Publicly targeting disadvantaged groups triggers stigma and limits take-up of educational opportunities

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Abstract

I investigate the unintended consequences of publicly informing individuals from disadvantaged groups that their selection for a beneficial opportunity, such as an educational program, is based on their group identity. In a field experiment in collaboration with a Colombian university, I target 4831 disadvantaged 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 effectively targeting disadvantaged groups without discouraging their take-up of beneficial opportunities.

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

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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, up-skilling

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for immigrants, funding for low-income students).[1] To reach their objective audience, such programs usually follow the strategy of publicly emphasizing the identities of the groups they target. 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 promote pride and increase chances of take-up of the offered opportunity (see e.g., Butera et al. 2022).[2] However, publicly informing individuals that they are targeted because of their group identities could have unintended consequences. If individuals believe they will be stigmatized for accepting an opportunity offered to them because of their demographics, strategies of public targeting may backfire. 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 disadvantaged 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 field experiment designed to evaluate how disclosing to individuals that they are chosen for an educational program because of their group identities impacts their choice to accept the offered opportunity. In partnership with a university in Colombia, I designed an educational program aimed at developing non-cognitive skills and offered it exclusively to students holding social categories that were previously identified as being in academic disadvantage: female, low and middle social class,[3] first generation, rural origins or ethnic minority. A total of 4831 students holding at least one of the identified categories received a personalized invitation email to the program.

The content of the invitation varies between treatments, as the information about 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 standard approach used by most program providers, where targets as well as third par-

[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] Bearson and Sunstein (2023) define take-up as receiving a benefit for which and individual is eligible, and take-up rate as the fraction of those eligible for a benefit who participate and receive the benefit.

[3] In Colombia, social stratification follows a six-number ranking assigned by the central government to households, which increases with the quality of the dwelling and its surroundings. It is used to define income situation 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. Individuals from low-middle social class are those from the lower strata in the ranking (see e.g., Bogliacino et al. 2018).

ties are informed that the program is offered to specific individuals because of who they are. When this is publicly revealed, it can activate *stigma* concerns on those targeted. 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, turning off any concerns about stigmatization.[4] 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 personal and social stigma.

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. In total, 1407 invited participants (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 motivate individuals from disadvantaged social groups to feel recognized and included. Instead, it has a stigmatizing effect that negatively impacts their willingness to take-up the offered opportunity. Similar effects are also 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 can hurt instead of help the social groups that are being targeted. In complement to the main result, the comparisons with the PRIVATE INFO treatment show that both forms of stigma, personal and social, can be triggered and play a role in limiting program participation.

The welfare implications of my study go beyond program participation. One year after the program was offered, the grade point average (GPA) of those who completed it increased by 0.06 standard deviations above those who were invited but did not partic-

[4] Moffitt (1983) defines stigma as a form of disutility that results from the decision to participate in a program, which can be *personal* and expressed as negative self-characterization or *social* and expressed as negative characterizations by others. This is also closely related to self-image concerns and social image concerns as defined in Bursztyn and Jensen (2017).

ipate. In complement, more than 90% of the participants who completed the program reported that it was intellectually stimulating and helped them improve their way of thinking. Thus suggesting that the negative consequences of public targeting also impacted academic performance and well-being.

I further explore the implications of the main results by looking at heterogeneous treatment effects across the different groups targeted to the program. 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). Similarly, every single category targeted (i.e., female, rural residents, middle-class, low-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 who have 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 stigma or pride.

To evaluate this potentially positive effect of public targeting, 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. So, explicitly targeting their identities while highlighting their high academic performance sends a strong signal that they have overcome an expected structural barrier. This acknowledgement of successfully overcoming a clearly negative expectation can trigger pride instead of stigma, which is not 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.

A natural challenge with informational experiments in the field is that of spillover effects between individuals assigned to different treatments. This poses the question of whether the negative impact on program participation arises from disclosing that selection is based on demographics (treatment effects) or from peers revealing to each other that they received different versions of the invitation email (spillover effects). To elucidate which effect is present, I use comprehensive administrative records on university courses to build a co-enrollment network of peer influence among all individuals invited to the program. Analysis of this network reveals that the number of peers invited to the program does not affect program take-up, irrespective of the information they received. This result supports the evidence that the negative effects on program participation in my study are predominantly driven by public targeting.

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. Some of the most prominent findings show that on top of standard 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 concerns about social stigma for taking-up the offered program (see e.g., Moffitt 1983).

Building upon these findings, my work delves into the unintended consequences of a common strategy employed by program providers— publicly targeting specific populations. I provide causal evidence that such public targeting, fundamentally a priming strategy, can impose psychological costs on potential participants, leading to lower take-up rates.[5] Specifically, my results reveal that priming natural identities triggers stigma concerns, hindering program participation (i.e., take-up and completion). This strategy, despite its widespread use, consistently affects individuals with different levels of performance as well as individuals belonging to a wide array of social groups, by activating stereotypes that threaten their identities (Steele and Aronson 1995; Shih et al. 1999, 2006; Fryer et al. 2008). Complementing existing evidence on the impact of potentially stigmatizing opportunities, my study underscores that informing individuals about the beneficial opportunity tied to their group identities can induce concerns of being stigmatized, negatively affecting both program take-up and completion.[6]

The policy implications of the main findings are as follows: while emphasizing iden-

[5] For a review on the literature on priming natural identities see Charness and Chen (2022).

[6] For related work on the role of image concerns in driving behavior see Bursztyn and Jensen (2015, 2017); Bursztyn et al. (2020); DellaVigna et al. (2012, 2017).

tities can be effective in some contexts as a tool of public recognition that showcases organizational commitment, this is not always applicable when extending opportunities to members of disadvantaged groups.[7] The public targeting of individuals may inadvertently trigger concerns for personal and social stigma, 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 psychological 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. 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.[8]

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 reports on mechanisms and the heterogeneity analysis of the different groups targeted. Section 5 concludes the paper.

2 The experiment

2.1 Selection of participants

This project is the result of a partnership I established with Universidad Autónoma de Bucaramanga (UNAB), a private university in Colombia with about 10000 students

[7] 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., Pope et al. (2018); Boring and Philippe (2021); Alesina et al. (2023).

[8] 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 disadvantaged category in the invitation message.

coming from a diverse set of backgrounds (see Cardenas et al. 2021).[9] This allowed me to access a rich set of administrative data that included academic records and socio-demographic characteristics of students from multiple cohorts, to identify which social groups were most disadvantaged academically. The aim of the partnership is to support students from disadvantaged social groups, and subjects belonging to such social groups were invited to participate in an educational program to help them develop skills to better attain their goals.

Identification of disadvantaged social groups. To identify which social groups were at a disadvantage on academic performance, I used administrative data on entry exam scores for 12 cohorts between 2016 and 2022 ($n = 8339$)[10] and tested differences in performance, as illustrated in Figure 1 (see details in Appendix A). The results from this process revealed which categories were consistently in disadvantage, with respect to their relevant comparison within a social group: females (vs. males), low-middle social class (vs. high class), first generation (vs. continuous education), rural (vs. urban), and ethnic minorities (vs. non). Individuals from these categories enter university with lower scores, on average, than their peers. Based on these findings, those holding at least one of these social categories were eligible for the program.

