima) Job 1 Job 2 Other skills	B Resume Indigenous (paternal only) *Address and contact information* *Brief personal statement* College signal (Beca 18/No Beca 18) High School signal (Lima/Province) Job 1 Job 2 Other skills
C Resume Indigenous (maternal only) *Address and contact information* *Brief personal statement* College signal (Beca 18/No Beca 18) High School signal (Lima/Province) Job 1 Job 2 Other skills	D Resume Indigenous (paternal and maternal) *Address and contact information* *Brief personal statement* College signal (Beca 18/No Beca 18) High School signal (Lima/Province) Job 1 Job 2 Other skills

The surnames used in this experiment come from a random sample drawn from the full list of surnames from real recipients of *Beca 18*. To construct the identities, we first classified the surnames of these recipients as Indigenous (I) and *Mestizos* (M) and, then, took a random sample without replacement of 400 surnames (200 I and 200 M), to construct 200 unique (and fictitious) combinations of paternal + maternal surnames, which are used in resumes. Sample surnames include Aylas, Ccori, Huasasquiche, Incahuamán, Mallqui, Ñahuin, Pomasoncco, Quispe, Rimaycuna, Sayritupac, Vilca, and Ynga, for Indigenous; and Alvarado, Baldeón, Castro, Delgado, Espejo, Fuentes, Hurtado, Mora, Porras, Segura, Valencia, and Zavala, for *Mestizos*. It is worth mentioning that we did not find any Anglo-Saxon surname in the administrative data of the program, so we decided to use only Indigenous and *Mestizo* surnames.

We validated our selection of surnames by conducting a survey with 82 freshmen undergraduate students. For each surname, they chose one of these three categories, *Mestizo*, Indigenous, or Other. Of our 100 Indigenous surnames, students considered them as such 85%; and 76% for the 100 *Mestizo* surnames. Our validation rates are in line with the findings from Button and Walker (2020) for Native Americans in the United States.

3.3 Age and given names

The age of the job applicant, inferred from the year of graduation from high school, was set in the early 20s. We used common a pool of first and middle names (e.g., Juan, María), which were randomly assigned without replacement, using a common basis for each of the four groups created from the surnames. Then, for each of the four elements of a job applicant's full name (2 given names + 2 surnames) the random assignment was without replacement. This allowed us to create 200 unique full names where no name appears more than once in any of the four elements (first name, middle name, paternal surname and maternal surname).

3.4 Brief personal statements

As common in Lima’s labor market, every resume included a statement summarizing the profile of the job candidate in the form of a brief personal statement. They were randomly assigned, without replacement, from a set of eleven gender neutral statements.

3.5 Residential addresses, e-mail addresses and telephone numbers

We created a database with 200 addresses, which were assigned at random with no replacement, every time we constructed the four resumes for each selected job ad. Moreover, for each of the 200 identities, we created an email account, using one of the following four randomly chosen formats:

(i) PaternalSurname.GivenName

(ii) PaternalSurname.MaternalSurname.GivenName

(iii) PaternalSurname.MaternalSurname10.GivenName

(iv) PaternalSurname.MaternalSurname.GivenName10

Every set of four resumes sent to each job ad was randomly drawn from those choices. We used (four) unique cellphone numbers for each job applicant in response to a job ad. Each cellphone was assigned to one of our research assistants. Our assistants were instructed to answer phone calls and e-mails and register the information of the successful candidates.[12] All invitations for an interview were promptly declined, to reduce the costs to the employers.

3.6 Job history

Job applicants have two entries for work experience in their resumes: past and current (all of them have been working during their last year in college), for a total of 2 to 3 years. These work experiences are specific to each job vacancy (we have at least 4 of them to be allocated to each

[12] Unlike other countries, setting up voice mails would not work in Peru, as callers almost never leave voice messages. WhatsApp messages are also extremely unusual as a way of contacting our job applicants.

entry), were adapted from real work experiences posted online for similar occupations and were randomly assigned to each job applicant.

3.7 Other information

English and Computing Skills: All resumes include a final section with information on the level of English and computing (Microsoft Office) proficiency. These levels were set at intermediate for the general case but were adjusted as requested by the job vacancy. All four job applicants for a given job ad, displayed the same level of proficiency, with the only change being the presentation format and wording. We further added any occupation-specific software requested in the job listing.

Formatting: Resumes vary independently and without replacement (when there are at least four choices) according to the four font types (e.g., Arial, Times New Roman), the alignment of the header with the name, residential address, email address and telephone (right, left, centered), heading of each section (e.g., education, work experience, other skills), heading format (in blue, in black, underlined, centered). Our database registers the type of format used for each resume sent.

4. Data

4.1 Sample size

We sent 3,548 resumes between July 2019 and March 2020,[13] in response to 887 job vacancies selected from help-wanted sections of newspapers in Lima, Peru. Power analysis suggested to send at least 2,210 resumes in order to detect a minimum effect of 0.07, for an intra-conglomerate correlation of 0.1, a significance level of 0.05 and a power of 0.8. Correcting that figure for the loss of variance resulting from sending more than one resume for each job listing (as in Lahey and Beasly, 2018) yielded a sample size of 2,873. Given that this power calculation uses as a reference studies for Peru that compare Whites with Indigenous, but we are comparing *Mestizos* with Indigenous (an effect more difficult to detect), our sample size required an additional upward adjustment.

4.2 Occupations

In terms of the occupations selected, we have a much broader types of jobs relative to most of the field experimental literature (as reviewed by Neumark, 2018 and Baertl, 2018). These are shown in Appendix Table 2 and largely responds to what the labor market demands. These occupations correspond to two types of jobs: technical (54% of our sample) and professional jobs (46%).

4.3 Identifying job ads

We identified potential job ads from the job listings published in two popular newspapers in Lima, *El Trome* and *El Comercio*, which print hundreds of ads from all economic activities. We did not restrict our selection to any particular occupational category. However, we excluded job ads that required in-person delivery of the resume or asked to include salary expectations in the resume.

[13] We had to stop the data collection due to the Covid-19 pandemic, when the Peruvian government declared a national lockdown. Part of our plan was to examine recruiters' hiring preferences, in order to better understand our empirical results.

We also excluded ads for advanced managerial positions and rather focused on entry-level jobs, with up to three years of work experience, in almost all cases for a recent graduate. Appendix 3 shows a complete batch (four resumes) sent in response to a graphical design position.

4.4 Emailing resumes

Resumes were electronically sent between Monday afternoon and Thursday morning each week (with a few exceptions) using *Thunderbird*. We used its "Send later" extension to schedule the sending of emails at different times of the day. Copies of all incoming went to a master email account, to keep a record of each submission. We only sent resumes for one job listing per firm or employer. Every email sent in the batch of four had a different opening, body, and closing, to ensure that employers would not notice these job applications were related. Text in the email was short, standardized and gender neutral.

4.5 Coding responses

We coded responses as positive ("We are calling to set a job interview"), ambiguous ("Could you please send a copy of your ID") or negative ("Thanks for your application, but we have filled the position"). For the analysis in this paper, we consider only positive responses as callbacks.

