Publicly targeting by group identities limits take-up of educational opportunities

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Abstract

I investigate the unintended consequences of publicly informing individuals from different social groups that their selection for a beneficial opportunity, such as an international training program, is based on their group identity. In a natural field experiment in collaboration with a Colombian university, I target 4831 students and only disclose to some that they were invited to the program because of their demographics. I find a 27% decrease in program take-up and a 20% decrease in completion rates when this information is disclosed. These findings hold direct policy implications for program providers interested in reach specific social groups, to effectively target them without discouraging their take-up of beneficial opportunities.

Keywords: Diversity, Identity, Stereotype, Information disclosure, Image concerns

JEL Classification: C93, D03, D83, I21

1 Introduction

Institutions and organizations are persistently developing programs to benefit members of different social groups, specially underrepresented or disadvantaged ones (e.g.,

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STEM for women, up-skilling for immigrants, funding for low-income students).[1] To reach their objective audience, such programs generally follow the strategy of publicly emphasizing the identities of the groups they target, as well as their merits or needs.[2] This strategy aims to explicitly inform targeted individuals and third parties that the institution is committed to recognize and support them, which in turn can increase chances of take-up of the offered opportunity.

However, publicly informing individuals that they are targeted because of their group identities could have unintended consequences. If individuals anticipate negative effects from an opportunity offered to them because of their demographics, strategies of public targeting may backfire. Thus, instead of leveling the playing-field, disclosing information on identity-based selection can reduce program participation. As such, an evaluation of how different targeting strategies impact members of various social groups is crucial to understand how to promote, instead of discourage, take-up of beneficial opportunities.

In this paper, I report the results of a natural field experiment designed to evaluate how disclosing to individuals that they are chosen for an international training program because of their group identities impacts their choice to accept the offered opportunity.

I leverage a collaboration partnership between two universities; a university in Colombia (i.e., the local partner) and an internationally recognized American university (i.e., the international partner). The alliance allowed me to offer a training program on behalf of the international partner to the local partner. The program was aimed at developing non-cognitive skills and was offered exclusively to students from the local partner holding at least one of the following social categories: female, low and middle social class, first generation, rural origins or ethnic minority. These identities had been previously requested by the local partner as those that should be targeted. A total of 4831 students holding at least one of the selected identities received a personalized email inviting them to take the training program.

The content of the invitation varies between treatments, as the information about

[1] See Alan and Ertac (2018); Alan et al. (2019); Carlana et al. (2022) for notable examples of educational programs targeting individuals from underrepresented or marginalized social groups. See also Ko and Moffitt (2022) for an overview of the take-up of social benefit and cash transfers.

[2] For instance, opportunities offered to low income students with high grades (see e.g., Dynarski et al. 2021) or for underprivileged students with low grades (see e.g., Carlana and La Ferrara 2024).

selection is either [i] disclosed to the targeted individual and a third party, [ii] privately disclosed only to the target, or [iii] not disclosed. The PUBLIC INFO condition follows the approach generally used by program providers, where targets as well as third parties are informed that the program is offered to specific individuals because of who they are. I contrast this against a NO INFO condition, in which neither targets nor third parties are informed that group identities are part of the selection criteria. This is the main comparison of the field experiment. For completeness, I also run a PRIVATE INFO condition, which informs targets but not third parties about the selection criteria, allowing me to further look into the separate impact of private and public information disclosure.

I focus on two outcome measures of how publicly revealing information on selection affects program participation. At the extensive margin, I assess program *take-up*, and a target is said to take up the program when she completes the registration process after receiving the personalized invitation. At the intensive margin, I assess program *completion*, which occurs when a participant finishes all sessions of the program. The main objective is to identify the behavioral consequences of public targeting, by looking specifically at whether it has a negative effect on program participation. I complement this first aim with the use of data from secondary sources (i.e., administrative records from the local partner) and additional primary sources I collected (i.e., online experiments and surveys), to explore which channels could be driving the behavioral findings.

In total, 1407 invited students (about 30% of the sample) took-up the program and 1066 (22%) completed it. The main finding of the study shows that take-up rates increase by 27% from PUBLIC INFO to NO INFO. Publicly disclosing that a target has been chosen because of her group identity does not appear to motivate individuals to feel recognized and included. Instead, it negatively impacts their willingness to take-up the offered opportunity. Similar effects are found on program completion, as observed by the 20% increase in completion rates from PUBLIC INFO to NO INFO. Further supporting that the widely used strategy of publicly disclosing how selection for an opportunity is identity-based may hurt instead of help those who are being targeted. In complement to the main result, the comparisons with the PRIVATE INFO treatment show that informing that selection is identity-based still has a negative effect, even if it is not publicly announced but revealed privately to those targeted.

The main finding, that public targeting negatively affects take-up and completion, is consistently observed across high and low performers (in terms of their GPA). This suggests that whether the program is perceived as a reward for high merit or as a remedial intervention for needs, there is an independent and negative effect of public targeting on participation.

Some potential channels through which public targeting could reduce take-up are: [i] peer effects; learning that a program targets certain social groups could lead to concerns about the quality of peers (see e.g., Bursztyn and Jensen 2015), [ii] low perceived benefits; individuals might interpret identity-based selection as an indicator that the program is of reduced value or benefit to them (see e.g., Cronin et al. 2024; Roth et al. 2024), or [iii] image concerns; individuals may believe that if others know selection is based on identities, it would reflect poorly on them (see e.g., Bursztyn and Jensen 2017; Moffitt 1983).

I control for the first channel by designing the training program as a self-paced online course, which requires no interactions with other students (similar to Massive Online Open Courses - MOOCs). But unlike most platforms offering MOOCs for which participants may not know who else took a course (see e.g., Athey and Palikot 2024, for the case of Coursera), the training program was offered at a university, and participants may know others who also got invited. To address this channel, I use network data to test the impact of having peers invited to the program and find no significant effect. This suggests that in my setting, peers effects are not a likely driver of program participation.

To test for concerns about perceived benefits, I designed an online experiment with students from the same university that had not receive any invitation to the program ($n = 398$), and elicited how beneficial the training would be for them. I varied whether they were informed that their selection would be based on their demographics or not (as in the main experiment). On average, respondents rated the program as being very valuable and beneficial (score of 89%), and there are no differences when disclosing that selection would be identity-based. Thus rendering anticipation of low benefits from the training program as an unlikely channel of the observed behavior.

To explore whether image concerns could be driving the main results, I follow two steps. First, I look at heterogeneous treatment effects across the different group identities targeted to the program. In line with the main result, every single category targeted (i.e., female, rural origins, low-middle class, first generation, and ethnic minority) has a positive response to NO INFO when compared to PUBLIC INFO. There are only two exceptions: low-class and first-generation students with high GPA. In these two cases, take-up and completion rates are higher in PUBLIC INFO than in NO INFO. This has the potential to further shed light on the role of public targeting in limiting or motivating program participation, contingent on it triggering image concerns.

Second, I evaluate the views people have about each of the targeted social groups (using survey data) and compare it to behavior for each of these groups in the experiment. For this, I use data from a survey eliciting beliefs about the ability of the different social groups ($n = 1200$). The results from the survey indicate that while there is no clear stereotype towards most identities, for low social class and first generation students the negative stereotype is strong: they are expected to underperform.

Combining the behavioral observations and the survey results, a plausible conjecture is that explicitly targeting their identities while highlighting their high academic performance could send a positive signal of achievement. This acknowledgement of successfully overcoming a negative expectation may have a positive effect on their image, which would not be the case for members of these same groups if they are low performers, nor for those holding any of the other targeted identities irrespective of their performance. Thus, rendering image concerns as a likely mechanism to help explain the drop in take-up.

The results of my work contribute to a prominent research agenda exploring the determinants of why take-up rates are low when the opportunities offered are advantageous (for a recent review see Bearson and Sunstein 2023). This line of inquiry is at the cross road of academic research and public policy, given the substantial investments from both the public and the private sector into developing socially beneficial programs, which are frequently underutilized due to low take-up rates. Some of the most prominent findings show that on top of structural barriers, e.g. limited time or resources, there are multiple behavioral barriers to the take-up of such opportunities. Example range from limitations in processing information (see e.g., Bhargava and Manoli 2015; Finkelstein and Notowidigdo 2019), aversion to uncertainty (see e.g., Dynarski et al. 2021; Burland et al. 2023), and psychological costs from taking-up potentially stigmatizing opportunities (see e.g., Butera et al. 2022; Moffitt 1983).

Building upon these findings, my work delves into the unintended consequences of a strategy generally employed by program providers— publicly targeting specific social groups. I provide causal evidence that such public targeting can negatively impact take-up rates. Specifically, the results suggest that this form of targeting may be triggering image concerns, hindering program participation. This strategy consistently affects individuals with different levels of performance as well as individuals belonging to a wide array of social groups.[3] Complementing existing evidence, my study underscores that informing individuals about the beneficial opportunity tied to their group identities may induce image concerns, negatively impacting take-up (see Bursztyn and Jensen 2015, 2017; Bursztyn et al. 2020; DellaVigna et al. 2012, 2017).

The policy implications of the main findings are as follows: while emphasizing identities can be effective in some contexts as a tool of public recognition that showcases organizational commitment (see e.g., Leslie et al. 2016), this does not appear to be universal when extending opportunities.[4] The public targeting of individuals may inadvertently trigger image concerns, dissuading a significant portion from seizing the offered opportunity.

My study proposes a potential solution— the NO INFO condition, which is consistently superior to public targeting. By not disclosing that selection is identity-based, targeted individuals are shielded from the image costs that are likely to prevent program participation. This strategy is effective because it puts the responsibility on program providers to identify eligible individuals before offering the beneficial opportunities, instead of imposing additional costs on potential beneficiaries. Empirical evidence from my study in conjunction with others, as for example Finkelstein and Notowidigdo (2019) and Dynarski et al. (2021), highlights the feasibility of program providers relying on administrative data to identify eligible individuals, eliminating the need for public targeting.[5]

[3] For references on how information could activate stereotypes that threaten peoples identities see Steele and Aronson (1995); Shih et al. (1999, 2006); Fryer et al. (2008).

[4] A complementary line of research explores the benefits of publicly emphasizing identity biases, as awareness can positively impact behavior and reduce discrimination, see e.g., Bohnet (2016); Pope et al. (2018); Boring and Philippe (2021); Alesina et al. (2024).

