More Women in Tech?
Evidence from a field experiment addressing social identity

Lucía Del Carpio
INSEAD

Maria Guadalupe
INSEAD

September 2018

Abstract

This paper investigates whether social identity considerations-through beliefs and norms-drive women's occupational choices. We implement two field experiments with potential applicants to a five-month software-coding program offered to women from low-income backgrounds in Peru and Mexico. When we correct the perception that women cannot succeed in technology by providing role models, information on returns and access to a female network, application rates double and the self-selection patterns change. Analysis of those patterns suggests that identity considerations act as barriers to entering the technology sector and that some high-cognitive skill women do not apply because of their high identity costs.

RCTR Trial AEARCTR-0001176 "Addressing gender biases and social identity in the technology sector in Peru." Funding for this project came from the INSEAD Randomized Controlled Trials Lab. We are grateful to Roland Bénabou, Sylvain Chassang, Guido Friebel, Rob Gertner, Bob Gibbons, Zoe Kinias, Thomas le Barbachon, Danielle Lee, Vlad Mares, Alexandra Roulet, Moses Shayo and John Van Reenen, as well as participants at the CEPR Labour and IMO meetings, Economics of Organizations Workshop, Paris-Berkeley Organizational Economics Workshop, MIT Organizational Economics seminar, NBER Organizational Economics workshop, NBER Summer Institute, LMU Identity workshop, INSEAD, Harvard Kennedy School conference on Women in Tech for their helpful comments and suggestions. The usual disclaimer applies.
Contacts: Lucia Del Carpio: lucia.delcarpio@insead.edu ;
Maria Guadalupe: maria.guadalupe@insead.edu

1. Introduction

Despite progress in the role of women in society in the last 50 years, the gender wage gap persists. A large part of that gap can be explained by the different occupational choices men and women make, but the reasons for those choices are still unclear (Blau and Kahn, 2017). Since at least Roy (1951), economists have explained people's self-selection into certain occupations as a function of the relative marginal returns to their skills. With that model in mind, the reason women do not self-select into male dominated industries is that their comparative advantage lies elsewhere. However, other elements are likely to come into play when making occupational choices such as *beliefs* (about skills and returns to skill) or preferences over the attributes of the occupations. In this paper, we propose and study social identity considerations – affecting beliefs and norms- as a possible driver of women's occupational choices, and its possible role in persistent occupational gender segregation patterns (see e.g. Bertrand, 2011; Goldin, 2014; Bertrand and Duflo, 2016).

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 ability and behavior of men and women. At the aggregate level, Miller et al (2015) finds a correlation between the prevalence of women in science in a country with (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).

The goal of our study is to bring together, and into the field, the economics of self-selection and the psychology social identity literatures to investigate the role of identity considerations in the occupational choices women make. How do potentially biased beliefs and gender norms affect women's occupational choices in the real world? Can they be changed? In particular, 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) as a function of their "technology" and "services" skills, the return to those skills and what we refer to as an "identity wedge" of entering a stereotypically male sector such as technology. This identity component affects the expected returns in technology by driving a wedge between the actual returns to skill and the expected returns. This wedge can capture several 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 Kranton, 2000).

As in the standard Roy model (without an identity wedge), self-selection will depend on the correlation between the two types of skills and the underlying identity wedge relative to their dispersion. Depending on these, we observe positive or negative self-selection into the technology sector both along the skills dimension and the identity dimension: i.e. we may end up with a sample that is more or less skilled, and that has higher or lower identity costs, with any combination being possible. Moreover, as a result of the identity wedge, women with very high cognitive skills may decide not to enter the industry because of their high identity cost, distorting the optimal allocation of talent across industries.

With this framework in mind, we run two field experiments that aim to reduce the strength of the identity wedge in decision making by changing women's perception on the role and prospects of 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 both experiments we randomly vary 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.[1]

We ran the first field experiment in Lima (Peru) where female coders represent only 7% of the occupation. The control group message contained generic information about the program (its goals, career opportunities, content and requirements). In the treatment message, we included a section aimed to correct misperceptions about the career prospects of women in technology: we emphasized that firms were actively seeking to recruit women, we 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. We call this the "identity de-biasing" message in the sense that it aims to reduce the identity wedge by countering prevailing stereotypes that women cannot be successful in this industry.

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

In the first field experiment (Lima), the identity de-biasing message was extremely successful: application rates rose from 7% to 15%, doubling the applicant pool to the training program. We then analyzed the self-selection patterns in the two groups to assess what barriers were 'loosened' by the message.

Our experiment leads to negative self-selection in average technology skills, average services skills, as well as in cognitive skills. We also find positive self-selection on the

[1] The goal of the organization is to identify high potential women, that because of their background may not have the option, knowledge or tools to enter the growing technology sector, where it is hard to find the kind of basic coding skills offered in the training.

identity wedge: on average, women with higher unconscious bias as measured by the IAT and potential identity costs as proxied by the traditional gender role survey measure apply following our identity de-biasing message. We argue that this is consistent with a world where the identity wedge matters for occupational choice and that this wedge varies across women.

Overall, however, what firms and organizations care about is the right tail of the skills distribution: does treatment increase the pool of *qualified* women to choose from? We find that even though average cognitive ability is lower in the treatment group, the identity de-biasing message significantly increases cognitive and tech-specific abilities of the top group of applicants, i.e, those that would have been selected for training. Why did higher cognitive skill women apply even if, on average, selection is negative? Beyond the obvious answer of noise in the distribution of skills or the effect of the experiment, we find evidence that some high skill women who did not apply before the treatment are also high "identity wedge" women and are now induced to apply. This is further evidence, beyond the effect of the experiment in the identity wedge at the mean that social identity matters for this occupational choice. Finally, we also measure a number of other characteristics and preferences of applicants, which allow us to rule out certain alternative mechanisms of the effects we find.

