Explicitly targeting disadvantaged groups prevents their take-up of an educational program

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Abstract

This paper studies how take-up rates for an educational program are impacted if individuals from disadvantaged groups are explicitly told they are pre-selected because of their group identity. Organizations tend to visibilize a person's group identity as a selection criteria to highlight their commitment to equity. I argue this strategy can backfire as candidates may be concerned of how they are perceived if accepting an opportunity because of their demographics. I test this in a field experiment in which 4831 university students from various disadvantaged groups were invited to taker-up an educational program. Invitations informed some students that they were chosen because of their group identities while it was not revealed to others. If identity targeting was made explicit, program take-up significantly decreased compared to the no information condition. This effect was persistent across different social groups. The evidence suggests targeting can be done without harming underrepresented groups by avoiding identity disclosure as a selection criterion.

Keywords: : Diversity, Inclusion, Minority, Stereotype, Information disclosure

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1 Introduction

Institutions and organizations are persistently developing programs to benefit members of underrepresented or disadvantaged groups (e.g., STEM for women, coding for immigrant children).[1] To reach their intended audiences, such prrograms usually follow the strategy of publicly visibilizing the identities of their targeted populations. This strategy is motivated by a well-intended desire to explicitly inform targeted candidates and third parties that the institution is committed to support them, which in turn is expected to maximize program take-up. However, explicitly informing individuals that they are targeted because of their group identities can have unintended consequences. If individuals believe they will be perceived negatively for accepting an opportunity offered to the because of their demographics, strategies of explicit targeting can backfire. Instead of equalizing the playing-field, explicit targeting can reduce program adoption and even hurt those the program intends to help. As such, an evaluation of how different targeting strategies impact targeted populations is crucial to understand how to promote, instead of discourage, take-up by members of disadvantaged groups.

In this project, I report the results of a field experiment designed to evaluate different strategies used to promote program adoption. In partnership with a university in Colombia, I designed an educational program aimed at developing non-cognitive skills to attain personal and professional goals. The program is offered exclusively to students belonging to previously identified groups that are in academic disadvantage: females, mid-low social class, first generation students, those from rural origins and ethnic minorities. Instead of making an open call announcing the program and the targeted population, a total of 4831 students holding at least one of the identified categories received a personalized invitation to take-up the program.

The content of the invitation is used to provide information on selection criteria in three different treatments. Treatments vary whether the targeted candidates and third parties know that selection is based on holding certain group identities. The PUBLIC INFO condition follows the standard approach used by most institutions, where candidates as well as third parties are informed that the program is offered to specific individuals because of who they are. When this is known to third parties, candidates may experience *social image* concerns and worry about how others perceive them for taking up the program. Also, they may experience *self-image* concerns and see themselves negatively if they were to accept such an opportunity. The PRIVATE INFO condition only informs candidates that they are targeted because of who they are, but does not disclose this to third parties. This strategy

[1] See Alan and Ertac (2018); Alan et al. (2019); Carlana et al. (2022) for cases of educational programs targeting individuals from underrepresented or marginalized social groups.

keeps the potential for self-image concerns active but turns off any apprehension about their social image. The third condition is NO INFO, in which neither targeted candidates nor third parties are informed that group identities are part of the selection criteria. Thus, turning off both social image and self-image concerns.

I run the field experiment in two waves, separately targeting individuals from different performance groups. The first wave focuses on students of high academic performance, who do not fit into the negative stereotype associated to their targeted group identities. In the second wave students of low academic performance were invited, who do confirm the negative associations with their social groups. Thus, I can test how the targeting strategies, i.e. the information contained in the invitations, impact program adoption for different performance groups.

I measure two outcome variables to assess the impact of targeting strategies on program adoption. The main variable is *take-up*, and a candidate is said to take-up the program when she completes the registration process after receiving the personalized invitation. The conjecture is that explicit forms of targeting, such as PUBLIC INFO and PRIVATE INFO, will lead to lower levels of take-up than the NO INFO strategy, as they would activate social image and self-image concerns. The second outcome variable is program *completion*, which occurs when a candidate attends to all sessions of the program. Completion is a more stringent measure because group identities are only made explicit in the invitation to take-up the program, but are not referenced anymore in any of the sessions. So, the effect of explicit targeting may soften as time goes by.

The main finding of the study shows that targeting strategies that inform candidates that their demographics are (part of) the reason why they are selected for an educational program, have a negative and significant impact on take-up and completion. This means that informing a candidate that she has been chosen because of her group identity is enough to reduce take-up. And, the effect is even more detrimental when the candidate knows that others also know about it. That is, instead of motivating individuals from certain social groups to feel seen and included and thus to take advantage of the offered opportunities, explicit targeting activates social image and self-image concerns that hinder program take-up. Specifically, there is a 13% increase in take-up from PUBLIC INFO to PRIVATE INFO as social image concerns are turned off, while there is a 30% increase in take-up from PUBLIC INFO to NO INFO, when both social image and self-image concerns disappear.

The negative effects of explicit targeting are observed separately for the high and low performance groups. While the levels of take-up are twice as high for candidates that elude the negative stereotypes associated to their group identities than for those that confirm them, both groups display a significant increase in take-up when neither the candidate nor others are informed about the role of group identities on selection. Such persistence of how negative explicit targeting can be needs to be taken into account, as programs are not only targeting the most disadvantaged individuals, but also the best performers among the members of a minority group (see e.g., Carlana et al. 2022; Dynarski et al. 2021). Moreover, the results show that the gap between explicit targeting and targeting that provides no information on identities is largest for the very top performers. Those in the top 10% performance are hurt the most when they are explicitly targeted.

I further evaluate how robust is this result across subgroups and find that it affects individuals who belong to a single disadvantaged group, as well as those that belong to multiple groups at the same time. The effect is also observed when looking at specific identities. For example, females are less likely to take-up the program when they are told the program targets female students, irrespective of their academic performance. Similar effects are found for students from rural origins, those from middle class families, as well as ethnic minorities.

There is however one exception for which providing no information actually reduces take-up: high performance students from low class families. When these students and third parties are informed that they have been pre-selected for the program because they are low class and have high academic performance, they respond positively to this information. Their response is weakened when only they know but no one else is informed, and is weakest when neither themselves or others are told they are chosen because they are high-performing low-class students. A possible reason why this subgroup responds differently to the information provided is that they in fact are eluding a strong stereotype associated to their group identity. They have overcome a structural barrier. I test for this mechanism in an online experiment with 245 students from the same university, where I ask them to report their beliefs about the academic performance of different social groups: females, males, low class, middle class and high class students. Participants were offered a bonus if their responses were accurate (with some room for error). The results of the experiment show that people do not believe there are big differences in performance between males and females, while they report significantly worse scores for low class when compared to both middle and high class peers. This result indicates that there are no negative stereotypes associated to gender in this population, while there are very strong stereotypes associated to social class. As such, signaling that a student has eluded an evident stereotype associated to his group identity, and suggesting she has been selected because of it, motivates this student to take up the program.

The policy implications of these results are clear: while highlighting identities can be a powerful strategy in some domains to show organizational commitment to equity, this is not always the case when granting opportunities to members of disadvantaged groups. The social and personal costs imposed on members of disadvantaged groups, when making explicitly that they are being targeted for an opportunity, are high enough to deter a significant share from taking up such an opportunity. Instead, the evidence suggests that organizations and institutions can still target disadvantaged and underrepresented groups without negatively impacting them through a strategy that avoids disclosing the identity elements in the selection criteria. For this, institutions can make use of administrative data to identify individuals from relevant social groups and then target them directly, without highlighting to their group identities. This is what I tested in the NO INFO treatment, which proves to be consistently superior to explicitly targeting individuals.

The paper is organized as follows. In section 3, I describe the setting and experimental design. In section 4, I report the main findings of the study. Section 6 concludes.

2 Related literature

[coming soon...]

3 The experiment and data

3.1 The partnership

The project was conducted during a period of two years, as part of a partnership with a private university in Colombia, starting in the Spring of 2021 and concluding in the Spring of 2023. This is illustrated in the timeline below (see Figure 1). I briefly explain each stage of the process here and then elaborate on specific details in the following sections.

During the academic year of 2020-2021, I established the partnership with a private university in Colombia to support students from disadvantaged social groups. Unlike public institutions in Colombia that are almost exclusively for low income students, private universities are diverse across multiple dimensions (REF Ferguson book).[2] This allows me to reach a wide variety of profiles of students.[3] The partnership was materialized

[2] Tuition fees in public universities are a function of family income and social strata. This means that those in lower strata pay very little and those in higher strata would pay substantial fees. On the contrary, there is no price discrimination in private universities, as they charge flat fees to all their students.

[3] An exception among private institutions are the few elite universities in the country, which are mostly for students from high income families... Cite references on the low levels of diversity in Elite colleges or community colleges.

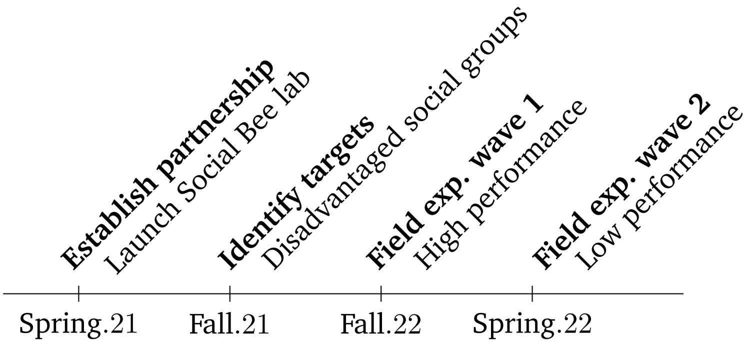


Figure 1 Timeline of the project.

through the creation of the Social Bee Lab (Social behavior and experimental economics laboratory), which channels all opportunities and resources offered to students in this study. Having such an entity mediating all the process is important, as it guarantees that both students and faculty know that the resources offered are coming from an international partner and not from the local university, and thus accepting an opportunity does not mean taking funds away from other initiatives.

Through the establishment of the partnership, I had access to a rich set of administrative data that allowed me to identify which social groups were most disadvantaged; as they would be the population targeted in the study. Subjects from pre-identified social groups will be offered access to an educational program to help them attain the goals they set for their personal and professional life. Details on the identification of social groups, the preselection of students, the invitation messages used to target them, the content of the program, as well as the experimental variations used to test the role of targeting policies (i.e, PUBLIC INFO VS. PRIVATE INFO VS.NO INFO) on take-up, are all discussed in detail in the following sections.

3.2 Disadvantaged social groups: Identification and pre-selection

The partnership aim is to support members of disadvantaged social groups by offering them access to an educational program. To do this, the first step was to identify which social groups are (on average) at an academic disadvantage. Subsequently, I used the identified categories to pre-select students that would be invited to take-up the program.

Identification of disadvantaged social groups. This process took place during the fall of 2021. I focused on identifying students from social groups who were at a disadvantage on at least one of two dimensions: academic performance or economic expectations (see details in Appendix A). To identify academic disadvantage, I used administrative data on entry exam scores for 12 cohorts between 2016 and 2021 ($n = 10,604$) and tested differences in performance between multiple social groups. To test for expectations, I conducted a survey under the umbrella of the Social Bee Lab ($n = 1924$), assessing what students expected after graduation. The survey focused on different indicators such as expected salary and expected time of unemployment before finding the first job after college (see e.g., Delavande and Zafar 2016). The results from this combined approach indicated that five social groups were consistently in disadvantage with respect to their relevant comparison groups: females (vs. males), lower-middle social class (vs. upper class), first generation (vs. continuous education), rural (vs. urban), and ethnic minorities (vs. non-ethnic). Individuals holding these categories enter university with lower scores, on average, than their peers, and expect to have lower economic opportunities and success after graduation.[4] Based on these findings, I pre-select individuals holding at least one of these social categories to be invited to take-up the up-skilling program.