[5] Finkelstein and Notowidigdo (2019) studies take-up of food stamp programs and discusses how the enrollment campaign used Medicare records to identify eligible recipients, freeing potential program adopters from the responsibility to prove they were eligible. In Dynarski et al. (2021), researchers used data on applications to free/subsidized lunch in high-school to pre-identify low income students, and then targeted them directly. This allowed them to avoid any reference to their social groups in the invitation message.

The rest of the paper is organized as follows. In section 2, I describe the setting and experimental design. In section 3, I report the main findings of the study. Section 4 explores potential mechanisms, and section 5 concludes.

2 The experiment

2.1 Setting of the study

This project is the result of a collaboration partnership between an American global university (the international partner) and a university from Colombia (the local partner). The local partner is a private university with about 10000 students belonging to a diverse set of social groups and backgrounds (see Cardenas et al. 2021). One of the aims of the collaboration is for the international partner to support students from the local university who belong to at least one of various social groups. The following categories were proposed by the local partner as the ones to be targeted for the program: female, low-middle social class, first generation, rural origins and ethnic minorities. Students belonging to any of the selected groups were directly offered the opportunity to participate in an international training program. The purpose of the program is to help them develop or strengthen skills to better attain their goals. Also, it provided certifications of completion from the international partner, which are valuable to access future opportunities.

A notable aspect of the Colombian setting is that there is a social stratification system assigned by the central government to households, which follows a six-number ranking. The number assigned to all members of a household increases with the quality of the dwelling and its surroundings. This number is the stratum of a family and follows a cross-subsidized system that determines the price households pay for utility bills: higher prices the higher the position in the 1 to 6 ranking (see e.g., Bogliacino et al. 2018). This has important implications for the socio-demographic composition of the student body at universities, which differs greatly between private and public institutions. Public universities are almost exclusively for low income students because tuition fees are a function of family social strata, which means that those in lower strata pay very little and those in higher strata would pay substantial fees. In private universities there is no price discrimination, but among the private there are two types: elite and non-elite. Private elite universities are mostly for students from high income families, as they charge very high tuition fees. Private non-elite reach students from all social classes as their prices are intermediate, so their diversity levels are highest among the universities in the country (see e.g., Londono-Velez 2022). The local partner university is private but not elite, which makes it a great setting to conduct my study.[6]

Selection of eligible participants for the training program. Participation in the program was by invitation only, which were sent exclusively to eligible students. I used administrative data to filter out any student who did not hold at least one of the social categories previously selected. The share of these categories in the student population is as follows: female (65%), rural (34%), middle class (46%), low class (32%), first generation (15%), and ethnic minority (3%). Then, using academic records on grade point average (GPA), I divided chosen students into two groups of high and low performers.[7] As a requirement of the local partner university, invitations to these groups were sent separately in two waves, during the fall and spring semesters of the same academic year (2022-2023). In the first wave (fall of 2022) only students with high GPA were targeted, and in the second wave (spring of 2023) were those with low GPA.

2.2 Features of the training program

The training program is offered as an international opportunity exclusively provided through a partnership between the local university in Colombia and an internationally recognized university abroad. It is a selective program and participation is by invitation only. The training provides a certification to those who complete it, which can be of great value for application to jobs, internships or scholarships (see e.g., Athey and

[6] Universities in Colombia regularly report the average strata of their student population. Recall strata goes from 1 for those with the lowest income to 6 for those most affluent. Private elite universities have an average strata above 4 with the highest case being 5.4, public universities have average strata below 2.5 with the lowest being 1.2. Private non-elite universities have an average strata ranging between 2.5 and 3.5. The partner university reported having an average strata of 3.3. See https://www.universidad.edu.co/de-mayor-a-menor-ies-colombianas-segun-el-estrato-socioeconomico-de-sus-estudiantes/.

[7] In Colombia, GPA ranges between 0 and 5.0, where 3.3 is the passing grade and 5.0 is the highest. Students with a GPA of at least 4.0 are in the high performance wave. In the low performance wave, are students with a GPA below 4.0 but above 3.3, as to include everyone who is passing. At no point in the invitation to the program I used the terms “high” or “low” to refer to their performance (see Appendix A for details).

Palikot 2024). The content of the program provides novel insights useful for anyone, irrespective of their current abilities and it is centered around *goal pursuit* and the development of non-cognitive skills.[8] 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.[9]

I put together a bundle of attractive features to motivate participation. To reduce participation costs, the invitation is personalized and explicitly states that the student already has a guaranteed slot in the program, thus eliminating uncertainty about eligibility and access to the opportunity. The program is free of charge. It is organized in 9 sessions of about 30 minutes each, all of which are pre-recorded and delivered online (similar to MOOCs).[10] The entire schedule was provided at the beginning of the program, where two sessions would be launched weekly (one on Mondays and one on Thursdays). This allowed participants to visualize their progress and make a personal plan. It also makes progression self-paced and allows for flexible planning. The program had no pre-requisites and was open for participation irrespective of which courses students had taken so far.[11] Finally, there are multiple computer rooms as well as free wifi on campus, solving any impediments to access equipments or the internet.[12]

As for benefits, on top of the knowledge acquired, participants received a completion certificate indicating the program was taught by faculty from an internationally recognized university. The program's name did not include references to any of the targeted social categories to prevent any form of negative signals, if they referenced it in their

[8] I designed the content of the program to closely follow the research presented in Milkman (2021).

[9] Other types of educational programs focus on more specialized *cognitive* abilities, such as coding or advance math (see e.g., Carlana and Fort 2022). Although important, these tend to be most relevant for specific academic majors, while the aim of this program was to reach a wide range of heterogeneous individuals across programs and group identities.

[10] In all sessions, video lectures are split in two. In between, students have to develop an individual class activity, intended to promote attention and increase engagement.

[11] The main features of the program are informed by key behavioral findings: [i] ensuring placement is motivated by evidence on the psychological value of certainty (see Tversky and Kahneman 1986), [ii] the program is free as individuals perceive free products as more valuable than the same product as a reduced cost (see Shampanier et al. 2007; Burland et al. 2023), [iii] prompting people to make a plan while allowing for a combination of routines (having a schedule) and flexibility (allowing for sessions to be completed within an ample timeframe) is likely to promote completion of the program (see Beshears et al. 2016, 2021).

[12] At the time the first wave of the program was launched in 2022, all COVID 19 restrictions had been lifted up on campus and classes were back in person, which also gave access to computer rooms, etc.

CVs.[13] In addition, there was a lottery of two last-generation iPads among those who completed the program.

By putting together a bundle of low participation costs and both symbolic and material benefits, I aim to control for most common structural and behavioral barriers preventing take-up. This increases the chances of program participation, reducing noise and allowing me to test the effects of public targeting as cleanly as possible.

2.3 Invitation messages

Each chosen 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 partner university. Because the Office of International Relations frequently organizes events linked to international institutions, there are no reasons to expect participants to think they are part of a study.[14] All communications were sent to the students' institutional email addresses, as these accounts are regularly used by students to receive information from courses they are enrolled in. Thus, maximizing chances that targeted students would see the invitation message.

The email informed targeted students about the partnership agreement between their university and an international university, and explained that as part of this partnership the international partner was offering a training program to help them acquire or further develop their skills to set and achieve goals. The email describes the program, the benefits of participating, and gives information on the *selection criteria*. I vary how this information is disclosed to experimentally manipulate the way individuals were targeted. In the invitation email (see the complete invitation in Appendix A), a randomly chosen set of students received the following message:

[13] Evidence from audit studies shows that strong signals on CVs that a candidate belongs to a stereotyped identity can significantly increase discrimination in the labor market (see e.g., Bertrand and Duflo 2017). So, instead of the standard approach in programs of this type that frequently emphasize the targeted social groups in their titles (e.g., "STEM for women" or "up-skilling for immigrants"), I used a name that made no reference to either abilities or group identities.

[14] The experiment can be classified as a natural field experiment, as participants are not aware they are part of a study (see Harrison and List 2004). The project was approved by the ethics committee at Universidad Autonoma de Bucaramanga (UNAB), the local partner in Colombia. As part of the institutional policies of UNAB, students give written consent that their administrative records can be used and shared with third parties for research purposes. Students have the possibility to remove consent at any moment. At the time of the study, all targeted students had maintained their consent.

> You have been chosen among all students at the university because you can benefit from this program, as your cumulative GPA is [Student's GPA].

The rest received a longer version that includes specific information about selection being based on group identities, as follows:

> You have been chosen among all students at the university because you can 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 low-middle 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).

Subjects who received the longer version of the message became privately aware that their group identities played a role in their selection. For those who received the shorter message, the role played by their identities was not disclosed.

Across treatments, the invitation email also informed students that to register to the program, they needed to ask a faculty member to send a message on their behalf, to the program's account, endorsing their participation. This is the channel I used to involve third parties in the targeting process. For this, I provided each student with a pre-defined message endorsers were required to send back. The content of this pre-defined message is part of the experimental variations and follows a similar structure to that of the information already given to the students in the first part of the invitation. The endorsement message is the following:

> I, [Professor's name] endorse student [Student's name] to take part in the training program..., because he/she can benefit from this 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 longer message in the first part of the invitation, the endorsement message is as follows:

> I, [Professor's name] endorse student [Student's name] to take part in the training program... because he/she can 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 low-middle 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).

All students needed an endorsement to register to the program, but only a subset had to reveal to the third-party endorser that their demographics were part of the selection criteria.

I focus on two outcome measures. At the extensive margin, I look at take-up rates (i.e., invited participants register by providing the endorsement from the third party). At the intensive margin, I look at completion rates (i.e., invited participants complete all 9 sessions of the program).[15]

A notable feature of the invitations is that, as a requirement of the partner university, the GPA of the selected students is displayed. On the one hand, this allows me to explore the impact of public targeting on individuals who could perceive their invitation as a reward for their merit (i.e., high GPA) or as a remedial strategy to overcome their needs (i.e., low GPA). On the other hand, it limits the comparability between the two waves of the study. Because of this, I do not compare high and low GPA students in the analysis of the experiment and focus exclusively on treatment differences within each wave.

