# 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- may be driving occupational choices by women. We implement a randomized field experiment to analyze how the self-selection of women into the technology sector changes when we randomly vary the recruitment message to potential applicants to a 5-month software-coding program offered only to low income women in Peru and Mexico. In addition to a control message with generic information, in a treatment message we correct misperceptions about expected returns for women and their ability to pursue a career in technology. This de-biasing message doubles the probability of applying (from 7% to 15%). We then analyze the stark differential self-selection patterns for the treatment and the control groups to infer the potential barriers that may explain occupational segregation. We find evidence that both expectations about monetary returns in the sector and a perceived non-pecuniary cost linked to "identity" (as reflected by an IAT test and survey measures) of a career in technology operate as barriers. We interpret our results in the light of a Roy model where women choose between the technology sector and an outside option as a function of their relative skill endowments in the two sectors and an identity wedge that reduces the attractiveness of technology. Through a follow up experiment in Mexico DF we are able to point to what dimensions of the initial treatment matter most. Our results suggest social identity can explain persistent occupational segregation in this setting and point towards policy interventions that may alleviate it.

## 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 (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;).

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 is dominantly male but has a very high growth potential.

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.

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

[1] The goal of the organization is to identify high potential women, that because of their

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 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. This implies that we are in a world of comparative (not absolute) advantage in technology vs. services skills and at the margin "worse" women apply.

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". In the light of our model, this result suggests, first, that identity bias matters for occupational choice and that the identity bias varies across women. Second, in the light of the model it implies that the correlation between identity costs and skills is not too large (relative to the dispersion of the two variables). In fact, in our sample there is no correlation between cognitive skills and the identity bias measures.

Overall, however, what firms and organizations care about is the right tail of the skills distribution: do we have more qualified women to chose from now? We find that even though average cognitive ability is lower in the treated group, the overall increase in applicants also raises the numbers of high-cognitive ability applicants: the de-biasing message significantly increases cognitive and tech specific abilities of the top group of applicants (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, another reason within our framework would be that given the distributions of skill and identity, there are some high skill women that are also high identity costs women that did not apply before treatment that are induced to apply when expected returns to skill increase or the expected identity cost falls. We find some evidence that supports this argument. 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, and also to hearing about the high expected returns for women in the technology sector. In contrast, the information that they would have a network of other women upon graduating made no significant difference to application rates.

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.

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

[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.

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 Roy 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, $\sigma_s^2$) and *lnT*= *t*~N(0, $\sigma_t^2$). The probability that a woman applies to the technology sector is :

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

Where *v = t –s* and $\Phi$ 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 $E(T \mid Apply) = \rho_{tv}\sigma_t\lambda(\frac{p_0 - p_1}{\sigma_v})$ where $\rho_{tv} = \sigma_{tv} / (\sigma_v\sigma_t)$ is the coefficient of correlation between *t* and *v*, and $\lambda(z)$ is the inverse mills ratio, with $\lambda' > 0$. Therefore:

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

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 $\rho_{ts} > \frac{\sigma_s}{\sigma_t} \Rightarrow \frac{dE(S \mid Apply)}{dp_1} < 0$; $\rho_{ts} < \frac{\sigma_s}{\sigma_t} \Rightarrow \frac{dE(S \mid Apply)}{dp_1} > 0$

Now we depart from the classic model to introduce the concept of identity to the basic framework. Women form an expectation of 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 $\beta$ 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 $\beta$ so that: $W_1 = P_1 T/\beta I$, and $\ln W_1 = p_1 + t - \beta - i$ with log normal I, $i \sim \mathrm{N}(0,\ \sigma_i^2)$.

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:

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

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

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. Context

Our study is conducted in Lima (Peru) and Mexico City in conjunction with a non-profit organization that seeks to empower women youth from low-income backgrounds in Peru, Mexico and Chile 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.* Calls for applications are launched twice a year. The training provider runs targeted advertising campaigns in social media while receiving publicity in various local media. Interested candidates are asked to apply online and directed to a registration website which provides detailed information about the program and the eligibility criteria, before providing a registration form.