Selection of eligible participants for the educational program. Participation in the program was by invitation only, which were sent exclusively to eligible students. To determine eligibility, I used administrative data to filter out any student who did not hold at least one of the social categories previously identified as disadvantaged. Then, using academic records, I divided chosen students into two groups of high and low performers. As a requirement of the partner university, invitations were sent in two separate waves during the fall and spring semesters of one same academic year. In the first wave only students with a high GPA were targeted, and in the second wave were those with

[9] In Colombia, the socio-demographic composition of the student body differs greatly between private and public universities. Public universities are almost exclusively for low income students because tuition fees are a function of family income and 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, so they reach students from all social classes. An exception are the few private elite universities, which are mostly for students from high income families (see Londono-Velez 2022). The partner university is private but not considered elite.

[10] Since 2015, all high-school students in Colombia take a standardized national exam before they graduate. The exam is divided into five areas: mathematics and logic, critical reading skills, natural sciences, social sciences, and English as a second language. Each area is scored between 0 and 100. The scores in the exam determine eligibility to access different universities, where cutoffs can also vary by program (see Bernal and Penney 2019).

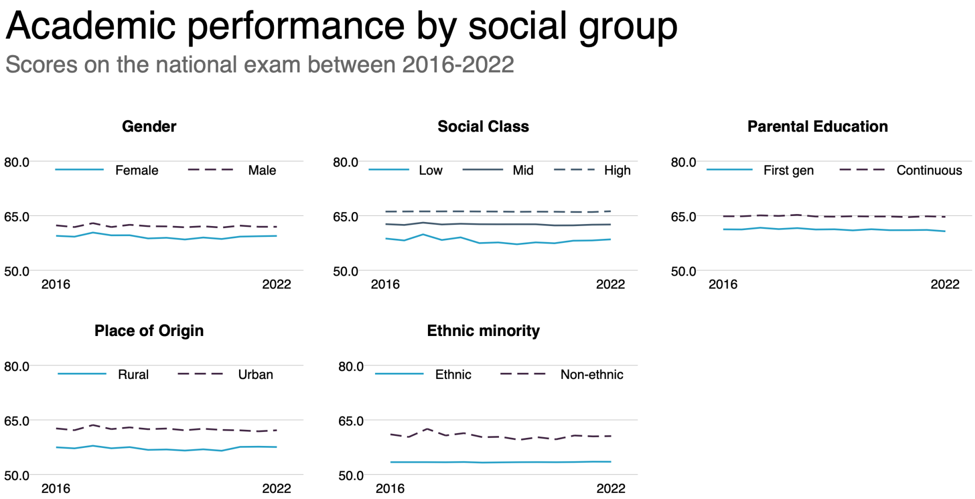

Figure 1 Performance in the national exam by social groups between 2016-2022.
The figure illustrates the trends of scores in the national exam students take at the end of high-school to enter university, for different social groups in each panel, and separately for each social category within a group. The score of the national exam is a value between 0 and 100.

a low GPA.[11]

2.2 Features of the offered educational program

The educational program centers around *goal pursuit* and aims to help students develop non-cognitive skills to better attain the goals they set for their personal and professional lives.[12] 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.[13] I put together a bundle of attractive features to increase the incentives to participate.

In terms of reducing participation costs, the invitation is personalized and explicitly states that the student already has a guaranteed slot in the program, thus eliminat-

[11] 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 B for details).

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

[13] 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.

ing 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. 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.[14] Finally, there are multiple computer rooms as well as free wifi on campus, solving any impediments to access equipments or the internet.[15]

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 CVs.[16] In addition, there was a lottery of monetary bonuses and 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.

[14] 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).

[15] At the time the first wave of the program was launched in 2022, all COVID 19 restrictions had been already lifted up on campus and classes were back in person.

[16] 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 the name: "How to change: scientific strategies to achieve the goals in your personal and professional life."

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 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. All communications were sent to the students' institutional email addresses, as these accounts are regularly used by faculty to send information from courses students 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 university was offering an educational program to help them better set and achieve goals in their personal and professional life. 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 B), a randomly chosen set of students received the following message:

> The workshop has a limited number of slots and 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:

> The workshop has a limited number of slots and 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. This is designed to evaluate the effects of potentially triggering stigma concerns on take-up and completion. For those who received the shorter message, the role played by their social identities was not disclosed.

Across treatments, the invitation email also informed students that to register to the program, they had 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, and thus to allow for the potential triggering of social stigma concerns. 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 workshop "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].

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 workshop "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 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 outcomes of program participation. 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).

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. These variations in information disclosure allow me to *turn-off* or *trigger* different stigma concerns that may impact take-up and completion rates. I run the field experiment in two separate waves, and in each I target students with different *academic performance*. This allows me to explore the impact of public targeting on individuals who either confirm (low) or elude (high) the label of "academic disadvantage" that may be associated with their group identities. 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 the main variations in information disclosure of the selection criteria (top). It also reports the sample sizes for each experimental treatment, separately for the high and low performance groups (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

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

PUBLIC INFO: targeted individuals 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. Therefore, PUBLIC INFO aims to activate concerns for both personal and social stigma.

PRIVATE INFO: targeted individuals are informed they are invited because of their demographics, as with PUBLIC INFO. However, the third-party endorsers do not receive any information of selection being based on demographics. As such, PRIVATE INFO aims to activate concerns for personal stigma but not social stigma.

NO INFO: targeted individuals are also selected because of their demographic characteristics, the same as with PUBLIC INFO and PRIVATE INFO, but neither the targets nor the endorsers are informed of this. All information provided avoids stating that invitations are based on group identities. Therefore, NO INFO does not activate concerns for stigma.

2.5 Sample

Table 2 Sample balance across experimental conditions

Columns I-III and V-VII report the average frequency of each social category, 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	

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 following categories: female, low-middle social class, rural, first-generation and ethnic (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. They had 5 weeks to complete all 9 sessions of the program.

2.6 Hypotheses

To generate the hypotheses that I test in the field experiment, I adapt the framework from Bursztyn and Jensen (2017) to my setting. I focus on the potential impact of public targeting the identity of those invited to the program has on their choice to participate in it. The framework develops a random utility model where an individual participates in the educational program based on whether the (unobserved) net utility is positive or negative. Specifically, there is a latent variable $\tilde{a}_i$ capturing the desirability of participating in the program, so that $a_i = 1$ if $\tilde{a}_i \geq 0$ and 0 (no participation) otherwise. The underlying utility is a function of the direct benefits from the program, B, the costs of participating, C, the identity-related consequence of public targeting, ϕ_i, and a random variable ϵ_i:

$$\tilde{a}_i = B - C + \phi_i + \epsilon_i \tag{1}$$

As the direct benefits and costs of participating in the program are maintained constant across participants (see Section 2.2), the main interest in my case is on the role of ϕ_i.

If disclosing that selection is contingent on demographics helps individuals feel publicly recognized and valued, then $\phi_i > 0$. In this case, public targeting works as a channel to trigger pride and motivate program participation compared to a setting that conceals this information (see e.g., Butera et al. 2022). This aims to capture the standard approach followed by program providers and leads to the following null hypothesis:

Hypothesis 0 ***(Pride)***. *If informing individuals that they are chosen for a program because of their demographics triggers pride, disclosure would positively impact participation compared to a setting where this information is concealed.*

H0 conjectures that both take-up and completion rates will be higher in the PUBLIC INFO condition than in the NO INFO condition.