2.4 Treatments

I designed three experimental treatments varying whether the eligibility criteria is disclosed to the targeted individual and to a third party, to the target only, or to none of them. The aim is to tests how these variations in information disclosure impact take-up and completion rates. I run the field experiment in two separate waves, and in each I

[15] Note that the term *take-up* generally refers to someone receiving a benefit for which he/she is eligible (Bearson and Sunstein 2023). For the case of a 9-session training program this definition is not as fitting, as it is unclear how many steps quality as "receiving the program". Instead, I will use take-up as a measure of a student completing the registration process that allows her to participate in the training. In the same line, the term *completion* may be used in other programs as participating in a certain number of steps (e.g., completing more than 50% or 75% of all sessions). Given that benefits like the certification or the lottery are linked to going through all sessions, I will use completion as a measure of a student finishing the entire program.

target students with different levels of *academic performance*. Table 1 summarizes the features of each treatment as well as the number of individuals invited in each wave.

Table 1 Experimental treatments

The table summarizes how information about the selection criteria was disclosed by treatment (top). It also reports the sample sizes, by treatment for each wave of the study (bottom).

	Treatments		
	PUBLIC INFO	PRIVATE INFO	NO INFO
Information is disclosed			
To student	✓	✓	×
To endorser	✓	×	×
Invitations per wave			
High performance	n=864	n=864	n=833
Low performance	n=776	n=757	n=737

Next, I explain in detail the treatment variations, which were implemented in the same way across the two waves of the study.

PUBLIC INFO: targeted students are informed they are invited because of their demographic characteristics (group identities). Similarly, the third-party endorsers receive information that selection was based on demographics, through the pre-defined endorsement message.

PRIVATE INFO: targeted students are informed they are invited because of their demographics, as with PUBLIC INFO. But, the third-party endorsers do not receive any information of selection being based on demographics.

NO INFO: targeted students are also selected because of their demographics, the same as with PUBLIC INFO and PRIVATE INFO, but neither the students nor the endorsers are informed of this. All information provided avoids disclosing that selection is based on group identities.

2.5 Sample

A total of 4831 students received the email inviting them to participate in 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 individuals into treatments through block randomization, balancing the categories se-

Table 2 Sample balance across experimental conditions

Columns I-III and V-VII report the average frequency of each social category in the targeted sample, with standard errors in parentheses, for the PUBLIC INFO, PRIVATE INFO, and NO INFO conditions. Columns IV and VIII report the p-values for the Anova test that the means are equal in the three treatments, for the high and low performance group, respectively.

	High Performance				**Low Performance**			
	PUBLIC INFO	PRIVATE INFO	NO INFO	p-value	PUBLIC INFO	PRIVATE INFO	NO INFO	p-value
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
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)	
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)	
Low-middle 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)	
First generation	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	0.02	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	

lected for targeting: female, low-middle social class, rural origins, first generation and ethnic minority (see Table 2). Those invited had two weeks to complete their registration (take-up) to the program. Then, once the program started, two sessions of the program were launched each week. Those registered had 5 weeks to finish all 9 sessions of the program (completion).

3 Results

In this section, I present the main results of the field experiment and show how disclosing information about selection affects participation in the training program. Results on take-up rates and completion rates are based on proportion tests, for which I report two-sided p-values in the main text. In complement, In Appendix B, I report regression outputs estimating the linear probability of take-up/completion while controlling for the different social categories (i.e., fixed effects for the targeted identities).

3.1 Program participation

First, I report results on the general effect of information disclosure on program participation, pooling the two waves of the program together. The aim of this analysis is to assess how the different targeting strategies affect program take-up (extensive margin), as it is the most immediate outcome after the invitation is sent. As a second measure, I also evaluate the impact of targeting on completion (intensive margin): finishing all sessions of the program (unconditional on take-up).

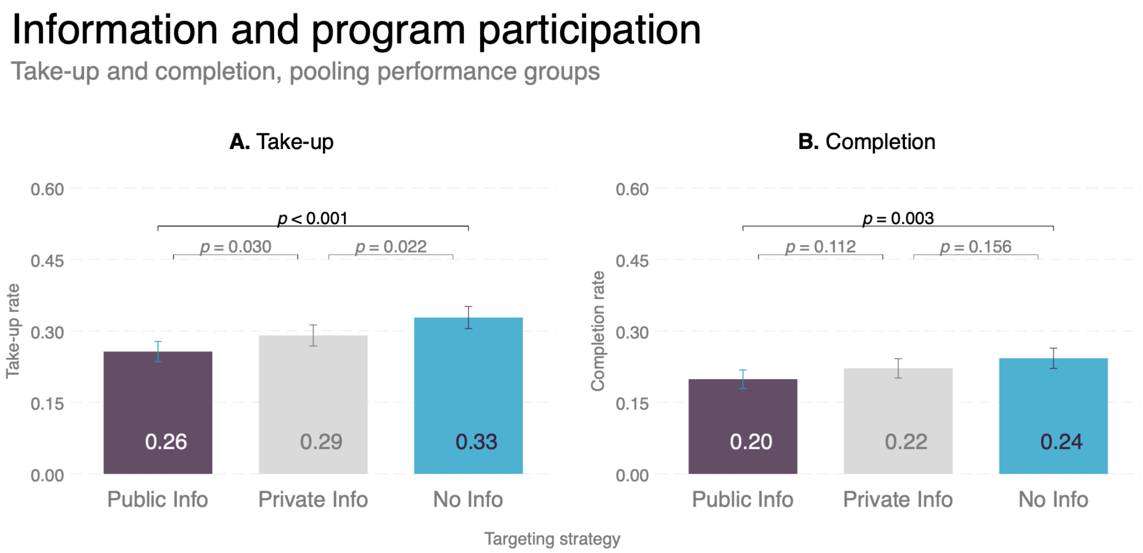

Figure 1 Take-up and completion rates by information condition.
The figure pools together high and low performance groups to illustrate the main effects of how variations in information disclosure impact take-up (Panel A) and completion (Panel B). Values inside the bars display average rates of take-up/completion. The p-values report the significance of two-sided proportion tests comparing information conditions.

The main result of the study suggests that public targeting has a negative and significant impact on take-up and completion rates, when compared to a strategy that avoids disclosing information about the selection criteria. As illustrated in Figure 1.A, take-up rates are 26% in PUBLIC INFO and they significantly increase to 33% in NO INFO ($p < 0.001$), when both targets and third parties are blind to identities being criteria for selection.[16] Moreover, as shown in Figure 1.B, the effect is also observed for completion

[16] Ko and Moffitt (2022) shows take-up rates for multiple beneficial opportunities circle around 40% or below. In an educational intervention offering STEM training (coding) for girls in schools, Carlana and Fort (2022) reports that about 16% of the eligible students took-up the program. In relation to these, the average take-up rate of 29% for the training program offered in my study is within the expected range for such an opportunity.

rates, which go from 20% in PUBLIC INFO to 24% in NO INFO ($p = 0.003$).[17] Note from the comparison to the PRIVATE INFO condition, that the negative impact on take-up and completion appears to be associated to information being disclosed to the target as well as to the third-party. I summarize the main finding in Result 1 below:

Result 1 *Publicly informing individuals that they are chosen for a training program because of their demographics has a negative impact on take-up and completion rates, compared to a setting where this information is not disclosed.*

Next, I test the effect of information disclosure separately for high and low performers.

3.2 Program participation by performance group

I conducted the field experiment in two waves that separately targeted high and low performing students. High performers may perceive their invitation as a reward for their merits, while low performers as a remedial strategy given their needs. In this section, I evaluate the effect of public targeting for each performance group.

Figure 2 illustrates the effects of the different targeting strategies on the high performance group (Panel A) and the low performance group (Panel B), and confirms that the negative impact of public targeting is present in both waves of the program. For high performers, take-up rates increase by 21% (7 p.p.) from PUBLIC INFO to NO INFO ($p = 0.001$), while completion increases qualitatively by 11% ($p = 0.121$). A similar pattern is observed for the low performance group, as take-up rates increase by 44% (7 p.p.) from PUBLIC INFO to NO INFO ($p < 0.001$), and completion rates by 42% ($p = 0.003$).[18] This suggests that the detrimental effects of publicly disclosing that selection is identity-based is robust to settings where opportunities could be perceived as either rewards or

[17] The main results are consistent also when controlling for the group identities of the targeted individuals, as reported in the regression outputs in Table B-1 in Appendix B.

[18] In Appendix B, I report results from a regression showing that NO INFO is superior to PUBLIC INFO both for High performers (see Table B-2) as well as for Low performers (see Table B-3), even when controlling for the group identities of those targeted.