4.6 Balance tests

Appendix Table 4 shows that the randomization of each element of the resumes was successful across treatment and control groups, that is, comparing resumes with and without the *Beca 18* statements. Out of 371 variables, less than 2% of them (7 variables) are unbalanced at the 5%

significance level. None remain unbalanced when accounting for multiple hypothesis testing using FDR-q adjustments of the p-values.

5. Methodology

We estimate the following equation, using Ordinary Least Squares (similar results are obtained using *Probit* models):

$$Callback_{ij} = \beta_0 + \beta_1 Beca\ 18_{ij} + \beta_C Controls_{ij} + \alpha_j + \varepsilon_{ij}, \qquad (1)$$

where $Callback_{ij}$ is equal to one if resume i received a callback in response to job ad j; $Beca18_{ij}$ equals 1, if the resume included a statement about being recipient of such scholarship; $Controls_{ij}$ is a vector of controls, for which we have three versions: (i) no controls; (ii) regular controls, which include controls at the individual level—sex, ethnicity (3 categories of surnames: Indigenous–Indigenous, Indigenous–Mestizo, and Mestizo–Indigenous, with Mestizo–Mestizo, as the base category), district of residence (to control for the socioeconomic status of the job applicant), type of occupation (technical or professional), whether the applicant graduated from a high school located in an indigenous location, or in Lima, and the phone number used in the job application—and job level—whether the major was prioritized and whether the college was prioritized[14]—in addition to the week the job was posted; and (iii) full controls (which adds controls at the resume level: format and style). We further include job ad fixed effects, α_j, and correct the standard errors for clustering at the resume level in all specifications.

[14] We use indicator variables for these two cases.

6. Results

6.1. Aggregate effect of Beca 18

We first examine the mean (raw) callback rates by *Beca 18* status, for each category of interest. As Table 3 shows, the callback rates for job applicants that indicated to be recipients of *Beca 18* in their resumes are higher than for those who did not (the former receives 20% more callbacks than the latter). And this "*Beca 18* effect" holds for all Indigenous categories considered (surnames and place of origin) and both genders, though the sample size for each category outlined below does not always allow to get statistical significance.

Table 3: Mean callbacks by ethnicity

	N	Total	*Beca 18 Recipient*	*Beca 18 Non-Recipient*	Difference (p-value)[1/]
Indigenous Signals					
A. Surnames (Paternal — Maternal)					
Indigenous—Indigenous	887	10.03	9.05	11.01	0.3310
Mestizo—Indigenous	887	9.02	8.33	9.74	0.4633
Indigenous—Mestizo	887	11.72	9.93	13.44	0.1048
Mestizo—Mestizo	887	10.60	10.38	10.81	0.8363
B. Place of Origin					
Rural High School	1559	10.58	9.52	11.62	0.1781
Lima High School	1989	10.16	9.33	11.00	0.2195
Gender					
Female	1798	11.96	11.27	12.65	0.3661
Male	1750	8.68	7.48	9.87	0.0752
Total	3548	10.34	9.41	11.27	0.0689

[1/] Two-sided test p-value.

The effects indicated above do not account for clustering nor do they control for the type of college, occupation, or district of residence. This is addressed in Table 4, which reports the *Beca 18* estimates from Equation (1). The estimate with no controls (column 1) shows that a resume listing

Beca 18 has a higher chance of receiving a callback for a job interview than a similarly-qualified resume not listing the scholarship. The *Beca 18* premium is meaningful as it increases in 20% the callback (=0.019/0.094). Adding candidate controls (column 2), job controls (column 3), and indicator variables for the week the job was posted (column 4) confirms the 20% difference in callbacks. The specification in column 4, which includes the regular controls, is our preferred one, and will be used in all remaining estimations.

Table 4: Regression results on callbacks

	(1)	(2)	(3)	(4)	(5)
Beca 18	0.019^{**}	0.019^{**}	0.019^{**}	0.019^{**}	0.020^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Randomized Inference: p-value	[0.014]	[0.009]	[0.012]	[0.016]	[0.010]
Candidate controls	No	Yes	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes
Week fixed effects	No	No	No	Yes	Yes
Resume controls	No	No	No	No	Yes
Adjusted R^2	0.481	0.485	0.486	0.486	0.484
Mean control (callback for *Beca 18* non-recipients)	0.094	0.094	0.094	0.094	0.094
N	3548	3548	3548	3548	3548

Notes: *Candidate controls* include sex, ethnicity, district of residence, type of occupation; *Job controls* include indicators for prioritized major and college; *Resume controls* include several resume's format and style indicators (personal statements, headings style, font types, personal information style). All specifications include a constant term and job ad fixed effects. Robust standard errors (in parenthesis) are clustered at the resume level. P-values using randomized inference (with 1000 repetitions) in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Furthermore, our estimates are robust to the inclusion of full controls (column 5); in fact, doing so only increases the magnitude and significance of our estimate (yielding a 21% difference in callbacks). Additional robustness checks include the use of clustered standard errors at the job ad level, as in Lahey and Beasley (2009), Button and Walker (2020) and Beam et al. (2020), and applying randomized inference, as in Young (2019) and Imbens and Rubin (2015). Our main results are robust to those alternative estimations (see Appendix Table 5 for results with clustering at the job ad level, and row 3 in Table 4 for the randomized inference's p-values).

To put our *Beca 18* coefficient estimate (20%) in perspective, it is equivalent to 44% of the premium from graduating from the top six colleges in our sample (Pontifical Catholic University of Peru—PUCP, National University of Engineering—UNI, Peruvian University Cayetano Heredia—UPCH, Southern Scientific University—UCSur, TECSUP, and the National Service of Training in Industrial Work—SENATI).[15] An additional comparison of our estimate with a related study (Galarza and Yamada, 2017) indicates that it may help reduce the beauty gap in employment access by 25% and the racial gap by 37%, though in that study the ethnic groups under scrutiny were Whites and Indigenous, both defined as having the paternal and maternal surnames from the referred category. All these findings indicate that the ability signal of Beca 18 dominates the negative poverty signal.

6.2 Heterogenous effects

To understand the relative role of the ability and poverty signal of Beca 18 we divide the sample in different groups according to where the poor are over- or under-represented. Our hypothesis is that the poverty signal will be larger in jobs, careers and for groups where the poor are under-represented. We start with splitting the sample by college type: 5-year vs. 3-year. There is a marked difference between universities (5-year colleges) and *Institutos* (3-year colleges), in terms of average tuition costs. With figures for 2015, the total average tuition cost of attending an *Instituto* in Lima was PEN 73.328 (equivalent to USD 21,500 at that time), PEN 162.883 for private

[15] Those colleges score within the top 10 universities and the top 5 *Institutos*, as of 2018 (SUNEDU, 2018).

universities, and PEN 80.759 for public universities (Apoyo, 2015). Specially comparing *Institutos* and private universities, this difference in tuition costs, may indicate a disparity in the socioeconomic status of the student population. This is further confirmed with data from representative household surveys. Students from low-socioeconomic status families are 2.8 times more likely to graduate from a 3-year college relative to a 5-year college. For students from high-socioeconomic status families the ratio is 0.25. [16] Thus, we expect the Beca 18 callback premium to be larger for candidates from 3-year colleges. This is shown and confirmed in Table 6.