In a second experiment, in Mexico City, we aim to disentangle the information in the first message that the women in Lima responded to. This allows us to directly test whether it is beliefs about the returns, the non-monetary component to being in an environment with fewer women, and/or the exposure to a role model which mattered most in our first message. It allows us to understand what kinds of information about women make a bigger difference. Here the control treatment is the complete message, and in each of three treatments we removed one feature of the initial message (returns, network of women, role model) at a time. We find that women responded mostly to the presence of a role model. Hearing about the high expected returns (for women in the technology sector) and that they would have a network of other women upon graduating were also significant, but had a smaller effect.

A specific feature of our setting is that the training was offered only to women, and all applicants knew that. Hence we are able to design a message that is specifically targeted to women without being concerned about negative externalities on men by providing, for example, a female role model. It therefore allows us to investigate mechanisms that would be harder to investigate as clearly in the presence of men. Admittedly, we do not know how men would respond in a setting where they also see the de-biasing 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, Leibbrant and List, 2014) where evidence from field experiments is limited. We empirically test a mechanism that relies on the role of gender identity and explicit de-biasing and are able to analyze the type self-selection induced by the treatment along different dimensions, including unconscious identity biases and gender roles. 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)

We also relate to the literature on socio-cognitive de-biasing under stereotype threat in social psychology (Steele and Aronson, 1995), where it is well established that disadvantaged groups under-perform under stereotype threat, and where successful de-biasing strategies have been devised (Good, Aronson, and Inzlicht, 2003; Kawakami et al., 2017; Forbes and Schmader, 2010). While this literature focuses on the effect of de-biasing on performance, we focus on its effect on self-selection (we cannot assess the effect of de-biasing on performance itself, but it is unlikely to be large in our setting given our findings and the context of the test and survey, as discussed later).

We also contribute evidence to the very limited literature on the performance effects of restricting the pool of applicants through expected discrimination or bias (Bertrand and Duflo, 2016). We identify improvements after de-biasing not only in the number of applicants, but most importantly in the number of top applicants available to select from, even though the average quality of candidates falls.

Finally, our paper is related to the literature showing how the way a position is advertised can change the applicant pool. Ashraf, Bandiera and Lee (2014) study how career incentives impact self-selection into public health jobs and, through this, performance while in service. They find that making career incentives salient attracts more qualified applicants with stronger career ambitions without displacing pro-social preferences. Marinescu and Wolthoff (2016) show that providing information of higher wages attracts more educated and experienced applicants. Dal Bó et al. (2013) explore two randomized wage offers for civil servant positions, finding that higher wages attract abler applicants as measured by their IQ, personality, and proclivity toward public sector work. In contrast to these papers we find negative self-selection on average. In other words, the informational treatment may backfire depending on the underlying parameters of choices and beliefs.

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.

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 lnS= s~N(0, σ_s^2) and lnT= t~N(0, σ_t^2). The probability that a woman applies to the technology sector is:

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

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 $\rho_{ts} > \frac{\sigma_t}{\sigma_s} \Rightarrow \frac{dE(T|Apply)}{dp_1} > 0$ and selection is positive. Conversely if $\rho_{ts} < \frac{\sigma_t}{\sigma_s} \Rightarrow \frac{dE(T|Apply)}{dp_1} < 0$ selection is negative and the average Tech skills of applicants decreases. Similarly, we can sign the selection for Services skills, S. If $\rho_{ts} > \frac{\sigma_s}{\sigma_t} \Rightarrow \frac{dE(S|Apply)}{dp_1} < 0$; $\rho_{ts} < \frac{\sigma_s}{\sigma_t} \Rightarrow \frac{dE(S|Apply)}{dp_1} > 0$

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.[2]

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

[2] 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.

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 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, $i \sim N(0,\ \sigma_i^2)$

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: It could reflect 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. It could also reflect the belief that women cannot succeed in the technology industry because there is discrimination and their skills are not valued.

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"). In the technology setting, since the sector is predominantly male and follows stereotypically male norms, high I women would suffer a larger penalty.

For simplicity, let $\hat{p}_1 = p_1 - \beta$, reflecting the "biased return". 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 (i=0), 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 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)

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

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

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 $\hat{p}_1$.

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 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.

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.[3] 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. They run 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

[3] 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.

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 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.[4] 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.[5]

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

[4] The network of companies to which the organization targets their graduates is constantly expanding.
[5] 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.

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.

4. Interventions and Research Design

The evidence we provide in what follows comes from two experiments, as well as selection examinations, and follow-up surveys of applicants to the program. In the first experiment (Lima, summer 2016) we tested the effect of a message that reduces the strength of the potential identity wedge (what we call the identity "de-biasing message") with three types of information. In the second experiment (Mexico City, winter 2016) we separated out the three components of the initial message to assess which was/were responsible for the increase in response rates.

The experiments aim 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. In the context of our framework, and 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.

Finally, before launching our two main interventions, we also piloted our treatment message, using a slightly different text, in a smaller location: Arequipa (Peru). Overall, all three experiments together allow us to better understand the main drivers.

4.1 The first experiment: Lima summer 2016

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

4.1.1. Treatment and control messages

The information provided on the program that all potential applicants saw (the control) includes the following text (this is 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."

In addition, our treatment message included the following text:

"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."

It was 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 1A.

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. Conceptually this 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. [6] This first experiment therefore "bundles" three different pieces of information with an additional general encouragement to apply. Our attempt to separate those out after seeing the results of this experiment is what gave rise to the Mexico City experiment a few months later where we explicitly varied these three components.

4.1.2. Registration forms and data collection at registration

Right after being exposed to the information about the program on the website, potential applicants have to decide whether to apply (or not) by completing a simple registration form. The information requested is minimal and includes name, age, email,

[6] A number of papers have studied the importance of role models in STEM, for example Cheryan et a (2011) and (2013); Breda et al (2018) and in finance, for example Adams et al (2017).

phone, where they heard about the program, and why they were interested in the program (see Figure 1B).