*Evaluation and selection of top candidates.* Applicants must 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 cognitive abilities tests as well as a simulation measuring specific coding abilities.

[3] www.laboratoria.la

In a second stage, interpersonal skills and traits like motivation, perseverance and commitment are evaluated through a personal interview and group dynamics.

*Training.* Admitted participants begin an intensive 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 reading lessons given that web languages and tools are written in English. Technical skill development is also 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 training completion, the organization places students in the job market. For this, the organization has built a local network of partner companies committed to hiring their graduates. 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, the organization's sustainability is based on an Impact Sourcing model in which they, as an organization, offer web development services to companies and hire recent graduates to deliver these services. On average, and combining both sources, around 2/3 of the program's trainees find a job in the tech sector upon graduation.[4]

*Cost of the program.* As part of their social design, the organization charges trainees a sum of around US$15 per month of training (below the actual cost of training). If trainees end up with a job in the tech sector, then they are asked to repay the full cost of the program (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, where the organization was not known. We then launched our first large scale

[4] We are currently also evaluating the impact of the program itself.

experiment in Lima, their 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 and the 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 mentioned, to apply to the training program, one 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.

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

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."

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 included 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.

In practice this is the exact text of the de-biasing message in Lima:

*"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."

This text was 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."

The actual control and treatment messages (in Spanish) can be seen in Figure 1.

### 3.1.1 Data Collection on Selection Days

After applying, women attended a two-day selection process where we were able to collect information on a number of relevant characteristics that try to capture the variables in the model. In particular we collected data about the following:

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 $\beta$). 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 three cognitive tests: two exams measuring math and logic skills, and a coding simulation exercise measuring tech capabilities. A test called "Code Academy" is a coding simulation that tested how quickly test takers are to understand basic coding and put it into place. This was taken from codeacademy.com. A second test "Prueba Laboratoria" is a test the training provider developed with psychologists to test cognitive skills. 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 perceptions of women and their association of women to success in technology, we used two variables. 1) The first is based on an implicit association test (IAT). The IAT measures the strength of association between different categories, and hence the strength of the stereotype. IATs have been created to study different implicit associations/biases/prejudices (race and intelligence, gender and career etc). We created a new IAT to see how much (how little!) people associate women and technology. It 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 2) The second variable is based on answer 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. The two identity variables are very highly correlated (correlation coefficient of 0.8).

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 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.

### 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. In addition to all the basic information, 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"). We implement three treatments that take one piece of information out at a time.

### 4.3 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.[5] To boost traffic, we launched three targeted ad campaigns in Facebook. Traffic results (total and by treatment message) are shown in Table 1. Our advertising campaigns launched in social media -as well as program publicity obtained through various local media- led to a total traffic to the program information and registration website of 5,387 unique users. Through our randomization, roughly half of these users saw each recruitment message.

## 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 and 5.3 , we examine the self-selection patterns on skills and identity respectively. Finally, in section 5.4 we report differences at the top of the skill distribution of applicants.

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[5] 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.

### 5.1 Application rates and attendance to selection examinations

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 2 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. 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 (with 22 applicants from the control and 64 applicants from the treatment).

This result means that the simple message had an impact on women's willingness to enter the technology training. The magnitude of the effect is quite striking, but in order to understand the mechanisms driving this change in behavior we need to do more. In particular, since this is a "bundled" treatment (many things changed at the same time between the treatment and the control). For example, 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. Could it be 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 the presence of a picture. 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. So, next we turn to analyze the change in self-selection with the treatment message 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.

As discussed, all registered applicants have to attend two days of examinations to be evaluated for admission into the program. 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 2 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: Expected returns and Cognitive Skills**

Table 3 shows the differential selection following the treatment on the logarithm of expected returns in technology (column1), in sales (column 2) and the difference between the two (column 3). We regress the variables of interest on the treatment variable. Note that here we are only estimating the differential selection in treatment and control, and not a causal effect of treatment on the outcome variables. 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 performance are minimal relative to the effect on selection.

The results in Table 3 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 to Laboratoria under treatment have an outside option that is 23% lower than those in the control. In terms of our model, given P0 is unchanged with the experiment this is 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 $p_1$ 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 4. 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 lower in the treatment group. There is clear negative selection in cognitive skills.

