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by

Jorge M. Agüero
University of Connecticut

Francisco B. Galarza
Universidad del Pacífico

Gustavo Yamada
Universidad del Pacífico

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365 Fairfield Way, Unit 1063
Storrs, CT 06269-1063
Phone: (860) 486-3022
Fax: (860) 486-4463
http://www.econ.uconn.edu/

Do Inclusive Education Policies Improve Employment Opportunities? Evidence from a Field Experiment[•]

Jorge M. Agüero		Francisco B. Galarza		Gustavo Yamada

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Abstract

We study the employment opportunity of a college scholarship for high-achieving, low-income students in a labor market where disadvantaged groups are discriminated against. Using a correspondence audit-study we find that including information of being a scholarship recipient in a resume increases the likelihood of getting a callback for a job interview by 20%. However, the effects are much smaller in jobs and careers where the poor are under-represented. We show that this is consistent with the scholarship also sending a negative signal to employers and helps explain why actual beneficiaries almost never mention the scholarship in their resumes.

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

JEL Codes: C93, I23, J7, J15.

[•] Agüero: University of Connecticut, Department of Economics and El Instituto (jorge.aguero@uconn.edu); Galarza: Universidad del Pacífico, Department of Economics (galarza_fb@up.edu.pe); Yamada: Universidad del Pacífico, Department of Economics (yamada_ga@up.edu.pe). Mayda Cama, Alejandra Jara, David Mata, Marco Ríos-Luna, Aeton Salas, Fernando Chu, Gabriela Rodriguez and Mary Vlamis provided excellent research assistance. We also thank comments from seminars participants at the University of Wisconsin, Madison, Universidad de Piura, Universidad del Pacífico, NIP-Uruguay, NEUDC, Southern Economic Association, University of Passau, Canadian Economics Association 2021, SEEDEC 2021, and BCDE 2021. Joanna Lahey, Maria Pia Basurto, Alberto Chong, Todd Sorensen, Jose Galdo and Juliana Londoño-Velez provided valuable feedback on previous versions of the paper. We thank the financial support from UConn's El Instituto and Pronabec. This study was approved by University of Connecticut's IRB (H18-256) and is registered with RCT ID: AEARCTR-0003842. All errors are our responsibility.

1. Introduction

Students from disadvantaged backgrounds are largely under-represented in higher education (UNESCO, 2020; Ferreyra et al., 2017). This is not fully driven by differences in achievement. Hoxby and Avery (2012) show that even among high-achieving students, those from low-income families are less likely to enroll in college and attend lower-quality higher institutions. This problem is more salient in developing countries where financial constraints are much more prevalent (Delavande and Zafar, 2019) and where the returns to postsecondary education are higher than in advanced economies (Goldin and Katz, 2008; Patrinos and Psacharopoulos, 2020). While there is important recent work 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; Laajaj et al. 2022; Solis, 2017), little is known about the labor market returns of these need- *and* merit-based scholarships.[1]

To address this gap, we study the labor market impact of a scholarship for talented low-income 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. The scholarship allows recipients 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 over-represented.

[1] For examples of research on related policies in advanced economies see Angrist et al. (2014), Bettinger et al. (2019), Dynarski et al. (2021) and Fack and Grenet (2015).

However, in labor markets where indigenous groups are discriminated against as in the case of Peru (e.g., Galarza and Yamada, 2014, 2017), a scholarship for high-achieving, low-income students could convey two possible signals to employers. First, there is a positive signal in terms of ability. To become eligible for *Beca 18*, a high school student must be at the top of her class, score very well in a qualifying standardized test and be admitted to a selective college before receiving the scholarship. Once in college, beneficiaries must maintain a high GPA until graduation. This must be done while coming from a poor household. Thus, to an employer, *Beca 18* could send a strong positive signal of cognitive abilities as well as "soft skills" such as resilience and grit.

There is a possible second, 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. In fact, in a report done by the Peruvian Ministry of Finance (MEF, 2019), *Beca 18* recipients declare that they feel discriminated in their colleges. Also, in a nationwide survey of recipients, 28% said they have been discriminated on campus. From those, 78% mentioned their scholarship as the main reason. This discrimination came mainly from other students (60%) and instructors (29%). See Rodriguez (2020) for details. So, even in a college environment, the perception that a low socioeconomic status may outweigh the recognition that the scholarship entails.

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.

From the point of view of beneficiaries, if they *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, placed 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 do 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 (graduates from 3-year colleges) and professional occupations (5-year college graduates).[2] Nearly 3500 fictitious resumes were sent in response to 877 job ads in Lima, 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) harmful 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

[2] As explained later, 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.

just 6% and not statistically different from zero. These findings suggest that the negative signal is not zero where 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) indigenous surnames, a result suggesting a greater ethnic equality in the access to the labor market.

We contribute to several literatures. First, the literature on the impact of financial aid and loan programs for higher education has largely focused on enrollment (see Angrist et al. 2014; Bettinger et al. 2019, Dynaski et al. (2021) and Fack and Grenet 2015, for developed countries, and Aguirre 2021; Card and Solis, 2020; Londoño-Velez et al., 2020; Laajaj et al., 2022 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.[3]

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 prescriptions to use to increase employment opportunities for disadvantaged groups. This gap is particularly relevant since anonymous job applications do not

[3] See Denning et al. (2019) for a study on the earning effects of additional grant aid from Pell Grant in the United States.

seem to help, as Behaghel et al. (2015) shows for France.[4] We evaluate the effect of an inclusive education policy on higher access to the labor market, as an alternative to using anonymous resumes. Also, while an affirmative action policy could reinforce discrimination (Coate and Loury, 1993; Fershtman and Pavan, 2021), sending a signal of ability could help candidates but depending on how the poverty and ability signals are perceived in the labor market.[5]

Related, our paper also contributes to the literature about labor market information frictions (e.g., Abel et al, 2020; Bassi and Nansamba 2022; Heller and Kesler, 2021; Orkin et al, 2020). These papers and ours show that employers react to signals regarding the quality of applicants, even for candidates from disadvantaged groups. Yet, such signals are not always provided by these candidates and these papers indicate that adding reference letters or certificates could reduce information frictions. The fact that very few actual beneficiaries of *Beca 18* include this award in their resumes, opens the possibility for a low-cost intervention to improve the job market opportunities of the scholarship recipients. We discuss this issue in the last section.

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. The *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

[4] Leibbrandt and List (2018) show that job advertisements in the United States that include an Equal Employment Opportunity statement dampen racial minorities' willingness to apply for jobs.
[5] 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 is an important topic for future research.

Peru and administered by the National Program of Scholarships and Education Loans (PRONABEC, for its acronym in Spanish), a branch from the Ministry of Education.[6] With the aim to reduce the poor's unequal access to higher education, *Beca 18* funds full tuition and the related expenses of young talented students coming from disadvantaged households who have been admitted to selective private and public universities (5-year college degrees) and post-secondary technical institutions (3-year college degrees). *Beca 18* granted 65,826 scholarships from 2012 to 2019, with just a few changes regarding the paperwork for the application process but keeping its focus on talented students from disadvantaged backgrounds.[7]

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 A1. The eligibility criteria are 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).[8] 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

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[6] Prior to *Beca 18*, PRONABEC had only had short-term loans financing tuition expenses for less than a year.