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, that no preparation was needed, etc.). As discussed in section 5, not all candidates attend the examination sessions.[7]

4.1.3 Data Collection on Selection Days

In the two-day selection process we were able to collect information on a number of relevant characteristics that try to capture the variables in the model. Some of these variables came directly from the program's selection process (e.g., cognitive abilities), and others from a baseline survey and additional tests we implemented to all candidates before they had to take their examinations (the same day). In particular we collected data about the following:[8]

A) Expected financial returns: In a survey, we asked them 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 which is a common services job and a concrete alternative option for these women. In the context of our model, this gives us a (self-reported) measure of $P_0 S$ and $P_1 T$, 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).

---

[7] As mentioned, data collected at registration is minimal, but we did perform an analysis of the motivation statements to understand: 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 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.

[8] Note that we are able to obtain this information on each candidate only if they attended the examinations required to be selected for training.

B) Cognitive Skills: The first stage in the training provider's selection process comprises two cognitive tests: an exam measuring math and logic skills, and a coding simulation exercise measuring tech capabilities. The general cognitive ability test measuring math and logic skills, "Prueba Laboratoria", is a test the training provider developed with psychologists following a standard Raven test. A second test called "Code Academy" is a coding simulation that tests how quickly test takers are to understand basic coding and put it into place (assuming no prior knowledge). This was taken from codeacademy.com. We also use an equally weighted average of the two (cognitive score). Both tests are very good predictors of the probability of success in the training, in particular the Code Academy test, so we interpret these as capturing the underlying cognitive skills that are useful in technology (a proxy for T).

C) Gender Identity: Measuring gender identity in the field is not a trivial task. In order to measure the identity wedge we use proxies for different possible causes of the wedge. These include possible implicit biases of women that associate a successful career or a career in technology to men over women, reflecting prevailing stereotypes, but also the strength of gender norms and the associated identity cost. We use three base variables we were able to record at the application stage. The first two are based on implicit association tests (IAT). Overall, IAT's measure the strength of an association between different categories, and hence the strength of a stereotype (Greenwald et al 1998). IATs have been created to study different implicit associations/biases/prejudices (e.g., race and intelligence, gender and career) and have been shown to have better predictive power than survey measures (Greenwald et al, 2009). 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. 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.

Our third variable is based on answers to survey questions. 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 1, 2 and 3 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 principal components 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.

D) Other variables: The training company also collected other information on applicants as part of the selection process. In the context of our work, we asked them to implement 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).

Descriptive statistics on all these variables are provided in Table 1.

4.1.4 Randomization

We randomized the messages directly at the training provider's registration website by unique user visiting the website. To randomize the information provided in the registration page we used the Visual Web Optimizer (VWO) software.[9] To boost

[9] The only 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.

traffic, we launched targeted ad campaigns in Facebook. Traffic results (total and by treatment message) are shown in Table 2. 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.

4.2 The second experiment: Mexico City winter 2016

In the first experiment, the treatment included several pieces of information bundled into the message. Given the very strong response we observed from the treatment, we wanted to assess what piece(s) of information women were actually responding to. We then ran a second 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, but the organization was gaining a lot of press and notoriety in Peru during the fall of 2016). Furthermore, given the success of the first experiment, the organization really wanted to use our identity message, and was concerned about jeopardizing applications if the old control was used. Thus, in the second experiment, the control group is the full "identity de-biasing" message and we take out one piece of information at a time. 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:

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

The Appendix shows the exact text of this intervention translated into English. A few differences are noteworthy relative to the Lima experiment. As the training provider developed its communication and the program, it included much more information on its landing page and the exact content of the program was changing. The additional information that all applicants saw included data on the expected increase in earnings after the training (2.5 times more), the employment probability in tech (84%), they made more salient the low upfront cost of the program, provided more information on Laboratoria and its prior success and overall there were more images and the webpage was more interactive. The content of the program was also changing: they now included continuous education to become a full stack developer after the 5-month bootcamp, they adopted agile methodologies for education and they introduced an English for coders course. These changes allow us to test our de-biasing treatment against a different and much richer informational background, reinforcing the external validity and rule out a number of alternative explanations for our results.

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 four sets of results from our first experiment. In section 5.1, we evaluate the effect of receiving the identity de-biasing message on the size of the pool of applicants (application rates) as well as rates of attendance to the examination by type of recruitment message. In section 5.2 we examine the self-selection patterns on skills and identity among those who came to the examinations. In section 5.3 we report differences at the top of the skill distribution of applicants (those that will be selected for training), while in section 5.4 we report differences all along the distribution. Finally, in section 5.5 we test for differences in other variables such as interest in technology and time and risk preferences.

5.1 Application rates and attendance to selection examinations

5.1.1. Application rates

The experiment is designed to raise the expected returns in technology for women ($\hat{p}_1$) by reducing the possible negative impact of the identity component on their expectations of success and the attractiveness of a career in software development. Column 1 in Table 3 reports the results on differential application rates by recruitment message: essentially, our de-biasing message doubled application 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.

While the magnitude of the effect is quite striking, in order to understand the mechanisms driving this increased willingness to enter the technology training, it is important to first address a few important issues. We will tackle individual mechanisms after reviewing the Mexico experiments, but we start with some general remarks. First, the treatment contains a photograph of Arabela and the control does not. Is the picture the driver? Our pilot in Arequipa did not contain any images (only text) and we obtained similar magnitudes of the treatment there (a 7% application rate in the control vs a 15% application rate in the treatment).[10] Second, is it the wording? As we will see later, the wording is different in our Mexico experiment and was slightly different in the Arequipa experiment, and we obtain similar results, so this suggests it is about the *information* provided in the treatment message, not the precise wording nor the picture. Third, could it be that the treatment offers just more information, or a general encouragement and with more information/encouragement candidates are more likely to apply? As we will see in the Mexico experiment, it is not just more information but *specific types* of information that women respond to more, and the key is to understand what "priors" that additional information is affecting. Results in section 5.2, where we analyze the change in self-selection with the treatment message, also allow us to infer the relevant information that is changing these women's priors, and to what extent identity is one of the dimensions affected.