Table 6 presents estimates from estimating equation (1) by type of college: for 3-year colleges (*Institutos*) and 5-year colleges (universities). Column 1 reports the estimate for all sample, for comparison. In column 2, when restricting the sample only to *Institutos* is there a significant effect: graduates from *Institutos* that received *Beca 18* increase their chances to get a callback by 39.2% (=0.031/0.079) relative to those without a scholarship. In the case of universities, column 3, though those graduates with a *Beca 18* receive 6.2% more callbacks (=0.007/0.112) than those without such scholarship, the coefficient is not statistically significant. This result suggests different dynamics within each segment of the labor market, with the ability signal prevailing over the poverty signal in the case of *Institutos*.

[16] We use data from the Peruvian National Household Survey (ENAHO, for its acronym in Spanish), which provides socioeconomic information, representative at the region level. We pooled the surveys from 2009 to 2019, for the population between ages 22-35, with some college education (complete or not), but no longer enrolled in college (dropouts or graduates). We further restricted the sample to those living with their parents (for ages 22-25, roughly 70% of them lived with at least one parent). The reported figures correspond to Metropolitan Lima. Low (high) socioeconomic status refers to the lowest (highest) quintile of parents' schooling, since schooling is highly correlated with poverty.

Table 6: Effects by college type: 3-year and 5-year

	(1) All	(2) 3-year college	(3) 5-year college
Beca 18	0.019**	0.031***	0.007
	(0.007)	(0.010)	(0.011)
Randomized Inference: p-value	[0.016]	[0.002]	[0.539]
Adjusted. R^2	0.486	0.410	0.561
Regular controls	Yes	Yes	Yes
Mean control (callback for *Beca 18* non-recipients)	0.094	0.079	0.112
N	3548	1903	1645

Note: All specifications include a constant term and job ad fixed effects. All specifications include a constant term and job ad fixed effects. Robust standard errors (in parenthesis) are clustered at the resume level. P-values using randomized inference (with 1000 repetitions) in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PRONABEC, the Peruvian government office administering the *Beca 18* program, has a list of prioritized colleges and careers that is used at every scholarship call. The criteria used for this prioritization are broadly based on quality indicators (see notes to Appendix Figure 1, for details). Yet, the poor are under-represented in these colleges and careers. Table 7 reports the estimates breaking the sample by these categories. As seen below, the effect of *Beca 18* for non-prioritized colleges is 58.5%, while that for prioritized colleges is 20.0%. This result is consistent with our prior findings.

Table 7: Effects by college type: prioritized and non-prioritized

	(1) All	(2) Prioritized	(3) Non-prioritized
Beca 18	0.019**	0.018**	0.072**
	(0.007)	(0.008)	(0.036)
Randomized Inference: p-value	[0.016]	[0.030]	[0.023]
Regular controls	Yes	Yes	Yes
Adjusted R^2	0.486	0.483	0.558
Mean control (callback for *Beca 18* non-recipients)	0.094	0.090	0.123
N	3548	3114	434

Note: Robust standard errors (in parenthesis) are clustered at the resume level. All specifications include a constant term and job ad fixed effects. P-values using randomized inference (with 1000 repetitions) in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 8 we split the sample by the district of residence (in Lima city) assigned to the resume. Using the 2017 Poverty Map at the district level (INEI, 2019), we classify districts as poor (below the median) and affluent (above the median). Again, we continue to see a larger callback premium when the candidate resides in the randomly assigned poorer districts. A much smaller callback premium and not statistically significant is observed in the affluent districts. In Appendix Table 9 we further divide the sample by this poverty level and by type of college. We find that the bulk of the effects come from job candidates from poorer districts who graduated from 3-year colleges. Overall, these results validate the hypothesis that the callback premium for *Beca 18* is larger for candidates where the poor are over-represented. This suggests that the negative signal of the scholarship is not zero.[17]

[17] Effects by gender are shown in Appendix Table 10. We find no difference in the *Beca 18* premium by gender.

Table 8. Effects by place of residence

	(1) All	(2) Poorer districts	(3) Affluent districts
Beca 18	0.019**	0.028***	0.010
	(0.007)	(0.010)	(0.022)
Randomized Inference: p-value	[0.016]	[0.004]	[0.586]
Regular controls	Yes	Yes	Yes
Adjusted R^2	0.486	0.515	0.424
Mean control (callback for *Beca 18* non-recipients)	0.094	0.086	0.110
N	3548	2320	1228

Note: All specifications include a constant term and job ad fixed effects.
Robust standard errors (in parenthesis) are clustered at the resume level. P-values using randomized inference (with 1000 repetitions) in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Beca 18 targets students from poor families. And poverty and ethnicity are correlated in Peru, with Indigenous being among the poorest of the poor. To examine whether the return to *Beca 18* differs by surname type, we add an interaction term to equation (1):

$$Callback_{ij} = \beta_0 + \beta_1 Beca\ 18_{ij} + \beta_S Surname\ Type_{ij} + \beta_{SB} Surname\ Type_{ij} * Beca\ 18_{ij} + \beta_C Controls_{ij} + \alpha_j + \varepsilon_{ij}, \qquad (2)$$

where: *Surname Type* is a vector that includes three categories (Indigenous – Indigenous, Indigenous – Mestizo, and Mestizo – Indigenous). From this equation, estimated for all sample, 3-year and 5-year colleges, we recover the estimates of interest, reported in Table 11. Those returns are relative to the average callback on non-recipients of *Beca 18*. Considering column 1, we see that job applicants, recipients of *Beca 18*, with paternal and maternal Indigenous surnames receive 37.7% more callbacks than applicants without *Beca 18*. This aggregate effect comes from the returns received by graduates from *Institutos*, where such return is 66.5% (column 2). Further note that the point estimate for Indigenous-Indigenous surnames is the highest among the four surname types, for the entire sample and each type of college, a result that suggests *Beca 18* could help reduce ethnic gaps in access to employment opportunities, at least for 3-year colleges.

Table 11: Returns to *Beca 18* by surname type

Paternal – Maternal Surnames	(1) All	(2) 3-year college	(3) 5-year college
Indigenous – Indigenous	0.377**	0.665**	0.226
	(0.179)	(0.301)	(0.219)
Indigenous – Mestizo	0.022	-0.200	0.177
	(0.189)	(0.314)	(0.231)
Mestizo – Indigenous	0.129	0.540*	-0.166
	(0.184)	(0.307)	(0.224)
Mestizo – Mestizo	0.258	0.558*	0.019
	(0.183)	(0.310)	(0.219)
Adjusted R^2	0.485	0.411	0.560
Mean control (callback for *Beca 18* non-recipients)	0.094	0.079	0.112
N	3548	1903	1645

Note: All specifications include a constant term and job ad fixed effects.
Robust standard errors (in parenthesis) are clustered at the resume level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7. Conclusion

Students from poor families in developing countries are largely under-represented in higher education. And Peru is not an exception: while there is almost no difference in access to primary education by household income levels, there is a 15 percentage points gap in access to secondary education between the richest quintile and the poorest quintile, and this gap increases to 44 percentage points in the case of higher education. One of the policies implemented by the governments in developing countries to reduce such inequality has been the creation of financial aid and student loan programs. We evaluate the effect of the need-based and merit-based *Beca 18* program, which grants scholarships to attend 3-year and 5-year colleges in Peru. We find a significant effect of *Beca 18* on employment opportunities for poor, talented students. This suggests that the ability signal dominates the poverty signal. Large callback premiums among the poor suggest that the poverty signal is not zero. We further observe that the *Beca 18* effect is the largest for job applicants with both paternal and maternal Indigenous surnames. Taking our results in perspective, scaling-up this merit-based scholarship program would allow to reduce not only the socioeconomic gaps in college enrollment, but also the income ethnic gaps among college graduates (a result to which our paper relates).

