More Women in Tech?

Evidence from a field experiment addressing social identity

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Abstract

This paper investigates whether social identity considerations -through beliefs and norms- drive occupational choices by women. We implement two randomized field experiments to de-bias potential applicants to a 5-month software-coding program offered only to low income women in Peru and Mexico. De-biasing women against the idea that women cannot succeed in technology (through role models, information on returns and female network) doubles application rates and changes the self-selection of applicants. By analyzing the self-selection induced by the treatment, we find evidence that identity considerations and information on expected returns act as barriers precluding women from entering the sector, with some high cognitive skill women staying away because of their high identity costs.

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1. Introduction

In spite of significant progress in the role of women in society in the last 50 years, an important gender wage gap persists today. Scholars have shown that a large share of that gap can be explained by the different industry and occupational choices men and women make. However, the reasons behind those stark differential choices are still unclear (Blau and Kahn, 2017). In this paper we propose and study "social identity" as a key driver of women's occupational choices, and in particular, its predominant role in the persistent occupational gender segregation patterns we observe (see e.g. Bertrand, 2011; Goldin, 2014; Bertrand and Duflo, 2016).

Starting with at least Roy (1951) economists have explained how people self-select into certain occupations/industries as a function of the relative marginal returns to their skills in different occupations. With that model in mind, women would not self-select into male dominated industries because their comparative advantage lies elsewhere. However, other things may matter when people may make occupational choices that do not follow exclusively their true occupational comparative advantage. For example, scholars have mentioned that the beliefs on expected success given existing gender norms, expected discrimination and stereotypes may matter, as well as the disutility of working in a given environment given one's gender (eg., Akerlof Kranton, 2000; Beaman et al 2012; Goldin 2014; Bordalo et al, 2016a and 2016b; Reuben et al 2014).

The fact that social identity and stereotypes are real has long been recognized and shown to be relevant empirically by social psychologists who have designed and tested strategies to reduce bias and stereotypical thinking (Spencer and Steele, 1999; see survey by Paluk and Green 2009). More recently, in a series of lab experiments Coffman (2014) showed that self-stereotyping affects behavior and Bordalo el al (2016b) show that both overconfidence and stereotyping are important in explaining behavior of men and women (with greater mis-calibration for men). But much of this evidence is in the lab or in the context of academic tests and looks at very short-term outcomes. At the aggregate level Miller et al (2015) show that the prevalence of women in science in a country is correlated with stereotypes (implicit and explicit). Relatedly, Akerlof and

Kranton (2000) argue that identity considerations affect a range of individual choices and Bertrand Kamenica and Pan (2015) show that gender identity norms can explain a number of important patterns in marriage.

The goal of this paper is to bring together, and into the field, the economics of self-selection and the psychology social identity literatures to investigate how important are identity considerations in the occupational choices women make. Do these biased beliefs matter for occupational choices in the real world, can we change them and what are the economic consequences for the optimal allocation of talent? In particular, we focus on the choice to enter the technology sector, which in spite of its high growth potential remains pre- dominantly male and where the male stereotype is 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 endowment of "technology" skills, "services" skills and what we will refer to an identity wedge (or bias) of entering a sector that is stereotypically male, such as the technology sector. This identity bias affects the expected returns in technology, and represents a wedge between the actual returns to skill and the expected returns. This wedge can be driven by a number of different mechanisms. One class of mechanisms are distorted beliefs that women cannot be successful in certain industries as implied, for example, by stereotypical thinking based on a "representative heuristic" (as in Kahneman and Tversky, 1973 and Bordalo et al 2016a). The wedge can also represent a non-monetary/psychological cost of working in an industry where the social norm is very different from one's social category (as in Akerlof Kranton, 2000).

As in the standard Roy model (without identity) self-selection will depend on the correlation between the two types of skills and the underlying identity bias relative to their dispersion. Depending on these correlations and dispersions, we may observe positive or negative self-selection into the technology sector both along the skills and the identity dimensions: i.e. we may end up with a sample that is on average more or less skilled, and more or less "biased", with any combination being possible. In addition, once on allows for the presence of an identity wedge, some very high cognitive skill women may decide not to enter the industry because they also have a high identity cost. This will distort the optimal allocation of talent across industries.