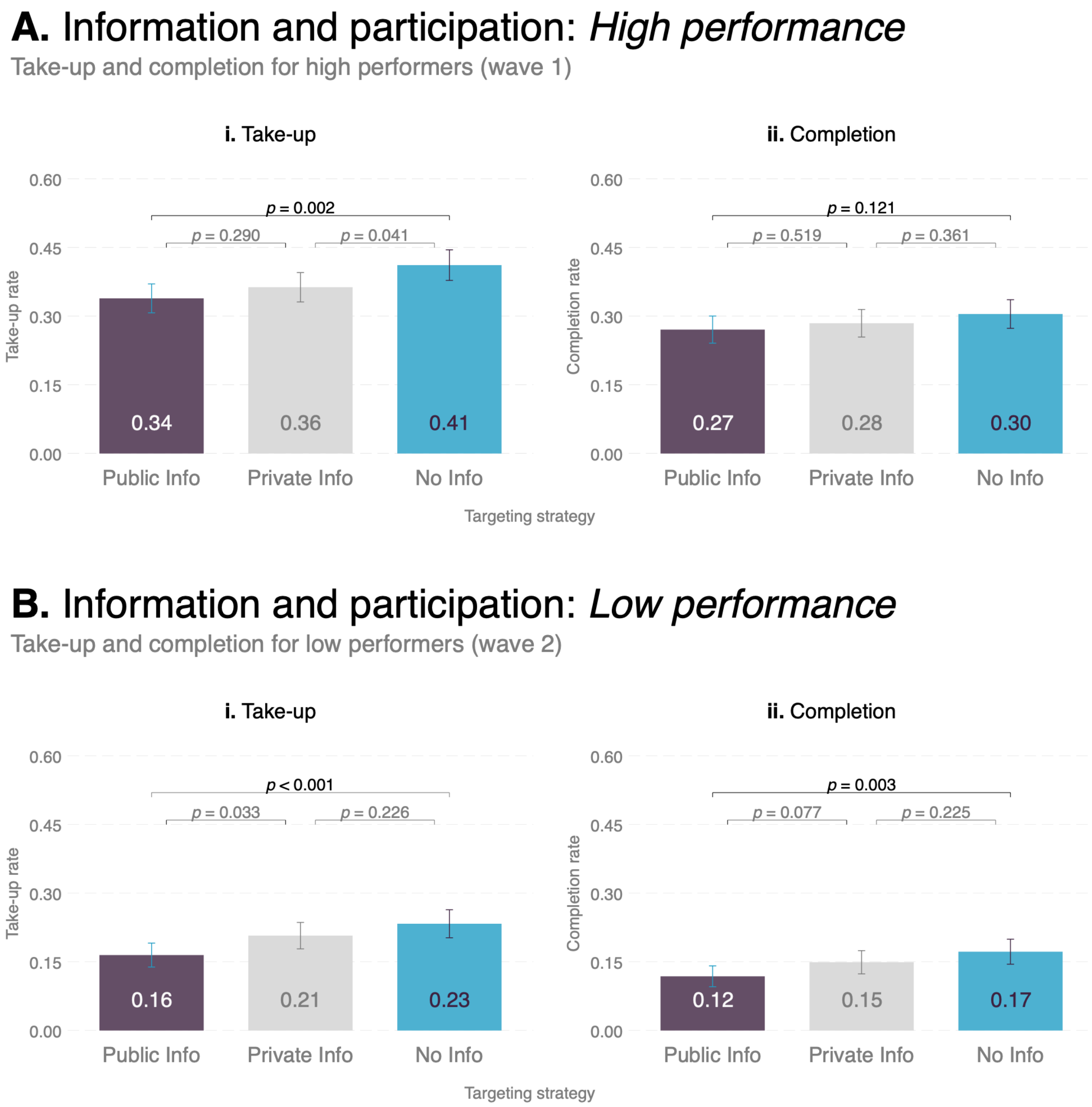

Figure 2 Take-up and completion rates for high and low performance groups.
The figure illustrates how variations in information disclosure impact take-up and completion, separately for the high (Panel A) and low (Panel B) performance groups. Values inside the bars display average rates of take-up/completion. The p-values report the significance of two-sided proportion tests comparing information conditions.

remedies.[19]

As for the comparison of the main treatments to the PRIVATE INFO condition, Figure

[19] In my setting, the negative effect of public targeting is present for each performance group (i.e., in each wave of the study). However, it is plausible that low GPA students would experience some additional negative effect, independent of that of public targeting, as their needs are being made explicit. The notable gap in take-up with respect to high GPA, even in the NO INFO treatment (23% vs. 41%, $p < 0.001$) suggests that low-grade image concerns can be very powerful and should be taken into account when offering remedial programs.

2 illustrates that both private and public information affect program participation, although the differences are in some cases not statistically significant. Together these results indicate that when targeting individuals for certain opportunities, explicit and public communication about the role of identities in the selection process can discourage participation for both high and low performers. I summarize this in the following result:

Result 2 *Publicly informing individuals that they are chosen for a training program because of their demographics has a negative impact on take-up and completion rates for both low and high performance targets, compared to a setting where this information is not disclosed.*

3.3 Program completion: steps

Next, I look in more detail at the effect of public targeting across the entire training program, by combining take-up and completion into a single metric on the number of steps in the nine-session program. Steps go from 1 to 10, where take-up (registration) is step 1 and the 9^{th} session is step 10. Figure 3 displays step progression, unconditional on take-up in Panel A and conditional on it in Panel B. Results for this section are derived from a regression analysis (see Table B-1 in Appendix B).

Participants in NO INFO complete an average of 2.75 steps, surpassing the 2.23 steps in PUBLIC INFO ($p < 0.001$). This underscores the consistency between the number of completed steps and the binary measures of take-up and completion used before. Once I condition on take-up (i.e., Step 1), there are no additional treatment effects on the number of steps completed: 8.67 out of 9 steps in NO INFO and 8.39 in PUBLIC INFO ($p = 0.156$).[20] This suggests that those who overcome the negative effect of public targeting and end-up participating in the program are also likely to come back to all sessions and successfully complete it.[21] I summarize this in the following result:

[20] Similar outcomes are observed when examining each performance group separately (see Tables B-2 and B-3 in Appendix B). For high performers, the steps go from 2.99 in PUBLIC INFO to 3.47 in NO INFO ($p = 0.022$), unconditional on take-up, and are on average 8.81 and 8.42 respectively when conditional ($p = 0.106$). For low performers it goes from 1.38 in PUBLIC INFO to 1.95 in NO INFO ($p = 0.002$), unconditional on take-up, and average on 8.34 in both cases when conditional ($p = 0.967$).

[21] Analysis of class activities by target? # of words and report it here to say that a complementary measure of completion is effort in class, which is conditional on taking the class, etc.

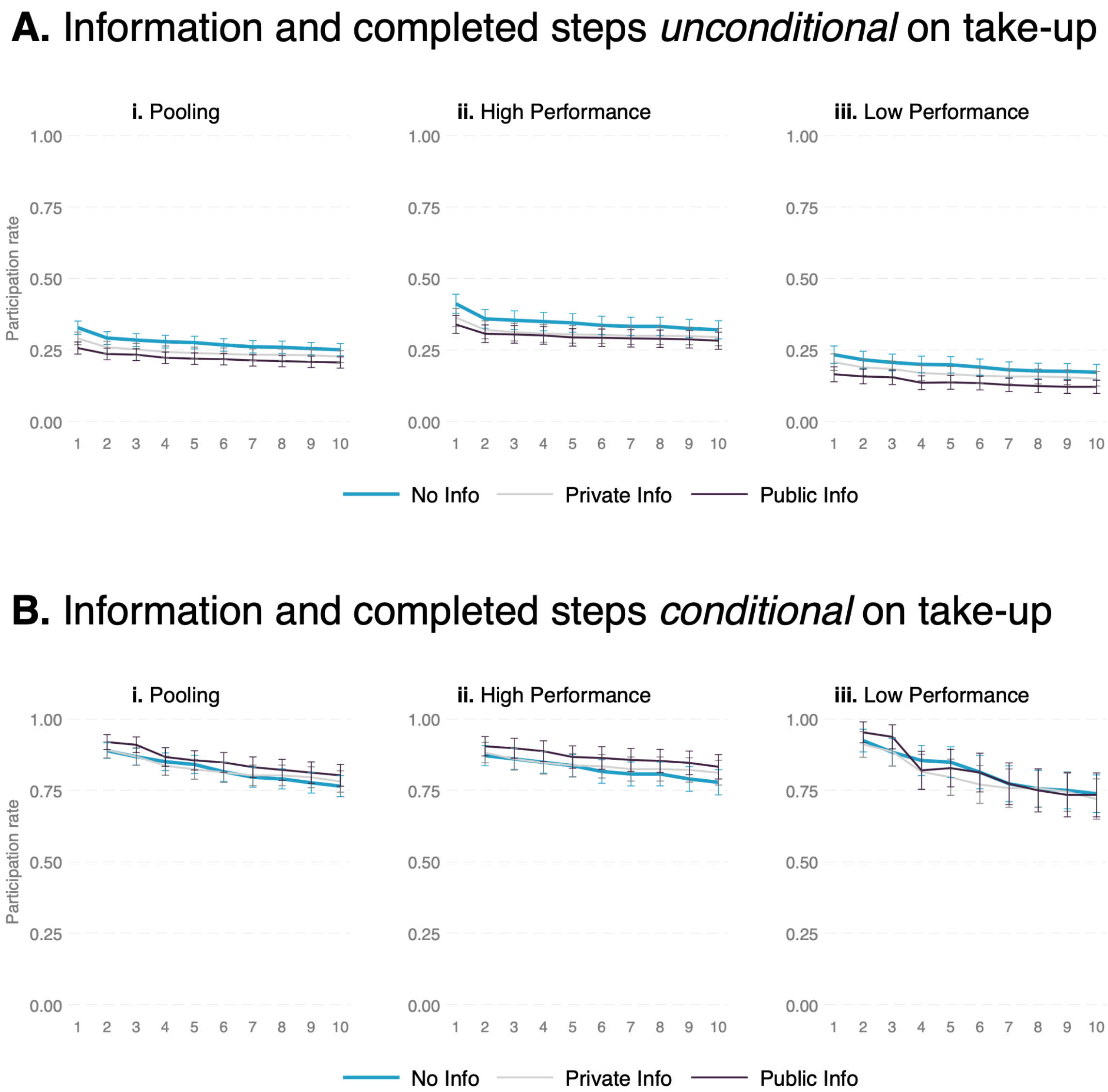

Figure 3 Number of steps completed in the program.
The figure illustrates how variations in information disclosure impact the rate of completed steps in the program, unconditional on take-up (Panel A) and conditional on it (Panel B).

Result 3 *Publicly informing individuals that they are chosen for a training program because of their demographics has a negative impact on the average number of completed steps unconditional on take-up, while there are no adverse effects among those who take-up the program.*

In conclusion, the main analysis shows that a strategy of explicitly informing individuals that they are offered a beneficial opportunity because of who they are (i.e., their group identities) can backfire, despite the well intended motivations driving it: showing organizational commitment towards those targeted. This negative effect is observed for cases where programs are aimed at rewarding the best performers, as well as when the program can be perceived as remedial to the needs of low performers. In both cases, information disclosure can limit take-up and completion rates. The results also show that there are no differences in completion for those who succeed in overcoming the barriers that public targeting poses on take-up, compared to the case where information is not disclosed. This suggests that addressing the negative impact of public targeting on take-up could greatly benefit program completion.

In the next section, I explore some potential mechanisms that could be driving the effects of public targeting.

