More Women in Tech?
Evidence from a Field Experiment addressing Social Identity

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Abstract

This paper studies how social identity interacts with comparative advantage to determine whether women will attempt a career in technology. We implement two field experiments with potential applicants to a five-month software-coding program targeted at low-income women in Peru and Mexico. When we counteract the male stereotype for a career in technology -through role models, information on returns and access to a female network- application rates double and self-selection patterns change substantially. These results suggest that identity considerations are a strong deterrent for women to attempt a career in technology, in particular for some high-cognitive skill women who would benefit the most from it.

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1. Introduction

Growth of firms in the digital economy and the technology sectors relies on a steady supply of talent that can innovate and adapt to changing customer needs. This requires diverse perspectives and a deep talent pool. Yet, a common concern is that women often shy away from attempting career in those industries, reducing the volume of potential talent entering the industry but also its diversity. This is particularly troubling since technology increasingly affects all sectors—from finance to healthcare.

In this paper we conduct two field experiments to study to what extent social-identity considerations act as barriers to women's occupational choices. In particular, we consider whether beliefs about skills and returns to skill, and preferences over the attributes of the occupations may both be shaped (or distorted) by societal norms and analyze their possible role in the self-selection of women away from the technology sector and in persistent occupational gender segregation patterns (e.g. Bertrand, 2011; Goldin, 2014; Bertrand and Duflo, 2016). Our experiments also provide a strategy for firms aiming to increase their female applicant pool, and uncovers the trade-offs of different strategies.

Social psychologists have long recognized and demonstrated that individuals reason using social categories, further linking those to norms and beliefs, which in turn affect behavior (Spencer and Steele, 1995; see survey by Paluk and Green 2009). Social identity (i.e. the group/social category the individual identifies with) can matter for choices for several reasons. For example, a large literature shows that it may affect beliefs of success given prevailing stereotypes. In a series of lab experiments Coffman (2014) and Bordalo el al (2016b) show that gender stereotyping of oneself and others affects beliefs about the abilities and behaviors of both men and women. At the aggregate level, Miller et al (2015) finds a correlation between the prevalence of women in science in a country and (implicit and explicit) stereotypes. Social identity can also affect preferences for working in an occupation as a function of how different the social norm for that occupation is from the individual's identity (Akerlof and Kranton, 2000) and alter behavior given the associated identity norms (Bertrand Kamenica and Pan, 2015; Flory, Leibbrandt and List, 2014).

In our study, we focus on the decision to attempt a career in software development, which in spite of its growth remains predominantly male, and where gender stereotypes are very strong (Cheryan et al 2011, 2013). Our framework introduces identity considerations into the Roy (1951)/Borjas (1987) model of self-selection. Women decide whether to enter the technology industry (rather than go to the "services" sector[1]) as a function of their "technology" and services skills, the returns to those skills, and what we refer to as an "identity wedge" from entering a stereotypically male sector such as technology. This identity component affects the overall expected returns in technology by driving a wedge between the actual returns to skill and the returns perceived by the individuals. This wedge can capture several classes of mechanisms associated with social identity. One is the distorted belief that women cannot be successful in certain industries as implied by stereotypical thinking based on a "representative heuristic" (as in Kahneman and Tversky, 1973; and Bordalo et al 2016a). Another is the non-monetary/psychological cost of working in an industry where social norms are at odds with one's own perceived social category (as in Akerlof and Kranton, 2000). In such a setting, self-selection will not only depend (as in the standard Roy model) on the correlation between the two types of skills, but also on their correlation with the underlying identity wedge (relative to their dispersion). As a result, we may observe different patterns of self-selection (positive and/or negative) into the technology sector both along the skills dimension and the identity dimension depending on the underlying distributions. In particular, in some circumstances, as a result of the identity wedge, women with high technology skills may decide not to enter the industry because of their high identity cost, thus distorting the optimal allocation of talent across industries.

With this framework in mind, we ran two field experiments that aimed to reduce the strength of the identity wedge in decision making, by highlighting the good prospects for women in the technology sector, the availability of a network of women in the sector, and in particular the perception that they cannot succeed; in short, counteracting the prevailing male stereotype. In both experiments we randomly varied the informational message to recruit applicants to a five-month "coding" bootcamp, offered exclusively to women from low-income backgrounds by a non-for-profit organization in Latin America.[2]

[1] We include here their traditional outside options: clerical/support occupations such as secretary and receptionist, as well as retail sales.

[2] The goal of the organization is to identify high potential women who because of their background may not have the option, knowledge or tools to enter the growing technology sector, in a context

Experiment 1: Lima, Peru. We ran the first field experiment in Lima, where female coders represent only 7% of the occupation. The control group recruitment message contained generic information about the program (its goals, career opportunities, content and requirements). In the treatment message, we added a section highlighting the career prospects of *women* in technology: we emphasized that firms were actively seeking to recruit women, provided a role model in the form of a successful recent graduate from the program, and highlighted the fact that the program was creating a network of women in the industry to which graduates would have access.

Subsequently applicants were invited to attend a set of tests and interviews (to determine who would be selected for the program) where we collected information on a host of applicant characteristics, in particular those deemed important for self-selection. We obtained measures of technology skills and overall cognitive abilities directly from the trainer's examinations, while we elicited applicants' expected monetary returns of pursuing a career in technology and of their outside option (a retail/support services job), as well as three measures of implicit social identity bias. The latter consisted of two implicit association tests (IAT) including one we created specifically to measure how much they identified gender (male/female) with occupational choice (technology/support services), and a survey-based measure of identification with a 'traditional' female role. We also collected demographic characteristics, the candidates' aspirations, and elicited time and risk preferences (using games) to evaluate alternative mechanisms for our findings.

This simple and low-cost treatment message was extremely successful: application rates rose from 7% to 15%, doubling the size of the applicant pool to the training program and attendance to the examinations also doubled. We then analyzed the self-selection patterns in the two groups to assess what barriers were 'loosened' by the message and found important effects on both the average and the upper tail of the distribution of applicants.

Average effects. Our first experiment led to negative self-selection in average cognitive skills (both general IQ and coding specific skills), and in average expected returns in

where it is hard to find the kind of basic coding skills offered in the training. The program launches extensive call for applications, implements a set of examinations, and selects the best candidates for training.

technology and in services. We also found evidence of self-selection on the measured identity wedge: on average, women with higher bias, as measured by the IAT and the traditional gender role survey measure applied following our identity treatment message. We argue that this is consistent with a world where the identity wedge matters for occupational choice and that the importance of this wedge varies across women.

Upper tail. What firms and organizations ultimately care about, however, is the right tail of the applicants' skill distribution: does treatment increase the pool of *qualified* women they get to choose from? We found that even though *average* cognitive ability was lower in the treatment group, the identity treatment message significantly increased cognitive and tech-specific abilities of the *top* group of applicants, i.e, those that would be selected for training. Why did higher cognitive skill women apply even if, on average, selection was negative? Here we found evidence that some high skill women who did not apply before the treatment were also high "identity wedge" women and were now induced to apply. This is further evidence, beyond the effect of the experiment on the average quality of the pool, that social identity matters for this occupational choice.

Experiment 2: Mexico City. In a follow up experiment in Mexico City, we aimed to disentangle the different *pieces* of information in the first message that the women in Lima responded to. This allowed us to understand what kinds of information made a bigger difference: information on success and returns for women, the non-monetary component of providing a network of women, and/or the exposure to a role model. Here the control was the complete message, and in each of three treatments we removed one feature of the initial message (success/returns, network of women, role model) at a time. This allowed us to assess the effect of each treatment conditional on the information provided by all others.[3] We found that women responded most strongly to the message that included a role model. However, hearing about the high expected returns (for women) in the technology sector, or that they would have a network of other women upon graduating, also had significant effects beyond those of the information already conveyed by the role model, and their size was in each case about half as large. Our study thus provides new evidence on the marginal effect of different types of identity-related information when women are making real career choices. We show, in particular, that

[3] The main reason for this was that after the success of our Lima experiment, the training provider worried about going back to their original message.

information on the success of women and the provision of a network of women impact the decision to apply.

A specific feature of our setting is that the training was offered only to women, and all applicants knew that. Hence, we were able to design a message that was specifically targeted to women without being concerned about spillovers on men (of providing, for example, a female role model) that might create confounding effects. Admittedly, we do not know how men would respond in a setting where they also see a similar "identity treatment" message, and thus cannot say anything about the role of identity for men or other social categories, or what message would work as an encouragement to other groups.

Our paper contributes to the literature on how women self-select into different industries (Goldin, 2014; Flory, Leibbrandt and List, 2014; Niessen-Ruenzi and Ruenzi, 2018), or into different contracts (Samek, 2019) and how informational nudges may alter their search / decision to apply behavior (Gee 2018), where evidence from field experiments is limited.[4] This is important, since at the macroeconomic level Hsieh et al (2013), also in the context of the Roy model, show that in the USA the reduction of barriers to the access of women and minorities to certain occupations can explain one quarter of GDP growth between 1960 and 2010, through improved allocation based on comparative advantage. To the best of our knowledge we are the first to show in the field that self-selection operates through the implicit stereotypes and identity costs that women hold and show that these are unrelated to cognitive skills, but interact with individual comparative advantage. As a result, we also provide microeconomic evidence on some of the barriers precluding the optimal allocation of talent in the economy. (Hsieh et al, 2013; Bell et al, 2017).

Our study is also related more broadly to the literature on socio-cognitive de-biasing under stereotype threat in social psychology (Steele and Aronson, 1995; Good, Aronson, and Inzlicht, 2003; Kawakami et al., 2017; Forbes and Schmader, 2010, and Spencer et al, 1999, in the context of women's math performance), and to the literature which encourages individuals' interest in further education, especially those coming from

[4] Applying to a training/education program is a key step in the career process, especially in the tech sector where upon graduating from these short training programs, people are ready to work. Low interest in this type of education is seen as contributing to the "pipeline" problem in many male-dominated industries.

disadvantaged or minority populations, through informational nudges (Hoxby and Turner 2013,) and peer mentors (Castleman and Page 2015). It is also complementary to the literature evaluating the importance of role models in STEM showing that female role models are more likely to encourage women attending school/college to stay in a male dominated track (eg., Carrell et al., 2010, Cheryan et al. 2011 and 2013, Dennehy & Dasgupta, 2017 and Breda et al., 2018 for STEM and Porter and Serra 2018 and Avilova and Goldin, 2018, for economics; Adams et al 2017 shows that women with STEM parents are more likely to do a career in finance). Our intervention includes a role model but also two other identity-related treatments and allows us to look beyond role models to identify what are the mechanisms through with they operate. In addition, we are able to identify empirically how "identity" considerations –which unlike earlier work we measure directly- interacts with expected returns to a career to create a barrier, as described in our theoretical framework.

Finally, our paper is related to the very limited literature on the performance effects of restricting the pool of applicants through expected discrimination or bias (Bertrand and Duflo, 2016) and to the literature showing how the way a position is advertised can change the applicant pool (Ashraf, Bandiera and Lee, 2014; Marinescu and Wolthoff, 2016; and Dal Bó et al. 2013).

The paper proceeds as follows: Section 2 presents a theoretical framework of self-selection in the presence of an identity wedge; Section 3 presents the context for the experiment, Section 4 describes the two interventions; Sections 5 and 6 discuss the results from our two experiments; and Section 7 concludes and discusses the managerial implications of our results.

2. Framework: Self-Selection into an industry

In this section we develop a simple theoretical framework to illustrate how changing the type of information provided on a career/industry (as in the field experiment) affects applicants' self-selection into that career. We start from a standard Roy/Borjas model (Roy, 1951; Borjas 1987) and add an identity component as a potential driver of the decision to enter an industry in addition to the relative return to skills in the two industries.