[7] Merit-based higher education scholarships targeting 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. Appendix Table A1 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 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%).

[8] Students can apply during their senior year (11^{th} grade) but also after high school graduation as long as they are younger than 22.

awarded to applicants in priority situations including indigenous groups.[9] As shown in Appendix Figure A1, using numbers from the 2019 process, only about one tenth of applicants (4,539 out of 43,906) made it to this stage. An additional third of applicants were eliminated in the final round of the process after considering college admission, quality of the colleges as well as careers chosen.[10] 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.[11] Two thirds of the scholarships were granted to fund 3-year technical degrees. 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 and housing), local transportation, and a round-trip ticket to the place of residence, if applicable.[12] Beca 18 is a very well-known program. For example, it was mentioned in the presidential debate of June 2021.[13]

3. Experimental design

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[9] 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.

[10] 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).

[11] See Appendix Table A1 for a comparison of Beca 18 with similar programs in Latin America.

[12] A significant proportion of the scholarship recipients are born in rural areas 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.

[13] One of the candidates proposed an expansion of the program to cover students whose families were affected by COVID-19. See YouTube video: https://youtu.be/uKQGeNx2t84 (2h 26m into the video). This was further covered in the financial media as well as in national radio.

We use a paired correspondence study design and send four resumes in response to each selected job ad. We use the resume randomizer program by Lahey and Beasley (2009), v.31, to construct all resumes, whose format and structure mirror those used by actual *Beca 18* recipients obtained thanks to PRONABEC. 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.[14]

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).[15] 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. 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). See Appendix B for examples of the resumes sent. We use the male variation for *Beneficiario* (beneficiary) in all

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[14] We did not include photographs in our resumes, which is common in Peru.

[15] 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.

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 focused on the extensive list of all colleges and majors available to *Beca 18* beneficiaries.[16] PRONABEC also identifies colleges and majors that could give additional points when calculating the score of applicants. These are called *prioritized* colleges and majors. See footnote 10 for an explanation on how those are selected.

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-identified 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 1). 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).

The surnames used in this experiment come from a random sample drawn from the full list of surnames from actual recipients of *Beca 18*. We first classified

[16] 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.

surnames of these recipients as Indigenous or *Mestizos* and then took a random sample without replacement of 400 surnames (200 of each group), to construct 200 unique (and fictitious) combinations of paternal and 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 surnames in the administrative data of the program, so we decided to use only Indigenous and *Mestizo* surnames.

Figure 1. 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

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. From the list of Indigenous surnames, students considered them as such 85%; and 76% for the list of *Mestizo* surnames. Our validation rates are in line with the findings from Button and Walker (2020) for Native Americans in the United States.

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 having 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.

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 a common 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). Every set of four resumes sent to each job ad was randomly drawn from those choices.

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

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.[17] 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 entry), were adapted from real work

[17] 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.

experiences posted online for similar occupations and were randomly assigned to each job applicant.

3.7 Other information

English and Computer Skills: All resumes include a final section with information on the level of English and software proficiency with Microsoft Office. These levels were set at intermediate for the general case but were adjusted as requested by the job vacancy. All four 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 and contact information (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, in response to 887 job vacancies selected from job-wanted sections of newspapers in Lima, Peru.[18] Power analysis suggested sending 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. Note that this power calculation uses as

[18] We had to stop the data collection due to the Covid-19 pandemic when the Peruvian government declared a national lockdown.

references studies from Peru that compared Whites with Indigenous surnames, but instead we are comparing *Mestizos* with Indigenous (an effect more difficult to detect), so 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 Baert, 2018). These are shown in Appendix Table A2 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. These were mainly posted on Sundays.[19] 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. We also excluded ads for advanced managerial positions and rather focused on entry-level jobs, with up to three years of work experience.

4.4 Emailing resumes

Resumes were electronically sent between Monday afternoon and Wednesday 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 sent and incoming emails went to a master email account, to keep a

[19] The Covid-19 pandemic moved all these printed ads to online portals.

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. Only eight responses requested additional information; these observations are excluded from the analysis.

4.6 Balance tests

Appendix C 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 324 variables, only 2.47% of them (8 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. As shown below, controlling for these eight variables does not alter our findings.

5. Methodology

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

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

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 covariates and we consider different versions. First, we consider a parsimonious model without controls. Second, we include only controls at the candidate level. These are sex, three categories ethnicity (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). Third, we add job-level descriptors: whether the major was prioritized and whether the college was prioritized.[20] The fourth group of covariates added fixed effects for the week the job was posted. We also consider resume features such as format and style. Finally, we add the eight variables where the randomization of the *Beca 18* statement was not balanced.

We correct the standard errors for clustering at the job ad level in all specifications. Yet, we discuss alternative ways below.

6. Results

6.1. Effect of Beca 18

We first examine the mean (raw) callback rates by *Beca 18* status, for each category of interest. As Table 1 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

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

both genders, though the sample size for each category outlined below does not always allow to get statistical significance.

Table 1: Callbacks rates by treatment status and demographic characteristics

	N	Total (%)	*Beca 18* Recipient (%) *No*	*Beca 18* Recipient (%) *Yes*	Difference (p-value)[1/]
A. Total	3,548	10.34	9.41	11.27	0.0689
B. Surnames (Paternal — Maternal)					
Indigenous—Indigenous	887	10.03	9.05	11.01	0.3310
Mestizo—Indigenous	887	9.02[2/]	8.33	9.74	0.4633
Indigenous—Mestizo	887	11.72[2/]	9.93	13.44	0.1048
Mestizo—Mestizo	887	10.60	10.38	10.81	0.8363
C. Place of Origin					
Rural High School	1,559	10.58	9.52	11.62	0.1781
Lima High School	1,989	10.16	9.33	11.00	0.2195
D. Gender					
Female	1,798	11.96	11.27	12.65	0.3661
Male	1,750	8.68	7.48	9.87	0.0752

[1/] Two-sided test p-value comparing treatment status.
[2/] Two-sided test p-value for the difference between Mestizo-Indigenous and Indigenous-Mestizo = 0.0616.