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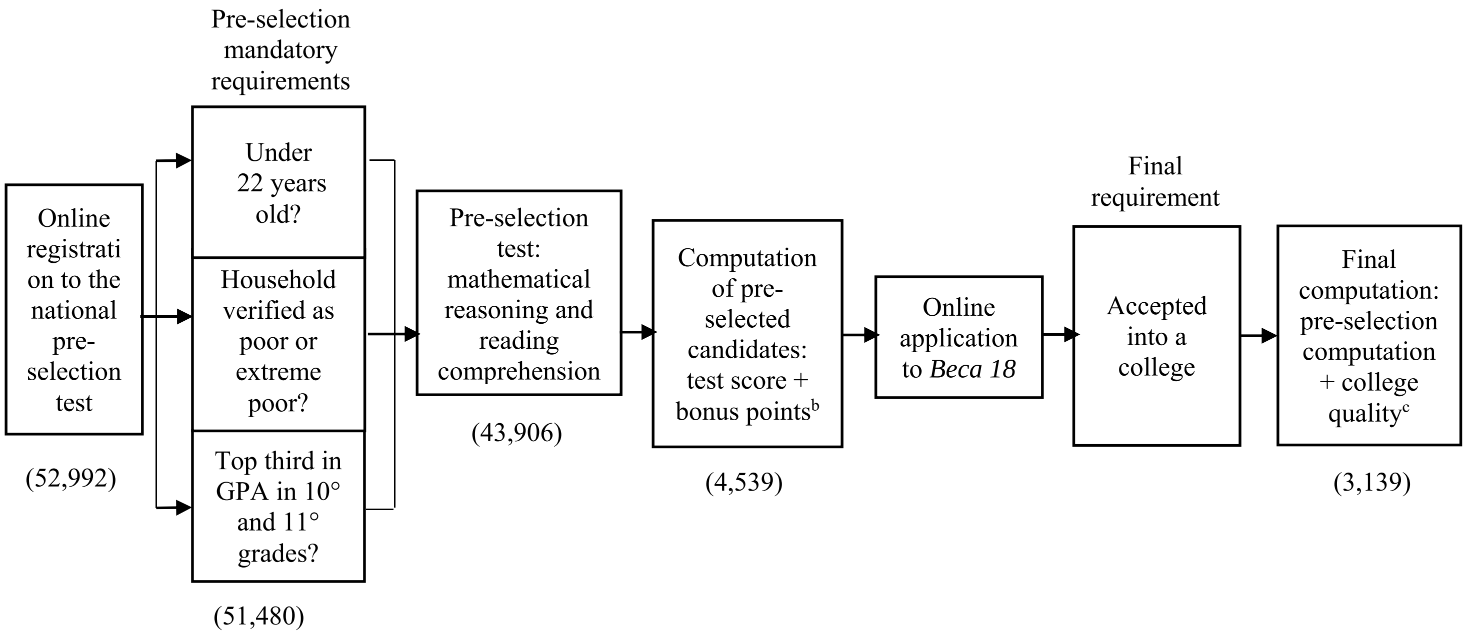
Appendix Figure 1: *Beca 18* Selection Process [a]



Source: Technical Dossier of the 2020 Call for *Beca 18*, PRONABEC (2020).

Notes:

[a] Mostly based on the 2019 scholarship call. Numbers within parenthesis are the students total in each stage of the process.

[b] Additional points are given to applicants in priority situations (disability, active fireperson or children of fireperson, volunteers registered by the Ministry of Women and Vulnerable Populations or indigenous or afro-descendant population).

[c] The quality of the colleges and careers chosen by applicants is considered in the final allocation of scholarships. Quality indicators must be reliable and from and external source. For 5-year colleges, these indicators include, research (publications), teaching (degrees attained by faculty, and student/teacher ratio), graduates| wages, acceptance rate, and students' perception about the services received, teaching, infrastructure and college reputation, while for 3-year colleges, includes, teaching (degrees and student/teacher ratio), graduates wages, acceptance rate, college physical infrastructure, Personal computer/student ratio, and share of graduates with a bachelor's degree (*Licenciate*).

Appendix Table 2: Occupations used

Occupation	N	Share (%)	Callback (%)
Accountant	56	1.6	3.57
Accounting Assistant	536	15.1	6.53
Business Administration Assistant	388	10.9	4.38
Business Administration/Management	228	6.4	4.39
Civil Engineering	102	2.9	3.92
Engineering (Others)[1/]	238	6.7	15.13
Cooking	152	4.3	9.87
Cooking Assistant	112	3.2	18.75
Dental Assistant	80	2.3	5.00
Graphical/Fashion/Design	164	4.6	12.80
Lawyer	136	3.8	13.24
Logistics	56	1.6	12.50
Marketing	48	1.4	16.67
Nursing Assistant	60	1.7	10.00
Pharmaceutical Chemist	40	1.1	17.50
Physician/Nurse	144	4.1	24.31
Sales Representative	220	6.2	18.18
Secretary	136	3.8	8.09
Teacher (Primary and Secondary Education)	172	4.8	7.56
Technician in Mechanics	96	2.7	10.42
Technician in Electricity/Mechanics/Electronics	308	8.7	12.34
Others[2/]	76	2.1	11.84
Technical Occupations	1903	53.6	9.25
Professional Occupations	1645	46.4	11.61
Total	3548	100.0	10.34

[1/] Includes Agrarian, Chemical, Electric, Electronic, Environmental, Food, Forestry, Industrial, Planning, and Telecommunications Engineering.
[2/] Includes Sociologist, Touristic Guide, Community Manager, Architect, Seamstress.

Appendix 3: Sample resumes sent for a graphical design (*diseño gráfico*) job

Darwin Nelson Cusiquispe Uchuypoma

cusiquispe.uchuypoma.darwin10@outlook.com
Cl Muquiyauyos Nro 147, Rímac
☎ 993.144.907

Tengo capacidad para trabajar en equipo, buena predisposición para asumir nuevos retos, rápida adaptación y sólidos valores personales, participando proactivamente en las labores que se encuentren bajo mi responsabilidad. Los cuales me permitan desarrollarme personal y profesionalmente.