Women choose whether to apply to the training program, i.e., to attempt a career in the technology sector. Each woman is endowed with a given level of skills that are useful in the technology sector *T* and skills that are useful in the services sector *S* (representing their outside option). Assume for now that social identity does not matter for choices: Total returns in Services and in Tech are given by $W_0 = P_0 S$ and $W_1 = P_1 T$, respectively, where P_0 and P_1 are the returns to skill (e.g. wage per unit of skill) in each sector. If we log linearize and assume log normality: $\ln W_0 = p_0 + s$ and $\ln W_1 = p_1 + t$ where *ln S*= s~N(0, σ_s^2) and *ln T*= t~N(0, σ_t^2). The probability that a woman applies to the technology sector is:

$$\Pr(Apply) = \Pr\left(p_1 + t > p_0 + s \right) = \Pr[\frac{D}{\sigma_D} > \frac{p_0 - p_1}{\sigma_D}] = 1 - \Phi[\frac{p_0 - p_1}{\sigma_D}] \qquad (1)$$

Where *D = t –s* and Φ is the CDF of a standard normal. *Pr (Apply)* is increasing in p_1 and decreasing in p_0, such that as expected returns in technology increase, more women will apply to Tech. This allows us to study how the selection of women (the average expected level of *t*) that apply will change with a change in returns to technology skill. Borjas (1987) shows that $E(t|Apply) = \rho_{tD}\sigma_t\lambda(\frac{p_0 - p_1}{\sigma_D})$ where $\rho_{tD} = \sigma_{tD} / (\sigma_D \sigma_t)$ is the coefficient of correlation between *t* and *D*, and $\lambda(z)$ is the inverse mills ratio, with $\lambda' > 0$. Therefore: $\frac{dE(t|Apply)}{dp_1} = \frac{\sigma_t^2 - \sigma_{st}}{\sigma_D}\frac{d\lambda(z)}{dp_1}$.

Given $\frac{d\lambda(z)}{dp_1} < 0$ and $\sigma_D > 0$ the sign of the selection will depend on the sign of $\sigma_t^2 - \sigma_{st}$. In particular, if $\rho_{ts} > \frac{\sigma_t}{\sigma_s} \Rightarrow \frac{dE(T \mid Apply)}{dp_1} > 0$ and selection is positive. Conversely if $\rho_{ts} < \frac{\sigma_t}{\sigma_s} \Rightarrow \frac{dE(T \mid Apply)}{dp_1} < 0$ selection is negative and the average Tech skills of applicants decreases. Similarly, we can sign the selection for Services skills, S. If $\rho_{ts} > \frac{\sigma_s}{\sigma_t} \Rightarrow \frac{dE(S \mid Apply)}{dp_1} < 0$; $\rho_{ts} < \frac{\sigma_s}{\sigma_t} \Rightarrow \frac{dE(S \mid Apply)}{dp_1} > 0$.

Now we depart from the classic model to introduce the concept of identity to the basic framework. Women form an expectation of the returns to their skill endowment in each sector and decide which to apply to accordingly. We posit that this expectation may have a social identity component.[5]

What we call an "identity wedge" alters the total expected returns relative to the skill endowment and could be reflecting different features identified in earlier research. For simplicity, and given we will not be able to cleanly separate out different possible sources for the identity wedge in the field experiment, we assume that, just as services and technology skills are distributed in the population, so are the underlying identity costs I, with some women experiencing higher identity costs than others. There is also a general unitary identity cost parameter β associated to I such that: $W_1 = P_1 T / \beta I$, and $\ln W_1 = p_1 + t - \beta - i$ with log normal I, $i \sim \mathrm{N}(0, \sigma_i^2)$

The idiosyncratic I may arise from a number of sources that have been identified in the literature. It may be a result of different beliefs held by women on the actual returns to their skills, either because they have biased estimates of their skill or because they have biased estimates of the returns to their skill reflecting stereotypes about who succeeds based on existing models in the industry, which includes few women (Bordalo et al., 2016a). The stronger the stereotype, the higher the identity wedge and the lower the expected returns. Coding is stereotypically male in Latin America just like in the USA (Guryan et al., 2009). In Peru, only 7% of coders are women, which following Kahneman and Tversky's belief formation mechanism under the representative heuristic can lead to strongly biased beliefs. For our sample in Mexico we were able to compare declared expected salaries at the time they applied with their actual salaries upon graduation and we observed that 60% (of those who reached the last evaluation stage) underestimated their salaries. Moreover, among those admitted to the program, actual salaries were on average 24% higher than expected. This suggests that beliefs on returns in this population were significantly biased downwards. [6]

[5] This is one form of hedonic pricing (Rosen, 1974; Brown, 1980). There could be others but in this paper we focus on the potential role of social identity.

[6] Note that for this sample everyone was subject to some type of identity intervention, so this is true even after the identity treatment.

I could also reflect an identity cost along the lines proposed by Akerlof and Kranton (2000). Higher identity cost women would be those who experience a larger psychological penalty from working in an environment that is more incongruent with the social category they identify with, their identity (as "sense of self"). The strength of these social categories is stronger in Peru than in most western countries. For example, of the seven the questions on gender equality in the World Value Survey, Peru has more unequal/stereotypical perceptions than the US in all seven questions, with beliefs on traditional gender roles significantly stronger. In the technology setting, since the sector is predominantly male and follows stereotypically male norms, high *I* women would suffer a larger penalty.[7]

For simplicity, let $\hat{p}_1 = p_1 - \beta$, reflecting the "biased return", which could arise from the different mechanisms above. Now, the probability of applying to the services sector is:

$$\Pr(Apply) = \Pr[t - s - i > p_0 - \hat{p}_1]$$
$$\Pr(Apply) = \Pr[D - i > p_0 - \hat{p}_1] = 1 - \Phi[\frac{p_0 - \hat{p}_1}{\sigma_h}]$$
$$D \sim N(0, \sigma_D^2), D = t - s, h = t - s - i$$

Result 1: Application rates: $d\Pr(Apply)/d\hat{p}_1 > 0$. Increasing $\hat{p}_1$ (from an increase in the expected returns to technology skills p_1 or a decrease in the identity cost parameter β) increases application rates.

Note, if there are no identity costs, applications will increase in p_1. In the presence of identity costs applications will increase if either p_1 increases or if β decreases.

We now turn to analyze selection in the presence of an identity wedge in the population. In this setting, we will expect that the average skill differential of applicants

[7] Note I could also reflect the belief that women cannot succeed in the technology industry because there is discrimination and their skills are not valued.

increases, $\frac{dE(D \mid Apply)}{d\hat{p}_1} > 0$ if $\rho_{Di} > \frac{\sigma_D}{\sigma_i}$. Conversely selection in D will be negative if $\rho_{Di} < \frac{\sigma_D}{\sigma_i}$. Similarly,

Result 2: Self-Selection on Skills: Increasing expected returns can lead to positive or negative self-selection on *t*, depending on the correlation between *t, s* and *i* in the underlying population relative to their dispersion. Similarly, it can lead to positive or negative self-selection in *s,* the outside option. In particular, there will be:

Negative (positive) selection in *t* if: $\sigma_{ts} + \sigma_{ti} < (>)\sigma_t^2$ (2)

Negative (positive) selection in *s* if: $\sigma_{ts} - \sigma_{is} > (<)\sigma_s^2$ (3)

As we can see from equations (2) and (3) the predictions differ from the standard Roy Model. In the Roy-Borjas model (without identity) there is negative selection in t if $\sigma_{ts} < \sigma_t^2$. From equation (2) we can see that if the correlation between *t* and *i* were positive and large enough, we could observe *positive* selection in *t* as we increase expected returns in tech, where the standard model would give us negative selection.

Further, we can see how average identity costs of applicants will change with an increase in expected returns. In particular, the average identity among applicants will be higher, $\frac{dE(i \mid Apply)}{dp_1} > 0$ if $\rho_{Di} < \frac{\sigma_i}{\sigma_D}$ and lower if $\rho_{Di} > \frac{\sigma_i}{\sigma_D}$.

Result 3: Self-Selection on Identity: If identity matters when women make their career choices and identity costs are distributed in the population, then increasing expected returns (by increasing p_1 or decreasing β) can lead to positive or negative self-selection on identity cost, depending on the correlation between *t, s* and *i* in the underlying population relative to their dispersion.

These conditions imply that there is negative (positive) selection in *i* if

$$\rho_{Di} > (<)\frac{\sigma_i}{\sigma_D} \Leftrightarrow \sigma_{it} - \sigma_{is} > (<){\sigma_i}^2 \tag{4}$$

This means that selection on identity will be negative --i.e. less biased women apply after increasing the returns to skill—if identity covaries significantly more with t than with s. It will be positive if identity does not covary too much more with t than with s.

Finally, note that once we introduce a second dimension that matters, such as identity, and even in the case of negative average selection in *t*, the expected increase in $\hat{p}_1$ through lower perceived identity costs may lead to some very high-skilled women applying that also have high identity costs. In this setting it is possible that even though, on average, selection in *t* is negative, some women who are high *t* but also have high *i* may apply after the increase in $\hat{p}_1$.

To see the intuition for this, consider the graphical example in Figure 1, where there is perfect correlation between the two types of skills *t* and *s*, and we assume there are only two levels of identity costs: low and high. Figure 1 (panel A) shows the ratio of expected marginal returns for both types of identity costs, as well as the distribution of skills. Women with skill combinations of *s* and *t* to the bottom/right (top/left) of the relative price line will apply to Tech (Services). In the depicted example, after an increase in $\hat{p}_1$ (panel B), we can observe that in addition to the low ability-low identity costs women who select into tech, now some high ability women, who had also high identity costs, also self-select into tech. Notice that with a different empirical distributions of (*t,s, i*) we would observe different self-selection patterns into the two sectors as a result of the same exogenous increase in $\hat{p}_1$.

As we will see, our experiment provides information that can be interpreted as raising the expected returns for women in the technology sector. This can be understood as operating through p_1(increase in the price of skills) or through β (a reduction in in the penalty to the identity cost, or the strength of the stereotype). We will attempt to separate these empirically, but in practice they all go in the same direction, the effect of $\hat{p}_1$. The Mexico experiment will allow us to tease out more concretely the information that women are responding to. The key variables to track in this model are expected returns in the tech sector, expected returns in the outside option, identity costs, and the underlying cognitive skills. We will measure all of these in the data.

3. Background and Context

Our study is conducted in Lima (Peru) and Mexico City in partnership with a non-profit organization seeking to empower young women from low-income backgrounds in Latin America with education and employment in the tech sector.[8] The program recruits young women (aged 18-30) who lack access to higher education, takes them through an immersive five-month software-coding "bootcamp" and connects them, upon graduation, with local tech companies in search for coders. In what follows, we describe the key aspects of the program.

Recruitment. In each city, the company launches calls for applications twice a year, usually in June and November, running targeted advertising campaigns in social media while receiving publicity in various local media. All interested candidates are asked to apply online and directed to a registration website (which is the only way of applying to the program). The website gives detailed information about the program and the eligibility criteria before providing a registration /application form.

Evaluation and selection of top candidates. The company is interested in selecting the best talent for training. Applicants are thus required to attend two exam sessions as part of the selection process and they are assessed and selected based on their results. In the first session, candidates take a general cognitive ability test as well as a simulation measuring specific coding abilities. In a second stage, interpersonal skills and traits like motivation, perseverance and commitment are evaluated through a personal interview and group dynamic exercises. Scores in the different categories are weighted into a final algorithm that defines admission into the program. Class size has increased since the program started, but at the time of our experiments, the top 50 candidates were selected for training.