While revealing, 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 2, 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 a callback by 20% (=0.019/0.094) relative to the mean of the control group. Adding candidate's controls (column 2), job controls (column 3), indicator variables for the week the job was posted (column 4), resume controls (column 5), and the significant variables in the balance test (column 6), 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 2: Regression results on callbacks

	(1)	(2)	(3)	(4)	(5)	(6)
Beca 18	0.019***	0.019**	0.018**	0.018**	0.019***	0.018**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Randomized inference p-value	[0.014]	[0.010]	[0.012]	[0.014]	[0.011]	[0.019]
Candidate controls	No	Yes	Yes	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes	Yes
Week fixed effects	No	No	No	Yes	Yes	Yes
Resume controls	No	No	No	No	Yes	Yes
Significant variables	No	No	No	No	No	Yes
Adjusted R^2	0.001	0.007	0.009	0.043	0.039	0.039
Mean control	0.094	0.094	0.094	0.094	0.094	0.094
Number of clusters	887	887	887	887	887	887
N	3,548	3,548	3,548	3,548	3,548	3,548

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). *Significant variables* includes eight resume characteristics that were unbalanced by treatment status. See Appendix C for a list. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To put our *Beca 18* estimated impact (20%) in perspective, it is equivalent to 27% 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).[21] 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 Robustness checks

Our estimates are robust to the inclusion of full controls (column 6) of Table 2. Additional robustness checks include the use of job ad fixed effects and clustered standard errors at the resume level, as in Button and Walker (2020) and Beam et al. (2020). Appendix Table A3 shows the results of adding job ad fixed effects and Appendix Table A4 displays our findings when adding job fixed effects and clustering the standard errors at the resume level. In both tables, the point estimates without controls are still 0.019 and they marginally increase to 0.020 when considering all controls. Thus, if anything, our main specification is slightly more conservative about the impact of *Beca 18*.

We also show the results of applying randomized inference, as in Young (2019) and Imbens and Rubin (2015). These p-values are shown in all our tables. We further estimated Equation (1) using Probit models. The results are reported in Appendix Table A5 and confirm our main findings.

6.3 Heterogenous effects

To understand the relative role of the ability and the poverty signals of *Beca 18* we divide the sample in different groups according to where the poor are over- or

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

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 by 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 costs. With figures for 2015, the total average cost (tuition, tutoring, food, housing, transportation, course materials) of attending and earning a degree from a private *Instituto* in Lima was PEN 73,328 (equivalent to USD 21,500 at that time), PEN 162,883 for private universities, and PEN 80,759 for public universities (Apoyo, 2015). Specially comparing *Institutos* and private universities, this difference in 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.[22] Thus, we expect the *Beca 18* callback premium to be larger for candidates from 3-year colleges. This is shown and confirmed in Table 3.

Table 3 presents estimates for Equation (1) by type of college: 3-year colleges (*Institutos*) and 5-year colleges (universities). Column 1 reports the estimate for the full sample, for comparison. In column 2, when restricting the sample only to *Institutos* there is a significant effect: graduates from these colleges with resumes listing *Beca 18* increase their chances to get a callback by 36.7% (=0.029/0.079) relative to those without listing the scholarship. In the case of

[22] 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.

universities, column 3, graduates listing *Beca 18* receive 3.6% more callbacks (=0.004/0.112) than those without the listing and 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* but mainly muted where the poor are under-represented.

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

	(1) All	(2) 3-year college	(3) 5-year college
Beca 18	0.018**	0.029***	0.004
	(0.007)	(0.010)	(0.011)
Randomized Inference: p-value	[0.014]	[0.007]	[0.718]
Adjusted R^2	0.043	0.048	0.048
Mean control (callback for *Beca 18* non-recipients)	0.094	0.079	0.112
Number of clusters	887	481	422
N	3,548	1,903	1,645

Note: All specifications include *candidate controls* include sex, ethnicity, district of residence, type of occupation; *job controls* include indicators for prioritized major and college as well as weeks fixed effects. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 4 we split the sample by the district of residence assigned to the resume, within the city of Lima. 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 A6 we further divide the sample by this poverty indicator 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.[23]

Table 4. Effects by poverty level of district of residence

	(1) All	(2) Poorer districts	(3) Affluent districts
Beca 18	0.018**	0.026**	0.001
	(0.007)	(0.011)	(0.015)
Randomized Inference: p-value	[0.014]	[0.000]	[0.891]
Adjusted R^2	0.043	0.046	0.036
Mean control (callback for *Beca 18* non-recipients)	0.094	0.085	0.190
Number of clusters	887	861	768
N	3,548	2,140	1,408

Note: All specifications include *candidate controls* include sex, ethnicity, district of residence, type of occupation; *job controls* include indicators for prioritized major and college as well as weeks fixed effects. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

When considering the place where the randomly assigned high school was located (Lima vs. rural towns) we continue to find larger effects among those from poorer backgrounds. This is shown in Table 5 below. Recall from section 3.2, that resumes are assigned a rural high school only if the candidate has an indigenous last name (either paternal or maternal). Among this group this is assigned with a 2/3 chance. The callback rate for resumes that had the *Beca 18* statement is around 23% (=0.022/0.095) when the candidate attended a rural high school (column 2) and 16% (=0.015/0.093) for a counterpart attending high school in Lima. While the

[23] Effects by gender are shown in Appendix Table A7.

standard errors in both cases are larger, the p-values from the randomized inference show a significant effect, at the ten percent, for the scholarship among candidates assigned to a rural high school in their resumes. For those assigned a high school in Lima, the p-value is larger than 0.10 (0.172).

Table 5. Effects by high school location

	(1) All	(2) Rural high school	(3) High school in Lima
Beca 18	0.018**	0.022	0.015
	(0.007)	(0.014)	(0.012)
Randomized Inference: p-value	[0.014]	[0.059]	[0.172]
Adjusted R^2	0.043	0.062	0.037
Mean control (callback for *Beca 18* non-recipients)	0.094	0.095	0.093
Number of clusters	887	818	887
N	3548	1559	1989

Note: All specifications include *candidate controls* include sex, ethnicity, district of residence, type of occupation; *job controls* include indicators for prioritized major and college as well as weeks fixed effects. Robust standard errors (in parenthesis) are clustered at the job ad 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, keeps a list of prioritized colleges and majors that is used in every scholarship call. The criterion for prioritization is broadly based on quality indicators (see footnote 10 and Appendix Figure A1 for details). Yet, the poor are under-represented in these colleges and careers. Table 6 reports the estimates breaking the sample by these categories. When comparing colleges by whether they are prioritized or not, the point estimates are very close to each other. For prioritized colleges the *Beca 18* parameter is 0.020 (column 2) and 0.019 (column 3) for the non-prioritized. Using the randomization inference, only the former is significant at the 5% level. However, when comparing across majors, columns (4) and (5), the effects are larger among those where the poor are under-represented (0.044 vs. 0.010).