Public targeting could instead threaten the identity of those invited to the program by triggering stigma concerns, both personally and socially. In such case there would be a psychological cost associated with being stigmatized: $\phi_i < 0$. To avoid experiencing stigma and incurring in the cost it brings, invited participants may choose not to take-up the opportunity. Program participation would then decrease compared to a no-information setting (i.e., $\phi_i = 0$). This leads to the following alternative hypothesis:

Hypothesis 1 ***(Stigma)***. *If informing individuals that they are chosen for a program because of their demographics triggers stigma, disclosure would negatively impact participation compared to a setting where this information is concealed.*

In contrast to the null hypothesis H0, the alternative hypothesis H1 conjectures that the NO INFO condition will be superior to PUBLIC INFO, by increasing take-up and completion rates. Irrespective of whether public targeting triggers pride (H0) or stigma (H1), participation rates in PRIVATE INFO are expected to fall between the two other information conditions.

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 educational 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 D, I report regression outputs estimating the linear probability of take-up/completion while controlling for the different targeted 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).

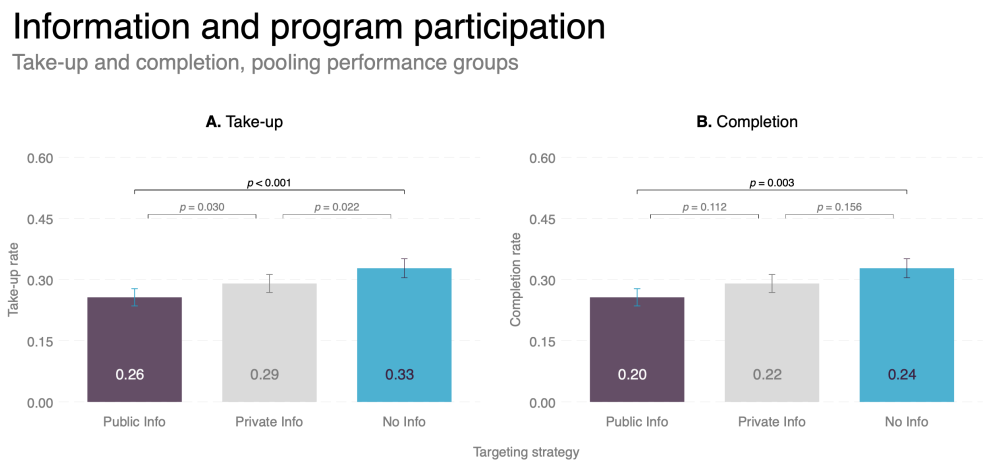

Figure 2 Take-up and completion rates by information condition.
The figure pools together high and low performance groups to illustrate the main effects of how variations in information disclosure impact take-up (Panel A) and completion (Panel B). Values inside the bars display average rates of take-up/completion. 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 2.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.[17] Moreover, as shown in Figure 2.B, the effect is also observed for completion

[17] Ko and Moffitt (2022) shows take-up rates for multiple beneficial opportunities are around 40% or less. 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 educational 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 ($p = 0.003$).[18] Note from the comparison to the PRIVATE INFO condition, that the negative impact on take-up and completion can be attributed to information disclosure triggering both personal and social stigma. I summarize the main finding in Result 1 below:

Result 1 *Informing individuals that they are chosen for a 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.*

The evidence from Result 1 gives support to the alternative Hypothesis 1 on stigma concerns when performance groups are pooled together. Next, I test the effect of information disclosure separately for high and low performers.

3.2 Program participation by performance group

As mentioned above, I conducted the field experiment in two waves that separately targeted high and low performance students. In this section, I evaluate the effect of public targeting for each performance group.

Figure 3 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 patter 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% ($p = 0.003$).[19]

As for the comparison of the main treatments to the PRIVATE INFO condition, Figure 3 illustrates that both concerns for personal and social stigma affect program participation, although the differences are in some cases not statistically significant. Together these results indicate that when targeting individuals for a certain opportunity, explicit

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

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

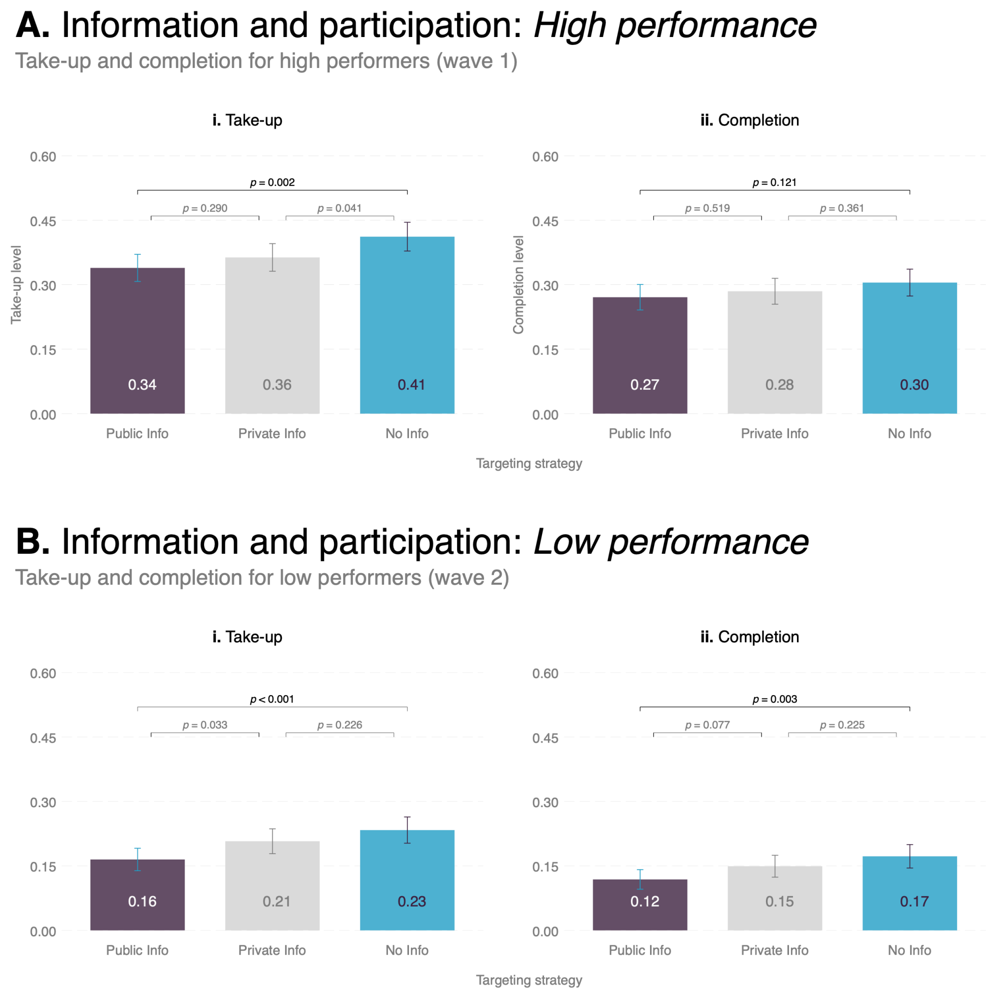

Figure 3 Take-up and completion rates for high and low performance groups.
The figure illustrates how variations in information disclosure impact take-up and completion, separately for the high (3.A) and low (3.B) performance groups. Values inside the bars display average rates of take-up/completion. The p-values report the significance of two-sided proportion tests comparing information conditions.