Training. Selected participants start a full-time (9am to 5pm) five-month training program in web development in which students achieve an intermediate level of the most common front-end web development languages and tools (HTML5, CCS3, JavaScript, Bootstrap, Sass and Github). They also receive English lessons (given that web languages and tools are written in English), while their technical skill development is further complemented with mentorship activities with professional psychologists that build the

[8] Laboratoria (www.laboratoria.la) was created in Lima in 2015, expanded to Mexico and Chile in 2016 and since recently operates also in Colombia and Brazil.

students' self-esteem, communication ability, conflict-resolution capacity and adaptability.

Placement in the Job Market. Upon completion of the training, the organization places students in the job market, having built a local network of partner companies committed to hiring their graduates.[9] These companies are also involved in the design of program's curricula as a way to ensure that participants develop skills in high demand. At the time of the experiments, the organization's sustainability was based on an Impact Sourcing model in which it offered web development services to companies and hired recent graduates to deliver these services. On average, and combining both sources, around two thirds of trainees found a job in the tech sector upon graduation.[10]

Cost of the program. According to their social design, the organization does not charge full tuition fees to their students during training, but a minimal fee equivalent to US$15 per month. If trainees end up with a job in the tech sector (and only if they do), they are asked to repay the full cost of the program (which is estimated at around US$3,000) by contributing between 10% to 15% of their monthly salary up to the total program cost.

As of 2016, the provider was interested in increasing application rates and assessing how to attract a better pool of applicants. The provider felt that despite the attractiveness of the program (over 60% of their graduates in their first two cohorts found a job in the tech sector upon graduation), sector growth potential and the low risk and cost of the program, total numbers of registered applicants were relatively low.

After two cohorts of trainees in Lima, the organization was launching a new operation in Arequipa in the first semester of 2016, and developing training sites in Mexico City and Santiago de Chile. We tested our intervention design in a pilot in Arequipa (January 2016), where the organization was not known. We then launched our first large-scale experiment in Lima, its largest operation, in their call for applications for the class starting training in the second semester of 2016. We launched the second experiment in Mexico City for the class starting training in the first semester of 2017.

[9] The network of companies to which the organization targets their graduates is constantly expanding.

[10] We are currently also evaluating the impact of the program itself. Employment data varies from city to city, but success rates are high everywhere. Given the recent growth of the training program, the company is no longer offering web development services to companies.

4. Interventions and Research Design

Our study comprises two *complementary* interventions that experimentally vary the information provided to potential applicants to the program. In the first experiment (Lima, summer 2016), we add to the recruitment message three pieces of information aimed at reducing the strength of the identity wedge (and thus raise the expected returns in technology for women ($\hat{p}_1$): a role model, information on the success of women in the sector, and information on the developing network of women. Our aim is to (i) assess whether this kind of message is effective in increasing application rates to the training program; and (ii) evaluate what type of *selection* is induced by the message. Against the background of the Roy-Borjas model, we infer from the changes in observed self-selection the types of barriers that women faced, limiting their decision to apply for training, and in particular whether "identity" played a role. In the second experiment (Mexico City, winter 2016) we *unbundle* the three components of the initial message, and control for more factual information about the program, to assess the main drivers.

Both experiments are implemented via the organization's webpage. As discussed in section 3, to apply to the training program, every potential applicant has to register via an application website, where the organization provides detailed information about the program as well as the eligibility criteria, with the registration form at the end of the page.

4.1 The first experiment: Lima summer 2016

4.1.1. Treatment and control messages

The baseline (control) information about the program provided to all potential applicants includes the following text (translated from the original, in Spanish):

<u>Intensive Web-Development Training: Call for Applications</u>

What does the program offer you?

Web Development: "You will learn to make web pages and applications with the latest languages and tools. You will learn to code in HTML, CSS, Java Script and others. In 5 months you will be able to build webpages like this one (that was done by one of our graduates)".

Personal growth: "Our objective is to prepare you for work, not only to give you a diploma. That is why we complement your technical training with personal training. With creativity workshops and mentorships, we will strengthen your abilities: we will work on your self-esteem, emotional intelligence, leadership and professional abilities."

A career in the tech sector. "Our basic training lasts 5 months, but that is just the beginning. If you succeed in this course, you will start a career as coder having access to more income. Through specializations, we offer you a program of continuous education for the next 2 years."

Our treatment message added the following paragraph to the baseline message:

"A program solely for women. The tech sector is in need for more women that bring diversity and innovation. That is why our program is solely for women. Our experience has taught us that women can have a lot of success in this sector, adding a special perspective and sensibility. We have already trained over 100 young women that are working with success in the digital sector. They all are part of our family of coders. Young women like you, with a lot of potential."

Followed by the story and picture of one of the organization's recent graduates, who is successfully working in the tech sector:

"Get to know the story of Arabela. Arabela is one of the graduates from Laboratoria. For economic reasons she had not been able to finish her studies in hostelry and had held several jobs to support herself and her family. After doing the basic Laboratoria course Arabela is now a web developer and has worked with great clients like UTEC and La Positiva. She even designed the webpage where Peruvians request their SOAT!
Currently she is doing a 3-month internship at the IDB (Interamerican Development Bank) in Washington DC with two other Laboratoria graduates.
You can also make it! We will help you break down barriers, dictate your destiny, and improve your labor prospects."

Webcaptures of the actual treatment message (in Spanish) can be seen in Figure 2A. As shown, the only difference between our control and treatment messages is that the treatment message included two additional paragraphs aiming to address the potential identity wedge on the prospects of women in the technology sector. Applicants in both treatment and control know that the training is only for women, but conceptually the treatment message includes three different additional pieces of information: (1) that women can be successful in the sector (2) that the organization gives access to a network of women in the sector and (3) a role model: the story of a recent graduate.

4.1.2. Treatment effects: Registration and Attendance to Exam Days

Right after being exposed to the information about the program on the website, potential applicants take the first step towards applying to the program by completing a simple registration form. The information requested is minimal and includes name, age, district, email, where they heard about the program, and why they were interested in the program (see Figure 2B). The organization then sends emails to all those who registered providing information logistics on the selection process (that two sessions of examinations were required, where to go to take the tests, and that no preparation was needed). As discussed in section 5, not all candidates attend the examination sessions. We measure the impact of the treatment message on both the probability of registering and of attending the selection examinations.

4.1.3 Data Collection on Selection Days

The two-day selection process allows us to collect information on a number of relevant characteristics from the two pools of applicants *attending examinations*. Some of these variables came directly from the program's selection process (e.g., cognitive abilities), and others from a baseline survey[11] and additional tests we administered to all candidates. On the day of the examinations, applicants are received by the program's core team, congratulated on wanting to pursue a career in Tech and briefed on the structure of the tests they are about to take to get admitted. They are told upfront that the first module, including the baseline questionnaire and two IAT tests, is not considered as part of their grades (note that no results were provided on the IAT tests to the applicants). After this initial stage is over the applicants are told that the admission process is about to start, and candidates take the cognitive tests.

We summarize below all data collected in this period:

<u>a) Cognitive skills:</u> The first stage in the training provider's selection process comprises two cognitive tests: an exam measuring math and logic skills (called "Prueba Laboratoria", developed with a team of psychologists following a standard Raven test), and a coding simulation exercise measuring tech capabilities (called "Code Academy",

[11] In which we were allowed to add a few questions about aspirations, expected returns, and time and risk preferences, in addition to the program's core questions on socioeconomic background and how they came to know their program.

testing the ability to understand and use basic coding assuming no prior knowledge[12]). The Code Academy test is a very good predictor of the probability of success in the training, and subsequent employment, so we interpret this as capturing the underlying cognitive skills that are useful in technology.[13] In our analysis, we also use an equally weighted average of the two tests ("Cognitive Score").

b) Expected financial returns: In the baseline survey, we asked all candidates what they would expect to earn after three years of experience as a web developer, and also what they would expect to earn after three years of experience as a sales person or in a support services job which are the concrete alternative options for these women.[14]

c) Gender Identity: Measuring gender identity in the field is not a trivial task. We thus proceeded by using proxies for different possible causes of the wedge. First, to measure implicit biases of women associating a successful career, or a career in technology, to men over women -reflecting prevailing stereotypes- we implement two implicit association tests (IAT). IATs measure the implicit associations between categories (e.g., race and intelligence, gender and career) and hence the strength of stereotypes (Greenwald et al 1998). Even though there is a discussion about their predictive ability (Blanton et al 2009, Oswald 2013) they have been shown to have better predictive power than survey measures (Greenwald et al, 2009) and to correlate to outcomes. For example, Reuben, Sapienza and Zingales (2014) provide evidence that the IAT correlates with beliefs and with the degree of belief updating. They show that a gender/math IAT test is predictive of beliefs about differences in performance by gender, and also predicts the extent of belief updating when provided with true information: more biased types are less likely to update their beliefs. See also Carlana (2018) about the empirical predictive power of the IAT.

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[12] This was taken from codeacademy.com.

[13] Within our broader collaboration with the training provider, for their entire 2016-I cohort - including the cities of Lima, Mexico and Arequipa- we tested whether the battery of admission tests the program had designed predicted program completion and subsequent employment (upon graduation). We ran correlations for the 145 women admitted into the program in these three cities, and we found that a one standard deviation increase in the Code Academy test led to a 23.5 percentage point increase in the probability of graduating, and a 16.1 percentage points rise in the probability of getting a job upon graduation.

[14] Note that in the context of our framework, this gives us a (self-reported) measure of P_0S and P_1T, which is close to actual returns to skill but may be biased by identity (partially capturing β and I). Note that it is unusual to have a measure of the outside option for those who apply, albeit subjective (in most applications of the Roy Model one observes returns only on the selected sample –e.g., migrants, or women in the workforce-, not their "expected" outside option).

In our case, in addition to administering the standard career/gender IAT, we created a new IAT to see how much (or how little) applicants associate women with technology. Our gender/tech IAT asks participants to associate male or female words (Man, Father, Masculine, Husband, Son vs/ Feminine, Daughter, Wife, Woman, Mother) to technology or services words (Programming, Computing, Web development, IT, Code, Technology vs/ Cooking, Hairdressing, Sewing, Hostelry, Tourism, Services, Secretariat). The test measures how much faster the applicant is to associate male to technology and female to services than the opposite combination. We interpret the IAT as capturing the strength of stereotypical beliefs or the implicit bias that women hold about women in technology.

Second, to measure the strength of gender norms, we use the answers to survey questions on aspirations. We asked participants: if you think about yourself 10 years from now, will you be: Married? With children? In charge of household duties? Three possible answers, (No, Maybe, Yes) were available to them. We coded these as 0, 1 and 2 and took the average answer. The higher the score the more the woman sees herself in a "traditional" role. We interpret this as capturing how much the aspirations of the woman conform to traditional gender roles.

Finally, we also take the first factor of a factor analysis in which we consider the three identity measures just described (IAT gender/career, IAT gender/tech and traditional role), and we call it the "identity wedge". The traditional role and IAT Gender/Tech variable are positively but not very strongly correlated (0.08 correlation, see Table 9), so the "identity wedge" variable will capture a distinct variation that combines both.[15]

d) Other variables: In the baseline survey, we also implemented tests to estimate risk and time preferences, with the idea that the self-selection may have also operated on women with different preferences. The time preference variable elicited the minimum monetary amount (in Peruvian Soles) the applicant required to - three months into the future - be indifferent between receiving 50 Soles today and that amount. The risk preference variable is the minimum required as certain instead of a lottery with 50% chances of winning 150 soles or 50% change of winning nothing. These are adapted from survey-validated instruments (e.g., Falk et al 2016). Finally, we also measure candidates "interest in technology" before the program (from a set of questions the organization ask directly).