Table 6: Effects by college and major type: prioritized and non-prioritized

	(1)	(2)	(3)	(4)	(5)
		Prioritized College		Prioritized Major	
	All	Yes	No	Yes	No
Beca 18	0.018**	0.020**	0.019	0.010	0.044**
	(0.007)	(0.008)	(0.034)	(0.009)	(0.020)
Randomized Inference: p-value	[0.014]	[0.018]	[0.538]	[0.229]	[0.004]
Adjusted R^2	0.043	0.047	0.041	0.045	0.047
Mean control (callback for *Beca 18* non-recipients)	0.094	0.090	0.123	0.093	0.098
Number of clusters	887	863	231	811	449
N	3548	3114	434	2640	908

Note: All specifications include *candidate controls* include sex, ethnicity, district of residence, type of occupation; *job controls* include indicators for prioritized major and college as well as weeks fixed effects. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. PRONABEC defines colleges and majors as prioritized based on the quality of the college and the major, which reflects mainly STEM oriented careers. See text for details. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we consider the effect of *Beca 18* by our stronger signal of indigenous status: surnames. As described above, we randomly assigned indigenous as well as mestizos (mixed-race) last names, yielding four possible combinations due to paternal and maternal surnames. These are shown in columns (2)-(5) of Table 7. The full sample effect is shown, as usual, in column (1). In all four combinations we find a positive effect of listing the scholarship in the resume. We also observe larger point estimates when the paternal name is indigenous. Yet, the size of each subsample is too small to obtain precise estimates as expected given our power calculations. For instance, the standard deviation for the entire sample is between 30%-35% of the size of the sub samples. Thus, in columns (6) and (7) we consider only two sub groups based on the paternal last name, regardless of the maternal surname. In column (6) we focus on the sample where the resume was randomly assigned an indigenous paternal surname. We find an effect of *Beca 18* that is around 26 percent of the callback rate of the control group (=0.025/0.095). This is significant at the 10 percent even when considering the p-values for the randomized inference. The effects are smaller for job applicants where the paternal surname indicates mixed-candidates (10.8%) and not statistically different from zero (column 7).

Table 7: Effects by surname type

	(1) All	(2) I/M	(3) I/I	(4) M/M	(5) M/I	(6) I/●	(7) M/●
Beca 18	0.018^{**}	0.037^{*}	0.019	0.012	0.007	0.025^{*}	0.010
	(0.007)	(0.023)	(0.021)	(0.021)	(0.020)	(0.014)	(0.014)
Randomized Inference: p-value	[0.014]	[1.000]	[1.000]	[1.000]	[1.000]	[0.087]	[0.267]
Adjusted R^2	0.043	0.029	0.042	0.026	0.038	0.040	0.041
Mean control	0.094	0.099	0.090	0.104	0.083	0.095	0.093
Number of clusters	887	887	887	887	887	887	887
N	3548	887	887	887	887	1774	1774

Note: All specifications include *candidate controls* include sex, ethnicity, district of residence, type of occupation; *job controls* include indicators for prioritized major and college as well as weeks fixed effects. For columns (2)-(7) the first letter refers to the paternal surname (Indigenous vs. Mestizo) and the second letter to the maternal last name. Column (6) refers to the sample with a paternal Indigenous name, regardless of the maternal surname. Colum (7) does the same but for Mestizo paternal surnames. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A8 shows that the *Beca 18* effect for indigenous surnames mainly comes the subsample of 3-year colleges and much less from 5-year colleges. For the former, including *Beca 18* increase the callback rate by 47.1% (column 3), which is statistically different from zero at the five percent when considering the randomized inference p-value (and at the 10% for the regular inference). For the latter, the gains in callback are around 13% with less precision (column 4). The table also confirms that the effects for mestizos are smaller (and less precise) and seem to be also concentrated among graduates from 3-year colleges.

7. Conclusion

Students from poor families in worldwide are under-represented in higher education. We focused on the case of Peru, where there is almost no difference in access to primary education by household income levels, however, there is a 15-percentage point gap in access to secondary education between the richest quintile and the poorest quintile. This gap further 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 nationwide need- 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 paternal Indigenous surnames.

The positive effect of *Beca 18* on callbacks suggests that current beneficiaries are leaving “money on the table” as very few of them include this scholarship in their resumes. This also implies that evaluations of the *Beca 18,* or any other program where applicants might fear discrimination if revealing achievements related to merit- and need-based education programs, are likely to suffer from a downward bias when exploring the labor market impacts using survey or administrative data comparing beneficiaries and non-beneficiaries. Our results indicate that beneficiaries have a callback premium, yet they are not including the scholarship in their resumes. This behavior increases information frictions in the hiring process. Firms are not able to learn about candidates' quality and would dilute the labor outcomes of *Beca 18* recipients relative to similar candidates that are non-beneficiaries.

Thus, a low-cost intervention to increase their labor market opportunities is to nudge recipients to change their resumes making the scholarship salient as we did in our experiment. Indeed, this nudge is part of PRONABEC's newly revised training when preparing *Beca 18* beneficiaries for the job market. There is now a module on resume preparation that emphasizes the gains of adding the scholarship and making it salient when applying for jobs.

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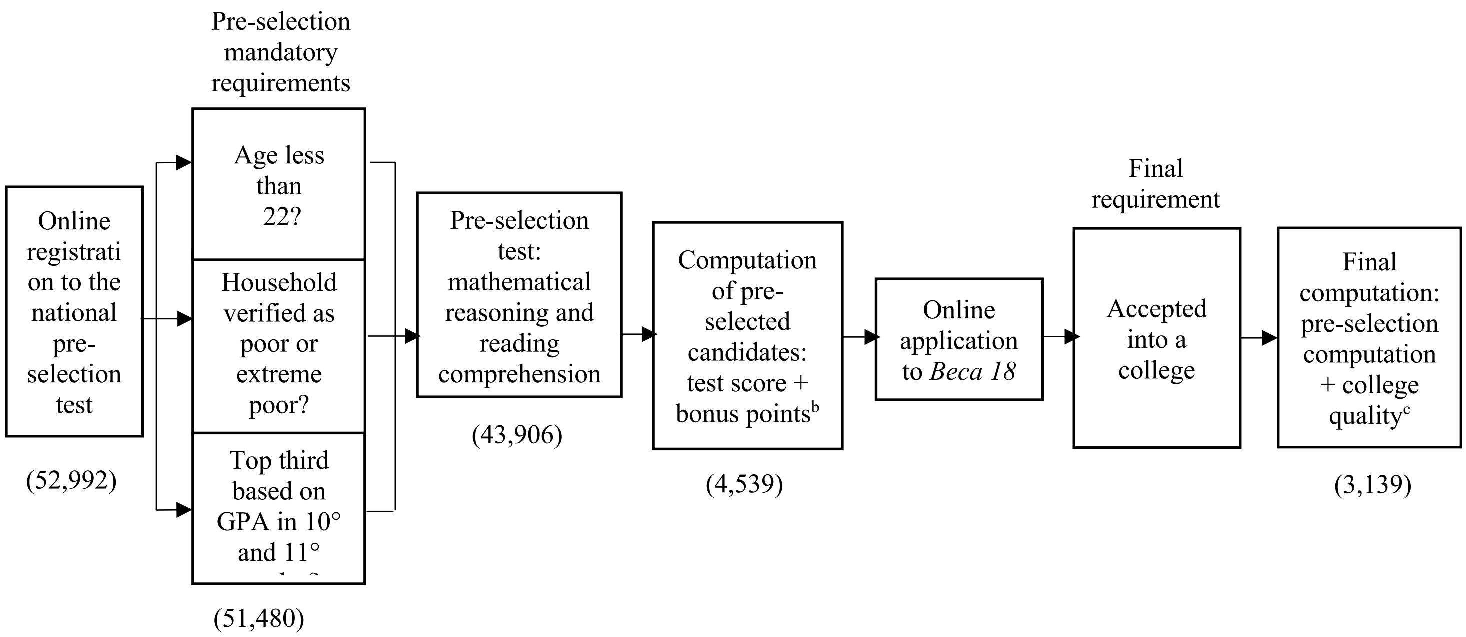
Online Appendices: Not for publication

Appendix Figure A1: *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 A1: 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 (high school national exam).	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] For Brazil, Costa Rica and Peru, the total student population figures 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.