With this framework in mind, we ran two field experiments that aimed to de-bias women against the perception that women cannot be successful in the technology sector, increasing their expected returns. In both experiments, we randomly varied the recruitment message to potential applicants to a 5-month "coding" bootcamp and leadership training program, offered only 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. In addition to sending a control group message with generic information about the program (its goals, career opportunities, content and requirements), in a treatment message, we added a section aiming to correct misperceptions about women's prospects in a career in technology: we emphasized that firms were actively seeking to recruit women, provided a role model in the form of a successful recent graduate from the program, and highlighted the fact that the program is creating a network of women in the industry that graduates have access to. The goal of the message was to change the stereotypical beliefs that women cannot be successful in this industry. Subsequently, applicants to the program were invited to attend a set of tests and interviews to determine who would be selected to the training. In those interviews we were able to collect a host of characteristics on the applicants, in particular those implied by the framework as being important to study self-selection: their expected monetary returns of pursuing a career in technology and of their outside option (a services job), their cognitive skills, and three measures of implicit gender bias --two implicit association tests (IAT) including one we created specifically to measure how much they identify gender (male/female) and occupational choice (technology/services) as well as a survey based measure of identification with traditional female role). We also collected an array of other demographic characteristics, aspirations and games aimed to eliciting time and risk preferences, which allow us to rule out alternative mechanisms for our findings.

In this first field experiment (Lima), we find that the de-biasing message was extremely successful and application rates doubled from 7% to 15%, doubling 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.

applicant pool to the training program. We then analyze the self-selection patterns in the two groups to assess what are the barriers that are being loosened by the message. We essentially estimate the equilibrium self-selection following an exogenous shock to the perceived returns to a career in technology. Our results suggest that there is negative self-selection in average technology skills, average services skills, as well as in cognitive skills.

We also find positive self-selection on identity costs (i.e. higher bias women apply): on average, women with higher identity cost as measured by the IAT and the traditional gender role survey measure apply following our de-biasing message, the marginal woman applying is “more biased”. 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 treated group, the 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? Besides the obvious answer of noise in the distribution of skills or the effect of the experiment, we find evidence that there are some high skill women that are also high identity wedge women that did not apply before treatment and are induced to apply. Finally, we also measured 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 aimed to disentangle what was 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 for women, the non-monetary component to being in an environment with fewer women and/or being presented with a role model which mattered most in our first message. It also allows us to rule out that it is any kind of information provided about women that makes a difference, and also tease out the relevant components of the identity wedge. Now the control treatment was the complete message and in each of three treatments we took out one feature of the initial message (returns, network of women and role model) at a time. We found that women respond mostly to the presence of a role model. Hearing about the high expected returns for women in the technology sector and the information that they would have a network of other women upon graduating are also significant, but to a lower extent.

A specificity of our setting is that the training is offered only to women, and all applicants know that. This has the advantage that we can 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. This comes at the cost that we do not know how men would respond in a setting where they also see the de-biasing message, and that we cannot say anything about the role of identity for men or other social categories or what kind of message would work as an encouragement to men.

This paper contributes to the literature on how women self-select to different industries (Goldin, 2014; Flory, Leibbrant and List, 2015) where field experimental evidence is limited. We test empirically a mechanism that relies on the role of gender identity and the explicit de-biasing or correction of misperceptions and we are able to analyze the type self-selection induced by the treatment along different dimensions. As a result, we also provide a microeconomic evidence on the barriers precluding optimal allocation of talent in the economy studied in Hsieh et al (2013) or 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). It is by now well established in this literature that disadvantaged groups under-perform under stereotype threat and the literature has devised successful de-biasing strategies (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 very big in our setting given the context of the test and surveys as we discuss later).