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 *Informing individuals that they are chosen for a 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

I look in more detail at the effect of public targeting across the entire educational program, by combining take-up and completion into a single metric on the number of steps in the program. Steps go from 1 to 10, where take-up is step 1 and the 9^{th} session is step 10. Figure 4 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 D-1 in Appendix D).

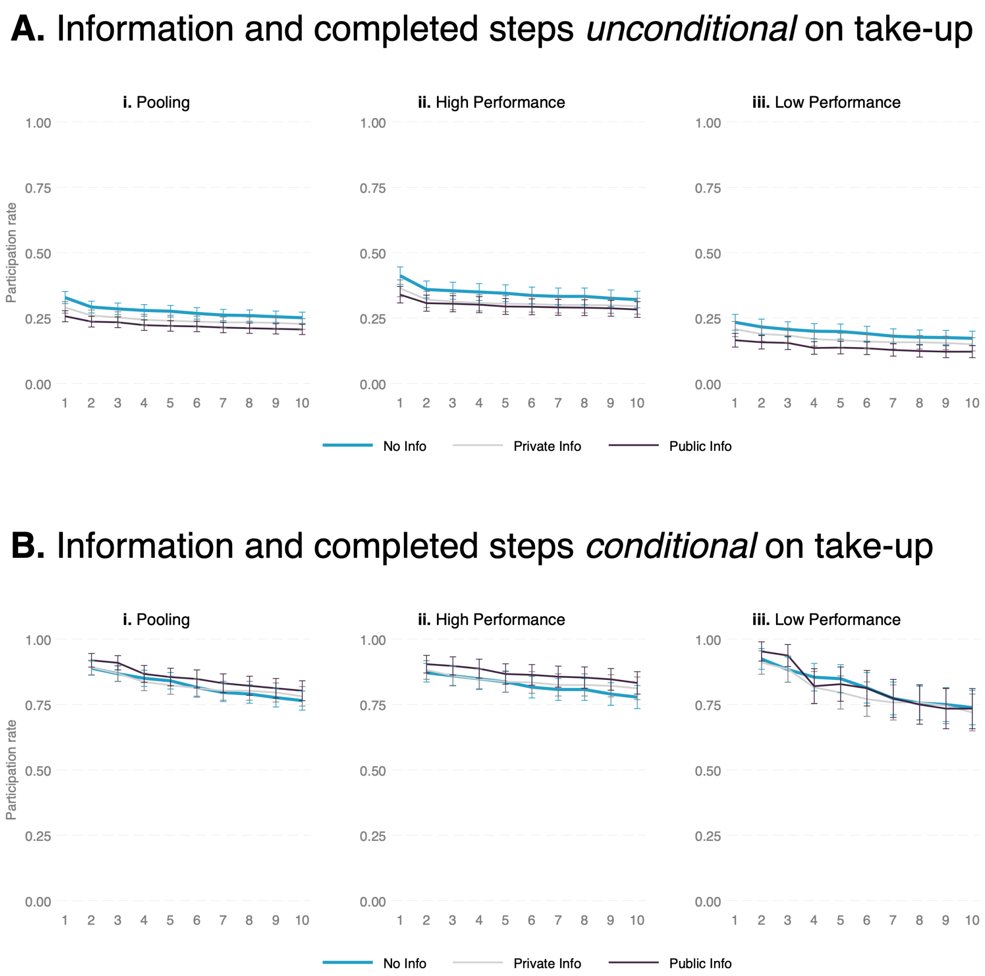

Figure 4 Program completion - number of steps.
The figure illustrates how variations in information disclosure impact the rate of completed steps in the program, unconditional on take-up (Panel A) and conditional on it (Panel B).

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. Once I condition the completion of steps on take-up, there are no additional treatment effects compared to the NO INFO condition: 8.67 steps in NO INFO and 8.39 in PUBLIC INFO ($p = 0.156$).[20] This suggests that those who overcome the negative influence of public targeting and end-up participating in the program are also likely to come back to all sessions and successfully complete it. I summarize this in the following result:

Result 3 *Informing individuals that they are chosen for a 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.*

3.4 Welfare and program participation

Although the current paper is not an evaluation of the program itself but of the targeting to the program, I end this results section by reporting on two measures of the impact the program had, as a way of exploring some of the welfare implications of public targeting: (i) program evaluations and (ii) GPA one year after the program ended.

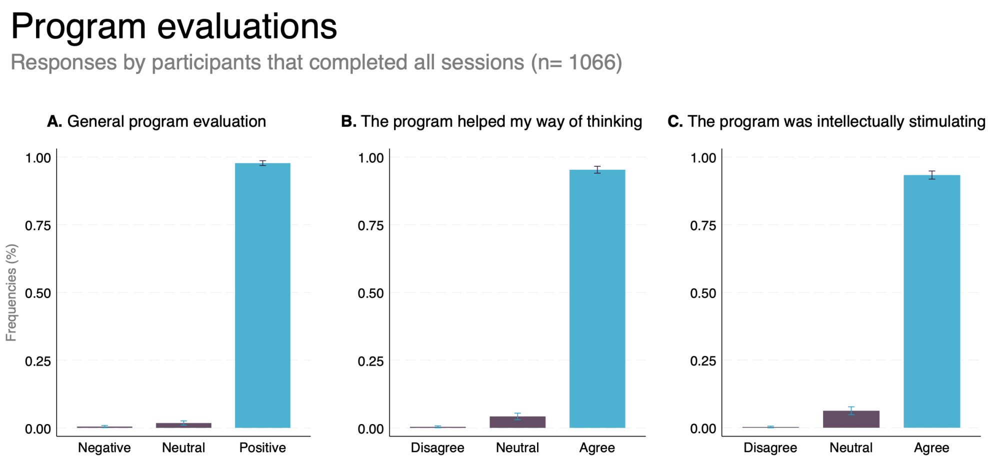

Figure 5 Responses to the program evaluation.
Responses from three measures: general program evaluation (Panel A), the program helped my way of thinking (Panel B), and the program was intellectually stimulating (Panel C).

Figure 5 reports responses to the three most relevant questions from the program

[20] Similar outcomes are observed when examining each performance group separately (see Tables D-2 and D-3 in Appendix D). 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 ($p = 0.967$).

evaluations, to understand the experience of the participants who completed it (for details see Appendix C). 97.8% evaluated the program as positive or very positive, 95.3% agreed and completely agreed that the program helped in their way of thinking, and 93.3% that it was intellectually stimulating. These measures can be understood as reflections of the positive impact the program had on the well-being of those who completed it, and consequently on the benefits that are not accrued for those deterred to participate due to the way the were targeted.

In complement, I follow the academic progression of those invited to the program one year after it was offered and test the difference in the grade point average (GPA) between those who completed the program and those who did not (see Table D-4 in Appendix D). The analysis shows that GPA for those who completed the program increased by close to 0.06 standard deviations above those who were invited but did not participate ($p = 0.003$). This, together with the outcomes on well-being, provide insights on how by deterring individuals from taking-up beneficial opportunities, public targeting can also have negative externalities beyond the direct participation in the program.[21]

In conclusion, the main analysis of the information variations in the experiment 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 helping the best performers among members of disadvantaged groups, as well as when the program focuses on those individuals who confirm the low-performance associations to their social group. 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 and lead to complementary benefits on academic performance and well-being.