5.1.2 Attendance rates

As discussed, all registered applicants have to attend two days of examinations to be evaluated for admission into the program, and 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. Our outcome of interest can be thought of as applying and attending the examination, but since this requires two separate decisions, we separate them out. In column 2 of Table 3 we report attendance rates to the examination dates by treatment group. We 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

[10] Results of the Arequipa pilot are reported in the Appendix, Table A1.

between the two groups. So this suggests that the main selection step is the application stage and not the decision to attend the examinations. At the end of this process differences in application rates strongly influence the distribution of candidates attending the selection process. Of the total 202 candidates attending, 66% had been exposed to the treatment message.

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 in treatment and control, not the causal effect of treatment on the outcome variables (as we only observe those who applied and attended the selection process). We are looking at how the equilibrium selection changes following the exogenous shock (treatment). We discuss below why we think treatment effects of de-biasing on exam/test performance are minimal relative to the effect on selection. In all cases we regress the variables of interest on the treatment variable.

5.2.1 Expected returns and Cognitive Skills

Table 4 shows 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 if average T decreases (negative selection) as we expect that the experiment message increases p_1. The net effect is negative although not significant.

In order to measure skills directly (not confounded by the returns that change with the experiment), we analyze the change in selection of cognitive skills following the de-biasing message, as shown in Table 5. We find that average cognitive skills 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. There is clear negative selection in cognitive skills.

5.2.2 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 de-biasing message are on average more "biased" as measured by the IAT 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).[11] Figures 3 and 4 show the raw distribution of the basic identity variables and reflect this pattern.

Finally, given the negative selection on skills and the positive selection on identity costs generated by the treatment and based on our augmented Roy model (in Section 2), we can infer the underlying correlations in those variables within the target population. If we equate cognitive skills and coding skills (prueba laboratoria and code academy) to T and expected returns in sales to S, then from equation (3) we can infer that $\sigma_{ts} > \sigma_{is}$ in the population. This means that sales skills covary more with tech skills than with identity. Based on equation (4) positive self-selection on identity suggests that the correlation between identity costs and the difference between technology and services skills is either negative or positive but not very high relative to the ratio of the variance of the identity wedge (I) to the skill differential (D=t-s). Unfortunately we do not observe the distributions of these variables in the population, so we can only infer their relationship based on the observed self-selection patterns given the framework we introduced earlier, and we cannot fully characterize them. We can, however, observe the correlations in the variables within our selected sample of women who apply. Since these are based on the selected sample they are not necessarily representative of the population, but they are nonetheless interesting and are shown in Table 9. We find that the correlation between the identity variables on the one hand and the different measures of skills (returns in technology, returns in sales,

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

and cognitive scores) are very low, close to zero, while the skills variables are highly correlated between themselves.

5.2.3. Selection vs. Treatment

We are interpreting our results as reflecting mostly "selection"; 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 de-biasing" message has a significant causal effect on most other of the outcome measures that aim to capture permanent characteristics (like cognitive skills and IAT tests). This is because (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 de-biasing 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.

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.

5.3. Selection at the Top: Trading Off Attributes

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. However, these mean effects obscure what is happening along the distribution. In fact, the training provider is interested in attracting a higher number of "right tail" candidates to select from. As overall numbers increase, do the number of highly qualified women increase in spite of the fall in the mean quality? In the bottom panel of Table 5 we compare 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).

These results suggest that the treatment affects candidates differentially by level of cognitive ability: it increases the number of applicants at all levels of cognitive ability, but it particularly does so at the bottom of the distribution. Figure 2 shows the frequency of applicants in treatment and control that reflects this pattern.

What about social identity at the top? Panel B in Table 6 shows the difference in the average IAT's, and traditional role variables for the top 50 candidates ranked by cognitive score. The results suggest that the average "top" applicant is more biased/has a larger identity cost in the treatment than in the control group, although this is statistically significant only for the identity wedge variable.

5.4. Selection along the skill distribution

Finally, we analyze whether there are differential identity patterns or differential impacts in expected monetary returns induced by treatment at different points of the cognitive ability distribution. In panel A of Table 7, we first estimate the difference in the identity wedge between treatment and control candidates at the bottom 10%, 25% and 50%, as well as the top 50%, 25% and 10% 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% and 10% of the distribution of cognitive ability, those in the treatment group report a much higher identity cost compared to the control (up 0.323 and 0.341 standard deviations, respectively).

Regarding expected monetary returns, we can see (columns (7) to (14)) that the log salary differential is significantly higher in the treatment group for those in the top 25% of cognitive ability. Table 8 shows the trade-off between social identity and the log salary differential. In particular, we estimate differential identity patterns induced by treatment at different points of the log salary differential distribution. The results here are less pronounced but are still consistent with the previous ones: identity is higher in the treatment group compared to the control, especially at the top.

Overall, 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.

5.5 Interest in Technology, time and risk preferences

During the provider's examination period, we also asked women about their prior interest in technology and were able to measure other non-cognitive traits for all applicants like time and risk preferences. [12] Just as "identity" can create a wedge between returns based on comparative advantage and utility, other non-monetary dimensions may preclude women from applying to the tech sector. For example, one might conjecture that women are overall less interested in technology, or that women are more risk averse, hence to the extent technology is perceived as risky it is less desirable than a secure services job. 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, 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. Although potentially interesting, our tests are unfortunately underpowered to establish anything more conclusive with our data.[13]

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

The Lima experiment shows that application rates doubled when women were exposed to the de-biasing message. However, we do not know which piece of information in the 'bundle' triggered the increase in applications. In order to see that,

[12] Using the survey modules in Falk et al. (2016)

[13] Power calculations for all estimations are provided in the Appendix, Table A4.

we collaborated again in the winter of 2016 with the organization to implement the second experiment in Mexico City.

As mentioned, in this follow-up experiment we decomposed each prior element of treatment. To address concerns by the training provider of not maximizing the number of applicants (they had seen how applications rates doubled with our prior treatment), we considered a control group with all previous treatment components, and eliminated one by one each of its components. 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)

Note that in the Mexico experiment, we chose to have several treatments to identify mechanisms, but then we do not have the power to infer selection by treatment group based on examinations, so we focus on application rates.