Estudios Realizados

2013 - 2015	Cibertec Profesional en Diseño Gráfico
2008 - 2012	Pedro A. Labarthe La Victoria

Trabajos Realizados

2017 - actualmente	Consorcio Carolina Diseño Gráfico Desarrollo de diversas piezas gráficas para los restaurantes Texas y Delibakery.
2016 - 2017	Approach BTL Diseño Gráfico - Practicante Crear y desarrollar ideas en textos creativos para el área de diseño y para el cliente final.

Otros

Computación	Microsoft Office: Word (avanzado), Excel (avanzado), Power Point (avanzado) y Outlook. Adobe Photoshop, Corel, Illustrator 3D, InDesign.
Idioma extranjero	Inglés (avanzado).

Jairo Giancarlo Diaz Quinteros

diaz.quinteros.jairo10@outlook.com
JR Raul Porras Barrenechea 125, Lince
Teléfono: 992 919 542

Persona responsable, creativa, con iniciativa y puntualidad, asumo con agrado los retos y metas que las organizaciones me pudieran plantear; con buen manejo de relaciones interpersonales, facilidad para trabajar en equipo, en condiciones de alta presioón, así como para resolver problemas eficientemente y lograr las metas trazadas por la empresa y mi grupo de trabajo.

Formación académica

2013 - 2015	Nobert Wiener Profesional en Diseño Gráfico **Premios**: Beca18 (PRONABEC)
2008 - 2012	Miguel Grau Magdalena

Experiencias

2017 - actualmente	Consorcio Carolina Diseño Gráfico Desarrollo de diversas piezas gráficas para los restaurantes Texas y Delibakery.
2016 - 2017	Fine Card Practicante de Diseño Gráfico Realicé diseño para los diversos clientes. Tenía a mi cargo el área de ventas y recepción de los diversos pedidos.

Otros

Idiomas	Inglés (avanzado)
Programas	Microsoft Office (avanzado),Illustrator 3D, Corel, InDesign y Adobe Photoshop.

Augusto Mari Hurtado Charccahuana

hurtado.charccahuana.augusto10@hotmail.com
JR Echenique 1853 Ur San Gregorio, Independencia
987 127 123

Soy una persona con capacidades orientadas al cumplimiento de los objetivos, optimista, proactiva, con facilidad para el trabajo en equipo, adaptable a los cambios y comunicación efectiva.

Educación

2013 - 2015	Toulouse Lautrec Profesional en Diseño Gráfico Beneficiario del Programa Nacional de **Beca18** - PRONABEC
2008 - 2012	I.E.P.S.M. Nº16458 Juan Velasco Alvarado

Experiencia Laboral

2017 - actualmente	Lapiceros y Publicidad Diseño Gráfico Elaboración y modificación de logos y textos para luego ser llevados a grabados con la máquina Láser, grabado en lapiceros, placas de metal, entre otros.
2016 - 2017	Pan de La Chola Diseño Gráfico: Practicante Asistente de producción y del área de servicio.

Otros Conocimientos

Computación	Microsoft Office (nivel avanzado),Adobe Photoshop, InDesign, Corel, Illustrator 3D.
Idiomas	Inglés (nivel avanzado en el Británico, 2017).

Adela Daniela Yurivilca Chavarry
yurivilca.chavarry.adela10@gmail.com
Jirón Juan Pablo Fernandini 1485, San Juan de Miraflores
Cel: 993-486-591

Soy una persona con un alto sentido de responsabilidad, creativa, pro-activa y con vocación de servicio. Con habilidad para generar compromisos con los demás, manejo eficaz de la comunicación, capaz de asumir nuevos retos. Actualmente estoy buscando una empresa donde pueda desarrollarme a nivel profesional y personal con muchos deseos de superación.

Estudios

2013 - 2015	Cibertec Profesional en Diseño Gráfico
2008 - 2012	Miguel Grau Magdalena

Historia Laboral

2017 - actualmente	Acosta Stock Diseño Gráfico Trabajo con Gravograf (Pantografía), realización de volantes y trípticos. Grabado en joyería y llaveros.
2016 - 2017	Approach BTL Diseño Gráfico - Practicante Crear y desarrollar ideas en textos creativos para el área de diseño y para el cliente final.

Información Adicional

Otros idiomas	Inglés: avanzado.
Computación e Informática	MS Office: avanzado. Adobe Photoshop, InDesign, Corel, Illustrator 3D.

Appendix Table 4. Balance test

	Beca 18			
	Yes	No	Difference	p-value
male or female applicant	0.500	0.504	0.004	0.78307
eth__1	0.251	0.249	-0.003	0.83216
eth__2	0.250	0.250	0.000	1.00000
eth__3	0.251	0.249	-0.003	0.83216
eth__4	0.247	0.253	0.006	0.67165
title_style__1	0.333	0.348	0.015	0.31703
title_style__2	0.338	0.321	-0.017	0.22849
title_style__3	0.329	0.331	0.003	0.84527
phone_format__1	0.255	0.245	-0.009	0.47989
phone_format__2	0.238	0.262	0.023*	0.07732
phone_format__3	0.255	0.245	-0.010	0.43708
phone_format__4	0.252	0.248	-0.004	0.77750
phone_number__1	0.259	0.241	-0.019	0.15763
phone_number__2	0.251	0.249	-0.003	0.83216
phone_number__3	0.239	0.261	0.022	0.10414
phone_number__4	0.250	0.250	0.000	1.00000
email__1	0.251	0.249	-0.003	0.83216
email__2	0.250	0.250	0.000	1.00000
email__3	0.251	0.249	-0.003	0.83216
email__4	0.247	0.253	0.006	0.67165
fonts__1	0.257	0.243	-0.014	0.28926
fonts__2	0.237	0.263	0.026**	0.04787
fonts__3	0.254	0.246	-0.007	0.57195
fonts__4	0.252	0.248	-0.005	0.72391
objective__1	0.082	0.098	0.015*	0.07791
objective__2	0.097	0.087	-0.010	0.24374
objective__3	0.096	0.083	-0.013	0.14825
objective__4	0.096	0.088	-0.007	0.39658
objective__5	0.087	0.089	0.002	0.82903
objective__6	0.095	0.088	-0.007	0.39549
objective__7	0.098	0.095	-0.003	0.75589
objective__8	0.089	0.094	0.005	0.59623
objective__9	0.078	0.098	0.020**	0.02038
objective__10	0.089	0.089	0.000	0.95720
objective__11	0.093	0.091	-0.002	0.83216
edu_style__1	0.251	0.249	-0.002	0.88764