We also contribute evidence to a very limited literature on the performance effects of restricting the pool of applicants through expected discrimination or bias. As Bertrand and Duflo (2015) state “the empirical evidence (even non-randomized) on any such consequence of discrimination is thin at best".[2] We identify improvements after de-biasing not only in the number of applicants, but also in the type of applicants and 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 affect who selects into public health jobs and, through selection, their 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 (2013) show that providing information of higher wages attracts more educated and experienced applicants. And 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, which highlights the fact that an informational treatment is not always a positive intervention and that it is important to take into account the returns of the outside option, and the correlations between returns, and whether the organization can screen candidates at a later stage. In other words: the informational treatment may backfire for the firm designing it 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

This section develops a simple theoretical framework to illustrate how changing the information provided on a career/an industry--as we will do in the field experiment--affects which applicants self-select into that career. We start from a standard

[2] Ahern and Dittmar (2012) and Matsa and Miller (2013) find negative consequences on profitability and stock prices of the Norway 2006 law mandating a gender quota in corporate board seats and find negative consequences on profitability and stock prices.

Roy/Borjas model (Roy, 1951; Borjas 1987) adapted to our setting 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, as in the classic model.

Women decide between applying or not applying to the training program, i.e., whether 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*. Assume for now that identity does not matter: 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:

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

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 $E(T \mid Apply) = \rho_{tD}\sigma_t \lambda(\frac{p_0 - p_1}{\sigma_D})$ 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:

$$\frac{dE(T \mid Apply)}{dp_1} = \frac{\sigma_t^2 - \sigma_{st}}{\sigma_D} \frac{d\lambda(z)}{dp_1}.$$

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

Finally, we have that in terms of relative skills *D*, the selection is always negative:

$$\frac{dE(D/Apply)}{dp_1} = \sigma_D \frac{d\lambda(z)}{dp_1} < 0$$

Now we depart from the classic model to introduce the concept of identity to the basic framework. Women form an expectation of their returns as a function of their skill endowments in each industry and decide whether to apply to one sector or the other. We propose that this expectation may be affected by a social identity component. We will call this an identity bias or identity wedge, that alters the total expected returns relative to the skill endowment and could be reflecting different features in the real world. This bias may arise from beliefs held by women on the effective returns to their skills. For example, a belief that women cannot succeed in the technology industry because there is discrimination and their skills are not valued. It could also reflect the fact that people form a stereotype of who can succeed in the industry based on existing represented models in the industry, which include few women (Bordalo et al 2016a). So the more strongly the stereotype is held, the higher the wedge and the lower the expected returns. It could also reflect, along the lines of the identity cost proposed by Akerlof and Kranton (2000) the perceived cost for a woman of operating in the industry, for example if women want to work with other women and the sector is predominantly male, their expected return on which they base their choices is lower. There are several reasons that have been proposed that could be affecting the formation of expectations and that we summarize in an identity wedge with two components, as described below: a general unitary identity cost parameter β and an underlying idiosyncratic identity cost I (empirically, we will attempt to measure I in different ways).

We assume thus that just as services and technology skills are distributed in the population so are the underlying identity costs *I*, with some women experiencing higher identity costs than others, and that there is a general unitary identity cost parameter β so that: $W_1 = P_1 T/\beta I$, and $\ln W_1 = p_1 + t - \beta - i$ with log normal I, $i \sim \text{N}(0, \sigma_i^2)$.

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: $d\Pr(Apply)/d\hat{p}_1 > 0$ Increasing $\hat{p}_1$ (expected returns in technology) increases application rates, whether or not there are identity costs.

Now we 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 $\frac{dE(D \mid Apply)}{d\hat{p}_1} > 0$ is higher if $\rho_{Di} > \frac{\sigma_D}{\sigma_i}$. Conversely selection in D will be negative if $\rho_{Di} < \frac{\sigma_D}{\sigma_i}$. This implies that an increase in p_1 now will have a positive or negative effect on average skills depending on the correlation between relative skills and identity.

Result 2: Increasing expected returns can lead to positive or negative self-selection of in *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.

Further, we can see how average identity costs of applicants will change with an increase in expected returns:

$$E(i \mid Apply) = \rho_{ih}\sigma_i\lambda(z)$$
$$\lambda(z) = \phi(z)/\Theta(-z),$$
$$\rho_{Di} > \frac{\sigma_i}{\sigma_D} \Rightarrow \frac{dE(i \mid Apply)}{d\hat{p}_1} < 0$$
$$\rho_{Di} < \frac{\sigma_i}{\sigma_D} \Rightarrow \frac{dE(i \mid Apply)}{d\hat{p}_1} > 0$$

Result 3: Increasing expected returns when identity costs are distributed in the population, can lead to positive or negative self-selection in identity cost, depending on the correlation between *t, s* and *i* in the underlying population relative to their dispersion.