In the next section, I dive further into the exploration of the mechanisms driving the

[21] As reported in the regression outputs in Table D-4 in Appendix D, the increase of 0.06 standard is a result for the entire sample. When looking at the effect separately by performance group, it becomes clearer that the positive effect on academic performance is mainly driven by high performers, for the which the increase in GPA is of 0.11 standard deviations ($p < 0.001$). The GPA improvement is, however, very small and not statistically significant for low performers: 0.01 standard deviations ($p = 0.587$).

effects of public targeting.

4 Mechanisms and heterogeneity

In this section, I summarize the results from a series of analyses exploring the mechanisms driving the main finding.[22] I begin by addressing two potential challenges of my design. First, I test if there are spillovers between individuals assigned to different treatments. Second, I test if the choice of not participating could be driven by distastes towards other social groups (see e.g., Oh 2023).

I also explore if there are heterogeneous treatment effects for the social groups invited to the program, and contrast the results from this last analysis with data from a survey eliciting beliefs on the expected abilities of the different social groups. 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.

4.1 Spillovers effects

A potential challenge with information experiments in the field, such as the one I report here, is that there may be spillovers between participants assigned to different treatments. Individuals could communicate with their peers and share that the information they received in the invitation was not the same for all, which may affect participation. In my study, this raises the question of whether the negative impact on program participation arises from disclosing that selection is based on demographics (treatment effects) or from peers revealing to each other that they received different versions of the invitation email (spillover effects).

To elucidate which effect is present, I build a network of peer influence between all the 4831 subjects invited to the program, using academic records on each course they have taken at the university. This dataset can be understood as a bipartite network that connects students to courses. The projection of this network results in a co-enrollment

[22] These analyses are exploratory and were not part of the pre-registration.

network of students connected to students, where a connection between two individuals 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.

This network is valuable to study potential information spillovers because it allows me to identify the connections (presence and strength) between every pair of students invited to the program, as well as the information treatment each was assigned to. That is, for each particular target I map the number of her peers also invited to the program, while differentiating the information each received. On average, students are connected to 76 others, where 33% of those belong to the same treatment (i.e., received the same invitation).

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 0.01, 0.05 and 0.10 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 info			0.006			0.000	
			(0.006)			(0.005)	
Different info				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

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 information spillovers. Using a binary measure of connectivity, i.e. a connection is either present or absent, I find that the number of peers invited does not have a negative 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 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 result 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 spillovers affecting the decision to take-up the program, which supports the evidence that limitations in program participation are predominantly driven by public targeting. If anything, although not statistically significant, the analysis of the network of peer influence suggests that having peers invited to the program could, instead, have a potentially motivating effect on take-up. [23]

4.2 Distaste towards other social groups

A second potential challenge in the interpretation of the main results is that people not holding some identities may have disliked being pooled together with those who do hold them.[24] This would suggest that they are not giving-up on the offered opportunity because their identity is made salient, but because they are grouped together with social categories they have a distaste for. If this were the case, individuals holding more identities would be less reactive to the information disclosed in PUBLIC INFO compared to NO INFO (i.e., treatment effects), and those holding fewer identities would be driving the main results.

To test for this conjecture, I run a difference-in-difference estimation of the treatment effects comparing identity profiles (see Table D-5 in Appendix D).[25] Specifically, I estimate average treatment effects for subjects who hold a *single* identity and for those holding *multiple* identities. Then, I test if the two effects are statistically different (i.e., difference-in-difference estimation). The conjecture is that if a distaste for being pooled

[23] See e.g., Bursztyn and Jensen (2015) for a case of peer influence on educational investments.

[24] Recall that to be eligible for the program, potential participants must hold at least one of the five targeted identities, but some held more than one at a time.

[25] The distribution of identity profiles in the study are as follows: 34.2% held a single identity while 65.8% held multiple identities (40.5% held two, 21.5% held three, 3.75% held four, and 0.006% five). Treatments were balanced in terms of the distribution of identity profiles in both the first wave with high performers (p = 0.321, ANOVA test) and the second wave with low performers (p = 0.657, ANOVA test).

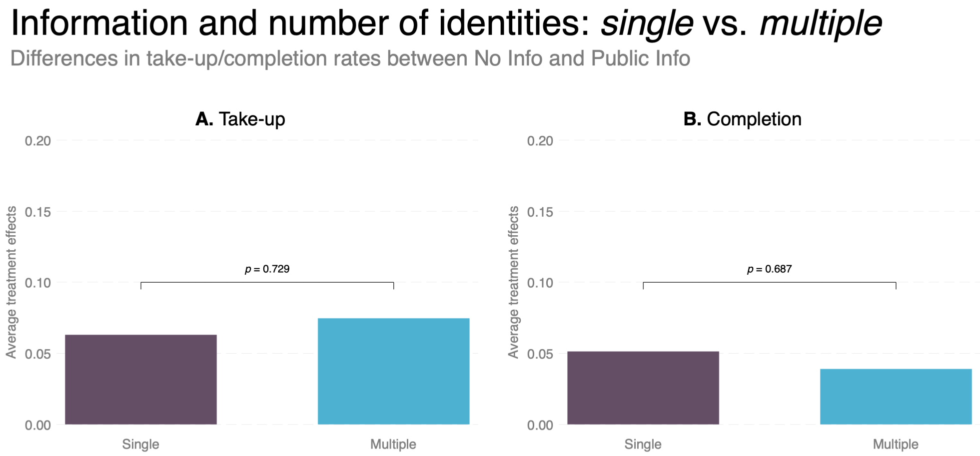

Figure 6 Differences in treatment effects by identity profiles.
The figure illustrates treatment effects on take-up (Panel A) and completion (Panel B) rates, comparing targets holding a single or multiple identities.

with other social groups drives the results, the difference-in-difference estimator would be significant as the difference between PUBLIC INFO and NO INFO (i.e., the average treatment effect) would be larger for those holding a single identity than for the rest.

Figure 6 illustrates the main result and shows that treatment effects on take-up rates are not more detrimental for those holding a single identity than for those holding multiple identities ($p = 0.729$). I run the same analysis separately for each performance group (see Table D-5 in Appendix D) as well as for each of the targeted identities (see Tables D-6 and D-7 in Appendix D) and found consistent results. For example, I estimate the treatment effects for female subjects who hold no other identity (i.e., single) and compare those to females who also belong to other targeted groups (i.e., multiple), and found no significant difference in treatment effects between them ($p = 0.775$). These results are consistent for the rest of targeted identities: rural ($p = 0.127$), middle class ($p = 0.278$), low class ($p = 0.950$), first generation ($p = 0.314$) and ethnic minority ($p = 0.833$).

This suggests that the differences in take-up and completion rates reported in the main analysis are not likely due to people giving up on the program because they dislike to be pooled together with members of other social groups, but because their identities are being publicly targeted.

4.3 Heterogeneous treatment effects on specific group identities

In this section, I assess how differences in information disclosure impacted take-up and completion rates 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. For this, I focus on individuals holding each of these categories, irrespective of whether they hold none or some others. All results in this section are descriptive and are aimed at exploring the potential mechanisms driving the effects of public targeting.[26]

Figure 7 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). A consistent finding can be observed 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 positively to the priming of their identities 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 lead to stigma concerns in most cases and to pride in some others. I address this in the next section.