Pre-selection of participants for the up-skilling program. This process took place in two waves in the fall and spring of 2022. Students could only participate in the program if pre-selected. Using demographic data, I first filtered out any student who did not hold at least one of the social categories previously identified as disadvantaged. Then, I used the grade point average as a second selection criterion to divide students into two groups of high and low performers, and offered the program to them in two separate waves. This is a novelty of the study, as I separately target students that confirm the stereotype of academic disadvantage associated to their social categories, low performers, and students for whom the stereotype does not apply, high performers.[5]

3.3 The educational program: incentives for take-up

The educational program centers around *goal pursuit*, and is aimed to help students develop non-cognitive skills to better attain the goals they set for their personal and pro-

[4] Female and Low Social Class students have lower subjective expectations than their comparison groups. The other social categories underperform academically, but the disadvantage is not as conclusive in expectations. This can be even more problematic, as having high aspirations without the knowledge to achieve them can be a source of frustration and giving upo (REFS: Ray, Dalton...

[5] In Colombia, the gpa ranges between 0 and 5.0, where 3.3 is the passing grade and 5.0 is the highest. To the *high* performance group, I assigned all students with a gpa of at least 4.0, which is the standard cutoff to be considered for scholarships and awards. To the *low* performance group, I assign all students with a gpa below 4.0 but above 3.3, as to include everyone who is at least passing. Students with a gpa below 3.3 were not considered, even when they held one or more relevant social categories. A total of 4831 students qualified for this opportunity and were invited to participate in the up-skilling program.

fessional lives.[6] The topic of the program was curated so that it could be of interest and benefit to participants irrespective of their major, year of study, and other relevant characteristics.[7] Also, it is designed to promote students' confidence on their chances to succeed in the goals they set, and as such, potentially benefitting academic performance and subjective expectations.

Reasons for taking up or letting go of a beneficial opportunity have been recurrently identified as a combination of extrinsic (benefits and costs), intrinsic (self-image), and reputational (social image) motives (see e.g., Benabou and Tirole, 2006). Because the experimental compares different targeting policies to disentangle the effects of signals that activate self-image and social image motives, I put together a bundle of attractive features within the program to increase extrinsic incentives for take-up: the program is free of charge, it is organized in 9 sessions of about 30 minutes each and all of them are pre-recorded and delivered online, making progression self-paced and eliminating conflicts of scheduling. Also because there are multiple computer rooms as well as free wifi on campus, limited access to equipments or the internet should not be an impediment. The program has no pre-requisites to participate, aside from being pre-selected, to motivate participation irrespective of which courses students had taken so far.

In terms of benefits, on top of the knowledge acquired, participants would receive a completion certificate which indicated the program was taught by faculty from an internationally recognized institution. The program's name did not include references to any of the targeted social categories to prevent any form of negative signals through the students' CVs. So, instead of the standard approach in programs of this type that frequently refer to the targeted social groups in their titles (e.g., "coding for women" or "STEM for immigrant children"), I used the name: "How to change: scientific strategies to achieve the goals in your personal and professional life".[8]

There were also monetary bonuses randomly assigned in each session plus a lottery of two last-generation iPads, all of this aimed at incentivizing take-up. By putting together a bundle of low participation costs and both symbolic and material benefits, I aim to control for most common structural barriers preventing take-up. This allows me to ascribe any variations on take-up rates between treatments to the way subjects were targeted in their invitation message, and to how their own performance confirms or eludes the stereotypes

[6] The content of the program is closely based on the research material contained in (Milkman 2021).

[7] Other types of up-skilling programs focus on more specialized *cognitive* abilities, such as coding or advance math. Although very important, these tend to be most relevant for specific academic programs, while the aim of this program was to reach a wide range of heterogeneous individuals.

[8] Evidence through audit studies shows that strong signals on CVs of belonging to stereotyped identities can significantly increase discrimination in the labor market (REFS).

associated to their identities.

Although the current paper is not an evaluation of the program, it is important to highlight that both faculty and students perceived the offered opportunity as very valuable. In Appendix C, I summarize this and show that faculty members consistently expressed that this was a great opportunity for the students. I also summarize results from the course evaluation provided by the 1135 students that completed the program, where 97.8% evaluated the course as positive or very positive, and 95.24% agreed and completely agreed that the course helped in their way of thinking. This is key to understand how the results of this study could generalize beyond the specifics of the offered educational program, to an evaluation of the policies to target individuals to take-up different beneficial opportunities.

3.4 Invitation to participate

Each pre-selected student received an invitation email from an institutional account created for the program (i.e., the program's email account) signed by the head of the Office of International Relations of the local university, to transmit complete legitimacy and increase trust in the quality of the opportunity and the benefits offered (e.g., certificates, bonuses, iPads). Because the office of international relations frequently offers opportunities and organizes events linked to international institutions, there are no reasons to expect students (or faculty) to think they are part of a study.[9] All communications were sent to their student's email addresses because these accounts are regularly used by faculty to send information from courses students are enrolled in, thus ensuring everyone pre-selected would see the invitation message.

The email informed invited subjects of the partnership agreement between their university and an international institution, and explained that as part of this partnership the international institution was offering an educational program to help them better set and achieve goals in their personal and professional life. The email gives information about the program and the benefits of participating. It explicitly states the student's gpa as a reason why they have been invited, which makes salient their academic performance. It also gives additional information on the *selection criteria*, which I vary to experimentally manipulate how individuals were targeted and, consequently, the types of concerns that might be activated: social image and/or self-image. In the invitation email (see the com-

[9] There is evidence that programs implemented by organizations that have had prior engagement with the targeted population increase effectivity (see Usmani et al. 2023). This means that only relying on the newly established Social Bee Lab, without jointly partnering with the office of international relations, may have been ineffective.

plete invitation in Appendix B), everyone received the following message:

> You have been chosen among all students at the university... as your cumulative GPA is [Student's GPA].

In addition, and irrespective of which performance group they were in, the message for a randomly chosen set of students included the following text:

> ... and also because you fulfill at least one of the following requirements: being a woman, being of middle-low social class, belonging to an ethnic minority (indigenous or afro-descending), being a first-generation student (neither of your parents has a college degree), or coming from a rural area (or not coming from any of the main cities in the country).

Subjects who receive the second part of the message become privately aware that their group identities played a role in guaranteeing them a slot in the program. This PRIVATE INFO signal is designed to evaluate the effects of self-image concerns on take-up. On the contrary, for those who only receive the first part of the message the role of their social identities was NO INFO.

The email also informed invited students that in order to ensure a placement in the program, they had to request a faculty member to send a message on their behalf, to the program's account, endorsing their participation in the program. To facilitate the endorsement process and to experimentally manipulate the public signal sent, I provided each student with a pre-defined message faculty members were required to send. The content of this pre-defined message is part of the experimental variations and follows a similar structure as that of the PRIVATE INFO messages. The endorsement message faculty had to send is the following:

> I, [Professor's name] recommend student [student's name] to take part in the program... as his/her cumulative GPA is [Student's GPA].

In addition, for a randomly chosen subset of students among those who had received the private signal, the endorsement message also included the following text:

> ... and also because he/she fulfills at least one of the following requirements: being a woman, being of middle-low social class, belonging to an ethnic minority (indigenous or afro-descending), being a first-generation student (neither of his/her parents has a university degree), coming from a rural area (or not coming from any of the main cities in the country).

This means that while all students needed an endorsement to secure placement in the program, only a subset had to reveal to the third-party endorser how their demographics were part of the pre-selection criteria.[10]

The main outcome of the study is take-up of the program, which is completed when a student registers and provides the endorsement from the third-party. In Appendix REF, I also evaluate the impact of targeting on completion: finishing all sessions of the program As the entire program eliminates any reference to social categories or academic performance, one could expect this to smooth some of the effects from targeting on completion.[11] However, the results on program completion are consistent with those on program take-up, but I only report results on take-up in the main text.

3.5 Treatments and procedures

For the field experiment, I use a 3×2 factorial design varying the way invited participants are *targeted* in two separate groups with different *academic performance*. Variations in targeting policies allow me to *turn-off* different motives that may impact take-up (i.e., self-image and social image motives). Variations in performance allow me to explore the impact of targeting on different groups of individuals, who either confirm or elude the stereotypes linked to their identities. This is summarized in Table 1 below:

Table 1 Experimental treatments

The table summarizes the main variations in the targeting policies (*Targeting*) and the group they are assigned to based on their gpa (*Academic Performance*).

		Targeting		
		PUBLIC INFO	PRIVATE INFO	NO INFO
Academic Performance	HIGH	n=864	n=864	n=833
	LOW	n=776	n=757	n=737

I now explain in detail variations in targeting, as they were implemented in the same way for both high and low performance groups.

PUBLIC INFO targeting: invited students are informed they are targeted because of their demographic characteristics (group identities). Similarly, the third-party endorser chosen

[10] Both the email requesting the endorsement and the response from the faculty member where required to be sent in copy to the program's email account, which allows me to follow the entire process for each invited subject.

[11] See for example Ashraf et al. (2020) for a similar study that experimentally varies how individuals are recruited for a training (which consequently leads to a job). The authors find that the process of signaling different values (prosociality vs. career advancement) affects who applies for and takes-up the training. But, as the training eliminates any focus on the values signaled in the recruitment, once they receive the trianing, there are no differences between participants with respect to the channel used to recruit them.

by participants receives information that selection was based on demographics, through the pre-defined endorsement message. Therefore, PUBLIC INFO targeting aims to activate both self-image and social-image concerns.

PRIVATE INFO targeting: invited students are informed they are targeted because of their demographics, as with PUBLIC INFO targeting. However, the third-party endorser does not receive any information of selection being based on demographics. As such, PRIVATE INFO targeting aims to activate self-image concerns while turning off social-image motives.

NO INFO targeting: invited students are also pre-selected according to their demographic characteristics, the same as with PUBLIC INFO or PRIVATE INFO targeting, but neither the targeted students nor the endorser are informed of this. All information provided avoids stating that invitations are based on demographics. Therefore, NO INFO targeting turns off both self-image and social-image motives.

A total of 4831 students received the invitation email pre-selecting them for the program during the 2022-2023 academic year. 2561 were in the *high* performance group and were invited at the beginning of the fall semester. 2270 had *low* performance and were invited at the beginning of the spring semester. For each wave of the program, I assigned students into treatments balancing the following categories: female, lower-middle social class, ethnic, first-generation and rural (see Table 2). Students had two weeks to complete their registration (take-up) to the program to guarantee a placement.

Table 2 Sample balance across experimental conditions

Columns I-III (V-VII) report the mean level of each variable, with standard errors in parentheses, for the PUBLIC INFO, PRIVATE INFO, and NO INFO conditions. Column IV (VIII) reports the p-value for the Anova test that the means are equal in the three conditions , separately for high and low performance.