Appendix Table A2: Occupations selected

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	1,903	53.6	9.25
Professional Occupations	1,645	46.4	11.61
Total	3,548	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 Table A3. Regression with job ad fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Beca 18	0.019***	0.019***	0.019***	0.019***	0.020***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Randomized Inference: p-value	[0.014]	[0.010]	[0.010]	[0.010]	[0.006]	[0.006]
Candidate controls	No	Yes	Yes	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes	Yes
Week fixed effects	No	No	No	Yes	Yes	Yes
Resume controls	No	No	No	No	Yes	Yes
Significant variables	No	No	No	No	No	Yes
Adjusted R^2	0.481	0.485	0.486	0.486	0.484	0.485
Mean control	0.094	0.094	0.094	0.094	0.094	0.094
Number of clusters	887	887	887	887	887	887
N	3,548	3,548	3,548	3,548	3,548	3,548

Note: All specifications include job ad fixed effects. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets.

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

Appendix Table A4: Regression with job ad fixed effects and standard errors clustered at the resume level

	(1)	(2)	(3)	(4)	(5)	(6)
Beca 18	0.019^{**}	0.019^{**}	0.019^{**}	0.019^{**}	0.020^{***}	0.020^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Randomized Inference: p-value	[0.014]	[0.012]	[0.012]	[0.012]	[0.007]	[0.007]
Candidate controls	No	Yes	Yes	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes	Yes
Week fixed effects	No	No	No	Yes	Yes	Yes
Resume controls	No	No	No	No	Yes	Yes
Significant variables	No	No	No	No	Yes	Yes
Adjusted R^2	0.481	0.485	0.486	0.486	0.484	0.485
Mean control (callback for *Beca 18* non-recipients)	0.094	0.094	0.094	0.094	0.094	0.094
Number of clusters	887	887	887	887	887	887
N	3,548	3,548	3,548	3,548	3,548	3,544

Note: All specifications include 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 A5: Regression results on callbacks using Probit models (marginal effects)

	(1)	(2)	(3)	(4)	(5)	(6)
Beca 18	0.019***	0.018***	0.018**	0.018**	0.17**	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Randomized inference: p-value	[0.013]	[0.013]	[0.019]	[0.020]	[0.028]	[0.042]
Candidate controls	No	Yes	Yes	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes	Yes
Week fixed effects	No	No	No	Yes	Yes	Yes
Resume controls	No	No	No	No	Yes	Yes
Significant variables	No	No	No	No	No	Yes
Pseudo R^2	0.001	0.025	0.029	0.077	0.085	0.088
Mean control	0.094	0.094	0.094	0.103	0.103	0.103
Number of clusters	887	887	887	808	808	808
N	3,548	3,548	3,548	3,232	3,232	3,232

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).

For columns (4)-(6), 316 observations were omitted because of collinearity in some week indicators (Stata dropped them automatically).

Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A6. 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
	(1)	(2)	(3)	(4)	(5)
Beca 18	0.018**	0.040***	0.012	0.008	-0.012
	(0.007)	(0.015)	(0.021)	(0.016)	(0.022)
Randomized Inference: p-value	[0.014]	[0.002]	[0.500]	[0.486]	[0.925]
Regular controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.043	0.073	-0.002	0.029	0.076
Mean control	0.094	0.069	0.092	0.102	0.129
Number of clusters	887	464	410	406	364
N	3,548	1,158	745	982	663

Note: All specifications include *candidate controls* include sex, ethnicity, district of residence, type of occupation; *job controls* include indicators for prioritized major and college as well as weeks fixed effects. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A7. Effects by gender

	(1) All	(2) Women	(3) Men
Beca 18	0.018**	0.014	0.024**
	(0.007)	(0.013)	(0.011)
Randomized Inference: p-value	[0.014]	[0.377]	[0.064]
Regular controls	Yes	Yes	Yes
Adjusted R^2	0.043	0.041	0.046
Mean control (callback for *Beca 18* non-recipients)	0.094	0.113	0.075
Number of clusters	887	836	827
N	3,548	1,798	1,750

Note: All specifications include *candidate controls* include sex, ethnicity, district of residence, type of occupation; *job controls* include indicators for prioritized major and college as well as weeks fixed effects. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A8. Effects by paternal surname and college type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Indigenous paternal surname (I/●)			Mestizo paternal surname (M/●)		
	All	All	3-year college	5-year college	All	3-year college	5-year college
Beca 18	0.018**	0.025*	0.040*	0.013	0.010	0.015	-0.003
	(0.007)	(0.014)	(0.018)	(0.022)	(0.014)	(0.018)	(0.022)
Randomized inference: p-values	[0.014]	[0.070]	[0.043]	[0.521]	[0.293]	[0.556]	[0.953]
Regular controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.043	0.040	0.049	0.030	0.041	0.031	0.034
Mean control (callback for *Beca 18* non-recipients)	0.094	0.095	0.085	0.106	0.093	0.072	0.118
Number of clusters	887	887	480	418	887	481	414
N	3,548	1,774	949	825	1,774	954	820

Note: All specifications include *candidate controls* include sex, ethnicity, district of residence, type of occupation; *job controls* include indicators for prioritized major and college as well as weeks fixed effects. Robust standard errors (in parenthesis) are clustered at the job ad level. P-values using randomized inference (with 1000 repetitions) in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Sample resumes sent for a graphics 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 C. Balance test