These selection patterns suggest that we are in a world of comparative advantage, where skills in technology and sales (the outside option) is positive but not very high (otherwise we'd have positive selection).

### 5.3. Self-Selection Patterns: Identity

We turn next to analyze self-selection patterns on our measures of gender identity in Table 5. 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 and 0.39 of a standard deviation higher association with a traditional role. Figures 3 and 4 show the raw distribution of the identity variables and reflects this pattern.

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.

We interpret 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 social identity and cognitive skills).[6] 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

[6] 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.

dimensions we think any treatment effect of the message on performance is dwarfed by the selection effects we identify.

### 5.4. 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 implict 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 panel of Table 4, 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 5 shows the difference in the average IAT, and traditional role variables for the top 50 candidates ranked by cognitive score. We have large standard errors and none of the variables is significant but, if anything, the results suggest that the average applicant, with the higher cognitive scores is more biased/has a larger identity cost in the treatment than in the control group.

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 were able to measure other non-cognitive traits for all applicants like time and risk preferences, and we asked women about their prior interest in Technology. [7] 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. However, Table 7 shows that there are no significant differences between those treated and non-treated in terms of prior interest in technology, time and risk preferences. This allows us to rule out that the selection is operating because the treatment affects those dimensions.

## 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 (in the pilot we ran in Arequipa application rates also doubled). However, given this was a bundled message we do not know what is the piece of information that triggered the increased 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.

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:

[7] Using Survey (Falk, cite)

- 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)

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. Results are provided in Table 8.

Conversion rates in the control group attain 8.9%. We can then see how both treatments that eliminate the role model and the "women can be successful" component significantly reduce the probability of applying for training: the treatment that eliminates the role model reduces the conversion rate by 2 percentage points or 23%, while the treatment that eliminates the "women can be successful" component, reduces the conversion rate by 18%. We conclude thus that the key components of treatment are the role model and addressing the fact women can be successful in the sector. The importance of the role model 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.

This experiment 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) or the perceived personal cost of being in a male dominated industry. The fact that telling women that they will have a network of other women has no effect favors the interpretation that this is an update in beliefs at the time of application. Both the role model and the success information are about belief updating after the de-biasing.

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 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 key components are the provision of a role model and the de-biasing about the success of women in the Tech sector.

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) resources and hence aggregate welfare, 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? For example, the infamous Google engineer fired in 2017 after writing a memo to the company seemed to think that women are intrinsically different in ways that disqualified them for a career in technology. This paper sheds light on that question.

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## Tables

Table 1: Traffic to site

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

Table 2: Effect of de-biasing message on application rates and exam attendance

| | (1)<br>Application rate | (2)<br>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 3: Expected Returns

| | (1)<br>Log Webdev income | (2)<br>Log Salesperson income | (3)<br>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 4: Cognitive abilities

| | Panel A: All Observations | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Code Academy (std) | Prueba Lab (std) | 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) | (2) | (3) |
| | Code Academy (std) | Prueba Lab (std) | 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 5: Social Identity

**Panel A: All Observations**

| | (1)<br>IAT Gender/Career<br>(std) | (2)<br>IAT Gender/Tech<br>(std) | (3)<br>Traditional Role<br>(std) |
|---|---|---|---|
| Treated | -0.125 | -0.290* | 0.380** |
| | (0.159) | (0.157) | (0.148) |
| Mean of the dependent variable in control | 0.080 | 0.190 | -0.252** |
| | (0.127) | (0.127) | (0.120) |
| Observations | 171 | 178 | 199 |
| Adjusted R-squared | -0.002 | 0.013 | 0.028 |

**Panel B: Top 50 Candidates by Cognitive Score**

| | (1)<br>IAT Gender/Career<br>(std) | (2)<br>IAT Gender/Tech<br>(std) | (3)<br>Traditional Role<br>(std) |
|---|---|---|---|
| Treated | -0.262 | -0.128 | 0.215 |
| | (0.206) | (0.187) | (0.189) |
| Mean of the dependent variable in control | 0.150 | 0.100 | -0.318** |
| | (0.144) | (0.134) | (0.134) |
| Observations | 92 | 95 | 100 |
| Adjusted R-squared | 0.007 | -0.006 | 0.003 |