edu_style__2	0.243	0.257	0.013	0.32261
edu_style__3	0.248	0.252	0.005	0.72391
edu_style__4	0.258	0.242	-0.016	0.22972
edu_edit__1	0.203	0.192	-0.011	0.37671
edu_edit__2	0.196	0.202	0.006	0.61828
edu_edit__3	0.190	0.210	0.020*	0.09986
edu_edit__4	0.210	0.196	-0.014	0.27006
edu_edit__5	0.202	0.200	-0.002	0.87873
work_style__1	0.253	0.247	-0.006	0.67165
work_style__2	0.246	0.254	0.008	0.52489
work_style__3	0.262	0.238	-0.023*	0.07732
work_style__4	0.240	0.260	0.021	0.12008
work_edit__1	0.203	0.192	-0.011	0.37671
work_edit__2	0.196	0.202	0.006	0.61828
work_edit__3	0.190	0.210	0.020*	0.09986
work_edit__4	0.210	0.196	-0.014	0.27006
work_edit__5	0.202	0.200	-0.002	0.87873
jobs_worked__1	0.159	0.178	0.019*	0.09366
jobs_worked__2	0.166	0.165	-0.001	0.90173
jobs_worked__3	0.161	0.178	0.018	0.12128
jobs_worked__4	0.167	0.165	-0.001	0.90184
jobs_worked__5	0.176	0.144	-0.032***	0.00401
jobs_worked__6	0.027	0.026	-0.001	0.84946
jobs_worked__7	0.027	0.030	0.003	0.52199
jobs_worked__8	0.030	0.028	-0.002	0.71553
jobs_worked__9	0.014	0.010	-0.004	0.25520
jobs_worked__10	0.006	0.008	0.002	0.36755
jobs_worked__11	0.007	0.005	-0.002	0.43148
jobs_worked__12	0.006	0.007	0.001	0.69408
jobs_worked__13	0.005	0.007	0.002	0.31601
jobs_worked__14	0.007	0.006	-0.001	0.70461
jobs_worked__15	0.008	0.006	-0.002	0.46375
jobs_worked__16	0.005	0.007	0.003	0.23799
jobs_worked__17	0.010	0.006	-0.005*	0.08514
jobs_worked__18	0.008	0.007	-0.001	0.58876
jobs_worked__19	0.007	0.007	0.000	0.85223
jobs_worked__20	0.006	0.009	0.003	0.20711
jobs_worked2__1	0.185	0.191	0.006	0.63866
jobs_worked2__2	0.195	0.186	-0.009	0.45909
jobs_worked2__3	0.190	0.189	-0.000	0.96886

jobs_worked2__4	0.181	0.189	0.008	0.50322
jobs_worked2__5	0.120	0.126	0.006	0.54541
jobs_worked2__6	0.017	0.017	0.000	0.90605
jobs_worked2__7	0.015	0.016	0.001	0.71190
jobs_worked2__8	0.019	0.018	-0.001	0.73341
jobs_worked2__9	0.016	0.013	-0.003	0.37439
jobs_worked2__10	0.015	0.013	-0.002	0.51227
jobs_worked2__11	0.014	0.014	0.000	1.00000
jobs_worked2__12	0.011	0.012	0.001	0.77608
jobs_worked2__13	0.012	0.007	-0.005	0.11221
jobs_worked2__14	0.010	0.008	-0.001	0.62948
job_title__1	0.019	0.019	0.000	1.00000
job_title__2	0.001	0.001	0.000	1.00000
job_title__3	0.001	0.001	0.000	1.00000
job_title__4	0.002	0.002	0.000	1.00000
job_title__5	0.002	0.002	0.000	1.00000
job_title__6	0.001	0.001	0.000	1.00000
job_title__7	0.049	0.049	0.000	1.00000
job_title__8	0.001	0.001	0.000	1.00000
job_title__9	0.002	0.002	0.000	1.00000
job_title__10	0.001	0.001	0.000	1.00000
job_title__11	0.001	0.001	0.000	1.00000
job_title__12	0.002	0.002	0.000	1.00000
job_title__13	0.004	0.004	0.000	1.00000
job_title__14	0.007	0.007	0.000	1.00000
job_title__15	0.006	0.006	0.000	1.00000
job_title__16	0.005	0.005	0.000	1.00000
job_title__17	0.004	0.004	0.000	1.00000
job_title__18	0.101	0.101	0.000	1.00000
job_title__19	0.003	0.003	0.000	1.00000
job_title__20	0.001	0.001	0.000	1.00000
job_title__21	0.160	0.160	0.000	1.00000
job_title__22	0.019	0.019	0.000	1.00000
job_title__23	0.001	0.001	0.000	1.00000
job_title__24	0.001	0.001	0.000	1.00000
job_title__25	0.006	0.006	0.000	1.00000
job_title__26	0.003	0.003	0.000	1.00000
job_title__27	0.007	0.007	0.000	1.00000
job_title__28	0.004	0.004	0.000	1.00000
job_title__29	0.001	0.001	0.000	1.00000

job_title__30	0.001	0.001	0.000	1.00000
job_title__31	0.001	0.001	0.000	1.00000
job_title__32	0.001	0.001	0.000	1.00000
job_title__33	0.002	0.002	0.000	1.00000
job_title__34	0.001	0.001	0.000	1.00000
job_title__35	0.005	0.005	0.000	1.00000
job_title__36	0.007	0.007	0.000	1.00000
job_title__37	0.001	0.001	0.000	1.00000
job_title__38	0.001	0.001	0.000	1.00000
job_title__39	0.002	0.002	0.000	1.00000
job_title__40	0.001	0.001	0.000	1.00000
job_title__41	0.022	0.022	0.000	1.00000
job_title__42	0.001	0.001	0.000	1.00000
job_title__43	0.001	0.001	0.000	1.00000
job_title__44	0.001	0.001	0.000	1.00000
job_title__45	0.033	0.033	0.000	1.00000
job_title__46	0.003	0.003	0.000	1.00000
job_title__47	0.001	0.001	0.000	1.00000
job_title__48	0.020	0.020	0.000	1.00000
job_title__49	0.001	0.001	0.000	1.00000
job_title__50	0.001	0.001	0.000	1.00000
job_title__51	0.001	0.001	0.000	1.00000
job_title__52	0.001	0.001	0.000	1.00000
job_title__53	0.002	0.002	0.000	1.00000
job_title__54	0.001	0.001	0.000	1.00000
job_title__55	0.028	0.028	0.000	1.00000
job_title__56	0.001	0.001	0.000	1.00000
job_title__57	0.003	0.003	0.000	1.00000
job_title__58	0.012	0.012	0.000	1.00000
job_title__59	0.001	0.001	0.000	1.00000
job_title__60	0.025	0.025	0.000	1.00000
job_title__61	0.001	0.001	0.000	1.00000
job_title__62	0.007	0.007	0.000	1.00000
job_title__63	0.027	0.027	0.000	1.00000
job_title__64	0.001	0.001	0.000	1.00000
job_title__65	0.001	0.001	0.000	1.00000
job_title__66	0.004	0.004	0.000	1.00000
job_title__67	0.009	0.009	0.000	1.00000
job_title__68	0.001	0.001	0.000	1.00000
job_title__69	0.001	0.001	0.000	1.00000