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. The treatment that eliminates the role model has the largest impact, reducing the conversion rate by 4 percentage points or 38%. The treatment that eliminates the "women can be successful" component reduces the conversion rate by 2.5 percentage points or 24%; the treatment that eliminates the network component leads to a 2 percentage points or 19% decline in the conversion rate.[14]

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 Arequipa pilot, Lima and Mexico DF experiments, i.e. in different time periods and different countries, suggesting that the informational content of our experiment really is able to alter behavior and self-selection into the industry.

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

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. 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: 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 component is the provision of a role model, but that the de-biasing about the success of women in the Tech sector and the development of a network of women are also relevant.

Whether women (or men) self-select out of certain industries for "identity" reasons is an important question, 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 (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.

References

Adams, Renee B. and Barber, Brad M. and Odean, Terrance. 2018. "STEM Parents and Women in Finance" *Financial Analysts Journal*, 74: 2.

Akerlof, George A., and Rachel E. Kranton. 2000. "Economics and identity." *The Quarterly Journal of Economics* 115(3): 715-753.

Ashraf, Nava, Oriana Bandiera and Scott S. Lee. 2014. "Do-gooders and go-getters: career incentives, selection, and performance in public service delivery." *STICERD-Economic Organisation and Public Policy Discussion Papers Series* 54.

Beaman, Lori, Esther Duflo, Rohini Pande and Petia Topalova. 2012. "Female leadership raises aspirations and educational attainment for girls: A policy experiment in India." *science* 335 No. 6068: 582-586.

Bell, Alexander M., Raj Chetty, Xavier Jaravel, Neviana Petkova and John Van Reenen. 2017. "Who Becomes an Inventor in America? The Importance of Exposure to Innovation." NBER Working Paper No. 24062.

Bertrand, Marianne. 2011. "New perspectives on gender." In *Handbook of Labor Economics*, O. Ashenfelter and D. Card eds., 1545-1592.

Bertrand, Marianne, and Esther Duflo. 2016. "Field Experiments on Discrimination." London, Centre for Economic Policy Research.

Bertrand, Marianne, Emir Kamenica and Jessica Pan. 2015. "Gender Identity and Relative Income within Households." *The Quarterly Journal of Economics* 571–614.

Blau, Francine D., and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature* 55(3): 789–865.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli and Andrei Shleifer. 2016a. "Stereotypes." *Quarterly Journal of Economics* 131(4): 1753-1794.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli and Andrei Shleifer. 2016b. "Beliefs about gender." NBER Working Paper No. w22972.

Borjas, George J. 1987. "Self-Selection and the Earnings of Immigrants." *The American Economic Review* 531-553.

Breda, Thomas, Julien Grenet, Marion Monnet and Clémentine Van Effenterre. 2018. "Can female role models reduce the gender gap in science? Evidence from classroom interventions in French high schools." PSE Working Papers No 2018-06.

Cheryan, Sapna, John O. Siy, Marissa Vichayapai, Benjamin J. Drury and Saenam Kim. 2011. "Do female and male role models who embody STEM stereotypes hinder women's anticipated success in STEM?" *Social Psychological and Personality*

Science 2(6): 656–664.

Cheryan, Sapna, Victoria C. Plaut, Caitlin Handron and Lauren Hudson. 2013. “The stereotypical computer scientist: gendered media representations as a barrier to inclusion for women.” *Sex Roles* 69: 58–71.

Coffman, Katherine Baldiga. 2014. “Evidence on Self-Stereotyping and the Contribution of Ideas.” *The Quarterly Journal of Economics* 129(4): 1625–1660.

Dal Bó, Ernesto, Frederico Finan and Martín A. Rossi. 2013. “Strengthening State Capabilities: The Role of Financial Incentives In The Call To Public Service.” *The Quarterly Journal of Economics* 128(3): 1169-1218.

Falk, Armin, Anke Becker, Thomas Dohmen, David B. Huffman and Uwe Sunde. 2016. “The preference survey module: A validated instrument for measuring risk, time, and social preferences.” IZA Discussion Paper No 9674.

Flory, Jeffrey, Andreas Leibbrandt and John List. 2015. “Do Competitive Workplaces Deter Female Workers? A Large-Scale Natural Field Experiment on Job Entry Decisions.” *The Review of Economic Studies* 82 (1): 122-155.

Forbes, Chad E., and Toni Schmader. 2010. “Retraining Attitudes and Stereotypes To Affect Motivation And Cognitive Capacity Under Stereotype Threat.” *Journal of Personality and Social Psychology* 99(5): 740-754.

Goldin, Claudia. 2014. “A Grand Gender Convergence: Its Last Chapter.” *American Economic Review* 104(4): 1091-1119.

Good, Catherine, Joshua Aronson and Michael Inzlicht. 2003. “Improving Adolescents' Standardized Test Performance: An Intervention To Reduce The Effects Of Stereotype Threat.” *Journal of Applied Developmental Psychology* 24(6): 645-662.

Greenwald, Anthony G., Debbie E. McGhee and Jordan L.K. Schwartz. 1998. “Measuring individual differences in implicit cognition: The implicit association test.” *Journal of Personality and Soclal Psychology* 74(6): 1464–1480.

Greenwald, Anthony G., T. Andrew Poehlman, Eric L. Uhlmann and Mahzarin R. Banaji. 2009. “Understanding and using the Implicit Association Test: III. Meta-analysis of predictive validity.” *Journal of Personality and Soclal Psychology* 97(1): 17–41.

Hsieh, Chang-Tai, Erik Hurst, Charles I. Jones and Peter J. Klenow. 2013. “The allocation of talent and us economic growth.” NBER Working Paper No 18693.

Kahneman, Daniel, and Amos Tversky. 1973. “On the psychology of prediction.” *Psychological review* 80(4): 237-251.

Kawakami, Kerry, David M. Amodio and Kurt Hugenberg. 2017. “Intergroup Perception and Cognition: An Integrative Framework for Understanding the Causes and Consequences of Social Categorization.” *Advances in Experimental Social Psychology* 55: 1-80.