[26] 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.

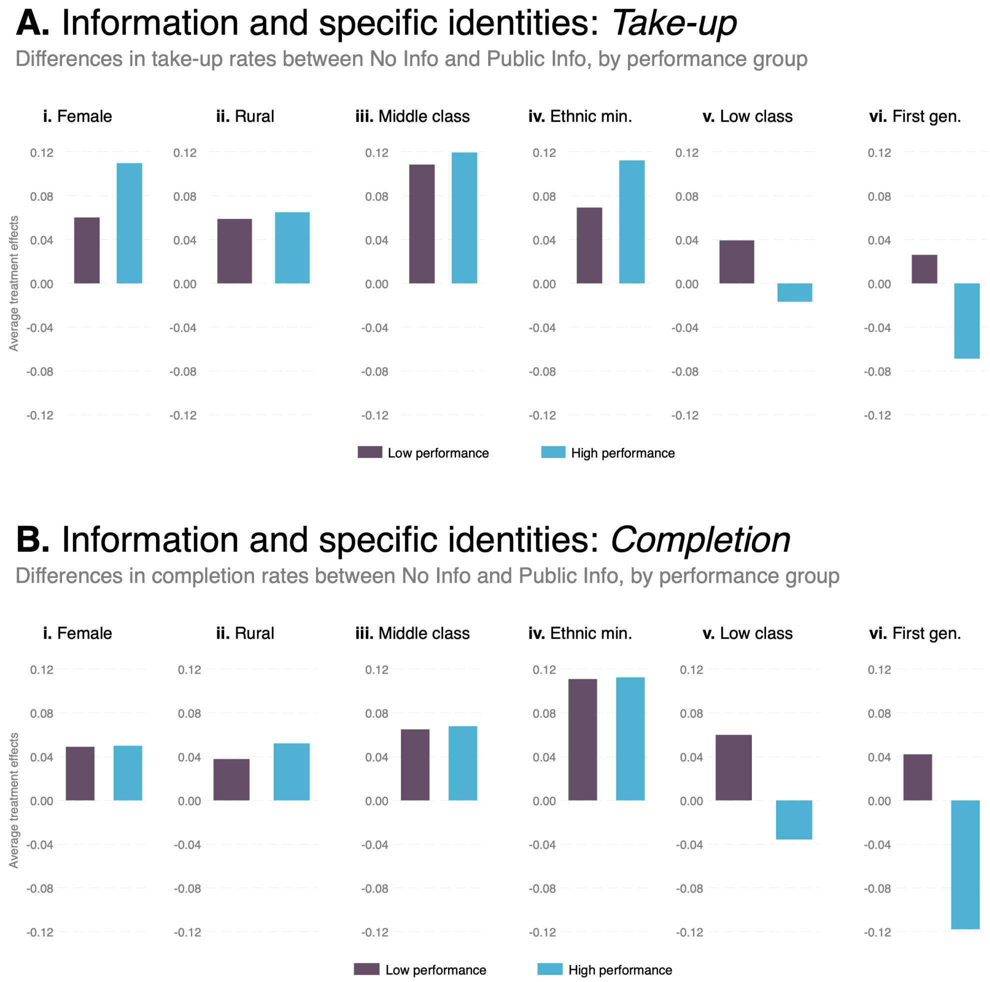

Figure 7 Treatment effects on take-up/completion rates for specific identities.
The figure illustrates gaps in take-up (Panel A) and completion (Panel B) rates between NO INFO and PUBLIC INFO, for each of the group identities targeted for the program, separately for high and low performance groups.

4.4 A survey on abilities of specific identities

To explore why most (but not all) identities are negatively affected by public targeting, I use data from a survey conducted by the partner university with a sample of 1200 students, 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.[27]

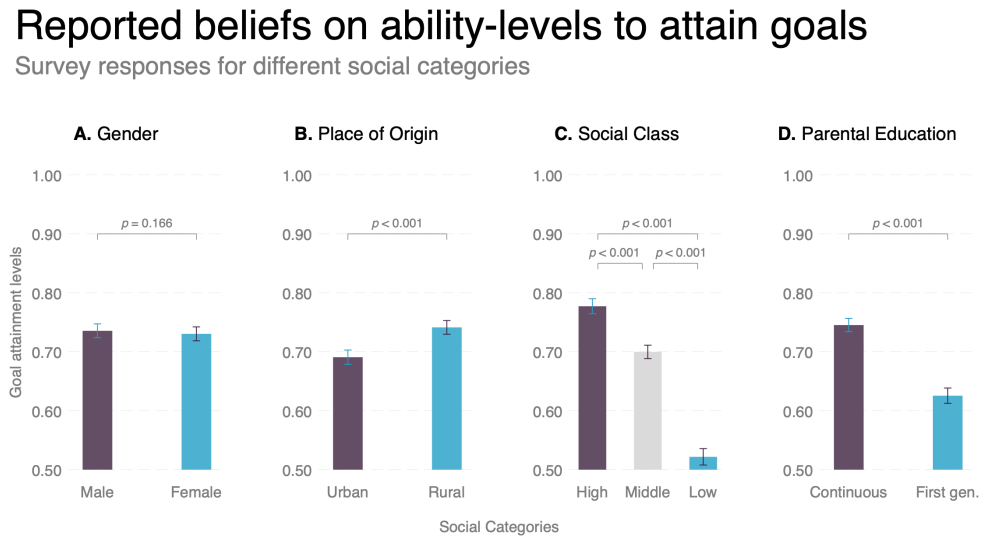

Figure 8 Survey responses on the believed abilities of different social groups.
The figure illustrates the average reported beliefs on the ability different social groups have to attain their goals, normalized between 0 and 1.

A summary of the survey results is illustrated in Figure 8, 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, 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. $74.5\%, p < 0.001$).

The results from the survey provide insights on why the effect of public targeting could activate stigma concerns for female, rural, and middle class students, while it may activate pride for low class and first generation students (conditional on being

[27] 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.

high performers). For the latter set of identities, the negative stereotype is strong: they are expected to underperform. So, publicly targeting their identities in a setting of high performance sends a strong signal of recognition that they have overcome a structural barrier, which can consequently trigger pride.

As such, it appears that public targeting triggers stigma concerns that deter take-up and completion, when there are no clear (or positive) stereotypes of academic disadvantage 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 can trigger pride as it signals that the stereotype has been overcome, potentially promoting program participation.

5 Conclusions

In this paper, I report the results from a 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 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 the opposite result, as it could trigger stigma 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 educational 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 stigma concerns associated to accepting an offer based on their demographics. To reduce this psychological cost, invited individuals 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 participants, which renders 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 allows 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 widely triggers stigma concerns, there are a few cases where it appears to promote pride. 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 individuals are targeted because the social expectation towards them is clearly negative (on top of being objectively disadvantaged, as in my paper). In such a setting, researchers could send signals, in the invitation to the program, indicating that targeted individuals have overcome such a stereotype. This is beyond the current scope of this project and has the potential to shed light on complementary strategies to promote take-up when explicit targeting cannot be avoided.