We can show that these conditions boil down to :

Negative (positive) selection in I: $\rho_{Di} > (<)\dfrac{\sigma_i}{\sigma_D} \Leftrightarrow \sigma_{is} - \sigma_{it} < (>)\sigma_i^2$

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

Negative (positive) selection in T: $\sigma_{ts} + \sigma_{it} < (>)\sigma_t^2$

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

Note that once we introduce identity, and even in the case of negative average selection on *t*, the expected increase in p_1 through lower perceived identity costs may lead to some very high-quality women applying that also have high identity costs. In this setting, it is possible that even though on average selection on T is negative, some women who are high T but also have high *i* may apply after the increase in $\hat{p}_1$.

Result 4: Once we introduce a second dimension that matters, such as identity, and even in the case of negative self-selection on skills on average, we may also be able to attract more high-skilled women that had also high identity costs.

As we will see, our experiment raises expected returns for women in the technology sector, so we interpret it as increasing $\hat{p}_1$ which has both the effect of increasing expected returns to skill for women but also of reducing the discount due to identity bias. The key variables to track in this model are expected returns in tech, 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 (18-30 years old) 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 provides 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 examination sessions as part of the selection process and they are assessed and selected to the program based on their results in these examinations. 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 been increasing throughout the program, but at the time of our experiments, the top 50 candidates were selected for training.

Training. Admitted 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

[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.

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

Placement in the Job Market. Upon training completion, the organization places students in the job market for which they have 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. In addition, at the time of the experiments, the organization's sustainability was based on an Impact Sourcing model in which they, as an organization, offered web development services to companies and hired recent graduates to deliver these services. On average, and combining both sources, around 2/3 of the program's 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 to their students during training, but a minimal fee equivalent to US$15 per month of training. If trainees end up with a job in the tech sector (and only if they do), then they are asked to repay the full cost of the program (which is estimated at around US$3,000) by contributing between 10% to 15% of their monthly salary up to the total program cost.

As of 2016, the training provider was interested in increasing application rates and assessing how to attract a better pool of applicants. They 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 completing 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, their largest operation, in their call for applications for the class starting training in the second semester of 2016. We launched

[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.

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, selection examinations and follow-up surveys of applicants to the program. In the first experiment (Lima, summer 2016) we tested the effect of a "de-biasing message" with three types of information on application rates and on the characteristics of women that self-select into the program. In the second experiment (Mexico City, winter 2016) we were able to separate out the three components of the initial message to assess which was/were responsible for the increase in response rates.

The experiments aim to first, assess whether a de-biasing message is effective in increasing application rates to the training program and second, evaluate what type of selection is induced by the de-biasing. In the context of our framework, and against the background of the Roy/Borjas model, we infer from the changes in observed self-selection what are the types of barriers that women were faced with, limiting their decision to apply for training, and in particular whether "identity" plays a role.

4.1 The first experiment: Lima summer 2016

As we discussed in section 3, to apply to the training program, every potential applicant has to go the organization's registration webpage. In the application page, the organization provides detailed information about the program as well as the eligibility criteria. At the end of this page, interested applicants can find the application form.

4.1.1. Treatment and control messages

The information provided on the program that all potential applicants saw (the control) includes the following text:

<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 formation 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 bringing diversity and innovation. That is why our program is solely for women. Our experience tells us that women can have a lot of success in this sector, adding up 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. Women youth like you, with a lot of potential.”

And was further followed by the story and picture of one of the organization’s recent graduates who was 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 barriers, dictate your destiny and improve your labor prospects.”

Webcaptures of the actual control and treatment messages (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 "de-bias" perceptions and beliefs on the prospects of women in the technology sector. Conceptually this message includes three different additional pieces of information: (1) the fact that women can be successful in the sector (2) the fact that the organization gives access to a network of women in the sector and (3) a role model: the story of a recent graduate. 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 in this form is minimal and includes name, age, email, phone, where had they heard about the program, and a brief motivation about 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 we will discuss in section 5, not all candidates attend the examination sessions. [6]

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

[6] 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 from these motivation statements are: (1) intrinsic motivation and family; (2) programming; and (3) growth/improvement.