	High Performance				**Low Performance**			
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**	**(VII)**	**(VIII)**
	PUBLIC INFO	PRIVATE INFO	NO INFO	p-value	PUBLIC INFO	PRIVATE INFO	NO INFO	p-valu
Female	0.69	0.68	0.66	0.43	0.62	0.62	0.58	0.18
	(0.46)	(0.46)	(0.47)		(0.48)	(0.48)	(0.49)	
Low-mid class	0.92	0.92	0.92	0.81	0.87	0.90	0.90	0.21
	(0.26)	(0.26)	(0.27)		(0.32)	(0.29)	(0.29)	
Rural	0.34	0.38	0.38	0.22	0.29	0.29	0.33	0.12
	(0.47)	(0.48)	(0.48)		(0.45)	(0.45)	(0.47)	
First gen	0.14	0.15	0.16	0.52	0.12	0.12	0.14	0.47
	(0.35)	(0.36)	(0.37)		(0.33)	(0.33)	(0.35)	
Ethnic	0.02	0.02	0l02	0.78	0.03	0.02	0.03	0.79
	(0.15)	(0.15)	(0.14)		(0.17)	(0.16)	(0.18)	
Observations	864	864	833		776	757	737	

3.6 Hypotheses

The main outcome variable in this paper is the decision to take-up the educational program. To study take-up, I systematically *turn-off* social image and self-image motives through the targeting policies, within each group of academic performance.

On the one hand, by publicly informing third parties that an opportunity is offered to some individuals because of their group identities, social image concerns may be activated (Bursztyn and Jensen 2015). Those candidates may be concerned with what others (e.g., third-party endorsers) think about them if they were to find out an opportunity was offered to them because of their demographics. Individuals' social-image may be affected negatively by accepting an opportunity when it is publicly known it has been offered to them because of their demographics. This is summarized in Hypothesis 1:

Hypothesis 1 ***(Social image)***. *If an individual knows that a third party is informed she accepted an opportunity offered because of her group identity, her social image can be negatively affected. To prevent the negative impact on social-image, individuals are less likely to take-up the program than those for whom the third party does not receive this information.*

The social image hypothesis conjectures that if activated, take-up rates will be lowest when targeting is PUBLIC INFO than when it is PRIVATE INFO or NO INFO. This because the third party providing the endorsement will be informed of the pre-selection criteria. In addition, self-image concerns may be at play for the candidates informed that their slot in the program is assigned to them because of their demographic characteristics (see e.g., Bursztyn and Jensen 2015). Individuals' self-image may be affected negatively by accepting such an opportunity. This is summarized in the following hypothesis:

Hypothesis 2 ***(Self-image)***. *If an individual accepts an opportunity that is offered because of her group identity her self-image can be negatively affected. To prevent the negative impact on self-image, individuals are less likely to take-up the program than those who do not receive this information.*

The self-image hypothesis conjectures that if activated, take-up rates will be lower when targeting is PUBLIC INFO or PRIVATE INFO than if it is NO INFO, as invited participants are informed of the role their demographics played in the pre-selection process. Any difference in take-up between PRIVATE INFO and NO INFO targeting would be caused by the effect of self-image concerns alone. Differences on take-up between PRIVATE INFO and PUBLIC INFO would be caused by the effect of social image concerns alone. Consequently, the gap in take-up between PUBLIC INFO and NO INFO will be due to the joint effect of social image and self-image concerns.

Finally, with respect to academic performance the conjecture is that students with high gpa are more motivated and more likely to see the value of opportunities offered to them, which will in turn impact their willingness to take-up the educational program. This is summarized in the following hypothesis:

Hypothesis 3 ***(Performance)***. *High performance individuals are more likely to take -up the program than low performance ones.*

4 Results

In this section, I present the main results of the field experiment. First, I test the effects of targeting on take-up and show evidence on the negative effect of explicit targeting, complemented by how NO INFO targeting can help promote take-up (see 4.1). I then test the effect of academic performance on take-up and show that take-up rates among high performers double those of low performers (see 4.2). Finally, I look at the interaction of targeting and performance, and show how the main results are not driven by one specific group but hold for both (see 4.3). Then, in Section 5, I conduct a heterogeneity analysis on specific subsets of the targeted population to further understand how the different targeting policies impact program take-up. The analysis shows that the negative impact of explicit targeting is robust, across different subgroups.[12]

4.1 The effects of targeting on take-up

The first consideration is to assess how the different targeting policies affect take-up of the educational program. For this, I evaluate two hypotheses by comparing the effect of three targeting policies on program take-up. The first two are policies of explicit targeting, as candidates (and at times also third-party endorses) are told their identities were a condition for selection. The last policy is one of hidden targeting, where the candidate is also targeted directly but there is no explicit reference about their demographics being part of the selection criteria. The main result of the study is that NO INFO targeting significantly outperforms the two types of explicit targeting by increasing take-up. This effect is also observed on the completion rates of the up-skilling program (see Appendix REF). Thus

[12] Results on take-up are based on proportion tests, for which I report one-sided p-values following the direction of the stated hypotheses on take-up levels: PUBLIC INFO ≤ PRIVATE INFO ≤ NO INFO. Also on the hypothesis on performance: LOW—≤HIGH. Results are also consistent when using two-sided tests.

suggesting that using administrative data to personalize targeting, without revealing this process to potential participants, can allow program providers to promote equity and inclusion by reaching populations of interest (e.g., disadvantaged groups) without reducing their willingness to take-up of the offered opportunity.

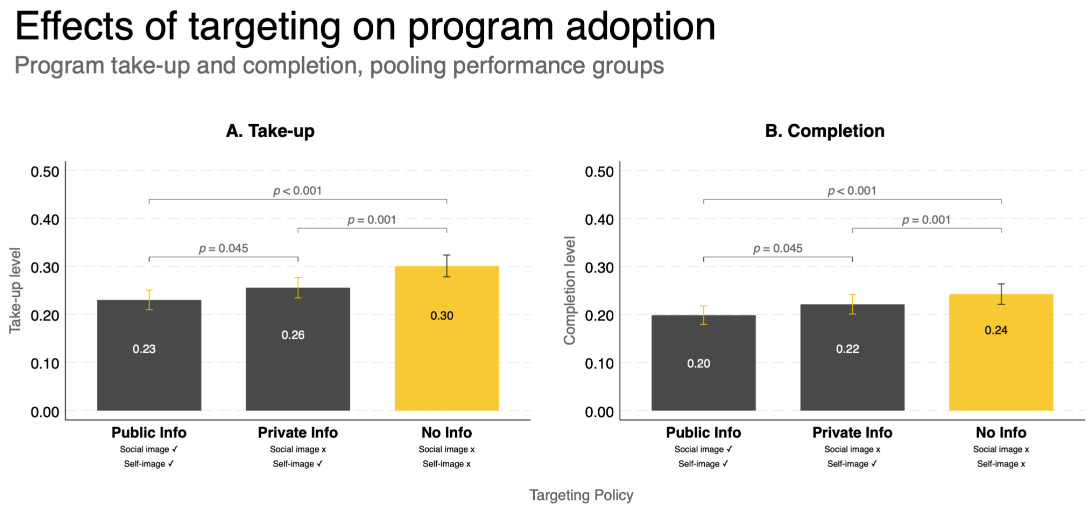


Figure 2 Take-up levels by targeting policy.
The figure pools together high and low performance groups to illustrate the main effects of targeting policies on take-up. Values inside the bars report average levels of take-up. The p-values report the significance of one-sided proportion tests comparing take-up between targeting policies.

Figure 2 illustrates this effect by showing that NO INFO targeting increased take-up by 7 percentage points (p.p.) compared to PUBLIC INFO targeting (23% vs. $30\%, p < 0.001$) and by 4 p.p. compared to PRIVATE INFO targeting (26% vs. $30\%, p = 0.001$). Notably, the average level of take-up is 23% in PUBLIC INFO when both the candidate and the third-party endorser are informed that the individual's group identities were a criterion in the selection process. The take-up levels increase when the social image concerns are turned off with PRIVATE INFO targeting: from 23% to 26% ($p = 0.045$), and also when turning off self-image concerns (from 26% to $30\%, p = 0.001$). This suggests that, in my study, there is a cumulative negative effect of explicit targeting driven by both social image and self-image concerns. I summarize the main finding in Result 1 below:

Result 1 *Explicit targeting negatively affects take-up because it activate social image and self-image concerns. These negative effects of signaling are cancelled through* NO INFO *targeting, which significantly increases take-up compared to both* PUBLIC INFO *and* PRIVATE INFO *targeting policies.*

The evidence from result 1 gives support to both Hypothesis 1 and Hypothesis 2. Next, I test Hypothesis 3 on the effects of performance on take-up.

4.2 The effects of academic performance on take-up

The second experimental variation of my study focuses on performance differences between candidates holding social categories that are stereotypically disadvantaged. By looking at high and low performers (in terms of their gpa), I can evaluate how effective it may be to target individuals who conform or elude the negative academic stereotypes associated with their group identities.

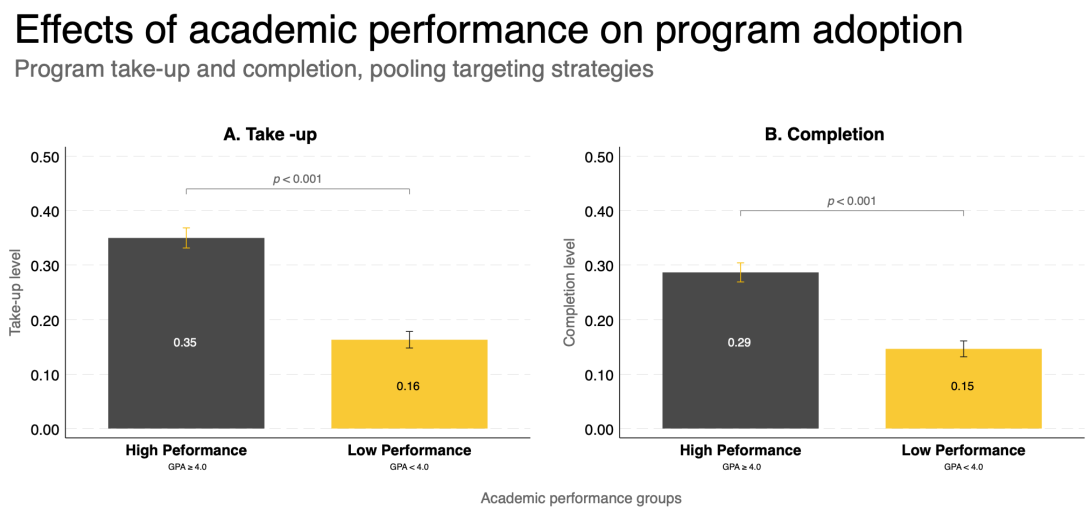


Figure 3 Take-up levels by academic performance groups.
The figure pools together the targeting policies (public info, private info, and no info) to illustrate the main effects of performance on take-up. Values inside the bars report average levels of take-up. The p-value reports the significance of one-sided proportion tests comparing take-up between performance groups.

Figure 3 reports the average levels of program take-up for targeted individuals in the low and high performance groups. While about 16% of low performers take up the educational program, the level more than doubles to 35% for the high performers ($p = 0.001$). This stark difference gives strong support to the conjecture in Hypothesis 3.