Variable	Beca 18 Yes (1)	Beca 18 No (2)	Difference (3)=(1)-(2)	P-values (4)	FDR-q (5)
Observations	1774	1774	3548	.	.
additional_info__1	0.359	0.338	-0.021	0.192	1.000
additional_info__2	0.329	0.330	0.001	0.943	1.000
additional_info__3	0.312	0.332	0.020	0.209	1.000
college_name__1	0.005	0.005	0.000	0.998	1.000
college_name__10	0.025	0.026	0.001	0.835	1.000
college_name__11	0.012	0.012	0.000	0.997	1.000
college_name__12	0.063	0.063	0.000	0.952	1.000
college_name__13	0.001	0.000	-0.001	0.317	1.000
college_name__14	0.034	0.028	-0.006	0.286	1.000
college_name__15	0.001	0.002	0.001	0.655	1.000
college_name__16	0.001	0.000	-0.001	0.317	1.000
college_name__17	0.007	0.005	-0.003	0.273	1.000
college_name__18	0.033	0.038	0.005	0.420	1.000
college_name__19	0.049	0.049	0.000	0.994	1.000
college_name__2	0.017	0.019	0.002	0.617	1.000
college_name__20	0.001	0.001	0.000	0.999	1.000
college_name__21	0.088	0.091	0.004	0.688	1.000
college_name__22	0.010	0.010	-0.001	0.863	1.000
college_name__23	0.006	0.007	0.001	0.684	1.000
college_name__24	0.010	0.007	-0.002	0.462	1.000
college_name__25	0.002	0.000	-0.002	0.083	1.000
college_name__26	0.003	0.003	0.000	0.999	1.000
college_name__27	0.011	0.009	-0.002	0.501	1.000
college_name__28	0.043	0.042	-0.001	0.863	1.000
college_name__29	0.002	0.001	-0.001	0.654	1.000
college_name__3	0.036	0.043	0.007	0.264	1.000
college_name__30	0.000	0.002	0.002	0.083	1.000
college_name__31	0.001	0.003	0.002	0.257	1.000
college_name__32	0.006	0.007	0.002	0.532	1.000
college_name__33	0.074	0.065	-0.009	0.318	1.000
college_name__34	0.008	0.006	-0.002	0.430	1.000
college_name__35	0.019	0.024	0.006	0.248	1.000
college_name__36	0.005	0.005	0.001	0.810	1.000
college_name__37	0.056	0.051	-0.005	0.496	1.000
college_name__38	0.003	0.005	0.002	0.439	1.000
college_name__39	0.018	0.020	0.002	0.715	1.000

college_name__4	0.085	0.080	-0.006	0.535	1.000
college_name__40	0.010	0.015	0.005	0.178	1.000
college_name__41	0.021	0.027	0.005	0.326	1.000
college_name__42	0.008	0.003	-0.005	0.049	1.000
college_name__43	0.007	0.007	0.001	0.843	1.000
college_name__44	0.021	0.022	0.001	0.912	1.000
college_name__45	0.059	0.058	-0.001	0.880	1.000
college_name__46	0.023	0.013	-0.010	0.030	1.000
college_name__47	0.001	0.002	0.001	0.318	1.000
college_name__5	0.004	0.005	0.001	0.798	1.000
college_name__6	0.065	0.064	-0.001	0.885	1.000
college_name__7	0.005	0.007	0.002	0.513	1.000
college_name__8	0.021	0.023	0.002	0.733	1.000
college_name__9	0.020	0.025	0.005	0.314	1.000
edu_edit__1	0.193	0.205	0.012	0.378	1.000
edu_edit__2	0.214	0.194	-0.019	0.157	1.000
edu_edit__3	0.202	0.196	-0.007	0.614	1.000
edu_edit__4	0.185	0.215	0.030	0.023	1.000
edu_edit__5	0.206	0.189	-0.016	0.222	1.000
edu_style__1	0.250	0.250	-0.001	0.969	1.000
edu_style__2	0.248	0.252	0.004	0.786	1.000
edu_style__3	0.242	0.258	0.015	0.295	1.000
edu_style__4	0.259	0.241	-0.019	0.201	1.000
edustyle__1	0.250	0.250	-0.001	0.969	1.000
edustyle__2	0.248	0.252	0.004	0.786	1.000
edustyle__3	0.242	0.258	0.015	0.295	1.000
edustyle__4	0.259	0.241	-0.019	0.201	1.000
email__1	0.250	0.250	-0.001	0.969	1.000
email__2	0.243	0.257	0.014	0.333	1.000
email__3	0.256	0.244	-0.012	0.416	1.000
email__4	0.251	0.249	-0.002	0.907	1.000
eth__1	0.251	0.249	-0.002	0.907	1.000
eth__2	0.256	0.244	-0.012	0.416	1.000
eth__3	0.243	0.257	0.014	0.333	1.000
eth__4	0.250	0.250	-0.001	0.969	1.000
female applicant	0.503	0.510	0.007	0.687	1.000
fonts__1	0.248	0.252	0.004	0.786	1.000
fonts__2	0.261	0.239	-0.022	0.131	1.000
fonts__3	0.238	0.262	0.023	0.112	1.000
fonts__4	0.253	0.247	-0.005	0.727	1.000
hs2_name__1	0.048	0.050	0.002	0.756	1.000

hs2_name__10	0.026	0.019	-0.008	0.113	1.000
hs2_name__11	0.050	0.053	0.003	0.704	1.000
hs2_name__12	0.045	0.049	0.004	0.579	1.000
hs2_name__13	0.046	0.040	-0.006	0.363	1.000
hs2_name__14	0.023	0.025	0.003	0.583	1.000
hs2_name__15	0.020	0.026	0.006	0.222	1.000
hs2_name__16	0.012	0.012	0.001	0.878	1.000
hs2_name__17	0.009	0.008	-0.001	0.857	1.000
hs2_name__18	0.021	0.017	-0.003	0.463	1.000
hs2_name__19	0.009	0.004	-0.005	0.060	1.000
hs2_name__2	0.011	0.010	-0.001	0.738	1.000
hs2_name__20	0.021	0.021	-0.001	0.907	1.000
hs2_name__21	0.024	0.023	-0.001	0.823	1.000
hs2_name__22	0.014	0.008	-0.006	0.103	1.000
hs2_name__23	0.008	0.010	0.002	0.478	1.000
hs2_name__24	0.008	0.012	0.004	0.247	1.000
hs2_name__25	0.047	0.041	-0.006	0.413	1.000
hs2_name__26	0.027	0.030	0.003	0.614	1.000
hs2_name__27	0.029	0.020	-0.009	0.084	1.000
hs2_name__28	0.045	0.055	0.010	0.166	1.000
hs2_name__29	0.046	0.043	-0.002	0.745	1.000
hs2_name__3	0.052	0.052	0.000	1.000	1.000
hs2_name__30	0.021	0.009	-0.012	0.003	0.826
hs2_name__31	0.041	0.045	0.003	0.619	1.000
hs2_name__32	0.017	0.015	-0.002	0.590	1.000
hs2_name__33	0.020	0.017	-0.002	0.619	1.000
hs2_name__34	0.014	0.018	0.005	0.281	1.000
hs2_name__35	0.024	0.024	0.000	1.000	1.000
hs2_name__36	0.018	0.021	0.003	0.543	1.000
hs2_name__37	0.013	0.019	0.006	0.142	1.000
hs2_name__38	0.023	0.025	0.002	0.742	1.000
hs2_name__39	0.016	0.023	0.007	0.148	1.000
hs2_name__4	0.019	0.026	0.007	0.139	1.000
hs2_name__40	0.020	0.016	-0.004	0.374	1.000
hs2_name__41	0.021	0.015	-0.007	0.130	1.000
hs2_name__5	0.024	0.021	-0.003	0.570	1.000
hs2_name__6	0.010	0.010	0.000	1.000	1.000
hs2_name__7	0.010	0.008	-0.002	0.478	1.000
hs2_name__8	0.007	0.012	0.005	0.168	1.000
hs2_name__9	0.042	0.048	0.006	0.372	1.000
job_title__1	0.034	0.034	0.000	1.000	1.000