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:[7]

A) Expected 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 outside option for these women. In the context of our model, this gives us a (self-reported) measure of P_0S and P_1T for those who applied, which may be biased by identity (partially capturing β). 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 the "expected" outside option).

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.

C) Gender Identity: In order to measure the identity costs or implicit biases of women and their association to success in technology, we use three base variables. 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

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

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 on 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 and 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 implicit bias that women hold about women in technology. Our third variable measuring identity costs 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 variable as capturing how much the aspirations of the woman conforms 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". It is important to mention that our identity variables are highly correlated, in particular the IAT gender/tech and the traditional role value which show correlation coefficient of 0.8.

<u>D) Other variables:</u> 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 operated on women with different preferences. The time preference variable elicited from applicants the minimum monetary amount (in Peruvian Soles) the applicant required to have 3 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.[8] To boost 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 "de-biasing" message, and was concerned about jeopardizing applications if the old control was used. So, in the second experiment, the control group is the full de-biasing message and we take out one piece of information at a time. The control thus 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

[8] 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.

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. Now, the training provided included much more information in the control and the exact content of the program was changing. The additional information 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, 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 in 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 de-biasing intervention: 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 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 expected returns in technology for women ($\hat{p}_1$) by de-biasing women from the expectation they cannot be successful in technology and making it more attractive. 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, we need to do more; in particular, since this is a "bundled" treatment and many things changed at the same time between the treatment and the control.

Two remarks are relevant here. First, we had piloted the de-biasing message in Arequipa a few months earlier on a smaller target population, with a slightly different control message, and we also found a significant more than doubling of application rates there (a 3.9% application rate in the control vs a 10% application rate in the treatment).[9] Second, as we will see later, our second experiment in Mexico runs several versions of the treatment to identify individual mechanisms. Overall, all three experiments together allow us to better understand the main drivers. While we will tackle individual mechanisms after reviewing the Mexico experiments, we discuss here a few important issues.

First, the treatment contains a photograph of Arabela and the control does not. Is a picture the driver? Our pilot in Arequipa did not contain any images (only text) and we obtained similar magnitudes of the treatment there. Second, is it the exact 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 or

[9] Results of the Arequipa pilot are reported in the Appendix.

the presence of a 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. Of course, de-biasing someone is typically associated to providing new information, but the key is to understand what "priors" is that additional information affecting. Results in section 5.2 where we turn to analyze the change in self-selection with the treatment message will also allow us to infer what is the relevant information that is changing these women's priors, and to what extent identity is one of the dimensions we are affecting.

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. 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 between the two groups. So this rules out that the results we describe in what follows on selection is driven by the fact that treatment affected attendance to the exams.

It is important to highlight that differences in application rates highly 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 are only estimating the differential selection in treatment and control, and not a 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 later 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 that 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 is suggesting 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 p_1 increases (the experiment message), the net effect of the two is ambiguous. P_1T . They fall, although not significantly.

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. This is shown in Table 5. We find that average cognitive skills measure 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 we developed on the association of women and technology as well as on the survey measure for "Traditional Role". The magnitude of the negative 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 and 0.14 of a standard deviation for the identity wedge variable (which is obtained as the first factor of the 3 other variables in Table 6). Figures 3 and 4 show the raw distribution of the identity variables and reflects this pattern.

Based on our augmented Roy model, this suggests that the correlation between identity costs and the difference between technology and services skills is positive but not very high. Therefore, the marginal women that apply are "more biased" following the treatment message.

5.2.3. Selection vs. Treatment

We are interpreting our results as reflecting mostly "selection" and argue that it is unlikely that the de-biasing message has a significant causal effect on some of the outcomes we measure (like underlying identity and cognitive skills).[10] 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 to 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 the de-biasing, to the extent that it reduces stereotype threat (Steele and Aaronson 1999) would help them do better in tests and have lower biases, and this would bias our estimates positively. 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.