Result 2 *The high performance group is more than twice as likely to take-up the educational program than the low performance group.*

4.3 The effects of targeting different performance groups on take-up

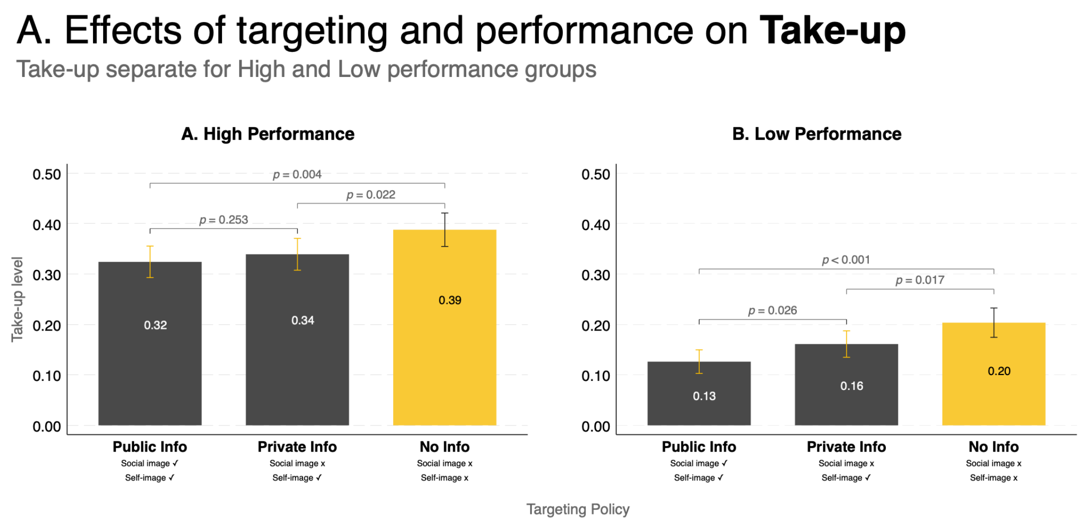
Given that explicit targeting (PUBLIC INFO or PRIVATE INFO) hurts take-up of the educational program compared to NO INFO, as they trigger social image and self-image concerns, and that being a low performer is correlated with letting go of such beneficial opportunities, I now test the effect of the targeting policies separately for the *high* and *low* performance groups. This distinction is important to see if the effects of explicit targeting are driven by the specific targeted population.

Figure 4 illustrates the effects of the different targeting policies separately for the high (Panel A) and low (Panel B) performance groups. For high performers, NO INFO targeting increased take-up by 7 percentage points compared to PUBLIC INFO targeting (39% vs. $32\%, p = 0.007$) and by 5 p.p. compared to PRIVATE INFO targeting (39% vs. $34\%, p = 0.044$). Similarly, for the low performance group (Panel B) NO INFO targeting increased take-up by 7 p.p. compared to PUBLIC INFO targeting (20% vs. $13\%, p < 0.001$) and by 4 p.p. compared to PRIVATE INFO targeting (20% vs. $16\%, p = 0.034$). This shows that the detrimental effects of explicit targeting are robust across performance groups.

Furthermore, as the average levels of take-up are significantly larger for high performers than for low performers, $33\% > 16\%$ ($p < 0.001$), it is key to move beyond the absolute to the relative effects of the policies. That is, although the increase in percentage points with NO INFO targeting is very close across groups, the relative effect of NO INFO targeting is more pronounced for the low performing group. Specifically, take-up increases with NO INFO targeting in the low performance group by 53% compared to PUBLIC INFO and by 25% compared to PRIVATE INFO, while the increase in the high performing group is more modest: 22% with respect to PUBLIC INFO and 15% with respect to PRIVATE INFO. Thus, suggesting that explicit forms of targeting (PUBLIC INFO or PRIVATE INFO) can be worse for the groups of people that could need the opportunity the most; those who hold disadvantaged identities and confirm the negative associations to their social groups.This is summarized in Result 3 below:

Result 3 *Compared to* NO INFO*, explicit targeting (*PUBLIC INFO *and* PRIVATE INFO*) negatively affects both low and high performance subjects. The negative effect is most harmful for those who need the opportunity the most.*

In conclusion, I find a very strong negative effect of explicit targeting policies on take-up, as they activate both social image and self-image concerns. Moreover, the effect is present for both high and low performance groups, although the negative impact is much stronger for low performers. In the next section, I present additional results diving into



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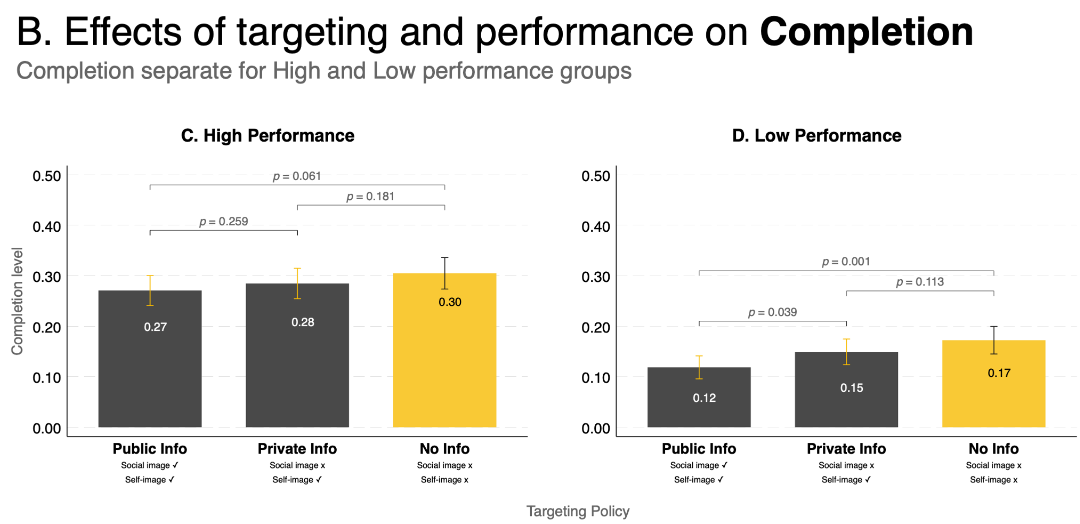


b

Figure 4 Take-up levels by targeting policy for high and low performance groups. The figure illustrates the effects of targeting policies on take-up, separately for each performance group. Values inside the bars report average levels of take-up. The p-values report the significance of one-sided proportion tests comparing take-up between targeting policies.

the effects of the different targeting policies on sub-samples of the population.

5 Additional results: Heterogeneity analysis

Now, I replicate the analysis on how the targeting policies impact take-up, for different subsets of the population of candidates. On the one hand, this allows me to show the robustness of the main results. On the other hand, this provides insights on additional effects that the different targeting policies may have on specific subgroups.

5.1 The effect of targeting on the best performers

One recurrent question that comes up when looking at interventions that aim to *level the playing field* for disadvantaged groups, is whether they attract average members of the targeted group or if they can draw in the most capable ones. In general this is hard to assess, as data on the performance of candidates that do not apply for the offered opportunity is not available. In my case, however, I have performance measures (i.e., gpa) for all candidates whether they take-up the program or not. This allows me to test how making identity salient affects the very best candidates' take-up decisions. To explore this question, I focus on the high performance group and I rank the cumulative gpa of all 2561 candidates that were invited to take-up the educational program. I divide them into top 10% performers (those in the 90^{th} percentile of above), and the rest (everyone below the 90^{th} percentile).

Figure 5, illustrates the level of take up for those in the top 10% (solid line connecting circles) and those in the remaining 90% (dashed line connecting triangles). As observed in the figure, the results when comparing performance groups are somewhat consistently observed between the top 10% and the rest: the levels of take-up are significantly higher for the top 10% than for the rest in PRIVATE INFO ($50\% > 32\%, p < 0.001$) and NO INFO ($48\% > 38\%, p = 0.022$). However, this is not the case when targeting is PUBLIC INFO where the gap not only disappears but is slightly inverted ($29\% < 32\%, p = 0.278$). This suggests that PUBLIC INFO targeting can be very detrimental in attracting top performers.

This result is confirmed when looking at the effect of the targeting policies. For the top 10%, take-up significantly decreases from NO INFO to PUBLIC INFO ($p = 0.005$), also from PRIVATE INFO to PUBLIC INFO ($p = 0.003$), while there is no difference between PRIVATE INFO and NO INFO ($p = 0.586$). For the rest of candidates, NO INFO targeting out-performs both PUBLIC INFO ($p = 0.024$) and PRIVATE INFO ($p = 0.013$), while there is no difference between PUBLIC INFO and PRIVATE INFO ($p = 0.606$). While the drop in take-up for the best performers appears to be driven by social image concerns and for the rest by self-image concerns, there results show: (i) that the negative effects of explicit targeting on take-up

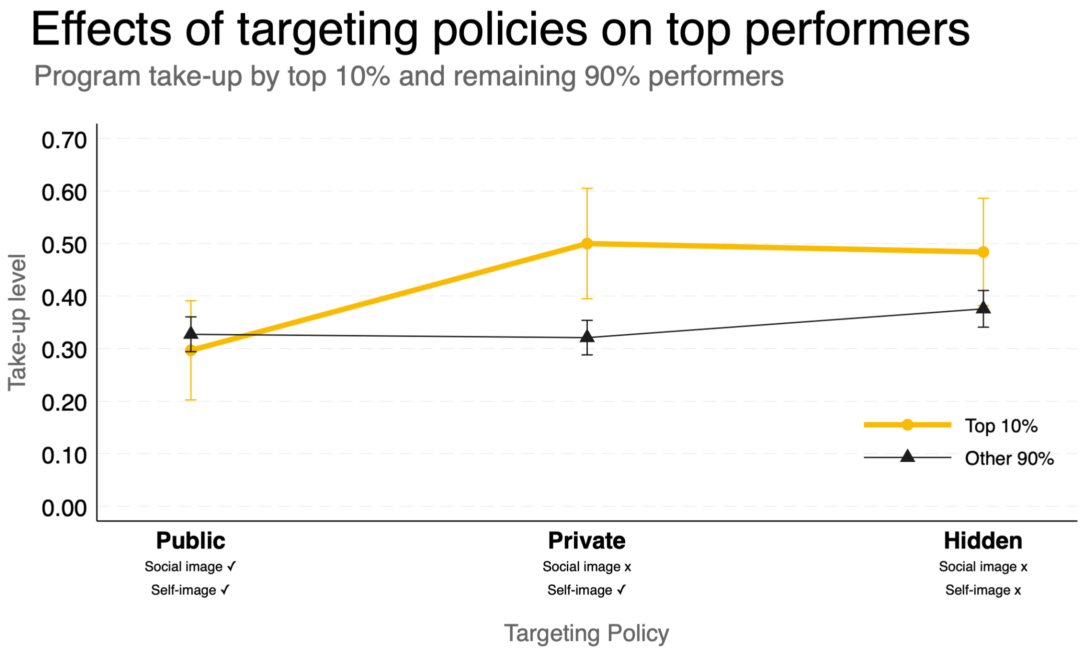


Figure 5 Take-up levels by targeting policy for top performers.
The figure illustrate the take-up levels across policies for the top 10% performers (thick line connecting circles) and for the other 90% (thin line connecting triangles).

are once again observed, but more importantly for the question in this section (ii) that the magnitude of the drop in take-up when social image and self-image are triggered is much larger for the top performers than for the rest: 19% compared to 5%. This is summarized in Result 4:

Result 4 *There is a strong negative impact of explicit targeting in deterring the best performers (top* 10%*) from taking-up the program, but this can be mitigated with a* NO INFO *targeting policy.*

5.2 The effect of targeting on holding multiple categories

For the field experiment, candidates holding *at least one* of the social categories chosen were invited to take-up the educational program. Some candidates held one single category (34.2%), while others held two or more (65.8%). Naturally, the more disadvantaged social categories a person holds, the more likely she is to feel disadvantaged or stereotyped. This could imply that individuals holding more than one of them may feel threatened when their different group identities are made salient. In this section, I report results from the assessment of whether the pooling of different social categories in the invitation messages triggered a negative reaction on those who hold multiple identities.[13]

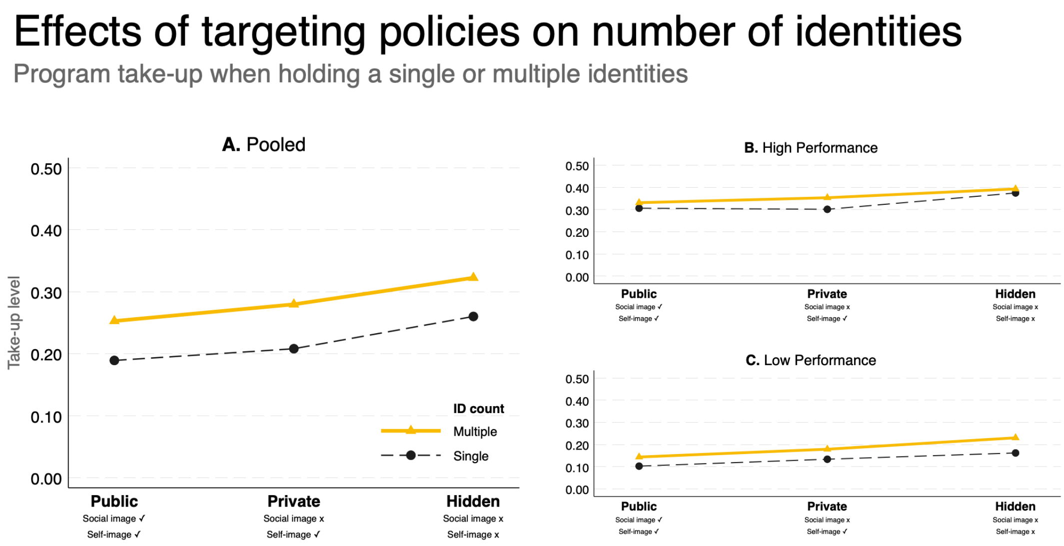


Figure 6 Take-up levels by targeting policy for different number of identities.
The figure illustrate the take-up levels across policies for candidates holding a multiple identities (solid line connecting triangles) and those a single identity (dashed line connecting circles), pooled across performance grouos (Panel A), and separately for high performance (Panel B) and low performance (Panel C) groups.

Figure 6 illustrate the take-up levels across targeting policies for candidates holding a single identity (dashed line connecting circles) and those two identities or more (solid line connecting triangles), pooled across performance groups (Panel A). Across identity counts, the trend of take-up is increasing as social image and self-image concerns are turned off, for those holding a single identity ($18\% - 20\% - 26\%$) or those holding multiple identities ($25\% - 28\% - 32\%$). Similar trends are present for the High performance (Panel B) and Low performance (Panel C) groups, separately.

The main effects of the different targeting policies on take-up appear to be robust to the different identity profiles. On top of that, instead of lower levels, candidates holding multiple identities display higher levels of take-up than those holding a single one. This can be interpreted as some suggestive evidence that targeting different identities at the same time may be an inclusive way of reaching candidates with identity profiles that belong to more than a single disadvantage social group. The more targeted categories a person holds the more included she feels and thus the higher the take-up. This is summarized in

[13] For ease of exposition I illustrate results pooling individuals holding 2 or more categories together. But, the results are consistent when separating into those holding, 1, 2 or at least 3 (only 3.8% of the sample hold more than 3 categories).

Result 5 below:

Result 5 *There is a strong negative impact of explicit targeting in deterring take-up, so that across identity profiles take-up is higher with a* NO INFO *targeting policy. However, the levels of take-up are higher the more targeted identities a candidate holds.*

5.3 The effect of targeting on specific categories: gender and social class

To conclude, I now go beyond the aggregate case and explore the impact of the targeting policies on holding specific social categories. I focus on gender and low social class, as these were identified, on average, as the most disadvantaged categories (see Appendix A).[14] By focusing on specific group identities, I am able to assess the interaction between holding a category that is stereotypically disadvantaged in academic terms *versus* actually conforming or eluding the stereotype: being either high or low performance.

Figure 7 (Panel A) shows take-up rates for female candidates, showing that these students increase take-up as social image and self-image concerns are turned off. For example, take-up goes up by 10 p.p. with NO INFO targeting compared to PUBLIC INFO targeting, both when they are high performers (from 35% to $45\%, p < 0.001$) and low performers (from 14% to $24\%, p = 0.001$). In contrast, Figure 7 (Panel B) shows that for low social class students activating social-image and self-image impacts take-up in a positive (although not statistically significant) way if their performance is high (from 30% to $37\%, p = 0.279$), but the impact is negative if their performance is low (from 26% to $16\%, p = 0.047$). That is, *females* are more likely to be deterred from taking up the program if their identity is highlighted as a selection criteria, irrespective of their performance level., while *low social class* students respond positively to explicit targeting if they are identified as high performers, but negatively if they are low performers.

The tests done to identify which social categories to target for the program showed that these categories are in academic disadvantage when contrasted with their relevant comparison group: females vs. males, as well as low social class vs. middle social class or vs. high social class. However, it does not follow directly that individuals actually believe this is the case and have negative stereotypes associated with these social categories. If this were not the case and individuals from a given social category do not perceive themselves as disadvantaged, they would react negatively when their identity is signaled as part of

[14] A detailed analysis of all possible identity profiles is out of the scope of this project. Five social categories were targeted: female, mid/low social class, rural origins, first generation students, and ethnic minorities. This results in 120 identity profiles. Instead, I look at individuals holding each of these categories, irrespective of whether they hold none or some others. I focus on females and low social class candidates in the main text, and report results on all five identities in the Appendix.

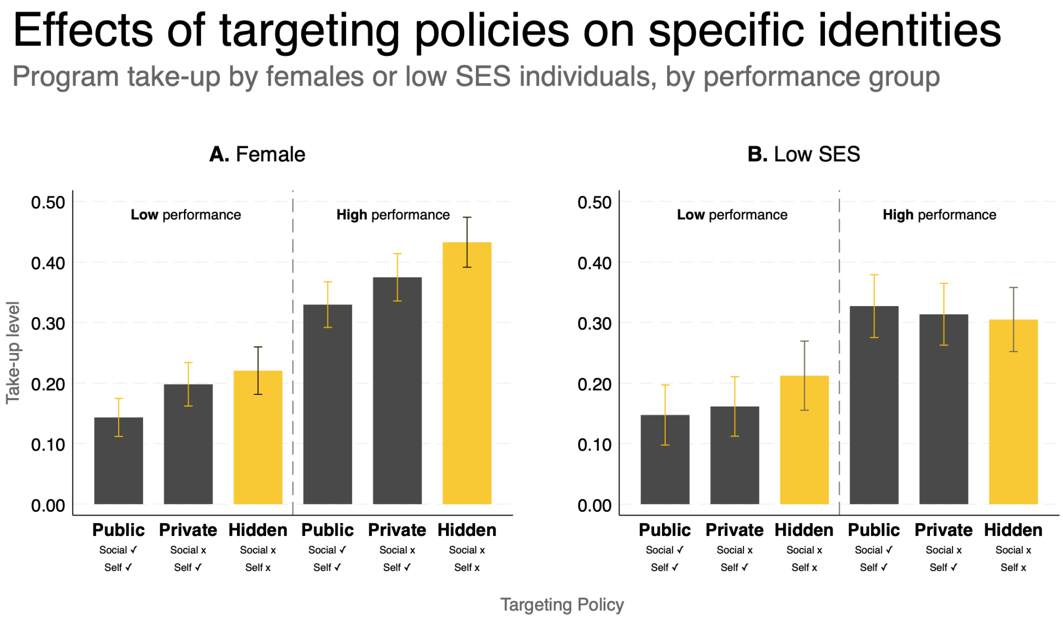


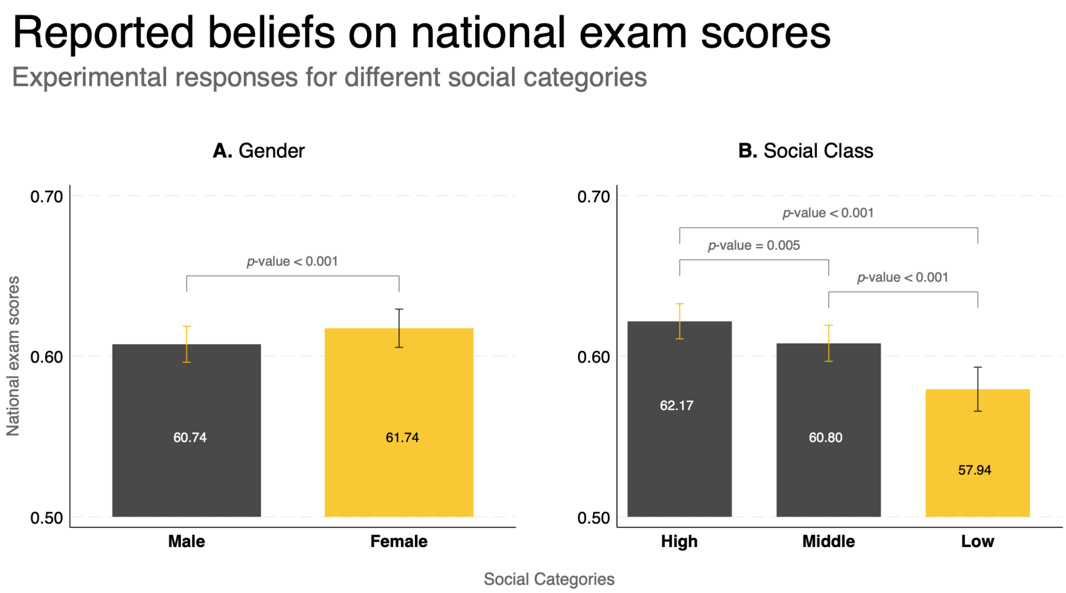
Figure 7 Take-up levels by targeting policy for female and low class candidates. The figure illustrate the take-up levels across policies for female (Panel A) or low social class (Panel B) candidates, separately for high and low performance groups.

the selection criteria. This would be a consequence of some form of entitlement, such that individuals from groups that are expected to do well are negatively affected if their group identity is highlighted as a *complement* to their high performance. However, if those holding a given social category not only perform worse than their counterparts, on average, but also hold the matching belief then they would be positively affected if their identities are highlighted together with a recognition of high performance, as they elude the stereotype, but negatively if they confirm the stereotype with their low performance.