[15] For details on the factor analysis see Table A.5 in the Appendix.

4.2 The second experiment: Mexico City winter 2016

The objective of our second experiment was twofold: (i) to unbundle each component of the treatment message in our first experiment, and (ii) to control for additional factual information about the program. We ran the experiment in Mexico City, which is a larger market and where the organization was less known so that information is more salient (this was only the second cohort of trainees in Mexico, while the organization was gaining a lot of press and notoriety in Peru during the fall of 2016).

In Mexico, we faced the additional constraint that the organization did not want to revert to the original baseline recruitment message, so we took the following approach: the "control" group receives the full identity message and we take out one piece of information at a time. That is, the control now includes explicit messages about (1) the fact that women can be successful in the sector ("returns") (2) the fact that the organization gives access to a network of women in the sector ("women network") and (3) a role model: the story of a recent graduate ("role model"). Our three treatments then take one piece of information out at a time as follows[16]:

- T1: network and role model (eliminate success/returns)
- T2: success/returns and role model (eliminate network)
- T3: success/returns and network (eliminate role model)

In addition, in the control message we now provide more *factual* information about the success (and recent expansion) of the program (see box in Figure 6). Specifically: (i) we have more than 400 students as of 2016, (ii) we have 4 training centers in Lima, Arequipa, Mexico and Chile, (iii) around 84% of our students are connected with jobs, and (iv) we report average salaries and expected increase in earnings after training (2.5 times more).

The Appendix shows the exact text of this intervention translated into English.[17]

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[16] Note that the different components of treatment we analyze may be complementary, and thus taking out each component at a time, may have different effects than adding each component at a time.

[17] A few additional differences are noteworthy relative to the Lima experiment. First, the organization made more salient the low upfront cost of the program and provided more information on the organization itself. Second, overall there were more images and the webpage was more interactive. Finally, the content of the program itself was also changing: the program now included continuous education to become a full stack developer after the 5-month bootcamp, and they adopted agile methodologies for education. These changes allow us to test our treatment against a different and

4.3 Randomization

We randomized the messages directly at the training provider's registration website by *unique user* visiting the website. To do this, we used the Visual Web Optimizer (VWO) software. To boost traffic, we launched targeted ad campaigns in Facebook.

Note that with this strategy, if one user accesses the webpage multiple times from the same device, she always sees the same page. Of course, a caveat to randomization with this strategy is that if the same user logged in multiple times from *different* computers, she may have seen different messages. We are only able to register the application of the last page she saw. If that were the case though, it would tend to eliminate any differences between treatment and control and bias towards zero any results we find.[18]

4.3.1 Lima experiment

Traffic results (total and by treatment message) are shown in Table 1. Our advertising campaigns launched in social media -as well as program publicity obtained through various local media- led to a total traffic to the program information and registration website of 5,387 unique users. Through our randomization, roughly half of these users saw each recruitment message.

4.3.2 Mexico experiment

Again, we randomized at the trainer providers' registration website URL by unique user, and we launched three targeted advertising campaigns on Facebook to attract more traffic. Our advertising campaigns as well as program publicity obtained through various local media led to a total traffic to the registration website of 6,183 unique users.

5. Impact of the intervention addressing social identity: Results from the first experiment (Lima 2016)

In this section we report two sets of results from our first experiment. In section 5.1, we evaluate the effect of receiving the identity message on the size of the pool of applicants (registration rates) as well as rates of attendance to the examination by type

much richer informational background, reinforcing the external validity and rule out a number of alternative explanations for our results.

[18] We cannot rule out either that people talk to each other, but this would again lead to an attenuation of the effect as information is shared across treatments.

of recruitment message. In section 5.2 we examine self-selection patterns induced by treatment; we start by analyzing potential selection at registration, and selection based on education and socioeconomic variables among those who come to examinations, to then focus on our main objectives: the *average* self-selection patterns in terms of skills and identity, as well as in candidates' expected returns, among those who come to the examinations. We then turn to differences along the skill distribution. Finally, we test for differences in other variables such as interest in technology and time and risk preferences.

5.1 Registration rates and attendance to selection examinations

As mentioned in section 3, applying to the program requires two stages: first, filling in the registration form, and second, attending a two-day examination session. Our outcome of interest can be thought of as applying *and* attending the examinations, but since this requires two separate decisions, we separate them out.[19] Column 1 in Table 2 reports the results on differential registration rates by recruitment message: essentially, our identity message doubled registration rates: 15% of those who were exposed to treatment, or 414, applied to the program, versus only 7%, or 191, in the control group, and this difference is highly significant.

In column 2 of Table 2 we also report unconditional attendance rates to examination dates by treatment group. As with the application rates, our identity message increases attendance substantially—4.9% of those who were exposed to treatment attended the examinations versus only 2.6% in the control group, and this difference is highly significant. Conditional on applying (column 3) we also observe that, despite the much larger numbers of applicants coming from the treatment message, there is no significant difference in the ratio of applicants coming to the examinations between the two groups.

5.2 Self-Selection Patterns

In this section we turn to the analysis of the potentially different self-selection patterns induced by treatment. Note that we only estimate the differential selection by experimental group, not the causal effect of treatment on the outcome variables (as we

[19] From the day of registration to the examination dates there could be up to a month difference. Traditionally, attendance to examinations has ranged between 30 to 35% of all registered applicants.

only observe those who applied and attended the selection process). We start by briefly describing potential self-selection patterns at registration to then focus on our main sample: those attending examinations.

5.2.1 Who applies: selection at registration

As discussed in the previous sections, our randomization takes place as potential applicants arrive at the organization's registration website, and we only observe basic information for those potential applicants who *decide* to apply. Table A.1 provides summary statistics for the variables elicited at registration (age, district, and where they heard from Laboratoria) by experimental group. As mentioned, the program is narrowly targeted to women from low-income backgrounds, aged 18-30, and most women arrive to the organization's website through social media. So not surprisingly, there is little variance in these variables and no statistical differences between the two treatment groups.[20]

5.2.2 Who applies: selection at examinations

We now turn to the analysis of self-selection patterns among those who attend examinations. In Table 3, we first summarize education and socioeconomic variables by experimental group to understand whether the sample is selected in terms of these relevant observables. Again, as a result of the strong targeting of the program, we observe no statistical differences between the two experimental groups.

In what follows, we focus on our main variables of interest: applicants' cognitive abilities and identity measures, as well as their expected returns to tech. We discuss below why we think treatment effects of our identity message on exam/test performance are minimal relative to the effect on selection. To measure selection, in all cases we

[20] We also perform a text analysis of their stated motivations to apply. In particular: 1) whether we observe any differences in word use or topics highlighted in treatment vs control, and 2) whether we observe any differences between those who come to examinations and those who don't. We find no statistical differences between treatment and control, or among those who attend examinations and those who don't in individual word use (for example, the treatment does not use "women" more often, or "career" or "programming"). Neither we do find any differences in the predominance of (endogenous) topics found by analyzing word clustering (using the Latent Dirichlet Allocation method. It is interesting, though, that three main topics which arose endogenously in both groups from these motivation statements are: (1) intrinsic motivation and family; (2) programming; and (3) growth/improvement.

regress the variables of interest on the treatment variable using specifications both without and with controls (which include level of education, family characteristics and other socioeconomic variables). Table 4 provides descriptive statistics on all the variables relevant to our analysis.

It is also important to mention that differential registration and attendance rates by treatment and control groups strongly influence the distribution of candidates attending examinations. Of the total 202 candidates attending, 66% had been exposed to the treatment message.

a) Cognitive Skills

We first analyze the change in selection of cognitive skills following the treatment message in Table 5. We find that average cognitive skills -as measured by both the "Code Academy" and "Prueba Laboratoria" tests- are 0.26 to 0.28 of a standard deviation *lower* in the treatment group. Thus we observe a clear negative selection in cognitive skills.

In Figure 3, we also show the full raw distribution of cognitive skills by treatment and control groups. As we can see from the figure, treatment increases the number of applicants at *all* levels of cognitive ability, but it particularly does so at the bottom of the distribution. These results suggest that the treatment may affect candidates differentially by level of cognitive ability.

b) Identity

We turn next to analyze self-selection patterns on our measures of gender identity in Table 6. We find that the women that apply following the identity message are on average more "biased" as measured by the IAT we developed on the association of women with technology, as well as on the survey measure for "Traditional Role". The magnitude of this "positive" self-selection on identity is large: 0.29 of a standard deviation more biased for the IAT; 0.39 of a standard deviation higher association with a traditional role; 0.14 of a standard deviation for the identity wedge variable (which is obtained as the first factor of the three other variables in Table 6).[21] Figures 4 and 5 show the raw distribution of the basic identity variables and reflect this pattern.

[21] Appendix Table A2 shows the significance levels for adjusting for multiple hypothesis testing, with quite similar results.

The results so far suggest that the average woman applying is of inferior technology/cognitive skills and has a higher average implicit bias against women in technology and a more traditional view of their own future. This allows us to understand, in the light of the Roy model, some of the barriers at work preventing more women from applying. We analyze next whether there are differential identity patterns induced by treatment at different points of the cognitive ability distribution to see how the two variables interact to drive selection.

c) Trading Off Attributes: Selection along the Skill Distribution

In panel A of Table 7, we estimate the difference in the identity wedge between treatment and control candidates at the bottom 25% and 50%, as well as the top 50%, 25% of the distribution based on the Code Academy test (panel B does the same thing for the average cognitive score). We can see that among those in the top 25% of the distribution of cognitive ability, those in the treatment group report a much higher identity cost compared to the control (up 0.323 standard deviations).

Overall, and in the context of our Roy model with identity, these selection patterns at the top are consistent with some women applying under treatment who are high skill but also have high identity costs, suggesting that identity not only matters on average, but is likely one of the dimensions precluding high cognitive skill women from attempting a career in the Tech sector. This is an important result given these high cognitive skills women are the ones that firms are trying to attract, that would typically go into lower paying services occupations and that could contribute to better allocation of human capital based only on comparative advantage.

To give some evidence on the magnitude of this effect, we perform some back of the envelope calculations, comparing the cognitive skills of the top 50 performers in each experimental group (50 is the size of the population to be admitted into the program). We find that those treated report significantly higher average cognitive scores and ad-hoc tech capabilities (0.37 standard deviation higher score in the Code Academy simulation and 0.36 higher average score).

d) Expected Returns and the Decision to apply

We now seek to explain the decision to apply based on candidates' expected returns. In Table 8A, we show first the raw differential selection on the logarithm of expected returns in technology (column1), in sales (column 2) and the difference between the two (column 3). The results suggest negative selection in both technology and services/sales skills. The effect is clear and highly significant in column 2, where the women who apply under treatment have an outside option (expected returns in sales) that is 23% lower than those in the control. In terms of our model, given P0 is unchanged with the experiment, this suggests average S falls. For technology skills, we see a negative effect (-0.115) that is not significant. But this is likely driven by the fact that average T decreases (negative selection) as we expect that the experiment message increases p_1. The net effect is negative although not significant.