job_title__10	0.003	0.003	0.000	1.000	1.000
job_title__100	0.001	0.001	0.000	1.000	1.000
job_title__101	0.001	0.001	0.000	1.000	1.000
job_title__102	0.001	0.001	0.000	1.000	1.000
job_title__103	0.003	0.003	0.000	1.000	1.000
job_title__104	0.001	0.001	0.000	1.000	1.000
job_title__11	0.001	0.001	0.000	1.000	1.000
job_title__12	0.148	0.148	0.000	1.000	1.000
job_title__13	0.021	0.021	0.000	1.000	1.000
job_title__14	0.001	0.001	0.000	1.000	1.000
job_title__15	0.001	0.001	0.000	1.000	1.000
job_title__16	0.006	0.006	0.000	1.000	1.000
job_title__17	0.002	0.002	0.000	1.000	1.000
job_title__18	0.003	0.003	0.000	1.000	1.000
job_title__19	0.001	0.001	0.000	1.000	1.000
job_title__2	0.048	0.048	0.000	1.000	1.000
job_title__20	0.001	0.001	0.000	1.000	1.000
job_title__21	0.001	0.001	0.000	1.000	1.000
job_title__22	0.002	0.002	0.000	1.000	1.000
job_title__23	0.001	0.001	0.000	1.000	1.000
job_title__24	0.003	0.003	0.000	1.000	1.000
job_title__25	0.008	0.008	0.000	1.000	1.000
job_title__26	0.001	0.001	0.000	1.000	1.000
job_title__27	0.002	0.002	0.000	1.000	1.000
job_title__28	0.025	0.025	0.000	1.000	1.000
job_title__29	0.001	0.001	0.000	1.000	1.000
job_title__3	0.002	0.002	0.000	1.000	1.000
job_title__30	0.038	0.038	0.000	1.000	1.000
job_title__31	0.002	0.002	0.000	1.000	1.000
job_title__32	0.016	0.016	0.000	1.000	1.000
job_title__33	0.001	0.001	0.000	1.000	1.000
job_title__34	0.001	0.001	0.000	1.000	1.000
job_title__35	0.001	0.001	0.000	1.000	1.000
job_title__36	0.001	0.001	0.000	1.000	1.000
job_title__37	0.002	0.002	0.000	1.000	1.000
job_title__38	0.001	0.001	0.000	1.000	1.000
job_title__39	0.029	0.029	0.000	1.000	1.000
job_title__4	0.003	0.003	0.000	1.000	1.000
job_title__40	0.001	0.001	0.000	1.000	1.000
job_title__41	0.002	0.002	0.000	1.000	1.000
job_title__42	0.012	0.012	0.000	1.000	1.000

job_title__43	0.001	0.001	0.000	1.000	1.000
job_title__44	0.032	0.032	0.000	1.000	1.000
job_title__45	0.001	0.001	0.000	1.000	1.000
job_title__46	0.006	0.006	0.000	1.000	1.000
job_title__47	0.028	0.028	0.000	1.000	1.000
job_title__48	0.001	0.001	0.000	1.000	1.000
job_title__49	0.005	0.005	0.000	1.000	1.000
job_title__5	0.008	0.008	0.000	1.000	1.000
job_title__50	0.010	0.010	0.000	1.000	1.000
job_title__51	0.001	0.001	0.000	1.000	1.000
job_title__52	0.001	0.001	0.000	1.000	1.000
job_title__53	0.003	0.003	0.000	1.000	1.000
job_title__54	0.001	0.001	0.000	1.000	1.000
job_title__55	0.002	0.002	0.000	1.000	1.000
job_title__56	0.007	0.007	0.000	1.000	1.000
job_title__57	0.002	0.002	0.000	1.000	1.000
job_title__58	0.002	0.002	0.000	1.000	1.000
job_title__59	0.028	0.028	0.000	1.000	1.000
job_title__6	0.007	0.007	0.000	1.000	1.000
job_title__60	0.001	0.001	0.000	1.000	1.000
job_title__61	0.005	0.005	0.000	1.000	1.000
job_title__62	0.001	0.001	0.000	1.000	1.000
job_title__63	0.019	0.019	0.000	1.000	1.000
job_title__64	0.016	0.016	0.000	1.000	1.000
job_title__65	0.001	0.001	0.000	1.000	1.000
job_title__66	0.001	0.001	0.000	1.000	1.000
job_title__67	0.006	0.006	0.000	1.000	1.000
job_title__68	0.001	0.001	0.000	1.000	1.000
job_title__69	0.001	0.001	0.000	1.000	1.000
job_title__7	0.006	0.006	0.000	1.000	1.000
job_title__70	0.003	0.003	0.000	1.000	1.000
job_title__71	0.001	0.001	0.000	1.000	1.000
job_title__72	0.012	0.012	0.000	1.000	1.000
job_title__73	0.035	0.035	0.000	1.000	1.000
job_title__74	0.003	0.003	0.000	1.000	1.000
job_title__75	0.001	0.001	0.000	1.000	1.000
job_title__76	0.001	0.001	0.000	1.000	1.000
job_title__77	0.005	0.005	0.000	1.000	1.000
job_title__78	0.009	0.009	0.000	1.000	1.000
job_title__79	0.002	0.002	0.000	1.000	1.000
job_title__8	0.005	0.005	0.000	1.000	1.000