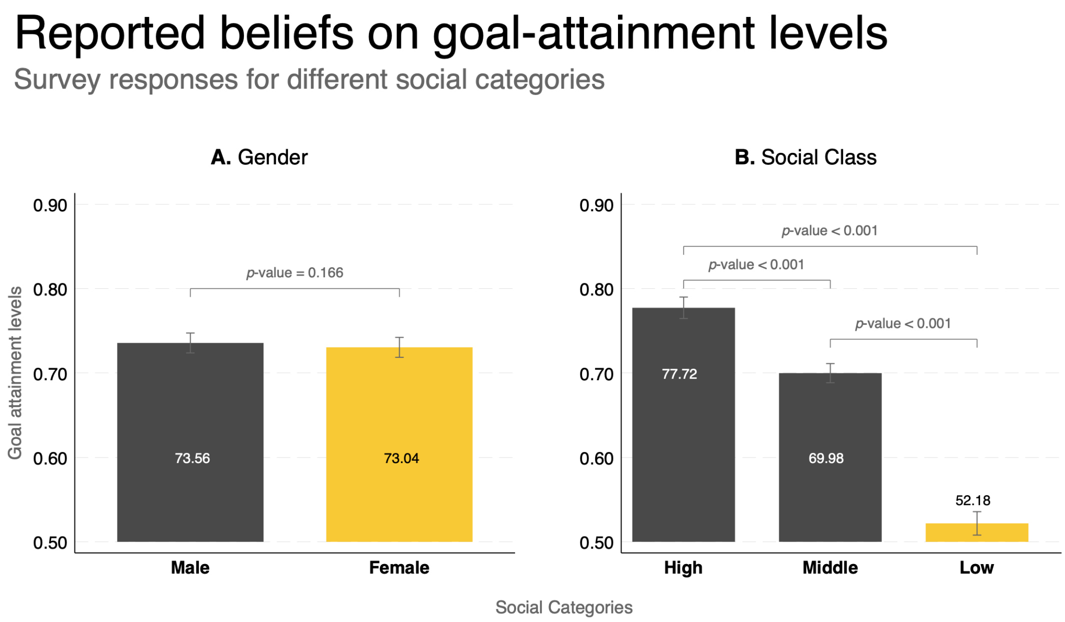
To explore this further, I first conducted an online experiment with 250 students from the same university. Students were asked to report the average scores they believed students got in their national exam depending on specific demographic characteristics. Scores in the exam range between 0 and 100, and payments for this experiments were contingent on accuracy on the predicted score matching the actual average score for each subgroup. Figure 8a (Panel A) illustrate the results of the experiment and show that females are expected to perform slightly better than males ($61.7 > 60.7, p < 0.001$), while low social class students are expected to underperform compared to middle class peers ($57.9 < 60.8, p =< 0.001$) and compared to high class peers ($57.9 < 62.1, p =< 0.001$). This provides support to the entitlement conjecture and would help explain why females react negatively to explicit targeting in both high and low performance groups, while low class students would react positively when their performance is high (as they elude the stereotype), while react negatively otherwise.

Note that candidates are invited to take-up an educational program on goal pursuit (i.e., setting and attaining goals) and not on academic performance. Arguably knowing how to attain goals is correlated to academic performance. But, to provide further support to the conjecture that social image and self-image trigger positive effects on take-up for those eluding the stereotype, but not for the rest, I conducted an online survey (non-incentivized). The survey asked 900 students to report out of a 100 students from a specific social category, how many attained the goals they set for their personal or professional life. Figure 8a (Panel B) illustrate the results of the survey which are consistent to those of the online experiment. Females are not expected to attain goals in a lower rate than males (73% vs. $73.5\%, p = 0.116$), while low social class students are expected to attain goals at a significantly lower rate than middle class ($52.1 < 69.9, p =< 0.001$) or high class peers ($52.1 < 77.7, p =< 0.001$). Further providing evidence that highlighting how a person eludes the stereotypes associated to her identity can have a positive impact on their willingness to take-up a beneficial opportunity offered to them because of the social categories they hold. I summarize the main finding in Result 6 below:

Result 6 *For social groups expected to underperform, explicit targeting (*PUBLIC INFO *and* PRIVATE INFO*) can have a positive effect on take-up if it highlights that individuals elude the stereotypes or have overcome the expected barriers (e.g., low class high performers), but the effect is negative is all other cases.*



a. Beliefs about scores on national exam



b. Beliefs about goal attainment

Figure 8 Reported beliefs for females and low social class.

6 Conclusions

In this paper I report a study testing different targeting strategies to promote take-up of beneficial opportunities to members of disadvantaged social groups. Running a large scale field experiment with almost 5000 university students, I evaluate the impact of explicitly informing individuals that their group identities are a selection criteria to receive an invitation to the program. Explicit targeting can be either PRIVATE INFO if only the targeted student is informed of the selection criteria, or PUBLIC INFO when also third parties know about this. I contrast explicit targeting against NO INFO targeting, a strategy that uses existing/available administrative data to pre-identify relevant individuals to target (by their group identities) without imposing on them the burden of either proving they hold the identities necessary for the opportunity (e.g., proving they are low income) nor revealing to them that their identities guaranteed their slot in the offered opportunity.

The main finding of the experiment is that NO INFO targeting outperforms any of the two forms of explicit targeting, and the reason why this works is because it eliminates any self and social image concerns. This suggests that most individuals do not want to feel like a *quota* even when others will not know about it, something that NO INFO targeting can turn off. The power of this result comes in the ease with which organizations and program providers can promote take-up of beneficial opportunities to those who need it the most. By using administrative data to pre-select relevant populations, take-up can be increased and the impact of intended policies and interventions maximized.

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Online Appendix:

Explicitly targeting disadvantaged groups prevents their take-up of an educational program

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A Selected identities

(+) Identification of identities appendix: try to add figures; (+) communication appendix: explain different of merit and potential; (+) Course evals: fix figure to match main text; (+) Appendix regressions: run regressions for all results, and show they hold when controling for identities, etc; (+) Complete the on the experiment eliciting beliefs on SABER 11 appendix and include results on all categories tested; (+) Beliefs on Goals appendix: complete the description of the belief survey and report results for each category; (+) Include appendix on top 10 percent: show the same holds for top 5 percent, and also show by quartiles; (+) include appendix on identity count, show results separate for 1, 2 or 3+; (+) include appendix on specific identities: show results on all other categories.

I combine two separate strategies to identify which groups of people are at a disadvantage and could benefit from the up-skilling program. I look at the academic performance of individuals at the moment of starting college (national entry exam) and at the economic expectations they have for their life after graduation.

A.1 College Entry Exam

First, I look at differences in academic performance in the national exam all high-school students must take to apply for college. The exam covers five areas: mathematics and logic, critical reading skills, natural sciences, social sciences, and English as a second language. Scores for each area are between 0 and 100. I focus on the average total score and look at the trends on the periods between 2016 and 2021, which comprises 12 semesters. This because at the moment of launching the program, all registered students at the university had started between those periods.

I have data on the entry exam for a total of $10,604$ students. However, not all administrative profiles were complete. This means that there are missing observations on at least one of the main demographic variables of interest. To complement the analysis, I imputed the data replaced missing observations with the average value for each variable.

Table A-1 reports OLS regressions where the dependent variable is the score in the national exam, with the raw data in column **I** (n = $3343, 31\%$ of the sample) and with the imputed data in column **II** (n = $8339, 78\%$ of the sample). The independent variables are different social categories such as gender (female vs. male), socio-economic status (low vs. middle vs. high), parental education (first generation vs. continuous education), origin (comes from out of the city where the university is located or not), ethnic (afro-

Table A-1 Academic performance on entry exam

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the score in the national entry exam in columns I-III and the score on economic expectations after graduation in columns IV-V. In all regressions, I control for the effect of different social categories such as gender, SES, parental education, origin, ethnic minority and scholarship holder. For the regression in column II, missing data on the different social categories was imputed as the average value for each variable. All regressions include academic major and starting semester as controls, except for column IV. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Exam score			**Expectations score**	
	I	**II**	**III**	**IV**	**V**
Female	-1.407^{**}	-1.623^{**}	-1.191^{**}	-0.017^{*}	-0.020^{**}
	(0.282)	(0.196)	(0.373)	(0.007)	(0.007)
Low SES	-2.795^{**}	-3.865^{**}	-2.035^{**}	-0.016^{+}	-0.020^{*}
	(0.352)	(0.230)	(0.493)	(0.009)	(0.009)
High SES	2.878^{**}	3.057^{**}	3.777^{**}	0.031^{**}	0.037^{**}
	(0.453)	(0.315)	(0.580)	(0.009)	(0.009)
First gen.	-2.945^{**}	-2.716^{**}	-2.282^{**}	-0.026^{**}	-0.021^{**}
	(0.315)	(0.311)	(0.433)	(0.008)	(0.008)
Rural	-1.417^{*}	-2.272^{**}	-1.378^{**}	0.003	0.000
	(0.311)	(0.223)	(0.439)	(0.008)	(0.008)
Ethnic	-3.143	-2.866^{**}	-3.523^{*}	0.032	0.017
	(1.166)	(0.678)	(1.515)	(0.046)	(0.046)
Scholarship	11.325^{**}	12.840^{**}	9.725^{**}	0.011	0.018^{+}
	(0.315)	(0.262)	(0.408)	(0.010)	(0.010)
Constant	66.807^{**}	68.787^{**}	63.261^{**}	0.413^{**}	0.429^{**}
	(0.493)	(0.296)	(0.632)	(0.007)	(0.011)
Controls	Yes	Yes	Yes	No	Yes
# Obs.	3343	8339	1636	1868	1865
R^2	0.237	0.250	0.220	0.025	0.061

descending or indigenous vs. not), scholarship (holds a scholarship from the national government). I also include as controls the semester in which the student started college as well as the academic program he/she chooses.

The results show that individuals from some social categories are clearly disadvantaged against their comparison groups. For instance, females significantly underperform compared to males ($p < 0.001$), even when controlling for chosen major. Similarly, students from low SES ($p < 0.001$) and middle SES ($p < 0.001$) underperformed when compared to those of high SES. In the same direction, the exam scores for first generation students ($p < 0.001$), those who come from rural areas out of the city where the university is located ($p < 0.001$), as well as ethnic minorities ($p < 0.001$) are not up to par with their counterparts.

A.2 Economic expectations after graduation

To complement the data on academic performance, and to assess another dimension in which these students may be behind their counterparts, I conducted a survey on the expectations students have for their future after graduation in the fall of 2021 (see survey questions below). I invited 6421 students to take a 5 minutes survey, out of which 1924 completed it (30% response rate.)

First, for comparability with the previous analysis on academic performance, I run the same model looking at differences in the scores on the entry exam (Table A-1 column **III**). I include exclusively those students who completed the expectations survey, and find consistent results showing that the same social categories underperform.

Next, I use the responses students gave to the survey to create an expectations score for each individual. For this, I combine the following indicators: (i) whether the student plans to continue studying after graduation (even if they also choose to work), (ii) how long do they expect to be unemployed after graduation, (iii) the expected salary for their first job, (iv) the number of students (between 0 and 100) who graduate from their major and find a job in less than 6 months, and (iv) the number of students (between 0 and 100) who graduate from their major and find a job through a social connection (referral). The expectation score ranges between 0 and 1, where 1 means students have high economic expectations. For instance, they plan to go to gradschool, they do not expect to be unemployed for too long, they expect a good salary, and also they expect people from their major to do well in finding a job (which can be a proxy for their views on their labor market and the value of social capital).