4 Potential mechanisms

The main aim of the study has been to identify whether there is a negative impact of public targeting on take-up. The results from the natural field experiment provide causal evidence that publicly informing individuals that they have been selected for a beneficial opportunity because of their demographics significantly reduces take-up. In this section, I explore some potential channels that could be driving the behavioral patterns observed in the field experiment. I focus on three channels that could explain the decrease in take-up rates: peer effects, perceived benefits and image concerns.[22]

4.1 Peer effects

One channel driving low take-up may be peer effects. I refer to peer effects in this context as the anticipation of interacting with certain types of peers and how that may drive behavior (see e.g., Bursztyn and Jensen 2015).[23] Specifically, receiving information that an opportunity targets members of certain (possibly disadvantaged) social groups, may lead to concerns about the quality of the peers participants may encounter

[22] These analyses are exploratory and were not part of the pre-registration (see Appendix F).

[23] There is extensive work on peer effects, which most commonly focuses on *peer influence*. That is, the influence that an individua's behavior, decisions or outcomes can have on others (see e.g., Sacerdote 2001; Angrist and Lang 2004; Zarate 2023). In this section, I use a specific definition of peer effects: the effect of anticipating encountering low-level peers on program take-up.

in class. By design, I address this channel as I exclude any interaction between peers in the training program. The entire program is delivered online, self-paced and all activities are individual. Thus, I do not expect any effect from knowing which other students take the course.[24] Also, invitations were sent privately and students did not have to reveal their participation in the course to any of their peers.[25]

Despite how this was controlled for in design of the program, the training was offered to thousands of students within one same institution and it is likely that those targeted would know each other. So, unlike platforms that provide MOOCs (see e.g., Athey and Palikot 2024), peers may still play a role in this setting. To further explore peer effects as a potential mechanism, I look at how being connected to others who are also invited to the training program could affect take-up. The conjecture is that because peer effects (in the sense described above) should not be at play, having more or less peers invited to the program would not impact take-up. For this, I use records on all courses taught at the local university, to build a co-enrollment network of peer relations between the students invited to the program.[26] Using co-enrollment networks is valuable to study potential peer effects because it allows me to identify, for each particular student, the number of her peers also invited to the program, and also differentiate the information each received (i.e., treatment assignment).

On average, students are connected to 76 others invited to the program, where 33% of those belong to the same treatment (i.e., received the same invitation). Table 3 reports results from a regression analysis on the effect that having peers invited to the program has on take-up, which is a proxy for peer effects. I find that the number of peers invited does not have an impact on take-up (see columns II-IV in Table 3). This is the case when I pool together all peers a participant is connected to irrespective of

[24] I complement this evaluation by testing how [multiple ID tests] in Appendix... and find that the effect of public targeting persists when knowing the program is offered to people from different social groups, irrespective of whether a student holds those identities or not.

[25] In a co-enrollment network, a connection between two students means they have taken at least one course together. The total number of shared courses between a pair of students is a weight of the strength of their connection. See Weeden and Cornwell (2020); Weeden and Park (2021) for a discussion of how the relations between students in such a co-enrollment network can be valuable assets for them.

[26] A key element of the Colombian context is that the majority of university campuses, including the local partner university, do not have student dorms. Students mostly live with their parents, relatives or rent rooms in family houses. Thus, most of the interactions between students are on campus, specially in class.

Table 3 The effect of peers on take-up

OLS regressions with robust standard errors (in parenthesis). The dependent variable is take-up. In all regressions, information disclosure is a categorical variable for which *No Info* is the omitted category. Regressions in columns II-IV include measures of connectivity (degree) when connections are binary (either present or absent). Columns V-VII include connectivity measures when connections are weighted by the frequency of interaction. ***, ** and * indicate statistical significance at the 0.001, 0.01 and 0.05 levels.

		Binary			Weighted		
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
Treatments							
PUBLIC INFO	-0.071^{**}	-0.071^{**}	-0.071^{**}	-0.071^{**}	-0.072^{**}	-0.071^{**}	-0.071^{**}
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
PRIVATE INFO	-0.037^{*}	-0.038^{*}	-0.038^{*}	-0.037^{*}	-0.038^{*}	-0.037^{*}	-0.038^{*}
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Degree							
Total		0.003			0.009^{+}		
		(0.005)			(0.005)		
Same treatment			0.006			0.000	
			(0.006)			(0.005)	
Different treatment				0.004			0.005
				(0.005)			(0.005)
Constant	0.328^{***}	0.321^{**}	0.318^{**}	0.320^{**}	0.305^{**}	0.327^{**}	0.317^{**}
	(0.012)	(0.018)	(0.015)	(0.017)	(0.018)	(0.015)	(0.017)
# Obs.	4831	4831	4831	4831	4831	4831	4831
R^2	0.004	0.004	0.004	0.004	0.004	0.004	0.004

which invitation they received (p = 0.592), and also when controlling for the number of peers who received the same (p = 0.265) or different information (p = 0.471). This is robust also if I use weighted links, which grow in strength the more courses a person takes with a given peer (see columns V-VII in Table 3).

These results suggest that there are no identifiable negative effects on take-up of potentially knowing others who are invited to the program, supporting the conjecture that by design peer effects are not impacting the choice to join the training program.

4.2 Perceived benefits

Informing individuals that their selection to the program is because of their group identities may affect their beliefs about the value and benefits they expect from the program, even if peers are not involved. That is, targets may believe that a program offered to certain social groups may be of low quality or value, which would negatively impact take-up (see e.g., Cronin et al. 2024; Roth et al. 2024).

To explore this mechanism, I designed an online experiment with students at the local partner university that had never been invited to the program (n=399). They received information about the collaboration alliance between the local and the international partner universities, about the training program and were presented with the message they would receive if invited to participate (see instructions in Appendix D).

I randomly assigned participants to either a NO INFO or an INFO condition. In the INFO condition, the invitation included the section of the message disclosing that selection is identity-based, while in NO INFO this was omitted.[27] The main outcome measure is their response to the following question "How much value, utility or benefit would the training program have for you?".

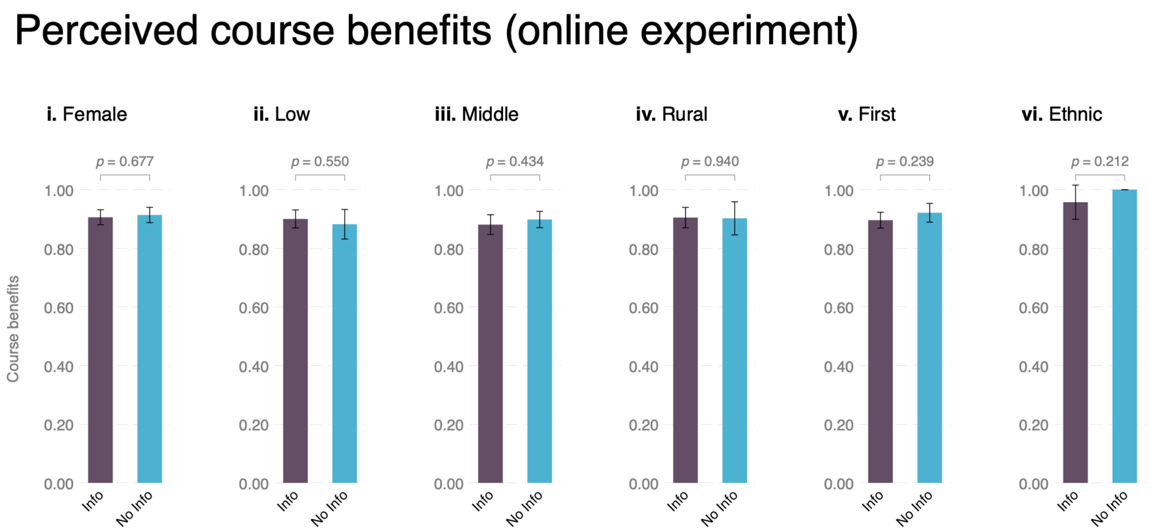

Figure 4 Perceived benefit of the training program by information condition.
The figure illustrates the reported benefits participants anticipate to get if they were offered the training program, normalized between 0 and 1, by information treatment and separately for each of the identities targeted for the program.

The results from the online experiment indicate that there are no differences in the expected benefit from the training program between INFO and NO INFO (88% vs. 89%, p=0.897). I further look at the impact that information (i.e., disclosing that selection is identity-based) has on perceived benefits, separately for each targeted social group. Figure 4 illustrates what female, middle and low class, rural origins, first generation

[27] Beliefs that the program is of low quality should arise when students are revealed that the program targets certain social groups, irrespective of whether this is revealed privately or publicly. Thus, I omit information about endorsers in the online experiment and focus only on the NO INFO and the INFO treatments.

and ethnic minority students reported to be their perceived benefits from taking the training program. Two elements become evident from the data: (i) students assign high value and expect high benefits from taking the training program if offered to them, and (ii) there are no differences in perceived benefit between information conditions, irrespective of the group identities students hold. This suggests that disclosing that selection is based on identities is not impacting the perceived value and benefits of the program, which makes this an unlikely mechanism for the observed take-up rates.

4.3 Image concerns

Finally, I evaluate whether image concerns can help explain how information disclosure impacted take-up (see e.g., Bursztyn and Jensen 2017; Moffitt 1983). I follow two steps for this. First, I look at average treatment effects for each specific group identity targeted to the program: female, rural, middle class, low class, first generation, and ethnic; separately for high and low performance groups. I focus on individuals holding each of these categories, irrespective of whether they hold none or some others. For simplicity in the exposition of this section, I restrict the analysis to the main comparison of the study: PUBLIC INFO vs. NO INFO. This means that *average treatment effects* in this section refer to the difference in take-up/completion rates between these two information conditions. All results in this section are descriptive and are aimed at exploring the potential mechanisms driving the effects of public targeting.[28]

Figure 5 illustrates the average treatment effects on take-up (Panel A) and completion (Panel B), separately for each targeted identity. For the low performers, take-up and completion rates are higher in NO INFO than in PUBLIC INFO, as shown by the positive difference for each of the targeted identities (see the darker bar on the left in each panel). The observation is consistent for the high performers on all but two cases: low class and first generation targets (see the lighter bar on the right in each panel).

Instead of displaying a negative response to public targeting, high-performing low-class students as well as high-performing first-generation students appear to react pos-

[28] As reported in Table 2, approximately 65% of the program's targeted individuals are females, 34% come from rural areas, 46% belong to the middle class, and 32% are low class. However, the representation of first-generation students is limited to 15%, and ethnic minorities constitute only around 3%. Consequently, the statistical power for identifying significant effects varies across targeted identities, and thus my focus here is on descriptive comparisons.