Next, we control for other variables that affect potential earnings: age, education, cognitive ability as well as parents' education and family income. As we can see in Table 8B, the results are similar when controlling for these variables, suggesting that it is not just selection on observables, but also selection on beliefs about returns which is likely driving the application rates.

e) Selection vs. Treatment

We are interpreting our results as reflecting mostly selection rather than treatment effects. We argue that with the exception of the direct impact of the treatment on expected returns in tech where we are raising $\hat{p}_1$, it is unlikely that the identity message has a significant causal effect on most other of the outcome measures that aim to capture permanent characteristics, in particular cognitive skills and IAT tests. The reasons for this are that: (1) up to a month passes between application and the days of the test, so any treatment effect is unlikely to persist into the selection days; (2) when applicants arrive at the training provider for the tests, they have received much more information on Laboratoria and the future of its graduates, where we think that the gap in information between the two groups is much smaller once they take the test; and finally, (3) because our prior is that, if anything, to the extent that it reduces stereotype threat (Steele and Aaronson 1995) the informational treatment would help them do better in tests and have less stereotypical beliefs, and this would bias our estimates in the other direction. Given we still find negative selection on all dimensions, we think any treatment effect of the message on performance is dwarfed by the selection effects we identify.

Finally, it also appears that the selection effects we find in skills and identity are operating separately given that the two variables are not very highly correlated in the sample (see Table 9), i.e. we are not finding this effect just because the two are very highly correlated.

f) Interest in Technology, time and risk preferences

Just as "identity" can create a wedge between returns based on comparative advantage and utility, other non-monetary dimensions (interest in technology, job stability/security) may also preclude women from applying to the tech sector. In as far as our treatment makes the sector look more attractive or less risky, we should also expect selection along these dimensions. Table 10 shows the differences between those treated and non-treated in terms of prior interest in technology, and time and risk preferences. The point estimate in column 1 (prior interest in technology) is small and insignificant, suggesting that the margin of adjustment was not to make women more interested in a sector they had little interest in before. In columns 2 (risk preferences) and 3 (time preferences), the coefficients are quite large, although also with large standard errors. If anything, the results are suggestive of the marginal women being more impatient and more risk-averse under treatment.

6. Identifying the drivers of the bias: Results from the second experiment (Mexico D.F. 2016):

As mentioned in Section 4, in our Mexico experiment we unbundle each component of treatment and control for more factual information about the program. The four experimental groups are as follows:

- Control: all components (success/returns, network, role model)
- T1: network and role model (eliminate success/returns)
- T2: success/returns and role model (eliminate network)
- T3: success/returns and network (eliminate role model)

As in with the Lima experiment, our outcome of interest can be thought of as applying *and* attending the examinations, but since this requires two separate decisions, we separate them out. Note also that in the Mexico experiment, since we chose to have several treatments to identify mechanisms, we do not have the power to infer selection by treatment group based on examinations.

Registration and attendance to examinations results are provided in Table 11. The conversion rate in the control group attains 10.5%. We can then see how all treatments significantly reduce the probability of applying for training, albeit with different effects. T1, the treatment that eliminates the "women can be successful" component reduces the conversion rate by 2.5 percentage points which is a 24% decline in the conversion rate. This is an effect conditional on all the information conveyed by the role model, network and the rest of the control message. Similarly, T2, the treatment that eliminates the network component leads to a 2 percentage points or 19% decline in the conversion rate.[22] This is an additional effect of emphasizing the importance of providing a network for women, controlling for all the information contained in the control (with role model, returns and rest of control information). The treatment that eliminates the role model has the largest impact, reducing the conversion rate by 4 percentage points or 38%. So the role model message conveys information beyond the fact that women's returns are high and that women will have a network of women upon graduating since we are conditioning on this information in the control for T3 (note that T2 is statistically different at 5% from T3 and T1 is marginally different, at 10.1%).

In column 2 of Table 11 we also report unconditional attendance rates to examination dates by treatment group. As with the application rates we see a larger effect of the role model, and effects that are half the size for the other two messages although these are not statistically different due to lack of power). As in Lima, there are no differences in the probability of attending the examination conditional on applying (column 3).

The importance of the female role model reported here is consistent with results for women in India in Beaman et al (2012) that shows that a role model can affect aspirations and educational achievement. It is also in line with recent work by Breda et al. (2018) in France in which role models influence high-school students' attitudes towards science and the probability of applying and of being admitted to a selective science major in college.

This second experiment also allows us to address external validity: we found similar results to the treatment in the Lima and Mexico DF experiments, i.e. in different time

[22] Results adjusting for Multiple Hypotheses Testing are provided in the Appendix Table A3.

periods and different countries, suggesting that the informational content of our experiment really is able to alter behavior and self-selection into the industry.

7. Conclusion

We experimentally varied the information provided to potential applicants to a 5-month digital coding bootcamp offered solely to women. In addition to a control message with generic information, in a first experiment we corrected misperceptions about women's ability to pursue a career in technology, provided role models, and highlighted the fact that the program facilitated the development of a network of friends and contacts in the Tech sector.

Treatment exposure doubled the probability of applying to training and attending the selection process. On average, however, the group exposed to treatment reported a cognitive score which was below the control group, and an identity cost (measured by an IAT test and self-reported aspirations) that was above the control group. Our message thus appears to be increasing the interest of women in pursuing a career in the tech sector and the fact that we observe self-selection not just along the skill but also along the social identity dimension suggests that social identity itself is acting as a barrier. In fact, we also find the message is able to attract significantly more high-cognitive skill women, that were not applying before because they also display a very high social identity cost.

In a follow-up experiment, we decomposed the three components of treatment so that we could more precisely isolate what kinds of identity related information had an effect on the probability of women applying: addressing the probability of success for women, the provision of a role model and the development of a network of friends and contacts. We find that the most important effect is the provision of a role model, but that the concrete information about the success of women in the Tech sector and the development of a network of women also have large effects.

This implies that when trying to attract more female talent through this type of interventions, managers and recruiters must expect that the applicant pool will change both along cognitive and non-cognitive dimensions, and those will interact. It is essential therefore to pair this intervention with good screening protocols so that firms can identity their preferred candidates in the larger talent pool. In the absence of those, the effort can backfire.

Finally, whether women (or men) self-select out of certain industries for "identity" reasons is an important question more broadly, because if identity matters it could distort the optimal patterns of comparative advantage based on value creation, and hence be a barrier to the efficient allocation of human capital and hence aggregate welfare (Hsieh et al, 2013; Bell et al 2017). In addition, taking identity into account brings us to the secular debate about nature versus nurture. Do women select out from certain industries because they are genetically different or because society is configured in a way that "biases" and conditions their choices? This paper sheds some light on these questions, but a complete answer is left to future research.

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Tables

Table 1: Traffic to site, first experiment – Lima, summer 2016

	Traffic to "Postula URL"	
	Traffic	Conversions
Total	5387	605
Identity message	2763	414
Control	2624	191

Note: Total traffic obtained directly from randomization software Visual Web Optimizer (VWO). Number of conversions obtained from the program's registration database.

Table 2: Effect of the identity message on application rates and exam attendance, first experiment – Lima, summer 2016

	(1)	(2)	(3)
	Application rate	Attendance rate	
		Unconditional	Conditional on Applying
Identity message	0.077***	0.023***	-0.025
	(-0.009)	(0.005)	(0.04)
Mean of the dependent variable in control group	0.070	0.026	0.35
Observations	5387	5387	605

Notes: All models estimated by OLS.
The omitted category is the group shown the standard recruitment message.
Dependent variables are indicator variables of registration and attendance to examinations obtained from the program's registration and selection databases.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level.

Table 3: Socioeconomic Variables

	(1) Mean	(2) Standard deviation	(3) Observations	(4) Mean in treatment group	(5) Mean in control group	(6) P-value
Age	23.513	6.122	199	23.735	23.075	0.473
Has child	0.161	0.368	199	0.174	0.134	0.471
Number siblings at home	1.606	1.316	198	1.621	1.576	0.819
Family income	1,290.271	583.579	199	1,277.455	1,315.522	0.665
Home material	2.930	0.275	199	2.939	2.910	0.485
Education	5.729	1.427	199	5.621	5.940	0.137
Private school	0.312	0.464	199	0.280	0.373	0.183
Education mother	4.284	2.030	197	4.412	4.030	0.214
Education father	4.711	1.874	194	4.700	4.734	0.905

Notes: All models estimated by OLS.
Dependent variables: All dependent variables are obtained from the program's baseline database. *Age* and *Number of siblings at home* are in their original scale. *Has child* is an indicator variable. *Home material* is a categorical is a categorical variable coded as 1 mats; 2 wood; 3 bricks. *Family income* is a categorical variable. It takes the following values: 799 soles (corresponding to category "Less than 800 soles" in the raw data); 1000 soles ("Between 800 and 1200 soles"); 1450 soles ("Between 1201 and 1700 soles"); 1950 soles ("Between 1701 and 2200 soles"); 2450 soles ("Between 2201 and 2700 soles"); 2950 soles ("Between 2701 and 3200 soles"); 3201 soles ("More than 3200 soles"). *Education*, *Education mother* and *Education father* are categorical variables. *Private school* is an indicator variable. Education level is coded as 1-incomplete primary; 2-complete primary; 3-incomplete secondary; 4-complete secondary; 5-incomplete superior technical school; 6-incomplete university; 7 complete superior technical school; 8-complete university.

Table 4: Descriptive Statistics of Main Variables

	(1) N	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max
Expected Returns					
Log Webdev income	197	7.893	0.541	6.215	9.210
Log Salesperson income	196	7.381	0.565	5.704	9.210
Log salary dif.	196	0.514	0.449	-0.405	1.897
Cognitive Abilities					
Code Academy	200	57.285	49.409	0.000	150.000
Prueba Lab	174	6.957	3.261	0.000	14.000
Cog. Score	174	33.990	25.643	1.000	81.250
Social Identity					
IAT Gender/Career	171	0.219	0.450	-1.059	1.069
IAT Gender/Tech	178	0.096	0.392	-0.865	1.395
Traditional Role	199	1.265	0.497	0.000	2.000
Other Preferences					
Wanted to study tech prior to application	182	0.505	0.501	0.000	1.000
Risk Preferences	168	79.455	22.330	51.500	110.000
Time Preferences	168	55.923	37.110	5.000	160.000

Note: All variables are in their original scales.

Table 5: Cognitive abilities

	(1)	(2)	(3)	(4)	(5)	(6)
	Code Academy (std)		Prueba Lab (std)		Cog. Score (std)	
Identity message	-0.268*	-0.268*	-0.278*	-0.293*	-0.316**	-0.327**
	(0.149)	(0.146)	(0.159)	(0.167)	(0.158)	(0.155)
Mean of the dependent variable in control group	0.178	-3.628***	0.182	-1.442	0.207	-3.686***
	(0.121)	(1.298)	(0.128)	(1.495)	(0.128)	(1.386)
Controls	No	Yes	No	Yes	No	Yes
Observations	200	190	174	164	174	164
Adjusted R-squared	0.011	0.141	0.012	0.010	0.017	0.137

Notes: All models estimated by OLS.
The omitted category is the group shown the standard recruitment message.
Dependent variables: *Code Academy* is the result of the coding test obtained from the program's selection database. *Prueba Lab* is the result of the general cognitive ability test obtained from the program's selection database. The *Cog score* variable is the equally weighted average of the two test results. All dependent variables are standardized.
Controls are Age, Family income, Education level, Education level of the mother, Education level of the father.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level.