Marinescu, Ioana, and Ronald Wolthoff. 2016. "Opening the Black Box of the Matching Function: The Power of Words." NBER Working Paper No 22508.

Miller, David I., Alice H. Eagly and Marcia C. Linn. 2015. "Women's representation in science predicts national gender-science stereotypes: Evidence from 66 nations." *Journal of Educational Psychology* 107(3): 631-644.

Paluck, Elizabeth Levy, and Donald P. Green. 2009. "Prejudice Reduction: What Works? A Review and Assessment of Research and Practice." *Annual Review of Psychology* 60(1): 339-367.

Reuben, Ernesto, Paola Sapienza and Luigi Zingales. 2014. "How stereotypes impair women's careers in science." *Proceedings of the National Academy of Sciences* 111(12): 4403-4408.

Roy, Andrew D. 1951. "Some Thoughts on The Distribution of Earnings." *Oxford Economic Papers* 3(2): 135-146.

Spencer, Steven J., Claude M. Steele and Diane M. Quinn. 1999. "Stereotype threat and women's math performance." *Journal of Experimental Social Psychology* 35(1): 4-28.

Steele, Claude M., and Joshua Aronson. 1995. "Stereotype Threat and the Intellectual Test Performance of African Americans." *Journal of Personality and Social Psychology* 69(5): 797-811.

Tables

Table 1: Descriptive Statistics

	(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 2: Traffic to site, first experiment – Lima, summer 2016

	Traffic to "Postula URL"	
	Traffic	Conversions
Total	5387	605
De-biasing message	2763	414
Control	2624	191

Table 3: Effect of de-biasing message on application rates and exam attendance, first experiment – Lima, summer 2016

	(1)	(2)
	Application rate	Attendance
Treated	0.077***	-0.022
	(-0.01)	(-0.04)
Mean of the dependent variable in control	0.07	0.35
Observations	5387	608

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

Table 4: Expected Returns

	(1)	(2)	(3)
	Log Webdev income	Log Salesperson income	Log salary dif.
Treated	-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

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

Table 5: Cognitive abilities

Panel A: All Observations

	(1) Code Academy (std)	(2) Prueba Lab (std)	(3) Cog. Score (std)
Treated	-0.268*	-0.278*	-0.316**
	(0.149)	(0.159)	(0.158)
Mean of the dependent variable in control	0.178	0.182	0.207
	(0.121)	(0.128)	(0.128)
Observations	200	174	174
Adjusted R-squared	0.011	0.012	0.017

Panel B: Top 50 Candidates by Cognitive Score

	(1) Code Academy (std)	(2) Prueba Lab (std)	(3) Cog. Score (std)
Treated	0.373**	-0.163	0.349**
	(0.159)	(0.190)	(0.155)
Mean of the dependent variable in control	0.552***	0.418***	0.486***
	(0.112)	(0.134)	(0.109)
Observations	100	100	100
Adjusted R-squared	0.044	-0.003	0.040

Standard errors in parentheses

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

Table 6: Social Identity

Panel A: All Observations

	(1) IAT Gender/Career (std)	(2) IAT Gender/Tech (std)	(3) Traditional Role (std)	(4) Identity Wedge
Treated	0.125	0.290*	0.380**	0.144**
	(0.159)	(0.157)	(0.148)	(0.058)
Mean of the dependent variable in control	-0.080	-0.190	-0.252**	-0.094**
	(0.127)	(0.127)	(0.120)	(0.047)
Observations	171	178	199	160
Adjusted R-squared	-0.002	0.013	0.028	0.031

Panel B: Top 50 Candidates by Cognitive Score

	(1) IAT Gender/Career (std)	(2) IAT Gender/Tech (std)	(3) Traditional Role (std)	(4) Identity Wedge
Treated	0.262	0.128	0.215	0.123*
	(0.206)	(0.187)	(0.189)	(0.070)
Mean of the dependent variable in control	-0.150	-0.100	-0.318**	-0.099*
	(0.144)	(0.134)	(0.134)	(0.050)
Observations	92	95	100	88
Adjusted R-squared	0.007	-0.006	0.003	0.023

Standard errors in parentheses

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

Note: The 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 the Principal Component Analysis using the first three variables (in their original scales).

able 7: Social identity and Expected monetary returns at quantiles of cognitive ability

Panel A: Percentiles based on Code Academy

	Dependent Variable: Identity Wedge						Dependent Variable: Log salary dif.					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Bottom 10%	Bottom 25%	Bottom 50%	Top 50%	Top 25%	Top 10%	Bottom 10%	Bottom 25%	Bottom 50%	Top 50%	Top 25%	Top 10%
reated	0.423	0.114	0.072	0.170**	0.323***	0.341**	0.092	0.100	0.092	0.109	0.302**	0.102
	(0.301)	(0.139)	(0.099)	(0.070)	(0.108)	(0.125)	(0.247)	(0.152)	(0.108)	(0.085)	(0.118)	(0.150)
lean of the ependent ariable	-0.278	0.001	-0.000	-0.141**	-0.249***	-0.126	0.632***	0.547***	0.451***	0.444***	0.423***	0.500***
ı control	(0.267)	(0.114)	(0.082)	(0.056)	(0.080)	(0.093)	(0.206)	(0.126)	(0.092)	(0.067)	(0.086)	(0.111)
bservations	14	40	71	90	44	18	23	54	96	102	50	20
djusted R-quared	0.070	-0.008	-0.007	0.052	0.156	0.274	-0.041	-0.011	-0.003	0.006	0.103	-0.029