5.3. Selection at the Top: Trading Off Attributes

The results so far suggest that the average woman applying is of worse 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, the underlying correlation between these dimensions in our populations, as well as the type of comparative advantage in place in this economy. However, from the point of view of the training firm, one might be worried that it is not allowing them to do what they were aiming for: attracting more high quality candidates.

Fortunately, 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

[10] The only exception is expected returns in tech, were treatment is likely to raise these beliefs. In this case, we have both a treatment effect on p1 and selection on tech skills.

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 differentially candidates 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 turn to 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 in turn, 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. Results here are less pronounced but are still consistent with the previous results: 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 a high identity costs, suggesting that identity not only matters on average, but also that it 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 training 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. [11] 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 and to the extent technology is perceived as risky it is less desirable than a secure services job. To the extent that our treatment makes the sector look more attractive or less risky, we should also expected 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, we are unfortunately underpowered to establish anything more conclusive with our data.

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

The results from the Lima experiment show that application rates doubled when women were exposed to the de-biasing message. However, given this was a bundled message we do not know what is the piece of information that triggered the increased

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

application rate. In order to see that, 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 component so that the four experimental groups resulted 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%, and the treatment that eliminates the network component leads to a 2 percentage points or 19% decline in the conversion rate.[12]

The importance of the role model reported here is consistent with the 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.

[12] Results adjusting for Multiple Hypotheses Testing are provided in the Appendix.

This experiment further allows us to speculate a bit more on what are the dimensions of social identity that enter the "I" in the framework. We acknowledge that the experiment may be affecting beliefs (e.g. by addressing gender stereotypes) and/or the perceived personal cost of being in a male dominated industry.

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, that is 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.

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 (from 7% to 15%). On average, however, the group exposed to treatment reported an average cognitive score which is 17% below the control group. We also find that among the population that would have been selected for training (top performers in examinations), cognitive and tech specific abilities are 22% and 23% higher than those that are treated. Our empowerment message thus appears to be increasing the interest of women in pursuing a career in the tech sector at all levels of ability, but proportionally more for those with lower ability.

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 components 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, not just because if “identity” matters it would be a barrier blocking the efficient allocation of human capital and hence aggregate welfare (Bell et al 2018), but also because it speaks 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 light on that question.

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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) Application rate	(2) 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) Log Webdev income	(2) Log Salesperson income	(3) 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).

Table 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%
Treated	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)
Mean of the dependent variable	-0.278	0.001	-0.000	-0.141**	-0.249***	-0.126	0.632***	0.547***	0.451***	0.444***	0.423***	0.500***
in 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)
Observations	14	40	71	90	44	18	23	54	96	102	50	20
Adjusted R-squared	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

	Dependente 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%
Treated	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)
Mean of the dependent variable	-0.396	-0.114	-0.052	-0.136**	-0.223**	-0.098	0.919***	0.791***	0.517***	0.416***	0.428***	0.520***
in 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)
Observations	10	30	63	77	39	16	16	41	82	87	44	18
Adjusted R-squared	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 Gender/Career*, *IAT Gender/Tech* and *Traditional Role* (in their original scales).