Table 6: Social Identity

	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
	IAT Gender/Career (std)		IAT Gender/Tech (std)		Traditional Role (std)		IdentityWedge	
Identity message	0.125	0.139	0.290*	0.348**	0.380**	0.368**	0.144**	0.156**
	(0.159)	(0.171)	(0.157)	(0.168)	(0.148)	(0.152)	(0.058)	(0.063)
Mean of the dependent variable in control group	-0.080	-2.128	-0.190	-1.884	-0.252**	0.692	-0.094**	-0.783
	(0.127)	(1.497)	(0.127)	(1.508)	(0.120)	(1.357)	(0.047)	(0.548)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	171	164	178	171	199	192	160	153
Adjusted R-squared	-0.002	-0.013	0.013	-0.002	0.028	0.036	0.031	0.033

Notes: All models estimated by OLS.
The omitted category is the group shown the standard recruitment message.
Dependent variables: The *IAT Gender/Career (std)* and *IAT Gender/Tech (std)* variables are the results of Implicit Association Tests implemented by us at the beginning of the selection process. The *Traditional role (std)* variable is the average of the answers to survey questions: "*If you think about yourself 10 years from now, will you be: married? With children? In charge of household duties?*" The dependent variables of columns 1 to 3 (i.e., *IAT Gender/Career (std)*, *IAT Gender/Tech (std)* and *Traditional Role (std)*, respectively) are standardized. The *Identity Wedge* variable (column 4) is the first factor of Factor Analysis using the first three variables (in their original scales).
Controls are Age, Family income, Education level, Education level of the mother, Education level of the father.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level.

Table 7: Social identity at quantiles of cognitive ability

Panel A: Percentiles based on Code Academy

	Dependent Variable: Identity Wedge			
	(1) Bottom 25%	(2) Bottom 50%	(3) Top 50%	(4) Top 25%
Identity message	0.114	0.072	0.170**	0.323***
	(0.139)	(0.099)	(0.070)	(0.108)
Mean of the dependent variable in control	0.001	-0.000	-0.141**	-0.249***
	(0.114)	(0.082)	(0.056)	(0.080)
Observations	40	71	90	44
Adjusted R-squared	-0.008	-0.007	0.052	0.156

Panel B: Percentiles based on Cognitive Score

	Dependent Variable: Identity Wedge			
	(1) Bottom 25%	(2) Bottom 50%	(3) Top 50%	(4) Top 25%
Identity message	0.159	0.079	0.166**	0.286**
	(0.151)	(0.101)	(0.077)	(0.116)
Mean of the dependent variable in control	-0.114	-0.052	-0.136**	-0.223**
	(0.127)	(0.084)	(0.059)	(0.083)
Observations	30	63	77	39
Adjusted R-squared	0.003	-0.006	0.046	0.117

Notes: All models estimated by OLS.
The omitted category is the group shown the standard recruitment message.
Dependent variables: The *Identity Wedge* variable is the first factor of a Factor Analysis using the variables *IAT Gender/Career*, *IAT Gender/Tech* and *Traditional Role* (in their original scales).
Percentiles are defined based on the cognitive ability measured as the equally weighted average of the Code Academy and Prueba Lab tests.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level

Table 8A: Expected Returns

	(1) Log Webdev income	(2) Log Salesperson income	(3) Log salary dif.
Identity message	-0.115	-0.231***	0.111
	(0.081)	(0.084)	(0.068)
Mean of the dependent variable in control	7.969***	7.534***	0.441***
	(0.066)	(0.068)	(0.055)
Observations	197	196	196
Adjusted R-squared	0.005	0.033	0.009

Notes: All models estimated by OLS.
The omitted category is the group shown the standard recruitment message.
Dependent variables: *Log Webdev income* is the natural logarithm of expected wage as a web developer, obtained from the survey question "*What salary (monthly) do you think you could earn as a web developer in the technology sector after three years of experience?*". The *Log Salesperson income* variable is the natural logarithm of expected wage as a salesperson, obtained from the survey question "*What salary (monthly) do you think you could earn as a salesperson of some product in the sales or services sector, after three years of experience?".* The *Log salary dif* variable is the difference between the natural logarithm of expected wage as a web developer and the natural logarithm of expected wage as a salesperson.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level.

Table 8B: Expected Returns

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Webdev income		Log Salesperson income		Log salary dif..	
Age	0.003 (0.006)	0.004 (0.006)	0.001 (0.007)	0.002 (0.006)	0.002 (0.006)	0.002 (0.006)
Log family income	0.350*** (0.104)	0.349*** (0.104)	0.300*** (0.109)	0.299*** (0.108)	0.053 (0.097)	0.054 (0.096)
Education	0.070** (0.027)	0.068** (0.027)	0.050* (0.028)	0.045 (0.028)	0.021 (0.025)	0.025 (0.025)
Education father	0.028 (0.022)	0.027 (0.022)	0.037 (0.023)	0.034 (0.023)	-0.010 (0.021)	-0.008 (0.020)
Education mother	0.007 (0.020)	0.008 (0.021)	-0.011 (0.022)	-0.003 (0.022)	0.019 (0.019)	0.014 (0.019)
Code Academy (std)	0.073* (0.038)	0.070* (0.039)	0.084** (0.041)	0.072* (0.041)	-0.015 (0.036)	-0.006 (0.036)
Treated		-0.043 (0.077)		-0.172** (0.081)		0.121* (0.072)
Constant	4.757*** (0.691)	4.788*** (0.694)	4.800*** (0.730)	4.915*** (0.725)	-0.073 (0.645)	-0.153 (0.643)
Observations	188	188	187	187	187	187
Adjusted R-squared	0.191	0.188	0.127	0.144	-0.017	-0.007

Notes: All models estimated by OLS.
Dependent variables: *Log Webdev income* is the natural logarithm of expected wage as a web developer, obtained from the survey question "*What salary (monthly) do you think you could earn as a web developer in the technology sector after three years of experience?*". The *Log Salesperson income* variable is the natural logarithm of expected wage as a salesperson, obtained from the survey question "*What salary (monthly) do you think you could earn as a salesperson of some product in the sales or services sector, after three years of experience?".* The *Log salary dif* variable is the difference between the natural logarithm of expected wage as a web developer and the natural logarithm of expected wage as a salesperson.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level.

Table 9: Pairwise Correlations between variables

	(1) Log Webdev income	(2) Log Salesperson income	(3) Log salary dif.	(4) Cog. Score (std)	(5) IAT Gender/Tech (std)	(6) Traditional Role (std)
Log Webdev income	1					
Log Salesperson income	0.671*** (0.000)	1				
Log salary dif.	0.363*** (0.000)	-0.448*** (0.00)	1			
Cog. Score (std)	0.254*** (0.000)	0.235*** (0.002)	0.013 (0.870)	1		
IAT Gender/Tech (std)	0.0051 (0.947)	-0.0173 (0.819)	0.0281 (0.711)	-0.0403 (0.621)	1	
Traditional Role (std)	0.081 (0.258)	0.017 (0.810)	0.077 (0.286)	-0.132* (0.085)	0.0807 (0.285)	1

p-Values in parentheses ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level

Table 10: Other Preferences

	(1) Wanted to study technology prior to application	(2) Risk Preferences (risk aversion) (std)	(3) Time Preferences (impatience) (std)
Identity message	-0.016	0.196	0.173
	(0.079)	(0.162)	(0.162)
Mean of the dependent variable in control	0.516***	-0.128	-0.113
	(0.064)	(0.131)	(0.131)
Observations	182	168	168
Adjusted R-squared	-0.005	0.003	0.001

Note: All models estimated by OLS.
The omitted category is the group shown the standard recruitment message.
Dependent variables: *Wanted to study technology prior to application* is an indicator variable coded from the answer to survey question *"Prior to applying to Laboratoria, what did you want to study?".* Time *preference* is the minimum required to have in 3 months instead of 50 soles today. *Risk preference* is the minimum required as certain instead of a lottery with 50% chances of winning 150 soles or same chance of winning nothing. The dependent variables of columns 2 and 3 (i.e., *Risk preferences (std)*, and *Time preferences (std)*, respectively) are standardized.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level

Table 11: Follow-up experiment in Mexico, Treatment Decomposition

	Dependent Variable:		
	Application Rate	Attendance rate	
		Unconditional	Conditional on applying
T1: Network and Role Model	-0.025**	-0.005	0.016
	(0.010)	(0.005)	(0.051)
T2: Success and Role Model	-0.020*	-0.005	-0.001
	(0.010)	(0.005)	(0.051)
T3: Network and Success	-0.040***	-0.009*	0.019
	(0.010)	(0.005)	(0.055)
Difference T1 - T2	0.005	-0.000	-0.018
	(0.01)	(0.021)	(0.055)
Difference T1 - T3	-0.015	-0.004	0.003
	(0.009)	(0.005)	(0.059)
Difference T2 - T3	-0.020**	-0.004	0.021
	(0.01)	(0.021)	(0.058)
Mean of dependent variable in the control group	0.105***	0.026***	0.246***
	(0.007)	(0.004)	(0.034)
Observations	6,183	6,183	522

Note: All models estimated by OLS.
The omitted category is the group shown the full identity-recruitment message.
Dependent variables are indicator variables of registration and attendance to examinations obtained from the program's registration and selection databases.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level.
*Significance at 10% level