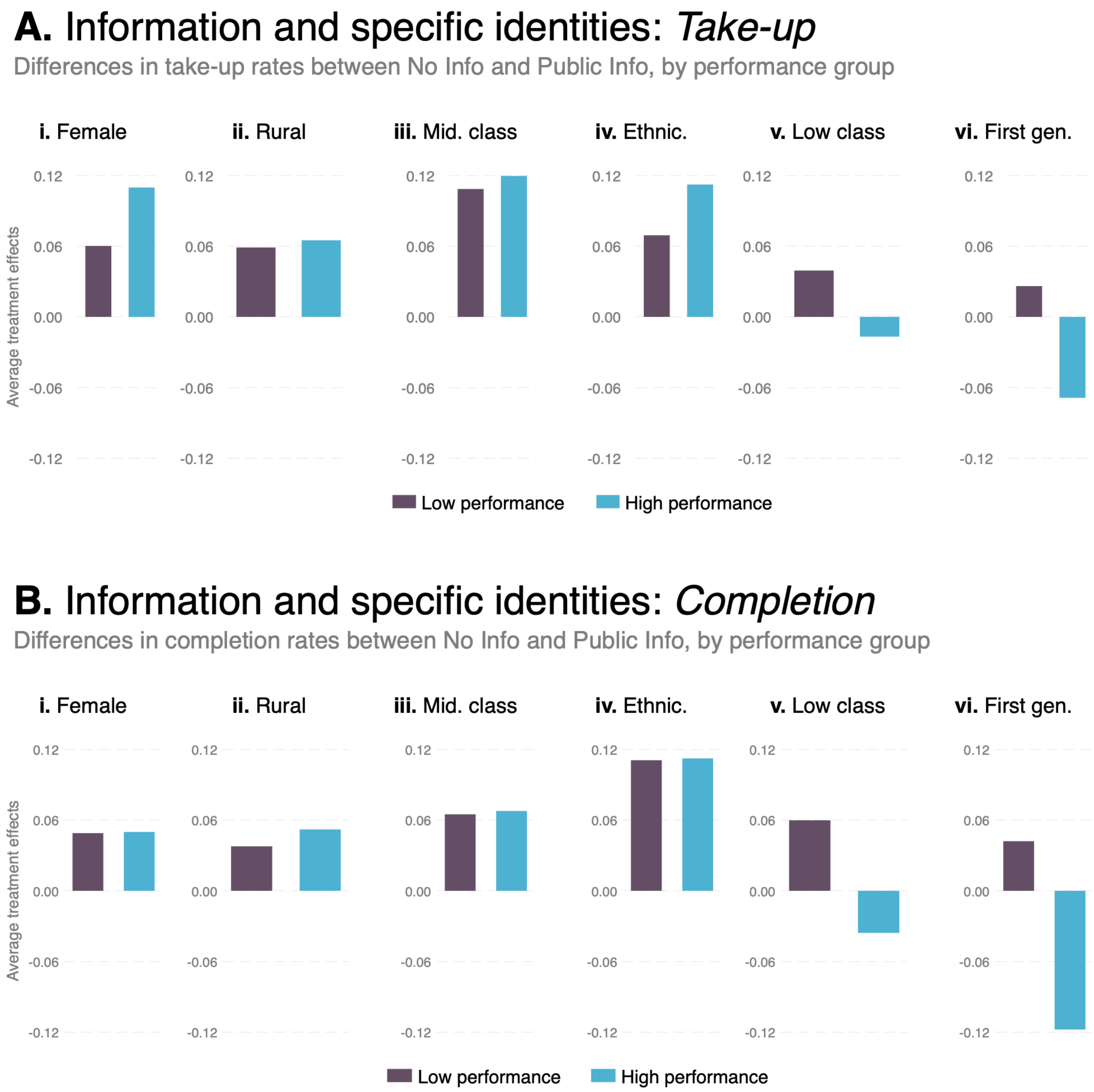

Figure 5 Average treatment effects on take-up/completion rates for specific identities. The figure illustrates gaps in take-up (Panel A) and completion (Panel B) rates between NO INFO and PUBLIC INFO, for each of the group identities targeted for the program, separately for high and low performance groups.

itively to being informed that their identities were part of the selection criteria. But, only when this is coupled with information about their academic achievement (i.e., the difference between NO INFO and PUBLIC INFO is negative). For students from low class backgrounds there is a difference of 2 p.p. as take-up goes from 33% in NO INFO to 35% in PUBLIC INFO. For first generation students take-up increases by 7 p.p. from NO INFO to PUBLIC INFO. This raises the question of why the same signal, explicitly targeting the identities of high performers, may have a negative impact in most cases and a positive one in some others.

To explore why most (but not all) identities are negatively affected by public targeting, I use data from a survey question asked to a sample of 1200 students from the local university, eliciting beliefs about the ability different groups of people have to attain their goals. Specifically, respondents were asked: "What is the probability that each group of people, in general, attain the goals they set for themselves?". Beliefs are elicited separately (and in random order) for the following categories: male, female, low class, middle class, high class, first generation, continuous education, rural and urban.[29]

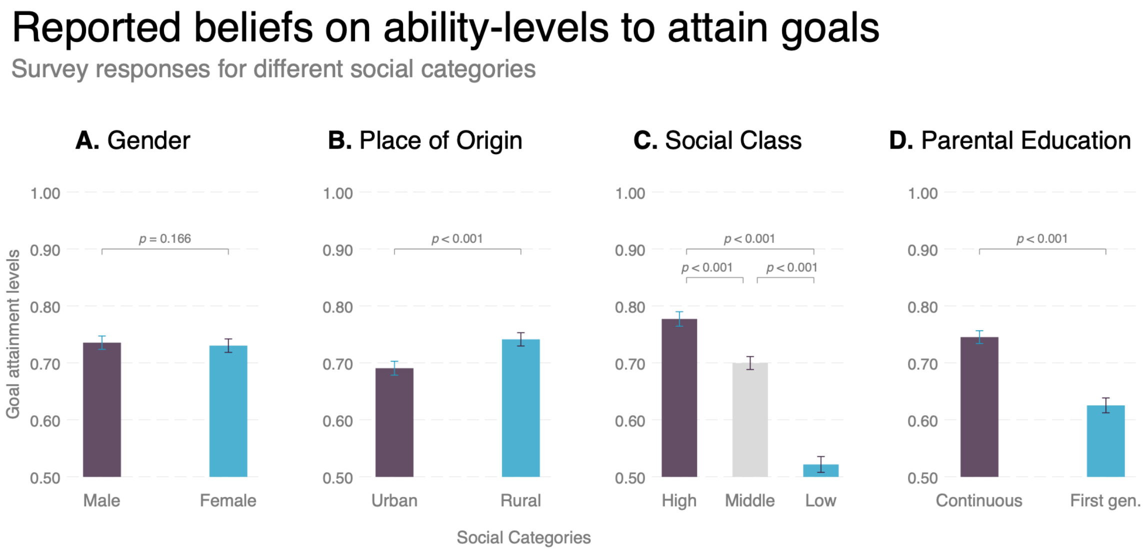

Figure 6 Survey responses on the believed abilities of different social groups.
The figure illustrates the average reported beliefs on the ability different social groups have to attain their goals, normalized between 0 and 1.

A summary of the survey results is illustrated in Figure 6, showing that beliefs vary widely across social groups. There are practically no reported differences between males and females (73.5% vs. $73\%, p = 0.917$), rural students are expected to be much better than those from urban origins (69.1% vs. $74.1\%, p < 0.001$), and those from middle class are expected to fall between the two other social classes, better than low class (69.9% vs. $52.2\%, p < 0.001$) but worse than high class (69.9% vs. $77.7\%, p < 0.001$). That is, the social expectation towards these groups is either absent, positive or ambiguous,

[29] This is part of an institutional survey conducted by the local partner, which allowed me to include this question. Participants were not incentivized on their responses but instead received a fixed incentive for completing the survey. Due to a programming error the survey did not elicit beliefs on the abilities of ethnic minorities.

respectively. On the contrary, the social expectation is clearly negative for low class students who are believed to be worse than the two other social classes, middle (as shown above) and high (52.2% vs. $77.7\%, p < 0.001$). Similarly, first generation students are expected to be worse than those whose parents hold a college degree (62.5% vs. $74.5\%, p < 0.001$).

An integration of the results from the survey and the heterogeneity analysis allows for a conjecture of why the effect of public targeting could activate image concerns for female, rural, and middle class students, while it may activate positive image views for low class and first generation students (conditional on being high performers). For the latter set of identities, the negative stereotype is strong: they are expected to underperform. Then, by publicly targeting their identities in a setting of high performance, the invitation could be sending a signal of recognition that they have succeeded in overcoming a structural barrier, which can consequently trigger positive image views.

As such, it seems plausible that public targeting may be triggering image concerns that deter take-up and completion, when there are positive (or no clear) stereotypes associated to an identity and/or when an individual's performance is low. However, if the stereotype towards a social group is clearly negative and individuals holding that identity are high performers, public targeting may be triggering positive views, potentially promoting program participation.

5 Conclusions

In this paper, I report the results from a natural field experiment that evaluates how informing individuals that they are invited to an educational program because of the group identities they hold, impacts their take-up and completion of the program. This is motivated by the way institutions and organizations generally make salient the identities of their targeted populations when offering these types of opportunities, as a signal of their commitment to equity and inclusion. I argue that such a strategy may have unintended consequences in some cases, as it could trigger image concerns. To test how different targeting strategies impact targeted populations, I run a field experiment with almost five thousand college students, invite them to take part in an international training program, and experimentally vary how much information is disclosed to them (or others) about selection being based on their group identities.

The main result of this study provides causal evidence that publicly targeting members of disadvantaged groups, by emphasizing that an opportunity is offered to them because of who they are, limits their take-up of such opportunity. This information appears to trigger image concerns associated to accepting an offer based on their demographics. To avoid this image cost, invited individuals may pass on the opportunity.

The implications for policy makers become evident when contrasting the results of public targeting to those of the *no-information* condition: to effectively target disadvantaged groups, program providers could use alternative strategies to guarantee eligibility without explicitly priming the identities of those chosen to receive the offered opportunity. For this, program providers can rely on administrative data to identify their targets. This puts the responsibility of ensuring eligibility on those providing the program and not on the potential beneficiaries, making it unnecessary to explicitly signal to individuals (or third parties) that they are being targeted because of their group identities.