Panel B: Percentiles based on Cognitive Score

	Dependent Variable: Identity Wedge						Dependent Variable: Log salary dif.					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Bottom 10%	Bottom 25%	Bottom 50%	Top 50%	Top 25%	Top 10%	Bottom 10%	Bottom 25%	Bottom 50%	Top 50%	Top 25%	Top 10%
reated	0.604*	0.159	0.079	0.166**	0.286**	0.306**	-0.435**	-0.211	-0.007	0.158*	0.326**	0.088
	(0.288)	(0.151)	(0.101)	(0.077)	(0.116)	(0.139)	(0.185)	(0.162)	(0.112)	(0.090)	(0.124)	(0.167)
lean of the ependent ariable	-0.396	-0.114	-0.052	-0.136**	-0.223**	-0.098	0.919***	0.791***	0.517***	0.416***	0.428***	0.520***
ı control	(0.241)	(0.127)	(0.084)	(0.059)	(0.083)	(0.104)	(0.153)	(0.139)	(0.096)	(0.069)	(0.087)	(0.124)
bservations	10	30	63	77	39	16	16	41	82	87	44	18
djusted R-quared	0.273	0.003	-0.006	0.046	0.117	0.205	0.233	0.017	-0.012	0.024	0.122	-0.044

Standard errors in parentheses.
* p<0.10 ** p<0.05 ***p<0.01

Note: The *Identity Wedge* variable is the first factor of the Principal Component Analysis using the variables *IAT Ge Gender/Tech* and *Traditional Role* (in their original scales).

Table 8: Social identity at quantiles of the difference in expected returns

	Dependent variable: Identity Wedge					
	(1)	(2)	(3)	(4)	(5)	(6)
	Bottom 10%	Bottom 25%	Bottom 50%	Top 50%	Top 25%	Top 10%
Treated	0.156	0.064	0.115	0.189**	0.151	0.278
	(0.124)	(0.125)	(0.087)	(0.081)	(0.132)	(0.244)
Mean of the dependent variable in control	-0.232**	-0.095	-0.070	-0.124*	-0.061	-0.215
	(0.086)	(0.098)	(0.067)	(0.067)	(0.108)	(0.212)
Observations	25	41	78	80	39	20
Adjusted R-squared	0.024	-0.019	0.010	0.053	0.008	0.015

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

Note: Percentiles are defined based on the difference between the Expected Returns in Tech and in sales. The *Identity Wedge* variable is the first factor of the Principal Component Analysis using the variables *IAT Gender/Career*, *IAT Gender/Tech* and *Traditional Role* (in their original scales).

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***	1				
	0.00					
Log salary dif.	0.363***	-0.448***	1			
	0.00	0.00				
Cog. Score (std)	0.254***	0.235***	0.013	1		
	0.00	0.002	0.87			
IAT Gender/Tech (std)	0.0051	-0.0173	0.0281	-0.0403	1	
	0.947	0.819	0.711	0.621		
Traditional Role (std)	0.081	0.017	0.077	-0.132*	0.0807	1
	0.258	0.81	0.286	0.085	0.285	

P-Values in parentheses
* p<0.10 ** p<0.05 ***p<0.01

Table 10: Other Preferences

	(1) Wanted to study technology prior to application	(2) Risk Preferences (risk aversion) (std)	(3) Time Preferences (impatience) (std)
Treated	-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

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

Note: *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.

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

	Dependent Variable: Application Rate
T1: Network and Role Model	-0.025**
	(0.010)
T2: Success and Role Model	-0.020*
	(0.010)
T3: Network and Success	-0.040***
	(0.010)
Control group	0.105***
	(0.007)
Observations	6,183