Standard errors in parentheses

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

Table 6: 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*** | -0.446*** | 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 | -0.281 | 0.0403 | 1 | |
| | 0.946 | 0.819 | 0.711 | 0.621 | | |
| Traditional Role (std) | 0.081 | 0.017 | 0.077 | -0.132* | -0.807 | 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 7: Other Preferences

| | (1) Wanted to study technology prior to application | (2) Risk Preferences (std) | (3) Time Preferences (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 8: Follow-up experiment in Mexico, Treatment Decomposition

| | Dependent Variable: |
|---|---|
| | Application Rate |
| T1: Network and Role Model | -.016* |
| | (0.01) |
| T2: Success and Role Model | -.001 |
| | (0.01) |
| T3:Network and Success | -.020** |
| | (0.01) |
| Control group | 0.087*** |
| | (0.007) |
| | |
| Observations | 6183 |

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

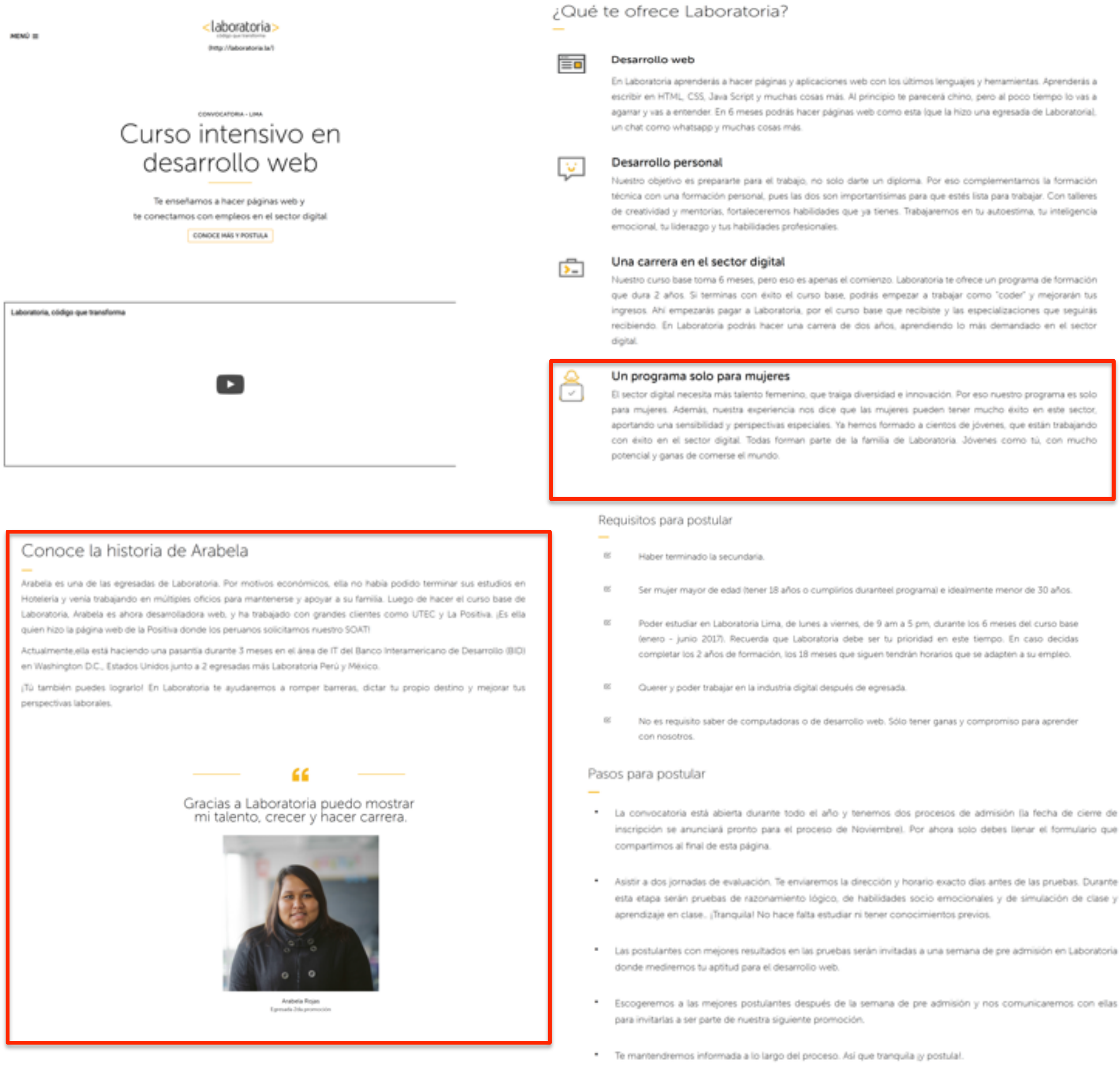

**Figure 1B: Application Message (continued)**


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)**

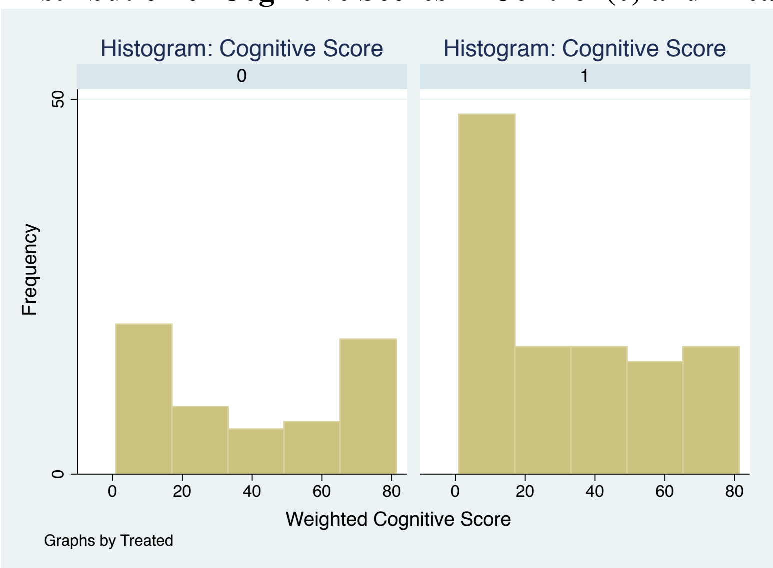

**Figure 3: Distribution of Traditional Role survey variable in Control (0) and Treatment (1)**

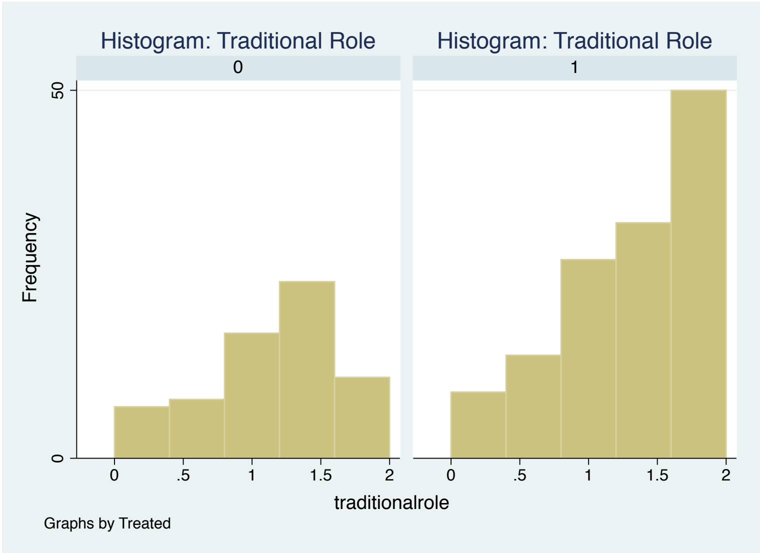


**Figure 4: Distribution of IAT Technology/Services in Control (0) and Treatment (1)**