By avoiding any reference to the groups people belong to, they are less likely to feel triggered by the invitation and more likely to see how beneficial the opportunity is. This would allow program providers and stakeholders to ensure they are reaching their population of interest and to further their goals of promoting equity and inclusion, without discouraging their targets from taking up the opportunities offered.

A potential trade-off of the proposed strategy is that it may not be best suited for program providers that are unable to access administrative data, or who are constrained to make public the groups they target (e.g., because stakeholders require it). In such cases, however, there is a potential avenue, by using public targeting as a clear signal of success. I explore this suggestive observation at the end of my paper: while the same strategy of public targeting appears to widely trigger image concerns, there are a few cases where it could be promoting positive image views. This suggests that if there is a clearly negative stereotype and individuals are shown to objectively elude it (e.g., low-class high-performing students), public targeting may promote instead of deter program participation.

Further research could advance this through a field experiment where researchers send explicit signals, in the invitation to the program, indicating that targeted individuals are successful in overcoming a clearly negative stereotype associated to their identities. Such a strategy can help explore whether triggering positive image views could help promote take-up. This is beyond the current scope of this project and has the potential to shed light on complementary strategies to increase take-up of beneficial opportunities, when explicit targeting cannot be avoided.

A second potential avenue of research is to evaluate different channels to further motivate take-up, as even without disclosing identity-based selection more than 50% of those invited pass on the opportunity. Future research could vary the channel through which the invitation is sent, by leveraging referrals from those who have taken it before. For example, in my study a total of 1066 participants completed the program. One could invite such a group of participants to *refer* the training program to peers and evaluate how referrals can motivate take-up compared to those invited directly by the university administrators (e.g., in my case the Office of International Relations). These two potential strategies can help complement the findings of this paper and further the agenda of improving take-up of beneficial opportunities for those individuals who need it the most.

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Online Appendix:
Publicly targeting by group identities limits take-up of educational opportunities

Manuel Munoz

A Invitation Emails

The invitation message below was sent to all eligible students. The original email was sent in Spanish by the Office of International Relations of the local university. I include below the English translation (by the autor). 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 and further develop the necessary tools to achieve their goals and increase their chances of personal and professional success (you can see details of the program at the end of this message).

This great opportunity provides multiple benefits. First, being able to learn from excellent professors. Second, by completing the program 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 program there will be a lottery of various iPads among those who complete the program, with the aim of giving students a tool that may help them in their academic endeavors.

- NO INFO: You have been chosen among all students at the university because you can benefit from this program, as your cumulative GPA is [Student's GPA].
- PRIVATE INFO or PUBLIC INFO: You have been chosen among all students at the university because you can 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).

In order to register for the program 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 program. 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] endorse student [Your Name] to take part in the training program "How to change: scientific tools to achieve the goals in your personal and professional life", because he/she can benefit from this program, as his/her cumulative GPA is [Student's GPA].
- PUBLIC INFO: I, [Professor's name] endorse student [Your Name] to take part in the training program "How to change: scientific tools to achieve the goals in your personal and professional life", because he/she can 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 faculty member 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 endorsement.

Additional information about the program:

- Name: "How to change: scientific tools to achieve the goals in your personal and professional life".
- Instructor(s): The program 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 program 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 lottery 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 program.

Sincerely,

[Signature]

Head / Office of International Relations

B Regression on take-up and completion rates

In this section, I reports OLS regressions with robust standard errors (in parenthesis) to complement the results from the proportion tests presented in the main text. Table B-1 reports outcomes pooling both performance groups. Table B-2 focuses only on high performance students (i.e., first wave). Table B-3 looks at results for low performers (i.e., second wave). As not all administrative profiles were complete, there are missing observations on at least one of the main demographic variables used as controls. To complement the analysis, I imputed the data replacing missing observations with the average value for each variable. For all three tables, the dependent variable is the rate of take-up in columns **I-II**, the completion rate in columns **III-IV**, and the number of completed steps (where take-up is step 1 and the 9^{th} session is step 10) in columns **V-VI** unconditional on take-up, and in columns **VII** and **VIII** conditional on it. In all regressions, targeting is a categorical variable for which NO INFO is the omitted category. Regressions in columns **II**, **IV**, **VI** and **VIII** include dummies for the targeted social categories as controls: female, low-middle class, rural, ethnic, and first generation. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

Table B-1 The effects of information disclosure on participation

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the rate of take-up in columns I-II, the completion rate in columns III-IV, and the number of completed steps (where take-up is step 1 and the 9^{th} session is step 10) in columns V-VI. In all regressions, targeting is a categorical variable for which *No Info* is the omitted category. Regressions in columns II, IV and VI include dummies for the targeted social categories as controls: female, low-middle class, rural, ethnic, and first generation. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Take-up		**Completion**		**Completed steps** *Unconditional*		**Completed steps** *Conditional*	
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
PUBLIC INFO	-0.071^{***}	-0.074^{***}	-0.044^{***}	-0.045^{***}	-0.528^{***}	-0.544^{***}	0.275	0.275
	(0.016)	(0.016)	(0.015)	(0.015)	(0.148)	(0.147)	(0.194)	(0.195)
PRIVATE INFO	-0.037^{**}	-0.040^{**}	-0.021	-0.023	-0.307^{**}	-0.324^{**}	0.024	0.046
	(0.016)	(0.016)	(0.015)	(0.015)	(0.151)	(0.150)	(0.199)	(0.198)
Constant	0.328^{***}	0.230^{***}	0.243^{***}	0.170^{***}	2.753^{***}	1.938^{***}	8.392^{***}	8.499^{***}
	(0.012)	(0.029)	(0.011)	(0.026)	(0.109)	(0.263)	(0.136)	(0.352)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
# Obs.	4831	4831	4831	4831	4831	4831	1407	1407
R^2	0.004	0.025	0.002	0.014	0.003	0.020	0.002	0.004
p-values of differences								
NO INFO VS. PRIVATE INFO	0.030	0.028	0.112	0.110	0.126	0.124	0.210	0.252

Table B-2 The effects of information disclosure on participation of high performers

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the rate of take-up in columns I-II, the completion rate in columns III-IV, and the number of completed steps (where take-up is step 1 and the 9^{th} session is step 10) in columns V-VI. In all regressions, targeting is a categorical variable for which *No Info* is the omitted category. Regressions in columns II, IV and VI include dummies for the targeted social categories as controls: female, low-middle class, rural, ethnic, and first generation. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Take-up		**Completion**		**Completed steps** *Unconditional*		**Completed steps** *Conditional*	
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
PUBLIC INFO	-0.073^{***}	-0.076^{***}	-0.034	-0.036^{*}	-0.479^{**}	-0.503^{**}	0.392^{*}	0.382
	(0.023)	(0.023)	(0.022)	(0.022)	(0.220)	(0.219)	(0.234)	(0.236)
PRIVATE INFO	-0.048^{**}	-0.048^{**}	-0.020	-0.020	-0.360	-0.357	0.128	0.152
	(0.024)	(0.023)	(0.022)	(0.022)	(0.221)	(0.219)	(0.242)	(0.240)
Constant	0.412^{***}	0.365^{***}	0.305^{***}	0.268^{***}	3.466^{***}	3.057^{***}	8.417^{***}	8.485^{***}
	(0.017)	(0.043)	(0.016)	(0.041)	(0.159)	(0.408)	(0.168)	(0.420)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
# Obs.	2561	2561	2561	2561	2561	2561	950	950
R^2	0.004	0.035	0.001	0.018	0.002	0.026	0.003	0.010
p-values of differences								
NO INFO VS. PRIVATE INFO	0.290	0.215	0.519	0.441	0.585	0.496	0.268	0.332

Table B-3 The effects of information disclosure on participation of low performers

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the rate of take-up in columns I-II, the completion rate in columns III-IV, and the number of completed steps (where take-up is step 1 and the 9^{th} session is step 10) in columns V-VI. In all regressions, targeting is a categorical variable for which *No Info* is the omitted category. Regressions in columns II, IV and VI include dummies for the targeted social categories as controls: female, low-middle class, rural, ethnic, and first generation. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Take-up		**Completion**		**Completed steps** *Unconditional*		**Completed steps** *Conditional*	
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
PUBLIC INFO	-0.068^{***}	-0.068^{***}	-0.054^{***}	-0.054^{***}	-0.571^{***}	-0.569^{***}	0.001	0.015
	(0.021)	(0.020)	(0.018)	(0.018)	(0.185)	(0.184)	(0.349)	(0.354)
PRIVATE INFO	−0.026	−0.026	−0.023	−0.023	−0.255	−0.259	−0.184	−0.187
	(0.021)	(0.021)	(0.019)	(0.019)	(0.193)	(0.192)	(0.348)	(0.350)
Constant	0.233^{***}	0.131^{***}	0.172^{***}	0.103^{***}	1.947^{***}	1.146^{***}	8.343^{***}	8.588^{***}
	(0.016)	(0.035)	(0.014)	(0.031)	(0.141)	(0.312)	(0.233)	(0.638)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
# Obs.	2270	2270	2270	2270	2270	2270	457	457
R^2	0.005	0.022	0.004	0.014	0.004	0.018	0.001	0.004
p-values of differences								
NO INFO VS. PRIVATE INFO	0.033	0.034	0.078	0.083	0.076	0.080	0.616	0.587

C Selection faculty

1. Explain why students may hold beliefs (even if incorrect) that faculty members may be biased against certain groups (or against students who request such resources), then we would expect fewer students to sign up for the program as they fear retaliation.

D Program evaluations - Anticipated and experienced benefits

In this Appendix, I report [i] on anticipated benefits from the program, as measured in an online experiment with a separate sample of students, and [ii] on program evaluations participants filled out at the end of the training program (Section D.2), and

D.1 Online experiment - Perceived course benefit

The online experiment was composed by three parts. Part 1 collects demographics. I use gender and social class to block randomize students into treatments in Part 2. Part 2 presented the information of the program and elicited the personal valuation. Participants who completed this section could earn a fixed bonus. Part 3 is a belief elicitation stage and depending on accuracy, participants could earn an additional bonus. *Below I include the main text and items of the questionnaire translated to English (by the author), as the original survey was conducted in Spanish.*

The questionnaire

PART 1

The first 5 questions are about you.