job_title__70	0.001	0.001	0.000	1.00000
job_title__71	0.004	0.004	0.000	1.00000
job_title__72	0.001	0.001	0.000	1.00000
job_title__73	0.014	0.014	0.000	1.00000
job_title__74	0.004	0.004	0.000	1.00000
job_title__75	0.001	0.001	0.000	1.00000
job_title__76	0.002	0.002	0.000	1.00000
job_title__77	0.006	0.006	0.000	1.00000
job_title__78	0.003	0.003	0.000	1.00000
job_title__79	0.002	0.002	0.000	1.00000
job_title__80	0.027	0.027	0.000	1.00000
job_title__81	0.001	0.001	0.000	1.00000
job_title__82	0.004	0.004	0.000	1.00000
job_title__83	0.002	0.002	0.000	1.00000
job_title__84	0.018	0.018	0.000	1.00000
job_title__85	0.001	0.001	0.000	1.00000
job_title__86	0.001	0.001	0.000	1.00000
job_title__87	0.002	0.002	0.000	1.00000
job_title__88	0.007	0.007	0.000	1.00000
job_title__89	0.001	0.001	0.000	1.00000
job_title__90	0.001	0.001	0.000	1.00000
job_title__91	0.001	0.001	0.000	1.00000
job_title__92	0.002	0.002	0.000	1.00000
job_title__93	0.001	0.001	0.000	1.00000
job_title__94	0.011	0.011	0.000	1.00000
job_title__95	0.033	0.033	0.000	1.00000
job_title__96	0.001	0.001	0.000	1.00000
job_title__97	0.003	0.003	0.000	1.00000
job_title__98	0.001	0.001	0.000	1.00000
job_title__99	0.001	0.001	0.000	1.00000
job_title__100	0.003	0.003	0.000	1.00000
job_title__101	0.008	0.008	0.000	1.00000
job_title__102	0.002	0.002	0.000	1.00000
job_title__103	0.001	0.001	0.000	1.00000
job_title__104	0.001	0.001	0.000	1.00000
job_title__105	0.008	0.008	0.000	1.00000
job_title__106	0.009	0.009	0.000	1.00000
job_title__107	0.009	0.009	0.000	1.00000
job_title__108	0.001	0.001	0.000	1.00000
job_title__109	0.005	0.005	0.000	1.00000

job_title__110	0.002	0.002	0.000	1.00000
job_title__111	0.007	0.007	0.000	1.00000
job_title__112	0.001	0.001	0.000	1.00000
job_title__113	0.001	0.001	0.000	1.00000
job_title__114	0.003	0.003	0.000	1.00000
job_title__115	0.007	0.007	0.000	1.00000
job_title__116	0.004	0.004	0.000	1.00000
job_title__117	0.011	0.011	0.000	1.00000
job_title__118	0.026	0.026	0.000	1.00000
job_title__119	0.002	0.002	0.000	1.00000
job_title__120	0.001	0.001	0.000	1.00000
job_title__121	0.001	0.001	0.000	1.00000
job_title__122	0.001	0.001	0.000	1.00000
job_title__123	0.001	0.001	0.000	1.00000
job_title__124	0.001	0.001	0.000	1.00000
job_title__125	0.001	0.001	0.000	1.00000
job_title__126	0.038	0.038	0.000	1.00000
job_title__127	0.017	0.017	0.000	1.00000
job_title__128	0.011	0.011	0.000	1.00000
job_title__129	0.005	0.005	0.000	1.00000
job_title__130	0.001	0.001	0.000	1.00000
job_title__131	0.001	0.001	0.000	1.00000
job_title__132	0.001	0.001	0.000	1.00000
job_title__133	0.007	0.007	0.000	1.00000
job_title__134	0.001	0.001	0.000	1.00000
job_title__135	0.003	0.003	0.000	1.00000
job_title__136	0.001	0.001	0.000	1.00000
job_title__137	0.001	0.001	0.000	1.00000
additional_info__1	0.335	0.336	0.001	0.94835
additional_info__2	0.352	0.334	-0.018	0.22068
additional_info__3	0.313	0.330	0.017	0.23843
software__1	0.256	0.244	-0.011	0.39656
software__2	0.242	0.258	0.016	0.22972
software__3	0.254	0.246	-0.008	0.52489
software__4	0.248	0.252	0.004	0.77750
week__1	0.037	0.037	0.000	1.00000
week__2	0.032	0.032	0.000	1.00000
week__3	0.057	0.057	0.000	1.00000
week__4	0.022	0.022	0.000	1.00000
week__5	0.041	0.041	0.000	1.00000

week__6	0.043	0.043	0.000	1.00000
week__7	0.029	0.029	0.000	1.00000
week__8	0.043	0.043	0.000	1.00000
week__9	0.040	0.040	0.000	1.00000
week__10	0.031	0.031	0.000	1.00000
week__11	0.054	0.054	0.000	1.00000
week__12	0.039	0.039	0.000	1.00000
week__13	0.031	0.031	0.000	1.00000
week__14	0.042	0.042	0.000	1.00000
week__15	0.027	0.027	0.000	1.00000
week__16	0.043	0.043	0.000	1.00000
week__17	0.043	0.043	0.000	1.00000
week__18	0.025	0.025	0.000	1.00000
week__19	0.034	0.034	0.000	1.00000
week__20	0.011	0.011	0.000	1.00000
week__21	0.022	0.022	0.000	1.00000
week__22	0.018	0.018	0.000	1.00000
week__23	0.024	0.024	0.000	1.00000
week__24	0.019	0.019	0.000	1.00000
week__25	0.042	0.042	0.000	1.00000
week__26	0.037	0.037	0.000	1.00000
week__27	0.018	0.018	0.000	1.00000
week__28	0.014	0.014	0.000	1.00000
week__29	0.020	0.020	0.000	1.00000
week__30	0.012	0.012	0.000	1.00000
week__31	0.021	0.021	0.000	1.00000
week__32	0.029	0.029	0.000	1.00000
hs_name__1	0.006	0.003	-0.003	0.10757
hs_name__2	0.025	0.020	-0.005	0.25867
hs_name__3	0.044	0.052	0.008	0.19871
hs_name__4	0.023	0.028	0.005	0.32985
hs_name__5	0.022	0.019	-0.002	0.58820
hs_name__6	0.024	0.024	-0.000	0.92057
hs_name__7	0.025	0.020	-0.005	0.25867
hs_name__8	0.019	0.024	0.005	0.24388
hs_name__9	0.050	0.053	0.003	0.62733
hs_name__10	0.020	0.021	0.001	0.74528
hs_name__11	0.007	0.005	-0.001	0.54744
hs_name__12	0.047	0.049	0.002	0.77418
hs_name__13	0.051	0.052	0.000	0.94494