Figures

Figure 1: Self-selection with Identity

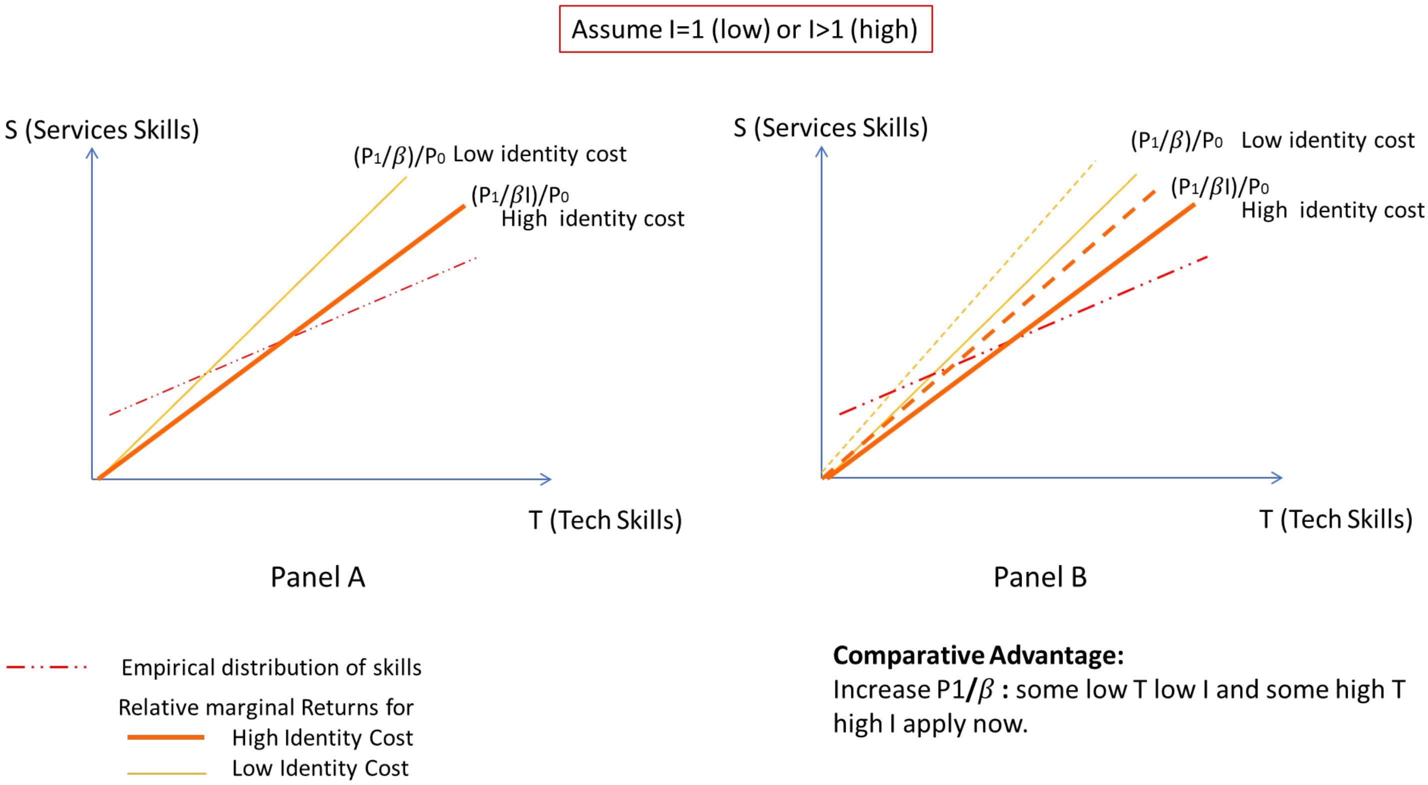

Figure 2A: Application Message in Lima 2016

The Treatment message added the elements that are circled in Red to the Control

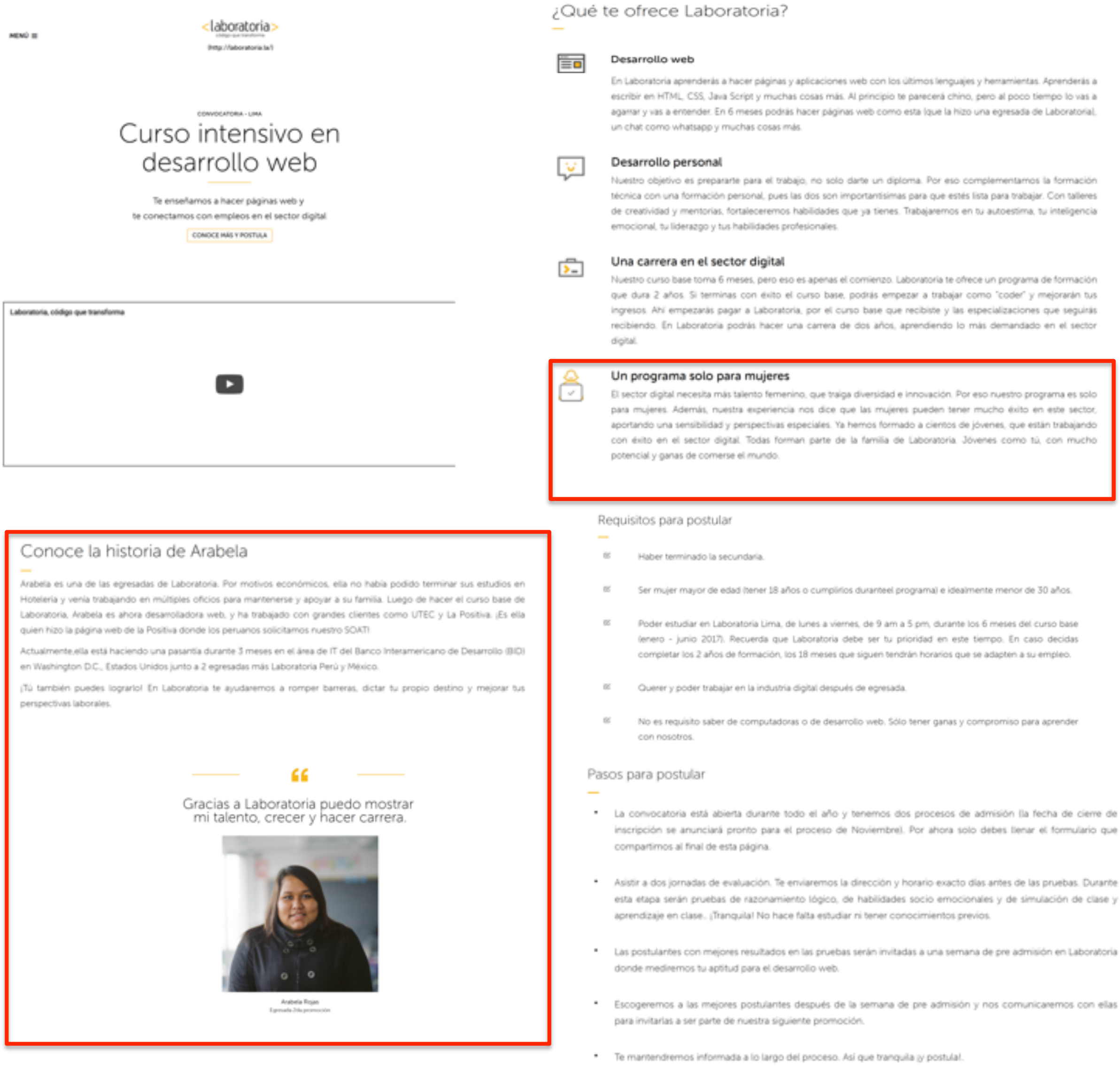

Figure 2B: Application Message (continued)

Postula

Nombres: *

Apellidos: *

Edad: *

Correo Electrónico: *

Documento de Identidad (DNI): *

Teléfono *

¿Cómo te enteraste de Laboratoria? *

- ☐ Facebook
- ☐ Radio
- ☐ Televisión
- ☐ Charla en mi comunidad
- ☐ Diarios o medios impresos
- ☐ Familia o amigo me avisó
- ☐ Otros

Si seleccionó otros medios

¿Cuál es tu motivación para estudiar en Laboratoria?: *

¡Recibe novedades de Laboratoria!*

- ☑ Acepto

Figure 3: Distribution of Cognitive Scores in Control (0) and Treatment (1)

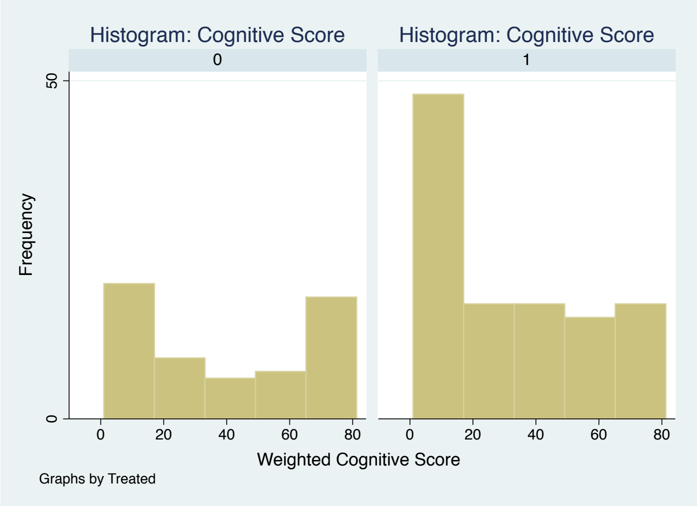

Figure 4: Distribution of Traditional Role in Control (0) and Treatment (1)

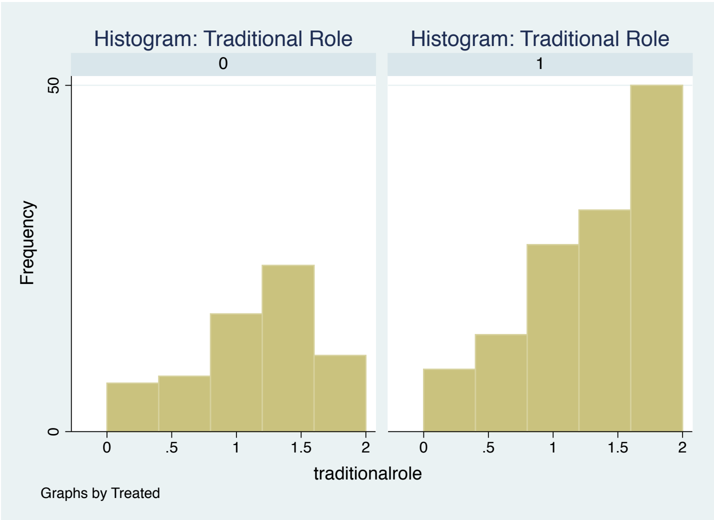

Figure 5: Distribution of IAT Tech/Services in Control (0) and Treatment (1)

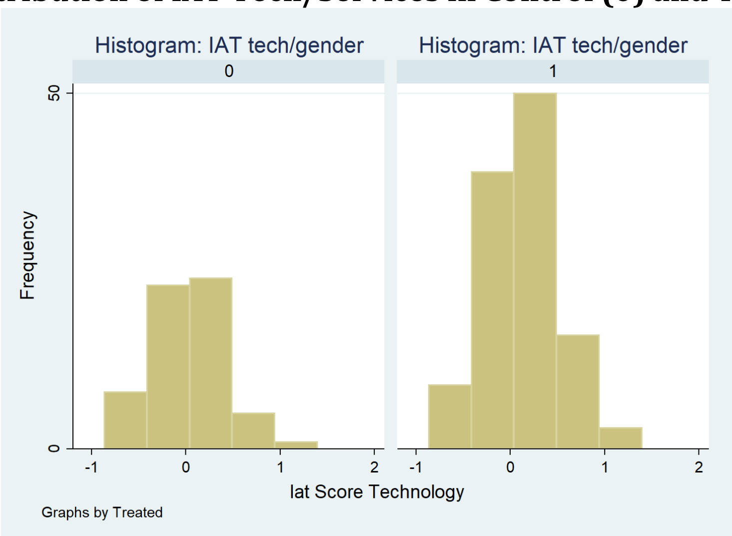

Figure 6: Additional information provided in Mexico

SUPPLEMENTAL APPENDIX: FOR ONLINE PUBLICATION

Appendices:

Table A1.A: Age and District of residence by Experimental group

	Dependent Variable					
	(1) Age	(2) Callao	(3) Central Lima	(4) Eastern Lima	(5) Northern Lima	(6) Southern Lima
Treated	0.376	-0.012	0.033	-0.015	-0.010	0.004
	(0.437)	(0.023)	(0.035)	(0.037)	(0.040)	(0.036)
Mean of dep var in control group	23.62***	0.083***	0.176***	0.238***	0.295***	0.207***
	(0.360)	(0.019)	(0.029)	(0.030)	(0.033)	(0.029)
Observations	600	600	600	600	600	600
Adjusted R-squared	-0.000	-0.001	-0.000	-0.001	-0.002	-0.002

Note: All models estimated by OLS.
The omitted category is the group shown the full identity-recruitment message.
Dependent variables are indicator variables indicating the age and district of residence of all people who registered and were assigned to treatment or control group.
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level

Table A1.B: Where you heard from Laboratoria by Experimental group

	Dependent Variable				
	(1) Facebook	(2) Family, friends	(3) Television	(4) Radio	(5) Community
Treated	0.056	-0.082**	-0.016	0.010	-0.003
	(0.042)	(0.038)	(0.022)	(0.018)	(0.008)
Mean of dep var in control group	0.585***	0.301***	0.078***	0.036**	0.010
	(0.035)	(0.031)	(0.018)	(0.015)	(0.007)
Observations	600	600	600	600	600
Adjusted R-squared	0.001	0.006	-0.001	-0.001	-0.001

Note: All models estimated by OLS.
The omitted category is the group shown the full identity-recruitment message.
Dependent variables are indicator variables indicating where the people who registered heard about Laboratoria
Standard errors in parentheses. ***Significance at 1% level. **Significance at 5% level. *Significance at 10% level