- What is your gender? *[male-female]*
- To what socio-economic strata does your family belong to? *[stratum 1 to stratum 6]*
- What is the highest education level (degree) completed by your father? *[Elementary/ Highschool/ Technical/ Undergraduate/ Graduate/ Not applicable]*
- What is the highest education level (degree) completed by your mother? *[Elementary/ Highschool/ Technical/ Undergraduate/ Graduate/ Not applicable]*
- What is your cumulative grade point average? (if you don't remember exactly, gives us your best guess)

PART 2

To answer the following question, you will need to watch a short video (below 2 minutes).

This video describes the international training program that we want to offer some students at [local university], in alliance with [international university].

Attention: *The video has audio. Please turn the volume up or use headphones.*

[page break]

Please watch the following video carefully.
If you are using a cellphone, turn it horizontally to watch the video better.

[page break]

If you were selected to participate in the program, you would get the following invitation:

[NO INFO treatment]

"You have been chosen among all students at the [local partner university] because you can benefit from this program, as you have a cumulative GPA of [student GPA]."

[INFO treatment]

"You have been chosen among all students at the [local partner university] because you can benefit from this program, as you have a cumulative GPA of [student GPA], and because you fulfill one of the following requirements... [COMPLETE!]"

- How much value, utility or benefit would the course have for you?

  Answer using a scale between 0 and 10, where 0 means "Very low value, utility or benefit" and 10 means "Very high value, utility or benefit" [0-10]

[page break]

You have completed your participation in this survey and will be included in the lottery to get one of the monetary bonuses.

You can end your participation here. But, you also have the chance to participate in an additional lottery for another bonus of 50 thousand pesos, if you answer to 9 multiple-choice questions about your beliefs regarding the course.

Among those who respond to the 9 additional questions, we will randomly allocate ten monetary bonuses of 50 thousand pesos. So you can participate independently in two lotteries **and may win up to 100 thousand pesos**.

if you want to participate click on **Continue**. If you want to conclude your participation here, choose **End**.

[page break]

PART 3

More than one thousand students at [local university] have completed the training program, and to all of them we have asked them to indicate how the rate the course, using the following options: Excellent, Good, Adequate, Deficient, Very Deficient.

We want to know your opinion about the valuation that 9 groups of students gave to the course. For each of these groups, please indicate which of the options you believe was chosen by most people.

If you are chosen for the lottery, the computer will randomly choose one of your 9 answers. If the option you indicate is the one that most participants in the course used for their evaluation, **you will win one of the 10 additional bonuses of 50 thousand pesos**.

- Which do you think is the course evaluation that was chosen by most **male** students?
- Which do you think is the course evaluation that was chosen by most **female** students?
- Which do you think is the course evaluation that was chosen by most **low SES (strata 1 and 2)** students?
- Which do you think is the course evaluation that was chosen by most **middle SES (strata 3 and 4)** students?
- Which do you think is the course evaluation that was chosen by most **high SES (strata 5 and 6)** students?
- Which do you think is the course evaluation that was chosen by most **first generation** (neither of their parents holds a college degree) students?
- Which do you think is the course evaluation that was chosen by most **continuous generation** (at least one of their parents holds a college degree) students?
- Which do you think is the course evaluation that was chosen by most students **from rural areas**?
- Which do you think is the course evaluation that was chosen by most students **from urban areas**?

D.2 Program evaluations

At the end of the training, participants were asked to complete an evaluation of the program. 1063 of 1066 (99%) who completed the training filled out the evaluation: 734 in the first wave (High GPA) and 329 in the second wave (Low GPA). I include the main text and items of the questionnaire translated to English (by the author), as the original one was conducted in Spanish in Section D.2. Then, I report results from a comparative analysis between program waves in Section D.2.

The questionnaire

Please answer to the following questions according to your own experience. There are no right or wrong answers.

- What is your general evaluation of the program?

  [Excellent (5), Good (4), Adequate (3), Deficient (2), Very deficient (1)]

- The program objectives were clearly stated.

  [Strongly agree (5), Agree (4), Neutral (3), Disagree (2), Strongly disagree (1)]

- The program was well organized.

  [Strongly agree (5), Agree (4), Neutral (3), Disagree (2), Strongly disagree (1)]

- The program was intellectually stimulating.

  [Strongly agree (5), Agree (4), Neutral (3), Disagree (2), Strongly disagree (1)]

- The program helped me improve my thinking.

  [Strongly agree (5), Agree (4), Neutral (3), Disagree (2), Strongly disagree (1)]

- What is your general evaluation of the online sessions?

  [Excellent (5), Good (4), Adequate (3), Deficient (2), Very deficient (1)]

- What is your general evaluation of the instructor?

  [Excellent (5), Good (4), Adequate (3), Deficient (2), Very deficient (1)]

- The instructor encourages learning.

  [Strongly agree (5), Agree (4), Neutral (3), Disagree (2), Strongly disagree (1)]

Note: There were three additional *open* questions, which I do not analyze here. The questions were "*In what ways did the instructor help you learn?*", "*Which aspects of the course were most valuable to you?*", and "*Which aspects of the course were least valuable to you?*"

Differences in program evaluations

Below I report descriptives of the program evaluations as well as regression analysis by wave of the program.

Table D-1 Program evaluations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Public	-0.082	0.037	0.061	-0.021	0.061	-0.044	-0.005	0.004
	(0.075)	(0.071)	(0.064)	(0.088)	(0.085)	(0.085)	(0.078)	(0.086)
Private	-0.051	-0.012	-0.006	-0.099	0.058	0.059	0.012	-0.026
	(0.070)	(0.058)	(0.066)	(0.081)	(0.078)	(0.074)	(0.074)	(0.081)
High gpa	-0.063	0.011	0.015	-0.039	0.017	-0.019	-0.012	-0.004
	(0.055)	(0.048)	(0.055)	(0.066)	(0.069)	(0.066)	(0.059)	(0.067)
Public # High gpa	0.130	0.026	0.009	-0.000	-0.007	0.125	0.046	0.088
	(0.089)	(0.081)	(0.075)	(0.105)	(0.101)	(0.100)	(0.091)	(0.101)
Private # High gpa	0.083	-0.009	0.008	0.102	-0.097	-0.040	-0.031	0.066
	(0.086)	(0.071)	(0.079)	(0.098)	(0.094)	(0.091)	(0.089)	(0.098)
Constant	4.709***	4.732***	4.709***	4.603***	4.528***	4.571***	4.709***	4.567***
	(0.042)	(0.039)	(0.046)	(0.053)	(0.058)	(0.056)	(0.049)	(0.055)
Observations	1063	1063	1062	1062	1062	1062	1063	1061
R^2								

Table D-2 Program evaluations controlling for identity groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Public	0.013	0.054	0.065*	-0.019	0.064	0.045	0.024	0.062
	(0.041)	(0.035)	(0.034)	(0.048)	(0.046)	(0.045)	(0.040)	(0.045)
Private	0.012	-0.022	-0.003	-0.029	-0.005	0.030	-0.015	0.012
	(0.041)	(0.034)	(0.037)	(0.046)	(0.044)	(0.043)	(0.041)	(0.046)
High gpa	0.002	0.019	0.016	-0.002	-0.008	0.005	-0.008	0.045
	(0.036)	(0.032)	(0.032)	(0.042)	(0.040)	(0.040)	(0.037)	(0.041)
Female	-0.052	0.019	0.019	0.034	0.065	0.024	0.104***	0.095**
	(0.035)	(0.032)	(0.033)	(0.044)	(0.042)	(0.041)	(0.039)	(0.044)
Mid-low class	0.138**	-0.032	-0.007	0.036	0.060	0.014	0.072	-0.044
	(0.063)	(0.047)	(0.046)	(0.065)	(0.067)	(0.059)	(0.062)	(0.060)
Rural	0.013	-0.040	-0.018	-0.013	0.063	-0.008	-0.001	0.009
	(0.037)	(0.031)	(0.032)	(0.042)	(0.039)	(0.039)	(0.037)	(0.040)
First generation	-0.041	0.002	-0.004	-0.103**	-0.098**	-0.028	0.017	0.005
	(0.042)	(0.035)	(0.036)	(0.050)	(0.046)	(0.045)	(0.041)	(0.044)
Ethnic minority	-0.185	0.165***	-0.088	0.008	0.214***	0.026	0.063	0.134
	(0.154)	(0.062)	(0.094)	(0.100)	(0.080)	(0.109)	(0.082)	(0.092)
Constant	4.583***	4.751***	4.711***	4.544***	4.434***	4.533***	4.565***	4.502***
	(0.075)	(0.058)	(0.061)	(0.083)	(0.086)	(0.078)	(0.076)	(0.081)
Observations	1063	1063	1062	1062	1062	1062	1063	1061
R^2								

D.3 Additional results: beliefs vs. actual program evaluations

E Online survey - Beliefs on goal attainment by social group

E.1 The questionnaire

Below I include the main text and items of the questionnaire translated to English (by the author), as the original survey was conducted in Spanish. These items were included as a section in a larger survey conducted by the university in Colombia.

Next you will answer a short questionnaire.

We will ask you to indicate, in your opinion, what is the probability (between 0 and 100) that different groups of people attain the goals they set for themselves.

For example, if we asked you for **the probability that astronauts attain the goals they set for themselves** and you answer 0, you are indicating that in this group no one ever attains they goals they set. On the other extreme, if you answer 100, you are indicating that everyone in this group always attains their goals they set.

What is the probability that each group of people, in general, attain the goals they set?

**The different options were displayed in random order.*

- Males
- Females
- People from strata 1 or 2
- People from strata 3 or 4
- People from strata 5 or 6
- People who left their city to go to college
- People who attended college in their city
- People whose parents went to college
- People whose parents did not go to college

F Details and deviations from the Pre-registration

1. This project clearly used a lot of personal data (potentially sensitive, eg.g., ethnicity), and by design presumably did not involve informed consent of the participants. There seems to be likely harms stemming from the treatments. Has an IRB approved this project, and what measures were taken to protect the vulnerable subjects?

2. Power calculations?

3. Adjustments to p-values for multiple hypotheses testing?