Table 8: Social identity at quantiles of the difference in skills

	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

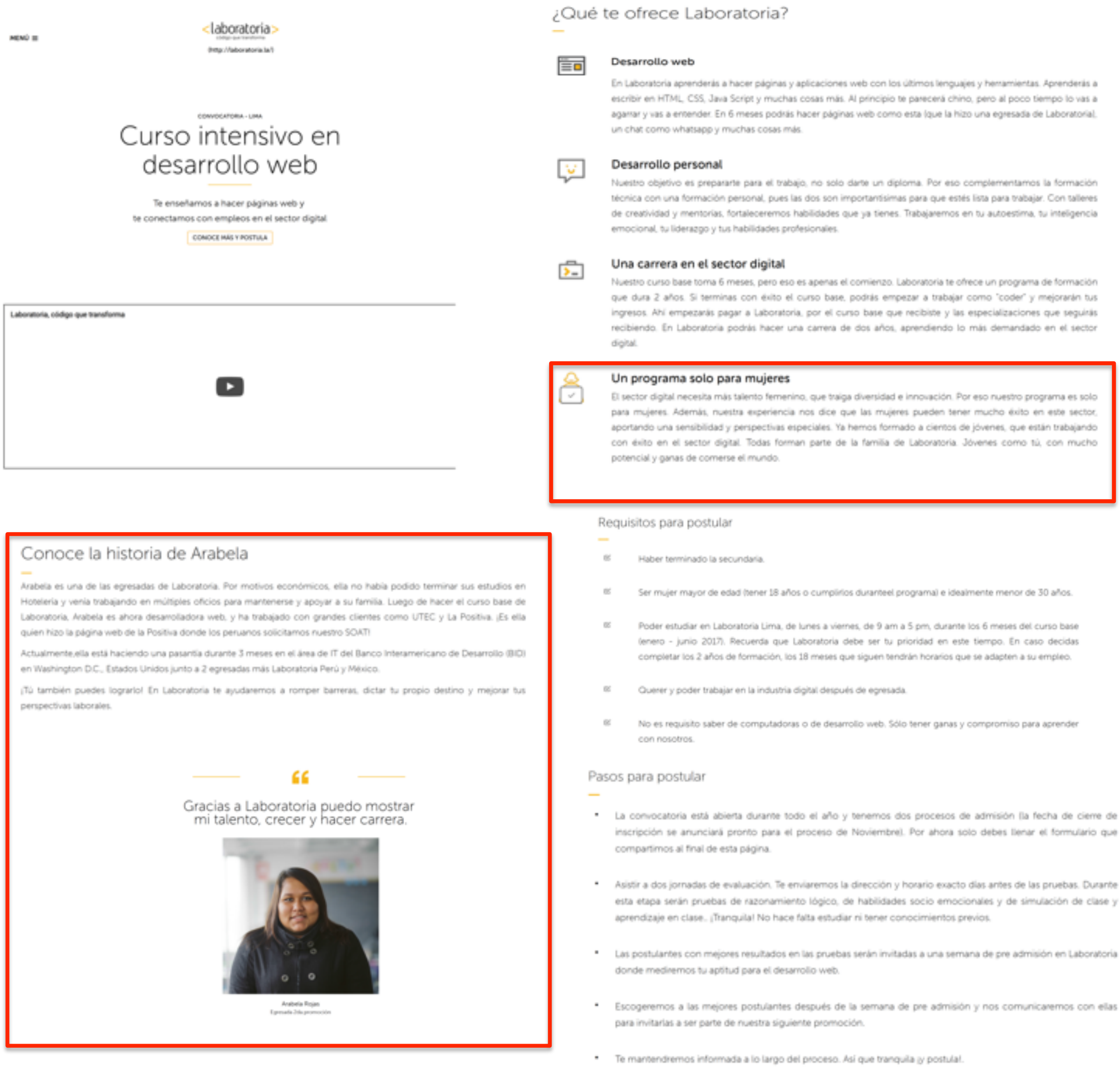


Figure 1B: Application Message (continued)

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)

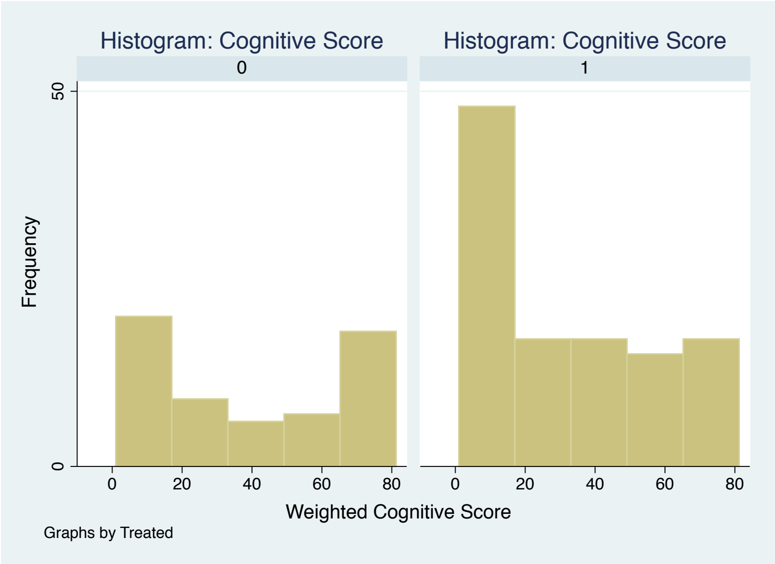


Figure 3: Distribution of Traditional Role in Control (0) and Treatment (1)