A second potential avenue of research is to evaluate the power of *program success* to reduce stigma concerns. For example, in my study a total of 1066 participants completed the program, they evaluated it as very beneficial, and their average GPA increased by about 0.06 standard deviations a year after. One could use information like this to create an intervention that shows how attractive and beneficial the program has been, and target again those 3400 students that were invited but chose not to participate. Such an information strategy could tackle any doubts about the quality of the program but also attenuate the potential stigma associated with public targeting, all by showing that many peers actually participated. 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 disadvantaged groups triggers stigma and limits take-up of educational opportunities

Manuel Muñoz-Herrera

A Selected identities

To identify which groups of people are at a disadvantage and could benefit from the program, 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 the 12 semesters preceding the launching of the program.

I have data on the entry exam for a total of 8339 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 replacing 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 categories within social groups. For example, gender (female vs. male), social class (low vs. middle vs. high), parental education (first generation vs. continuous education), origin (rural or urban), ethnic minority (afro-descending or indigenous vs. not). I also include as controls the semester in which the student started college, whether he/she holds a scholarship as well as the academic program he/she is enrolled in.

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 all regressions, I control for the effect of different social categories such as gender, social class, parental education, origin, and ethnic minority. 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, scholarship and starting semester as controls. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Exam score	
	I	**II**
Female	-1.407^{**}	-1.623^{**}
	(0.282)	(0.196)
Low class	-2.795^{**}	-3.865^{**}
	(0.352)	(0.230)
High class	2.878^{**}	3.057^{**}
	(0.453)	(0.315)
First generation	-2.945^{**}	-2.716^{**}
	(0.315)	(0.311)
Rural	-1.417^{*}	-2.272^{**}
	(0.311)	(0.223)
Ethnic	-3.143	-2.866^{**}
	(1.166)	(0.678)
Constant	66.807^{**}	68.787^{**}
	(0.493)	(0.296)
Controls	Yes	Yes
# Obs.	3343	8339
R^2	0.237	0.250

The results show that individuals holding specific 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 social class ($p < 0.001$) and middle class ($p < 0.001$) underperformed when compared to those of high class. In the same direction, the exam scores for first generation students ($p < 0.001$), those who come from rural areas ($p < 0.001$), as well as ethnic minorities ($p < 0.001$) are not up to par with their counterparts.

I use these results to focus the targeting of the program to individuals holding at least one of the following categories: female, low-middle class, rural, first generation, or ethnic minority; as described in Section 2.1 of the main text.

B Invitation Emails

The invitation message below was sent to all eligible students. The original email was sent in Spanish, I include below the English translation. To maintain anonymity about 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 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: The workshop has a limited number of slots and 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: The workshop has a limited number of slots and 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).

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] endorse 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 can benefit from this program, as his/her cumulative GPA is [Student's GPA].
- PUBLIC INFO: I, [Professor's name] endorse 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 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 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 endorsement.

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 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 workshop.

Sincerely,

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

[Signature Person - 2]
Director Social Bee Lab

C Program evaluations

In this section, I present suggestive evidence that the program offered was considered valuable by both faculty and students. For this, I report (i) indications of value from faculty in their email responses, and (ii) program evaluations in the two waves.

C.1 By faculty

All faculty members were informed about the program and their role in endorsing students. So any faculty member considering this was a beneficial opportunity could endorse those students who asked them to. Among those who made an endorsement, 27 (9.5%) also included in their response emails positive messages about the program offered. Below, I include some samples (translated from Spanish to English):

- What a great opportunity for the students!
- Thank you for including us in these important processes for our students.
- 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 By students

The program evaluation was completed by 1066 students, 69% of which belong to the high performance group. Below, I first report the results on the two most relevant questions for understanding the value students assigned to the program. First, "General evaluation of the program", for which answers ranged from 1 "Very deficient", 2 "Deficient", 3 "Adequate", 4 "Good" and 5 "Excellent". The two other items are "The program helped my way of thinking" and "The program was intellectually stimulating", for which answers ranged from 1 "Completely disagree", 2 "Disagree", 3 "Neutral", 4 "Agree" and 5 "Completely agree". For all three items, I combine answers 1 and 2 into a "Negative" category, I relabel 3 as "Neutral", and I combine 4 and 5 into a "Positive" category. Figure C-1 summarizes the responses for these items in the program evaluation.

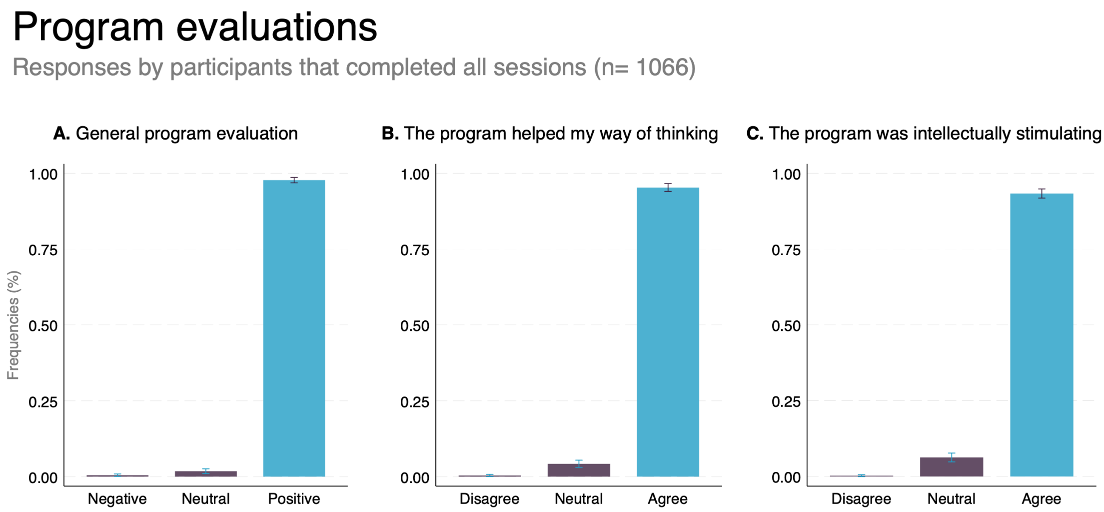

Figure C-1 Responses to the program evaluation.
Responses from three measures: general program evaluation (Panel A), the course helped my way of thinking (Panel B), and the program was intellectually stimulating (Panel C).

In the first case 97.8% of responses evaluated the program as positive. Similarly, 95.2% agreed that the program impacted their way of thinking and 93.3% that the program was intellectually stimulating. Thus, indicating that in line with comments from faculty endorsers, students are very positive about the program.

Table C-1 reports regressions outputs for the items illustrated in Figure 5: "General program evaluation" (column I), "The program helped my way of thinking" (column II), and "The program was intellectually stimulating" (column III). It also reports on a "General evaluation of the instructor" (column IV). All items are evaluated above 4 (in a 1 to 5 scale). Also, I find no effect of treatment variations or performance groups on the way students evaluated the program.

Table C-1 The effect of information disclosure on program evaluations.

OLS regressions with robust standard errors (in parenthesis). The dependent variable is the item evaluated: "general program evaluation" in column I, "the program helped my way of thinking" in column II, "the program was intellectually stimulating" in column III, and "general evaluation of the instructor" in column IV. In all regressions, targeting is a categorical variable for which NO INFO 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.