Table A-1 (columns **IV** and **V**) reports regressions on the expectations score and shows that most of the social categories displaying low academic performance also display lower levels of economic expectations for the future after graduation. For instance, when compared to their male counterparts, female students are less likely to have a job or be in an internship during their studies, expect to be unemployed for much longer after graduation and to earn less. Similarly, they believe this is somewhat generalized and expect graduates from their major to be less likely to find a job in the first 6 months after graduation. A similar thing happens with low and middle SES when compared to high SES. An exception in terms of expectations is for students coming from rural areas of belonging to ethnic minorities, who do not differ significantly to their counterparts in their expectations.

Based on the results from the assessment of academic performance at the time of entering university and on the assessment of economic expectations after graduation from university, I chose females, low and middle SES, first generation, rural, and ethnic as the social categories that would be targeted and offered the upskilling program.

Questionnaire on economic expectations. Below, I include the questions from the survey on economic expectations. In addition to these questions, I also collected data on socio-demographics (e.g., gender, social class, etc).

- What is your work status? [Do not work (only study); Work independently (entrepreneur); Work in business/company of family; Work in business/company (non-family)]
- What are your plans after graduation? [Continue studying; Work in my field of study; Work out of my field of study; Entrepreneur; Continue in my current job; Other]
- Independently of your previous answer, consider the case in which you decided work after graduation in a job in your field of study. In which sector do you expect you can find that job? [Private; Public]
- How long do you expect it would take you to find that job? [Less than 6 months; Between 6 months and 1 year; Between 1 and 2 years; More than 2 years]
- How many minimum wages do you expect to earn as your salary for that job? (The minimum wage in 2021 is $908,526$ Pesos) [0-20]
- For every 100 students that graduate from your program, how many do you expect to find a job in less than 6 months? [0-100]
- For every 100 students that graduate from your program, how many do you expect to find a job through someone they at university? (for instance a classmate or a friend) [0-100]
- How competitive are you? (Please choose a value, where 0 means *Not competitive at all* and 10 means *Very competitive*) [0-10]

B Invitation Emails

The invitation message below was sent to pre-selected students. The original email was sent in Spanish, I include below the English translation. To maintain anonymity on the involved institutions, I replace names and identifiable information in the emails with placeholders. Experimental variations in the content of the email are indicated with the label of each treatment: NO INFO, PRIVATE INFO, and PUBLIC INFO.

Message to students

Dear [Student Name],

The [Local University] has a collaboration agreement with the [International University], a global university of re-known quality. As part of the agreement, professors from the [International University] will teach a workshop to help students at [Local University] acquire the necessary tools to achieve their goals and increase their chances of personal and professional success (you can see details of the workshop at the end of this message).

This great opportunity provides multiple benefits. First, being able to learn from excellent professors. Second, by completing the workshop participants will receive an attendance certificate from the [International University]. These types of certificates can have a very large impact in your CV and open doors for future jobs or scholarships. In addition, at the end of the workshop there will be a ruffle of various iPads among those who complete it, with the aim of giving students a tool that may help them in their academic endeavors.

- NO INFO: The workshop has a limited number of slots and you have been chosen among all students at the university because you have the [merit/potential] to benefit from this program, as your cumulative GPA is [Student's GPA].
- PRIVATE INFO or PUBLIC INFO: The workshop has a limited number of slots and you have been chosen among all students at the university because you have the [merit/potential] to benefit from this program, as your cumulative GPA is [Student's GPA], and also because you fulfill one of the following requirements: being a woman, being of middle-low social class, belonging to an ethnic minority (indigenous or afro-descendant), being a first-generation student (neither of your parents has a college degree), or coming from a rural area (or not coming from any of the main cities in the country).

As slots are limited, in order to register for the workshop and indicate you are interested in benefiting from this great opportunity, you will need to follow two very simple steps:

1. Pre-registration: Respond to this message indicating your interest in taking part of the workshop. This will count as a pre-registration.
2. Endorsement from a faculty member at [Local University]: Send an email message to a faculty member including this email address [Program's Email Address] in copy (cc), asking him/her to reply with the following message:

- NO INFO or PRIVATE INFO: I, [Professor's name] recommend student [YourName] to take part in the workshop "How to change: scientific tools to achieve the goals in your personal and professional life", because he/she has the academic merit/potential to benefit from this program, as his/her cumulative GPA is [Student's GPA].
- PUBLIC INFO: I, [Professor's name] recommend student [YourName] to take part in the workshop "How to change: scientific tools to achieve the goals in your personal and professional life", because he/she has the academic merit/potential to benefit from this program, as his/her cumulative GPA is [Student's GPA], and also because he/she fulfills at least one of the following requirements: being a woman, being of middle-low social class, belonging to an ethnic minority (indigenous or afro-descendant), being a first-generation student (neither of his/her parents has a college degree), or coming from a rural area (or not coming from any of the main cities in the country).

Once the professor has replied, you will be officially registered. It is indispensable that both you and the professor include this email address in copy for all communication.

All professors at the [Local University] have been informed about this great opportunity, so they will be willing to help you with the required recommendation.

Additional information about the workshop:

- Name: "How to change: scientific tools to achieve the goals in your personal and professional life".
- Instructor(s): The workshop will be taught by professors of high international standing from the [International University].
- Language: Spanish.
- Duration: 9 online sessions, half an hour each. All sessions are independent and you will be able to complete them at your own pace. So, you will not have any conflicts of scheduling with other academic activities.

- Start: The workshop will start on [Start date].
- Costs: Free course.
- Requirements: To be pre-selected and to be endorsed by a faculty member from the [Local University].
- Benefits: An international certificate of attendance. Also, you will participate in the ruffle of various iPads.
- Registration deadline: Please pre-register before [Deadline date].

We await for your positive response so you can benefit from the opportunities in this workshop.

Sincerely,

[Signature Person - 1]
Head / Office of International Relations

[Signature Person - 2]
Director Social Bee Lab

C Course evaluations

In this section, I present suggestive evidence that the program offered was considered valuable by both faculty and students. For this, I follow two strategies: (i) indications of value from faculty in their email responses to the nomination experiment, and (ii) course evaluations by students that completed the program in both the high and low gpa groups.

C.1 Faculty perceptions

All faculty members were part of a field experiment in which each of them was invited to nominate one single student. This experiment took place a couple of weeks before the take-up experiments (see the timeline in Figure 1). Each nominated student was guaranteed a slot in the program, so any faculty member considering this was a beneficial opportunity could nominate a student. Out of the 692 faculty members invited, 284 made a nomination. Thus suggesting that 41% of the invited faculty found the course valuable enough to nominate a student for it. In addition, among those who made a nomination, 23 requested the possibility to nominate at least one other student. This means that 8% of those nominating further signaled the value they attributed to the program on benefiting students by requesting additional slots. Also, 27 (9.5%) of those providing a nomination also included in their response emails positive messages about the program offered. Below, I include some samples (translated from Spanish to English by the author):

- What a great opportunity for the students!
- Thank you for including us in these important processes for our students with academic merit.
- To the team of the Office of International Relations, I want to thank you for the opportunities you provide to our students.
- Thank you for the possibility you give for students to strengthen their competencies.
- I find the topic of the workshop very relevant, especially for those who are concluding their academic program or beginning their professional lives, as well as for everyone else.
- For me as a faculty member, it is very gratifying to learn about such opportunities to benefit students. Initiatives like this strengthen the value of academic research.
- Thank you for the opportunity offered to the students, I am sure they will take advantage of it to the fullest.

- Thank you for such wonderful opportunity for our students.
- I think this workshop is fantastic and a great opportunity of growth for students.
- I greatly value these spaces of development for our students.

C.2 Course evaluations

The course evaluation was completed by 1135 students, 795 from the high gpa group and 340 from the low gpa group. The evaluation included a set of questions and here I report the results on the two most relevant for understanding the value students assigned to the program. First, "General evaluation of the course", for which answers ranged from 1 "Very deficient", 2 "Deficient", 3 "Adequate", 4 "Good" and 5 "Excellent". The second item is "The course helped my way of thinking", for which answers ranged from 1 "Completely disagree", 2 "Disagree", 3 "Neutral", 4 "Agree" and 5 "Completely agree". In both cases, I combine answers 1 and 2 into a "Negative" category, 3 I relabel as "Neutral", and 4 and 5 I combine into a "Positive" category. Figure 9 summarizes the responses for these items in the course evaluation.

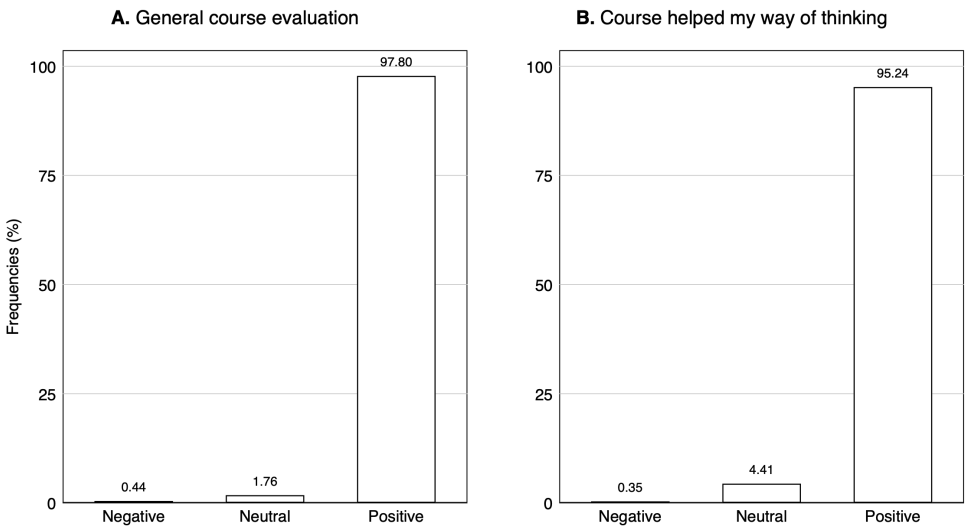

Figure 9

In the first case 97.8% of responses evaluated the course as positive (69.5% *Excellent* and 28.3% *Good*). Similarly, 95.2% agreed that the course impacted their way of thinking (59.5% *Completely agree* and 35.7% *Agree*). Thus, indicating that similar to the faculty evaluations, students are very positive about the program. Note that these course evaluations are measured ex-post, only for those who completed the program, which limits the extent to which I can state that all students valued the course in the same way despite the signal they received. But, if I test how course evaluations vary depending on the performance group or the way they were targeted, I find no effect of treatment variations on the way students evaluated the course. This is reported in Table C-1 below.

Table C-1 The effect of targeting on course evaluations.

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the item evaluated" general course evaluation in column I, "the course helped my way of thinking" in column II, "the course was intellectually stimulating" in column III, and "general evaluation of the instructor" in columns IV. In all regressions, targeting is a categorical variable for which *Public* is the omitted category. Similarly, performance is a categorical variable for which *Low gpa* is the omitted category. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Course **I**	Think **II**	Stimulate **III**	Instructor **IV**
PRIVATE INFO	0.014	−0.057	0.014	−0.015
	(0.041)	(0.044)	(0.047)	(0.042)
NO INFO	0.004	−0.058	0.042	−0.005
	(0.040)	(0.044)	(0.046)	(0.039)
High gpa	−0.005	−0.026	−0.007	−0.019
	(0.035)	(0.039)	(0.041)	(0.036)
Constant	4.664^{**}	4.602^{**}	4.543^{**}	4.722^{**}
	(0.040)	(0.043)	(0.046)	(0.040)
# Obs.	1135	1134	1134	1135

Table C-1 includes regressions for the two items illustrated above: general course evaluation (column I) and a statement that the "course helped my way of thinking" (column II). Also, for the following two other statements: "The course was intellectually stimulating" (column III) and "General evaluation of the instructor" (column IV). All items are evaluated above 4 (in a 1 to 5 scale) and there is no effect of targeting on any of the items evaluated.