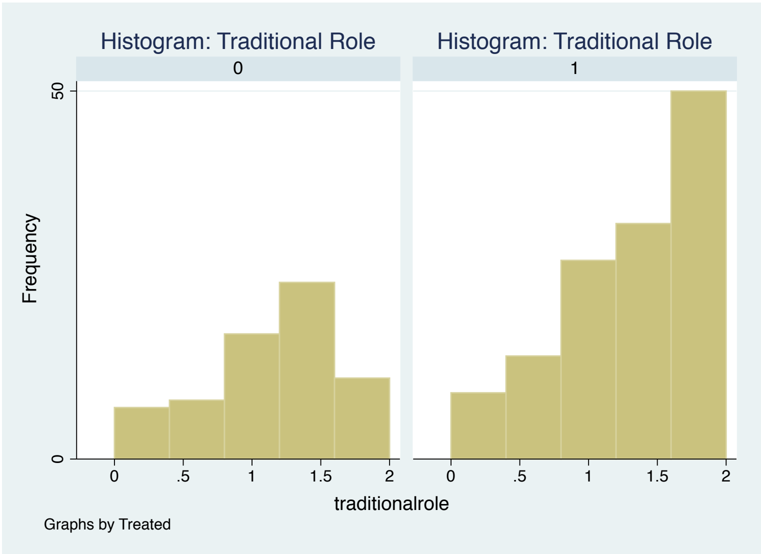
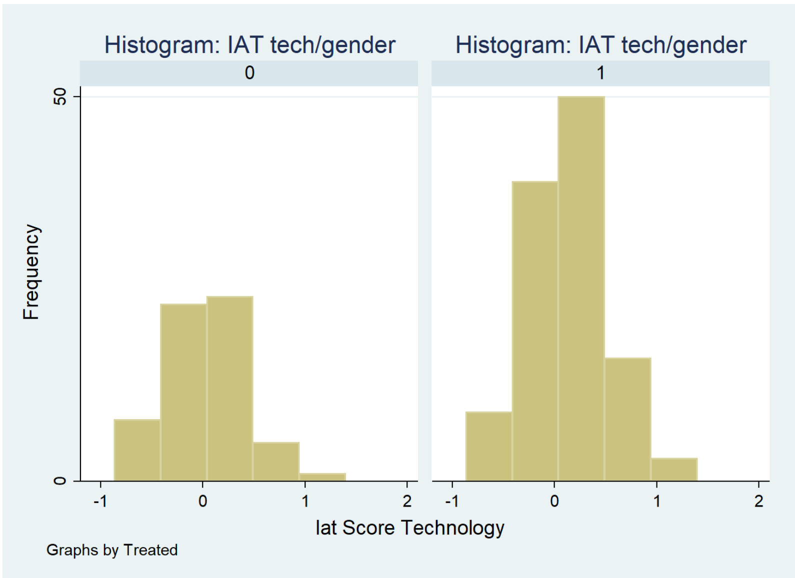


Figure 4: Distribution of IAT Technology/Services in Control (0) and Treatment (1)



Appendices:

Table A1: Multyple Hypohtheses 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 A2: Multyple Hypohtheses 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 A3: 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%.

Table A4: Treatment effect on application rates, Arequipa pilot

	(1) Facebook ADs	(2) Facebook Posts	(3) Total
Treated	0.062***	0.078*	0.069***
	(0.014)	(0.041)	(0.014)
Constant	0.039***	0.176***	0.069***
	(0.010)	(0.030)	(0.010)
Observations	1,376	415	1,791
R-squared	0.014	0.009	0.013

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

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.</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 now 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 50 soles monthly, to get used to the discipline of monthly pay. Afterwards, when you start working, you will pay 24 installments of 490 or 570 soles. 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>