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

Figures

Figure 1A: Application Message in Lima 2016

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

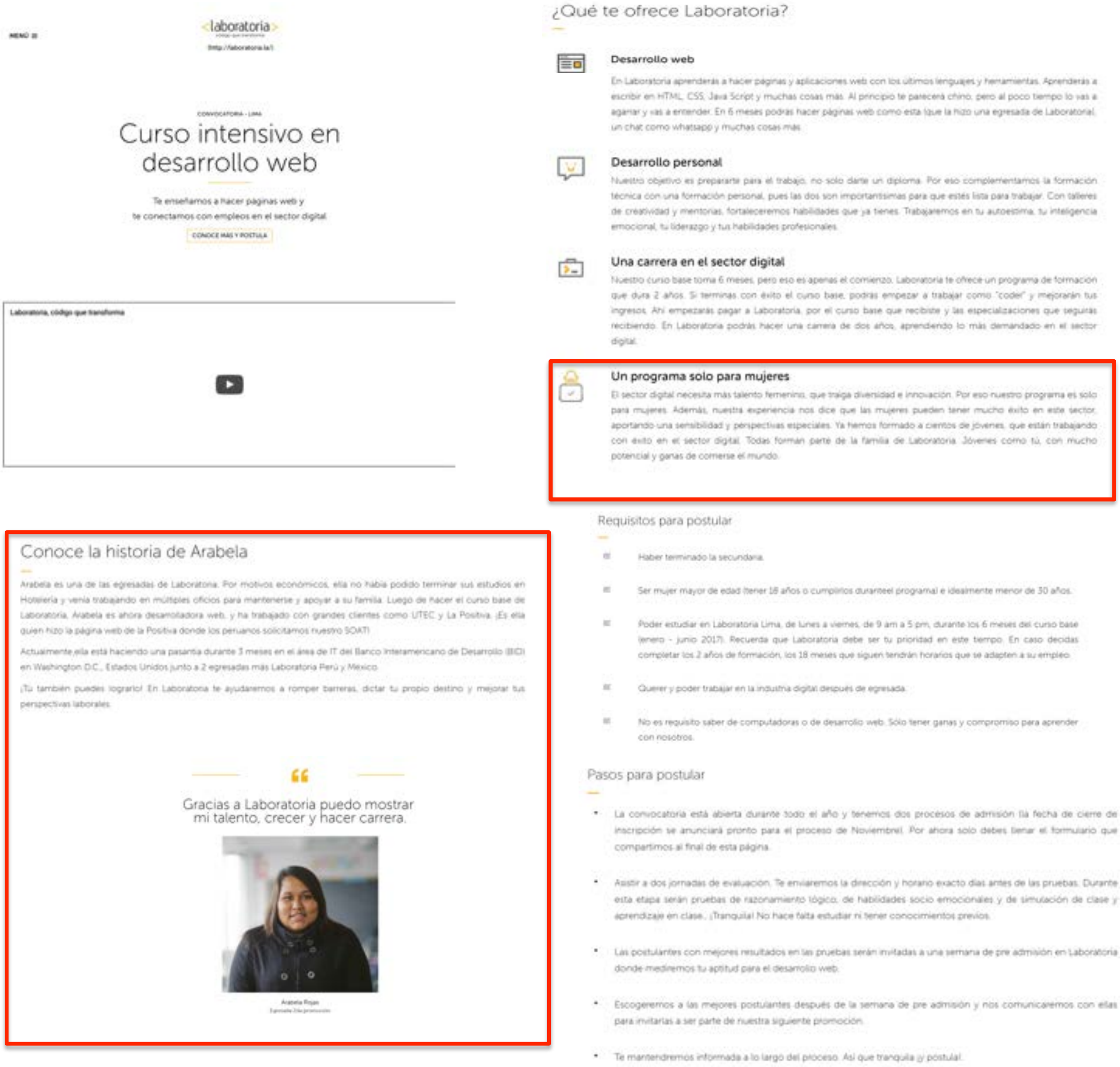


Figure 1B: Application Message (continued)

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

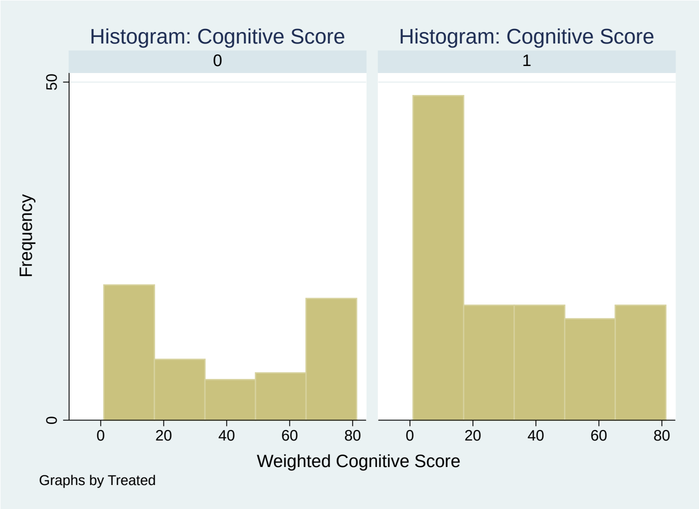


Figure 3: Distribution of Traditional Role in Control (0) and Treatment (1)

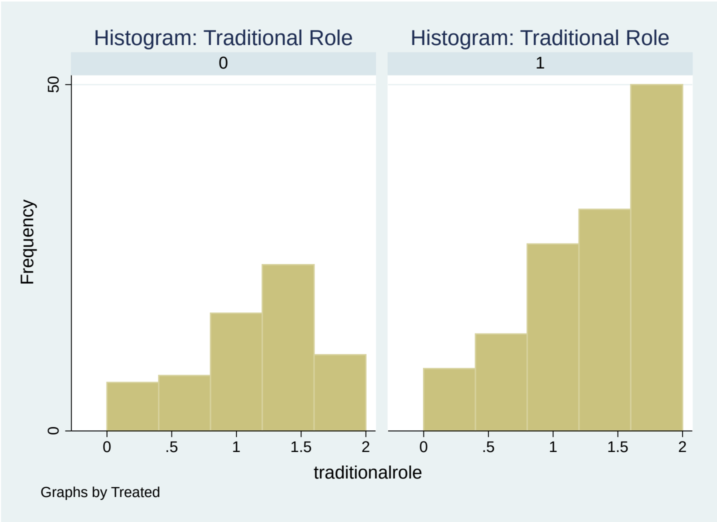
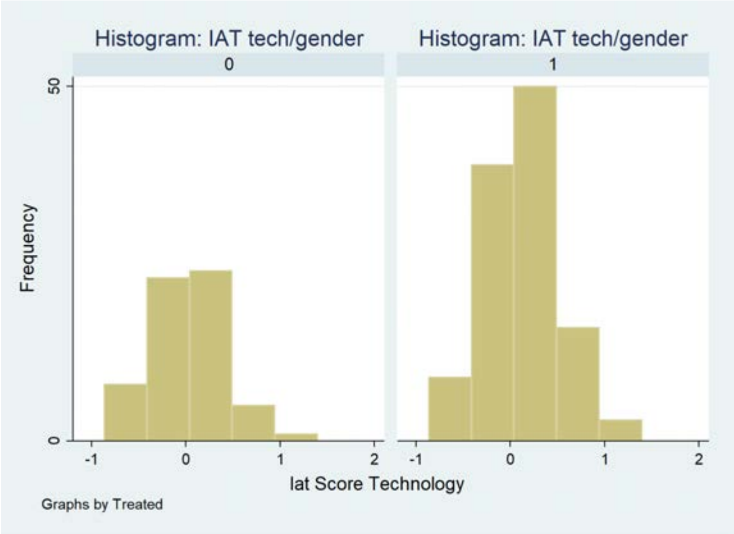


Figure 4: Distribution of IAT Technology/Services in Control (0) and Treatment (1)



SUPPLEMENTAL APPENDIX: FOR ONLINE PUBLICATION

Appendices:

Table A1: Treatment effect on application rates, Arequipa pilot

	(1)
	Total
Treated	0.069***
	(0.014)
Constant	0.069***
	(0.010)
Observations	1,791
R-squared	0.013

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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

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%.

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

Become a Web Developer:

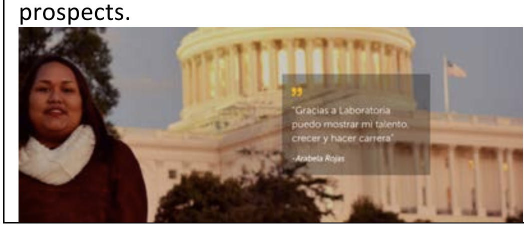
In 6 months we will teach you to make web pages and connect you to jobs while you pursue your education for another 18 months

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.

A program only for women:

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	**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	**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. Besides, our	**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

<table>
<tr>
<td>with other 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>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.</td>
<td>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>with other 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>
</tr>
<tr>
<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>
</tr>
</table>

<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%.

<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>