D Peer effects

In this section, I evaluate the impact on take-up of having peers invited to the program. This is a way to assess potential spillover effects between treatments, if an individual decreases take-up when becoming aware that her peers have received a different invitation message (see Section B). But also, to measure peer influence, if an individual's willingness to take-up increases the more of her peers have received the same message.

To evaluate peer effects, I construct a network of relations between students using administrative data on each course taught across all academic programs. This dataset can be understood as a bipartite network that connects students to courses. The projection of this network results in a co-enrollment network of students connected to students. There is a connection between two individuals if they have attended to a course together, where the weight of a connection is the number of courses two students have co-attended. For each group, I use data on all courses up to the point where the experiment was launched: fall (spring) term of 2022-2023 for the high (low) gpa cohort. In each case, I maintain in the network only students who have been invited to the program, separate for each cohort. I am able to trace 2193 of the 2626 students invited for the high gpa cohort (83.5%) and 2233 of the 2270 students from the low gpa cohort (98.37%). The missing observations are due to errors in the academic database of the university, which prevents matching between student ids in the administrative data and the course enrollment data. This results in 2616 (2677) courses connecting all students invited in the high (low) gpa group. The average student is connected to 76 other students invited to the program, out of which about 25 are invited to the same treatment as herself (33%).

Table D-1 summarizes the main regressions testing for the effects of peers on take-up.

To do: ALSO DO THE RELATIVE COMPARISON: SHARE OF DEGREE OF INVITED (DEGREE INVITED PEERS/TOTAL DEGREE) - Create categorical var on degrees with 10 as ceiling for any value of 10 or greater. Then run the same regression with fixed effects for all categories "i.degree-cat", etc.

Table D-1 The effect of peers on take-up choices

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the level of take-up of the up-skilling program. In all regressions, targeting is a categorical variable for which *Public* is the omitted category. Column I does not include peer effects. Column II looks at the absolute effect of the number of peers invited to the program. Column III looks at the effect of peers invited to the program using the same targeting message. Finally, column IV looks at the effect of peers invited to the program using a different targeting message. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	I	**II**	**III**	**IV**
PRIVATE INFO	0.024^{+}	0.026^{+}	0.026^{+}	0.026^{+}
	(0.015)	(0.015)	(0.015)	(0.015)
NO INFO	0.069^{**}	0.071^{**}	0.072^{**}	0.071^{**}
	(0.015)	(0.016)	(0.016)	(0.016)
High gpa	0.186^{**}	0.191	0.190^{**}	0.191^{**}
	(0.012)	(0.013)	(0.0413)	(0.013)
Degree		0.000^{+}		
		(0.000)		
Degree same			0.001	
			(0.000)	
Degree different				0.000^{+}
				(0.000)
Constant	0.133^{**}	0.115^{**}	0.117^{**}	0.115^{**}
	(0.011)	(0.0415)	(0.015)	(0.015)
# Obs.	4896	4426	4426	4426
R^2	0.049	0.050	0.050	0.050

E Regressions

Table E-1 The effect of targeting on take-up choices

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the level of take-up of the up-skilling program for the high performance group in columns I-II and for the low performance group in columns III-IV. In all regressions, targeting is a categorical variable for which *Public* is the omitted category. Regressions in columns II and IV include group identity dummies as controls: female, low class, middle class, rural, ethnic, and first generation. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	High Performance		**Low Performance**	
	I	**II**	**III**	**IV**
PRIVATE INFO	0.008	0.012	0.035^{+}	0.027
	(0.022)	(0.024)	(0.018)	(0.019)
NO INFO	0.055^{*}	0.064^{**}	0.077^{**}	0.088^{**}
	(0.023)	(0.024)	(0.019)	(0.021)
Constant	0.310^{**}	0.296^{**}	0.126^{**}	0.044
	(0.016)	(0.040)	(0.012)	(0.030)
Controls	No	Yes	No	Yes
# Obs.	2626	2327	2270	1886
R^2	0.003	0.039	0.007	0.023
p-values of differences				
NO INFO VS. PRIVATE INFO	0.037	0.029	0.034	0.005

Table E-2 The effect of targeting on quality of participants

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the standardized grade point average (gpa) of for the high performance group in columns I-III and for the low performance group in columns IV-VI. In all regressions, targeting is a categorical variable for which *Public* is the omitted category. Regressions in columns I and IV focus on the entire pool of invited subjects, while in columns II and V only on those who took-up the program. In columns III and VI the regressions test the interaction between targeting and take-up. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	High Performance			**Low Performance**		
	I	**II**	**III**	**IV**	**V**	**VI**
PRIVATE INFO	−0.017	0.101		0.064	0.004	
	(0.048)	(0.086)		(0.051)	(0.133)	
NO INFO	−0.026	0.041		0.008	0.186	
	(0.048)	(0.082)		(0.052)	(0.124)	
PUBLIC INFO×No Take-up			0.077			0.244^{*}
			(0.073)			(0.105)
PRIVATE INFO×Take-up			−0.073			0.065
			(0.058)			(0.055)
PRIVATE INFO×No Take-up			0.178^{*}			0.248^{*}
			(0.075)			(0.098)
NO INFO×Take-up			−0.072			−0.061
			(0.059)			(0.057)
NO INFO×No Take-up			0.118^{+}			0.430^{**}
			(0.071)			(0.086)
Constant	0.015	0.068	−0.009	−0.024	0.189^{+}	−0.055
	(0.034)	(0.059)	(0.042)	(0.036)	(0.098)	(0.039)
# Obs.	2620	868	2620	2270	370	2270
R^2	0.000	0.002	0.008	0.000	0.008	0.017
p-values of differences						
NO INFO vs. PRIVATE INFO	0.845	0.471		0.282	0.123	
NO INFO(Take-No Take) vs. PUBLIC INFO(Take-No Take)			0.267			0.070
NO INFO(Take-No Take) vs. PRIVATE INFO(Take-No Take)			0.542			0.018
PRIVATE INFO(Take-No Take) vs. PUBLIC INFO(Take-No Take)			0.092			0.671

F Belief elicitation on performance by social group

I conducted an incentivized with 245 students from the same university. The task is to report their beliefs on the average score of different social groups as well as the share of different social groups on the group of students in the top 25% for two areas of the national exam: mathematics and reading comprehension (see details of the survey below).

I now summarize the main findings for the survey, reporting p-values from t-tests. As illustrated on Figure REF.A, On average, students believe that males outperform females in mathematics (62.17 vs. $61.37, p = XXX$), while females outperform males in reading (62.75 vs. $59.20, p = XXX$).

Unlike gender, Figure REF.B shows that the ranking on social class is consistent across areas of the exam and composition of the top scoring group. Students believe that in mathematics low class students underperform compared to middle class (58.83 vs. $61.62, p = XXX$) and to high class (58.83 vs. $62.61, p = XXX$), and middle class underperforms compared to high class (61.62 vs. $62.61, p = XXX$). Similarly, for reading low class students rank in the bottom compared to middle (57.96 vs. $59.72, p = XXX$) and high class (57.96 vs. $61.27, p = XXX$), and middle ranks below high class (59.72 vs. $61.27, p = XXX$).

Respondents believe there are more males than females among the top scorers in math (), while the composition flips and there are more females than males among the top scorers in reading (). As such, there is no clear hierarchy between female and male students in the beliefs reported.

Write the paragraph for the composition of social class among top performers. Also make the two figures (performance (done) and composition (to do).

F.1 The survey

Below I include the main text and questions of the survey translated to English (by the author), as the original survey was conducted in Spanish.

You have been invited to participate in this survey, with an estimated duration of 10 minutes.

Among all participants, we will randomly choose **1** out of every **10** to get paid. The chosen people will receive a fixed payment of $50,000$ pesos for completing the study, and an additional payment of $50,000$ pesos, depending on your decisions. That is, in total, if you are chosen to receive payment, you could earn up to $100,000$ pesos for completing this study. You will be paid online using Nequi.

[Page break]

Instructions

We will ask you to report your belief about the average score that the students at [Local University] got in different areas of the Saber 11 exam. The two areas of interest are **Mathematics** and **Critical reading comprehension**.

In each area we will present to you cases where we vary the characteristics of the students.

In case you are chosen to receive payment, one of your responses will be randomly selected to calculate your earnings. In that case, if the score that you reported is less than 1.5 points away from the real score, you will receive a bonus payment of 50 thousand pesos.

[Page break]

Math

In the **area of MATHEMATICS** of the Saber 11 exam, the average score of all students at the university was **63.77** points.

Report what was the average score in **MATHEMATICS** for students according to the following characteristics.

Remember you can earn a bonus of 50 thousand pesos fir the score you report is less than 1.5 points away from the true value for that group of students.

[**Choices:** Male students; Female students; Strata 1 or 2 students; Strata 3 or 4 students; Strata 5 or 6 students]

[Page break]

Reading

In the **area of CRITICAL READING** of the Saber 11 exam, the average score of all students at the university was **62.49** points.

Report what was the average score in **CRITICAL READING** for students according to the following characteristics.

Remember you can earn a bonus of 50 thousand pesos fir the score you report is less than 1.5 points away from the true value for that group of students.

[**Choices:** Male students; Female students; Strata 1 or 2 students; Strata 3 or 4 students; Strata 5 or 6 students]

[Page break]

Instructions 2

Think about the students from [Local University] that are ranked in the **top 25%** of the scores in **Mathematics** and **Critical reading**.

Next we will ask you to estimate the percentage of students with different characteristics in this group of the top 25%.

In case you are chosen to receive payment, one of your responses will be randomly selected to calculate your earnings. In that case, if the score that you reported is less than 1.5 points away from the real score, you will receive a bonus payment of 50 thousand pesos.

[Page break]

Of all students of Local University], 34.11% are from strata 1 or 2, 50.56% are from strata 3 or 4, and 15.33% are from strata 5 or 6.

Now think in the students whose score in the **Critical reading** area is on the top 25% of all scores, what fraction of these students are:

[**Choices:** Strata 1 or 2 students; Strata 3 or 4 students; Strata 5 or 6 students]

[Page break]

Of all students of Local University], 34.11% are from strata 1 or 2, 50.56% are from strata 3 or 4, and 15.33% are from strata 5 or 6.

Now think in the students whose score in the **Mathematics** area is on the top 25% of all scores, what fraction of these students are:

[**Choices:** Strata 1 or 2 students; Strata 3 or 4 students; Strata 5 or 6 students]

[Page break]

Of all students of Local University], 56.75% are female and 43.25% are male.

Now think in the students whose score in the **Critical reading** area is on the top 25% of all scores, what fraction of these students are:

[**Choices:** Male students; Female students]

[Page break]

Of all students of Local University], 56.75% are female and 43.25% are male.

Now think in the students whose score in the **Mathematics** area is on the top 25% of all scores, what fraction of these students are:

[**Choices:** Male students; Female students]

G Belief elicitation on goal attainment by social group

Describe belief-goals survey, questions and sample. Present main results...