hs_name__14	0.022	0.023	0.002	0.67976
hs_name__15	0.028	0.018	-0.009**	0.04098
hs_name__16	0.022	0.027	0.006	0.23364
hs_name__17	0.023	0.022	-0.001	0.83810
hs_name__18	0.023	0.025	0.002	0.61808
hs_name__19	0.019	0.021	0.001	0.74247
hs_name__20	0.018	0.026	0.007*	0.09521
hs_name__21	0.026	0.028	0.002	0.70660
hs_name__22	0.028	0.024	-0.003	0.50093
hs_name__23	0.026	0.023	-0.003	0.48925
hs_name__24	0.002	0.004	0.002	0.24766
hs_name__25	0.003	0.002	-0.001	0.56326
hs_name__26	0.023	0.021	-0.003	0.53157
hs_name__27	0.027	0.021	-0.006	0.22922
hs_name__28	0.048	0.043	-0.005	0.46256
hs_name__29	0.003	0.004	0.001	0.43789
hs_name__30	0.048	0.036	-0.012**	0.04771
hs_name__31	0.002	0.004	0.002	0.24766
hs_name__32	0.005	0.005	0.000	1.00000
hs_name__33	0.042	0.037	-0.005	0.38532
hs_name__34	0.005	0.006	0.001	0.68233
hs_name__35	0.044	0.057	0.013*	0.05057
hs_name__36	0.020	0.020	0.000	1.00000
hs_name__37	0.003	0.005	0.002	0.22443
hs_name__38	0.046	0.047	0.001	0.82764
hs_name__39	0.023	0.023	0.000	0.91903
hs_name__40	0.051	0.052	0.001	0.83587
hs_name__41	0.004	0.001	-0.003**	0.03460
hs_name__42	0.005	0.003	-0.001	0.46608
hs2_name__1	0.050	0.052	0.002	0.72763
hs2_name__2	0.010	0.009	-0.000	0.87534
hs2_name__3	0.052	0.051	-0.001	0.88992
hs2_name__4	0.024	0.025	0.001	0.84266
hs2_name__5	0.024	0.023	-0.000	0.91981
hs2_name__6	0.010	0.010	0.000	1.00000
hs2_name__7	0.010	0.008	-0.002	0.42133
hs2_name__8	0.008	0.011	0.003	0.27209
hs2_name__9	0.042	0.047	0.005	0.41322
hs2_name__10	0.026	0.020	-0.007	0.15258
hs2_name__11	0.056	0.051	-0.004	0.54108

hs2_name__12	0.046	0.051	0.005	0.47524
hs2_name__13	0.044	0.040	-0.005	0.44643
hs2_name__14	0.021	0.026	0.005	0.26809
hs2_name__15	0.020	0.029	0.009*	0.06048
hs2_name__16	0.011	0.012	0.001	0.66652
hs2_name__17	0.008	0.011	0.003	0.35228
hs2_name__18	0.022	0.018	-0.004	0.32423
hs2_name__19	0.008	0.005	-0.003	0.25538
hs2_name__20	0.022	0.020	-0.001	0.74800
hs2_name__21	0.026	0.023	-0.002	0.62136
hs2_name__22	0.013	0.008	-0.005	0.13830
hs2_name__23	0.008	0.008	0.000	0.86526
hs2_name__24	0.008	0.012	0.004	0.21487
hs2_name__25	0.045	0.037	-0.008	0.18953
hs2_name__26	0.025	0.028	0.003	0.56905
hs2_name__27	0.028	0.021	-0.007	0.13468
hs2_name__28	0.046	0.055	0.008	0.20887
hs2_name__29	0.046	0.044	-0.002	0.76887
hs2_name__30	0.021	0.010	-0.011***	0.00404
hs2_name__31	0.043	0.043	-0.000	0.93979
hs2_name__32	0.015	0.014	-0.001	0.70344
hs2_name__33	0.019	0.017	-0.001	0.73016
hs2_name__34	0.012	0.019	0.007*	0.08247
hs2_name__35	0.023	0.025	0.001	0.76483
hs2_name__36	0.018	0.020	0.002	0.65175
hs2_name__37	0.013	0.019	0.006	0.11467
hs2_name__38	0.021	0.027	0.006	0.19058
hs2_name__39	0.016	0.023	0.007	0.12295
hs2_name__40	0.021	0.014	-0.007	0.10069
hs2_name__41	0.020	0.014	-0.006	0.11981
DistritoResidencia__1	0.046	0.048	0.002	0.77315
DistritoResidencia__2	0.034	0.027	-0.007	0.21249
DistritoResidencia__3	0.056	0.052	-0.004	0.58771
DistritoResidencia__4	0.015	0.017	0.002	0.54406
DistritoResidencia__5	0.024	0.021	-0.003	0.53578
DistritoResidencia__6	0.076	0.063	-0.013	0.10439
DistritoResidencia__7	0.074	0.071	-0.004	0.63716
DistritoResidencia__8	0.050	0.045	-0.005	0.47319
DistritoResidencia__9	0.081	0.074	-0.007	0.39079
DistritoResidencia__10	0.057	0.046	-0.011	0.11062

DistritoResidencia__11	0.049	0.052	0.003	0.62583
DistritoResidencia__12	0.021	0.026	0.006	0.22473
DistritoResidencia__13	0.054	0.050	-0.004	0.58143
DistritoResidencia__14	0.049	0.055	0.006	0.40826
DistritoResidencia__15	0.022	0.030	0.007	0.12556
DistritoResidencia__16	0.024	0.027	0.003	0.55880
DistritoResidencia__17	0.035	0.035	0.000	1.00000
DistritoResidencia__18	0.040	0.048	0.008	0.20371
DistritoResidencia__19	0.040	0.048	0.008	0.17946
DistritoResidencia__20	0.032	0.031	-0.001	0.86069
DistritoResidencia__21	0.029	0.031	0.002	0.65495
DistritoResidencia__22	0.093	0.102	0.009	0.32746

Appendix Table 5. Regression with clusters at the job ad level

	(1)	(2)	(3)	(4)	(5)
Beca 18	0.019***	0.019**	0.018**	0.018**	0.019***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Randomized Inference: p-value	[0.072]	[0.068]	[0.078]	[0.074]	[0.071]
Candidate controls	No	Yes	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes
Week fixed effects	No	No	No	Yes	Yes
Resume. controls	No	No	No	No	Yes
Adjusted R^2	0.001	0.007	0.009	0.043	0.039
Mean control	0.094	0.094	0.094	0.094	0.094
Number of clusters	887	887	887	887	887
N	3548	3548	3548	3548	3548

Robust standard errors (in brackets) are clustered at the job ad level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 9. Effects by college type and poverty level of district of residence

	All	3-year college		5-year college	
		Poor district	Affluent district	Poor district	Affluent district
Beca 18	0.019**	0.042***	0.027	0.010	0.001
	(0.007)	(0.014)	(0.036)	(0.014)	(0.027)
Randomized Inference: p-value	[0.016]	[0.000]	[0.370]	[0.511]	[0.960]
Adjusted R^2	0.486	0.439	0.248	0.588	0.611
Mean control	0.094	0.071	0.092	0.102	0.133
N	3548	1253	650	1067	578

Note: All specifications include a constant term and job ad fixed effects.
Robust standard errors (in parenthesis) are clustered at the resume level. P-values using randomized inference (with 1000 repetitions) in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 10: Returns to *Beca 18* by gender

	(1) All	(2) 3-year college	(3) 5-year college
Beca 18	0.023**	0.027*	0.015
	(0.010)	(0.014)	(0.015)
Woman	0.031***	0.030*	0.026
	(0.012)	(0.016)	(0.017)
*Beca 18**Woman	-0.008	0.008	-0.016
	(0.017)	(0.023)	(0.024)
Regular controls	Yes	Yes	Yes
Adjusted R^2	0.485	0.410	0.560
Mean control (callback for *Beca 18* non-recipients)	0.094	0.079	0.112
N	3548	1903	1645

Note: All specifications include a constant term and job ad fixed effects.
Robust standard errors (in parenthesis) are clustered at the resume level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$