job_title__80	0.001	0.001	0.000	1.000	1.000
job_title__81	0.009	0.009	0.000	1.000	1.000
job_title__82	0.001	0.001	0.000	1.000	1.000
job_title__83	0.010	0.010	0.000	1.000	1.000
job_title__84	0.009	0.009	0.000	1.000	1.000
job_title__85	0.006	0.006	0.000	1.000	1.000
job_title__86	0.001	0.001	0.000	1.000	1.000
job_title__87	0.005	0.005	0.000	1.000	1.000
job_title__88	0.006	0.006	0.000	1.000	1.000
job_title__89	0.005	0.005	0.000	1.000	1.000
job_title__9	0.107	0.107	0.000	1.000	1.000
job_title__90	0.014	0.014	0.000	1.000	1.000
job_title__91	0.032	0.032	0.000	1.000	1.000
job_title__92	0.001	0.001	0.000	1.000	1.000
job_title__93	0.001	0.001	0.000	1.000	1.000
job_title__94	0.001	0.001	0.000	1.000	1.000
job_title__95	0.038	0.038	0.000	1.000	1.000
job_title__96	0.016	0.016	0.000	1.000	1.000
job_title__97	0.011	0.011	0.000	1.000	1.000
job_title__98	0.005	0.005	0.000	1.000	1.000
job_title__99	0.001	0.001	0.000	1.000	1.000
jobs_worked2__1	0.192	0.191	-0.001	0.932	1.000
jobs_worked2__10	0.014	0.009	-0.005	0.203	1.000
jobs_worked2__11	0.013	0.012	-0.001	0.881	1.000
jobs_worked2__12	0.011	0.011	0.001	0.872	1.000
jobs_worked2__13	0.012	0.007	-0.006	0.085	1.000
jobs_worked2__14	0.009	0.008	-0.001	0.857	1.000
jobs_worked2__2	0.189	0.193	0.005	0.733	1.000
jobs_worked2__3	0.187	0.191	0.004	0.764	1.000
jobs_worked2__4	0.188	0.188	0.000	1.000	1.000
jobs_worked2__5	0.125	0.128	0.003	0.801	1.000
jobs_worked2__6	0.014	0.015	0.001	0.888	1.000
jobs_worked2__7	0.015	0.016	0.001	0.788	1.000
jobs_worked2__8	0.017	0.018	0.001	0.899	1.000
jobs_worked2__9	0.014	0.012	-0.002	0.653	1.000
jobs_worked__1	0.165	0.178	0.012	0.327	1.000
jobs_worked__10	0.005	0.006	0.001	0.654	1.000
jobs_worked__11	0.007	0.006	-0.001	0.834	1.000
jobs_worked__12	0.005	0.005	0.000	1.000	1.000
jobs_worked__13	0.006	0.006	0.000	1.000	1.000
jobs_worked__14	0.007	0.006	-0.001	0.682	1.000

jobs_worked__15	0.008	0.006	-0.002	0.413	1.000
jobs_worked__16	0.004	0.006	0.002	0.466	1.000
jobs_worked__17	0.008	0.005	-0.003	0.296	1.000
jobs_worked__18	0.006	0.007	0.001	0.834	1.000
jobs_worked__19	0.008	0.003	-0.005	0.073	1.000
jobs_worked__2	0.177	0.165	-0.012	0.327	1.000
jobs_worked__20	0.006	0.010	0.004	0.176	1.000
jobs_worked__3	0.155	0.183	0.028	0.028	1.000
jobs_worked__4	0.163	0.167	0.004	0.752	1.000
jobs_worked__5	0.174	0.147	-0.027	0.028	1.000
jobs_worked__6	0.027	0.027	0.000	1.000	1.000
jobs_worked__7	0.028	0.033	0.005	0.377	1.000
jobs_worked__8	0.030	0.029	-0.001	0.842	1.000
jobs_worked__9	0.013	0.008	-0.005	0.192	1.000
objective__1	0.081	0.099	0.017	0.069	1.000
objective__10	0.088	0.090	0.002	0.814	1.000
objective__11	0.091	0.086	-0.005	0.594	1.000
objective__2	0.099	0.088	-0.011	0.273	1.000
objective__3	0.094	0.085	-0.009	0.346	1.000
objective__4	0.096	0.087	-0.009	0.351	1.000
objective__5	0.088	0.088	0.000	1.000	1.000
objective__6	0.095	0.091	-0.003	0.729	1.000
objective__7	0.094	0.094	0.001	0.954	1.000
objective__8	0.096	0.092	-0.003	0.730	1.000
objective__9	0.080	0.100	0.020	0.035	1.000
p50_poor	0.606	0.600	-0.006	0.732	1.000
phone_format__1	0.259	0.241	-0.017	0.230	1.000
phone_format__2	0.248	0.252	0.004	0.786	1.000
phone_format__3	0.244	0.256	0.013	0.373	1.000
phone_format__4	0.250	0.250	0.001	0.969	1.000
phone_number__1	0.259	0.241	-0.019	0.201	1.000
phone_number__2	0.250	0.250	-0.001	0.969	1.000
phone_number__3	0.246	0.254	0.007	0.614	1.000
phone_number__4	0.244	0.256	0.012	0.416	1.000
software__1	0.254	0.246	-0.007	0.614	1.000
software__2	0.249	0.251	0.002	0.907	1.000
software__3	0.250	0.250	0.001	0.969	1.000
software__4	0.247	0.253	0.005	0.727	1.000
tech	0.535	0.538	0.003	0.866	1.000
title_style__1	0.333	0.357	0.024	0.129	1.000
title_style__2	0.334	0.319	-0.015	0.352	1.000

title_style__3	0.333	0.324	-0.010	0.543	1.000
week__1	0.027	0.027	0.000	1.000	1.000
week__10	0.033	0.033	0.000	1.000	1.000
week__11	0.045	0.045	0.000	1.000	1.000
week__12	0.044	0.044	0.000	1.000	1.000
week__13	0.028	0.028	0.000	1.000	1.000
week__14	0.045	0.045	0.000	1.000	1.000
week__15	0.032	0.032	0.000	1.000	1.000
week__16	0.043	0.043	0.000	1.000	1.000
week__17	0.050	0.050	0.000	1.000	1.000
week__18	0.026	0.026	0.000	1.000	1.000
week__19	0.033	0.033	0.000	1.000	1.000
week__2	0.029	0.029	0.000	1.000	1.000
week__20	0.009	0.009	0.000	1.000	1.000
week__21	0.025	0.025	0.000	1.000	1.000
week__22	0.020	0.020	0.000	1.000	1.000
week__23	0.026	0.026	0.000	1.000	1.000
week__24	0.015	0.015	0.000	1.000	1.000
week__25	0.038	0.038	0.000	1.000	1.000
week__26	0.030	0.030	0.000	1.000	1.000
week__27	0.018	0.018	0.000	1.000	1.000
week__28	0.010	0.010	0.000	1.000	1.000
week__29	0.024	0.024	0.000	1.000	1.000
week__3	0.056	0.056	0.000	1.000	1.000
week__30	0.010	0.010	0.000	1.000	1.000
week__31	0.023	0.023	0.000	1.000	1.000
week__32	0.029	0.029	0.000	1.000	1.000
week__4	0.024	0.024	0.000	1.000	1.000
week__5	0.046	0.046	0.000	1.000	1.000
week__6	0.041	0.041	0.000	1.000	1.000
week__7	0.030	0.030	0.000	1.000	1.000
week__8	0.048	0.048	0.000	1.000	1.000
week__9	0.043	0.043	0.000	1.000	1.000
work_edit__1	0.193	0.205	0.012	0.378	1.000
work_edit__2	0.214	0.194	-0.019	0.157	1.000
work_edit__3	0.202	0.196	-0.007	0.614	1.000
work_edit__4	0.185	0.215	0.030	0.023	1.000
work_edit__5	0.206	0.189	-0.016	0.222	1.000
work_style__1	0.247	0.253	0.006	0.670	1.000
work_style__2	0.240	0.260	0.021	0.152	1.000
work_style__3	0.259	0.241	-0.017	0.230	1.000

work_style__4	0.255	0.245	-0.010	0.510	1.000

Note: P-values refer to the statistical significance of column (3) unadjusted for multiple hypotheses testing. Instead, FDR q-values are computed over all outcomes and indicate the probability of false positives among significant tests.