Table A2: Multiple Hypotheses Testing with Multiple Outcomes

Outcome	Diff. in means	p-values			
		Unadj.	Multiplicity Adj.		
		Remark 3.1	Thm. 3.1	Bonf.	Holm
Panel A					
Log Webdev income	0.115	0.154	0.283	1	0.309
Log Salesperson income	0.232	0.009***	0.056*	0.063*	0.063*
Code Academy (std)	0.268	0.093*	0.247	0.651	0.279
Prueba Lab (std)	0.278	0.085*	0.292	0.593	0.339
IAT Gender/Career (std)	0.125	0.449	0.449	1	0.449
IAT Gender/Tech (std)	0.290	0.064*	0.276	0.448	0.320
Traditional Role (std)	0.380	0.009***	0.052*	0.065*	0.056*
Panel B					
Log Webdev income	0.115	0.154	0.154	0.617	0.154
Log Salesperson income	0.232	0.009***	0.032**	0.036**	0.036**
Code Academy (std)	0.268	0.093*	0.171	0.372	0.186
Identity Wedge	0.144	0.015**	0.044**	0.061*	0.046**

* p<0.10 ** p<0.05 *** p<0.01

Table A3: Multiple Hypotheses Testing with Multiple Treatments (Mexico follow-up experiment)

Treatment/Control Groups	Diff. in means	p-values				
		Unadj.	Multiplicity Adj.			
		Remark 3.1	Thm. 3.1	Remark 3.7	Bonf.	Holm
Control vs T1	0.025	0.015**	0.027**	0.027**	0.045**	0.03**
Control vs T2	0.02	0.059*	0.059*	0.059*	0.178	0.059*
Control vs T3	0.04	0.000***	0.000***	0.000***	0.001***	0.001***

* p<0.10 ** p<0.05 *** p<0.01

Table A4: T-Tests and Power Calculations

	(1) Treated	(2) Control	(3) Diff. (2)-(1)	(4) Power	(5) MDE
Expected Returns					
Log Webdev income	7.854 (0.554) *130*	7.969 (0.511) *67*	0.115 (0.081)	0.328	0.222
Log Salesperson income	7.303 (0.552) *130*	7.534 (0.561) *66*	0.231*** (0.084)	0.774	0.238
Log Salary dif.	0.551 (0.454) *130*	0.441 (0.434) *66*	-0.111 (0.068)	0.380	0.186
Cognitive abilities					
Code Academy (std)	-0.090 (0.953) *133*	0.178 (1.072) *67*	0.268* (0.149)	0.411	0.436
Prueba Lab (std)	-0.096 (0.978) *114*	0.182 (1.024) *60*	0.278* (0.159)	0.409	0.454
Cog. Score (std)	-0.109 (0.954) *114*	0.207 (1.059) *60*	0.316** (0.158)	0.493	0.461
Social Identity					
IAT Gender/Career (std)	0.045 (0.968) *109*	-0.080 (1.056) *62*	-0.125 (0.159)	0.124	0.462
IAT Gender/Tech (std)	0.099 (0.997) *117*	-0.190 (0.985) *61*	-0.290* (0.157)	0.450	0.443
Traditional Role (std)	0.128 (1.038) *132*	-0.252 (0.874) *67*	-0.380** (0.148)	0.772	0.394
Other Preferences					
Wanted to study tech prior to application	0.500 (0.502) *120*	0.516 (0.504) *62*	0.016 (0.079)	0.057	0.221
Risk Preferences (std)	0.068 (1.005) *110*	-0.128 (0.987) *58*	-0.196 (0.162)	0.234	0.455
Time Preferences (std)	0.060 (1.066) *110*	-0.113 (0.859) *58*	-0.173 (0.162)	0.199	0.429

Note. Columns (1) and (2) report means, standard deviations (in parentheses) and sample sizes (in italics) for treated and control individuals, respectively. Column (3) reports differences of group means between control and treated individuals with standard errors (in parentheses). Column (4) reports the estimated power for a two-sample means test ($H_0 : mean_C = mean_T$ versus $H_1 : mean_C \neq mean_T$) assuming unequal variances and sample sizes in the two groups. Column (5) reports the minimum detectable effect size for a two-sample means test ($H_0 : mean_C = mean_T$ versus $H_1 : mean_C \neq mean_T$; $mean_T > mean_C$) assuming power = 0.80 and α = 0.05. * significant at 10%; **significant at 5%; *** significant at 1%.

Table A.5: Factor Analysis

Panel A

	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	0.14533	0.16424	4.9223	4.9223
Factor 2	-0.01892	0.07797	-0.6407	4.2815
Factor 3	-0.09688	-	-3.2815	1.0000

Panel B

	Factor 1	Uniqueness
IAT Tech	0.2573	0.9338
Traditional Role	0.1623	0.9737
IAT Career	0.2298	0.9472

APPENDIX: Text of Mexico D.F. experiment in English (Four Treatments)

<u>Become a Web Developer:</u>

In 6 months we will teach you to make web pages and connect you to jobs while you pursue your education for another 18 months

Control	*Networks + Role Model (no success)*	*Returns + Role Model (no networks)*	*Returns + Networks (no role model)*
Laboratoria is only for women because we believe in the transformation of the digital sector. Our experience has taught us that women can be very successful in the sector. Young talented women like you will create a network of contacts in the digital world.	Laboratoria is only for women because we believe in the transformation of the digital sector. Young talented women like you will create a network of contacts in the digital world.	Laboratoria is only for women because we believe in the transformation of the digital sector. Our experience has taught us that women can be very successful and in high demand in the sector.	Laboratoria is only for women because we believe in the transformation of the digital sector. Our experience has taught us that women can be very successful in the sector. Young talented women like you will create a network of contacts in the digital world.

Integral Education: We offer a career in web development not just a course. You will learn technical and personal abilities that are demanded by firms.
A job in the digital world: Our objective is not just to give you a diploma but to get you a job. We will connect you to local jobs in 6 months and then with jobs in the USA.
Fair price: You will only pay the cost of the program if we get you a job in the digital world. Seriously.

<u>A program only for women:</u>

Control	*Networks + Role Model (no success)*	*Returns + Role Model (no networks)*	*Returns + Networks (no role model)*
A network of talented women like yourself, in high demand by the digital sector **A network of women and success in the digital sector** The digital sector needs more female talent that will bring diversity and innovation. That is why our program is only for women. You will study with other	**You will have a network of women talented like yourself** **Network of Women** The digital sector needs more female talent that will bring diversity and innovation. That is why our program is only for women. You will study with other talented young women that want to make progress and that will	**Like our graduates, you will be in high demand in the digital sector** **Successful women in the digital sector** The digital sector needs more female talent that will bring diversity and innovation. That is why our program is only for women. We are looking to women that want to go far.	**A network of talented women like yourself, in high demand by the digital sector** **A network of women and success in the digital sector** The digital sector needs more female talent that will bring diversity and innovation. That is why our program is only for women. You will study with other

<table>
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<td>talented young women that want to make progress and that will become part of your family. We have already trained hundreds of women that are now working in the digital sector. All of them are part of Laboratoria and will be your network when you graduate. Young women like you, with a lot of potential and hunger to conquer the world. Besides, our experience shows us that women can be very successful in this sector, bringing a special perspective and sensibility. Our graduates are in high demand by firms in the digital sector and having successful careers. You can also do it.</td>
<td>become part of your family. We have already trained hundreds of women that are now working in the digital sector. All of them are part of Laboratoria and will be your network when you graduate. Young women like you, with a lot of potential and hunger to conquer the world.</td>
<td>Besides, our experience shows us that women can be very successful in this sector, bringing a special perspective and sensibility. Our graduates are in high demand by firms in the digital sector and having successful careers. You can also do it.</td>
<td>talented young women that want to make progress and that will become part of your family. We have already trained hundreds of women that are now working in the digital sector. All of them are part of Laboratoria and will be your network when you graduate. Young women like you, with a lot of potential and hunger to conquer the world. Besides, our experience shows us that women can be very successful in this sector, bringing a special perspective and sensibility. Our graduates are in high demand by firms in the digital sector and having successful careers. You can also do it.</td>
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<td colspan="3">Get to know the story of Arabela
Arabela is one of the Laboratoria graduates. For economics reasons, she had not been able to finish her studies on Hostelry and had take on several jobs to support herself and her family. After doing the Laboratoria “bootcamp” she started working in Peru as a web developer and worked for large clients such as UTEC and La Positiva. She was the one who develop the web page of La Positiva where Peruvians apply for their SOAT! Then we connected her to a job in the IT department of the Interamerican Development Bank (IDB) in Washington D.C., USA, along with two other Laboratoria graduates. Arabela is very successful as a developer in the USA and got to discover big cities such as Washington and New York. You can also do it! In Laboratoria we will help you break barriers, dictate your own destiny and improve your professional prospects.

</td>
<td>[n.a.]</td>
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<u>Integral Education</u>

Web development, personal abilities, English and much more

Web Development

In our first intensive semester, the "bootcamp", you will learn to make web pages and applications with the latest languages and tools. You will learn HTML5, CSS3, Java Script and many more things. At the beginning it will sounds like Greek to you, but you will learn it over time. In few months you will be able to make pages like this one (that was made by a Laboratoria coder) and more complex products such as the Airbnb webpage.

Personal Development
Our objective is to prepare you for a job. That is why we complete the technical training with personal training since both are highly valued by firms. With trainings and mentorships directed by psychologist and experts, we will strengthen your personal abilities. We will work on your self-confidence, your emotional intelligence, your communication and your leadership.

Continuous Education and English
In Laboratoria we will give you a career in web development. Not just a course. After the "bootcamp" you will have access to 3 more semesters of continuous education that you can do while you work. You will be able to specialize in more technical subjects to make more complex web products and graduate as a "full stack" Javascript web developer, with both "front end" and "back end" capabilities. You will also learn English in a specialized course called "English for Developers: that we have developed with experts from the United States embassy.

Agile Teaching Methods
In Laboratoria, classes take place in a very different format from the traditional format (and a more efficient one). We call our methodology the "Agile Classroom". With this methodology you will work in teams ("squads") with classmates that will learn with you and a coach that will guide you closely. This methodology will make you more autodidact, will facilitate your learning and will be more fun.

Diplomas and Levels
[explanation of the levels achived in each semester]

Bootcamp
6 intensive months
Continous Education
18 months with flexible schedule

Employment
Our objective is to get you a job and a career in the digital sector

Laboratoria is already a source of talent for hundreds of firms in Peru, Mexico, Chile and the USA that come to us because of the high performance of our "coders" and the diversity they bring to their teams. You cannot imagine how in demand web developers women are and the potential that you have to have a job in the digital world.
To improve your trust, here are our results to date: our employment rate is higher than the employment rate of the USA bootcamps, which is 73%.

*Resultados de última promoción en Lima (graduadas del bootcamp en Junio 2016).

<u>Fair Price</u>
In Laboratoria you will only pay for the course if we get you a job
We are against traditional training centers that charge students without preparing them for a job and without opening the doors to a good future professional future. In Laboratoria you only begin to pay when your income improves.

During the bootcamp you will only pay a symbolic fee, to get used to the discipline of monthly pay. Afterwards, when you start working, you will pay 24 installments. The exact amount will depend on your performance in the bootcamps and will never exceed 35% of your new salary, so that you can cover other needs. With that monthly payment you will reimburse the training you receive in the bootcamp and the continuous education that you will continue to receive, which will include technical, personal skills as well as English.

If after the 6 month bootcamp Laboratoria considers that you are not ready for a job and is not able to connect you to one, you will not pay for the course. That is fair, as it should be.

<u>Is Laboratoria for me?</u>
If you want more for your future, the answer is YES!

<u>Requisites</u>
[Text on steps to apply]
<u>Steps to apply</u>
[Text on steps to apply]

<u>F.A.Q</u>

<u>Apply</u>