	Take-up		**Completion**		**Completed steps** *Unconditional*		**Completed steps** *Conditional*	
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
PUBLIC INFO	0.008	0.013	0.058	0.064	−0.023	−0.019	0.027	0.024
	(0.041)	(0.041)	(0.045)	(0.046)	(0.048)	(0.048)	(0.040)	(0.040)
PRIVATE INFO	0.005	0.012	−0.008	−0.005	−0.029	−0.029	−0.009	−0.015
	(0.040)	(0.041)	(0.044)	(0.044)	(0.045)	(0.046)	(0.041)	(0.041)
High perform.	0.003	0.002	−0.017	−0.008	−0.005	−0.002	−0.009	−0.008
	(0.037)	(0.036)	(0.040)	(0.040)	(0.042)	(0.042)	(0.037)	(0.037)
Constant	4.665^{**}	4.583^{**}	4.551^{**}	4.434^{**}	4.580^{**}	4.544^{**}	4.707^{**}	4.565^{**}
	(0.035)	(0.075)	(0.042)	(0.086)	(0.042)	(0.083)	(0.037)	(0.076)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
# Obs.	1063	1063	1062	1062	1062	1062	1063	1063
R^2	0.000	0.012	0.002	0.016	0.001	0.005	0.001	0.010
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

D Regression Tables

D.1 Regressions 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 D-1 reports outcomes pooling both performance groups. Table D-2 focuses only on high performance students. Table D-3 looks at results for low performers. 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 D-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

D.2 Regressions on changes in grade point average

In this section, I report the regression outputs for the welfare analysis on grade point average (GPA) of the students invited to the program. Table D-4 reports outputs of difference-in-difference estimations of those who completed the program versus those who did not, before and after the program was offered. Specifically, the time *after* the program is one semester for the low performance group (second wave) and one year for the high performance group (first wave), as the latter participated in the program during the fall and the former during the spring. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

Note that the analysis only accounts for 3603 of the 4831 students invited to the program.

Table D-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 D-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

This is because the remaining 1228 either graduated in the semester in which they were invited to the program or did not enroll back to the university after it. Due to limitations in the access to additional academic records, I am unable to identify how many students graduated and how many dropped out of college.

Table D-4 Program completion and GPA

Difference-in-difference estimation. The dependent is the GPA of students invited to the program. As time points, I use the semester before and after the program was launched. I compare the effect for those who completed the program versus those who did not ,pooling all invited students in column I, those from the low performance wave in column II, and those from the high performance wave in column III. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Pooled **I**	High **II**	Low **III**
Time with respect to program			
Diff (After - Before)	-0.101^{***}	0.070^{***}	-0.116^{***}
	(0.010)	(0.011)	(0.014)
Program participation			
Diff (Completed - incomplete)	0.451^{***}	0.169^{***}	0.086^{***}
	(0.036)	(0.034)	(0.028)
Diff-in-Diff	0.055^{***}	0.013	0.106^{***}
	(0.019)	(0.024)	(0.023)
Constant	-0.064^{***}	-0.895^{***}	0.793^{***}
	(0.019)	(0.014)	(0.015)
# Obs.	7206	3488	3718
R^2	0.043	0.017	0.016

D.3 Regressions on distastes towards other social groups

In this section, I report the regression outputs for the heterogeneity analysis on the identities of the individuals invited to the program. Table D-5 reports outputs of difference-in-difference estimations looking at the treatment effects on take-up and completion rates between PUBLIC INFO and NO INFO, comparing individuals holding a single or multiple identities. In complement, Tables D-6 and D-7 report results of differences in treatment effects for each targeted identity, for take-up and completion rates respectively. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

Table D-5 Single vs. Multiple identities by performance group

Difference-in-difference estimation results. The dependent variable is the rate of take-up in columns I-II and the completion rate in columns III-IV. In all regressions, I compare the average treatment effects in take-up/completion rates between PUBLIC INFO and NO INFO, where PUBLIC INFO is the omitted category, for individuals holding a single versus multiple identities. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Take-up			**Completion**		
	Pooled	High	Low	Pooled	High	Low
	I	**II**	**III**	**IV**	**V**	**VI**
Single IDs						
Diff (NO INFO- PUBLIC INFO)	0.063^{**}	0.081^{*}	0.036	0.051^{**}	0.050	0.042
	(0.027)	(0.044)	(0.032)	(0.025)	(0.041)	(0.028)
Multiple IDs						
Diff (NO INFO- PUBLIC INFO)	0.075^{***}	0.070^{**}	0.086^{***}	0.039^{**}	0.028	0.058^{**}
	(0.020)	(0.028)	(0.026)	(0.018)	(0.026)	(0.023)
Diff-in-Diff	0.012	−0.011	0.051	−0.012	−0.021	0.015
	(0.034)	(0.052)	(0.041)	(0.031)	(0.048)	(0.037)
# Obs.	3210	1697	1513	3210	1697	1513
R^2	0.010	0.010	0.020	0.010	0.010	0.020

Table D-6 Take-up by single vs. multiple specific identities

Difference-in-difference estimation results. The dependent variable is the rate of take-up in columns I-II and the completion rate in columns III-IV. In all regressions, I compare the the average treatment effects in take-up/completion rates between PUBLIC INFO and NO INFO, where PUBLIC INFO is the omitted category, for individuals holding a single versus multiple identities. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Female	Rural	Middle class	Low class	First gen.	Ethnic min.
	I	**II**	**III**	**IV**	**V**	**VI**
Single IDs						
Diff (NO INFO- PUBLIC INFO)	0.099^{**}	−0.072	0.075^{*}	0.009	0.257	−0.000
	(0.046)	(0.091)	(0.043)	(0.081)	(0.287)	(0.427)
Multiple IDs						
Diff (NO INFO- PUBLIC INFO)	0.084^{***}	0.074^{***}	0.130^{***}	0.004	−0.036	0.093^{**}
	(0.023)	(0.028)	(0.028)	(0.031)	(0.046)	(0.092)
Diff-in-Diff	−0.015	0.146	0.055	−0.005	−0.293	0.093
	(0.051)	(0.095)	(0.051)	(0.087)	(0.290)	(0.437)
# Obs.	2069	1096	1511	1002	471	90
R^2	0.010	0.010	0.020	0.010	0.010	0.030

Table D-7 Completion by single vs. multiple specific identities

Difference-in-difference estimation results. The dependent variable is the rate of take-up in columns I-II and the completion rate in columns III-IV. In all regressions, I compare the the average treatment effects in take-up/completion rates between PUBLIC INFO and NO INFO, where PUBLIC INFO is the omitted category, for individuals holding a single versus multiple identities. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels.

	Female	Rural	Middle class	Low class	First gen.	Ethnic min.
	I	**II**	**III**	**IV**	**V**	**VI**
Single IDs						
Diff (NO INFO- PUBLIC INFO)	0.067	−0.027	0.050	0.057	0.057	−0.000
	(0.042)	(0.084)	(0.039)	(0.075)	(0.266)	(0.403)
Multiple IDs						
Diff (NO INFO- PUBLIC INFO)	0.043**	0.052**	0.072***	−0.007	−0.051	0.113**
	(0.021)	(0.026)	(0.026)	(0.029)	(0.043)	(0.087)
Diff-in-Diff	−0.024	0.079	0.022	−0.064	−0.109	0.113
	(0.047)	(0.088)	(0.047)	(0.080)	(0.270)	(0.412)
# Obs.	2069	1096	1511	1002	471	90
R^2	0.010	0.010	0.010	0.000	0.010	0.030

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.

Welcome. 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